How do Behavioral Approaches to Increase Savings Compare? Evidence from Multiple Interventions in the U.S. Army

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September 2022

Abstract

Information provision, choice simplification, social messaging, active-choice frameworks, and automatic enrollment all increase retirement savings. However, gauging the relative efficacy of these approaches is challenging because the supporting evidence spans widely different institutional settings, populations, and time periods. In this study, we leverage experimental and quasi-experimental variation in a constant setting, the U.S. military between 2016-2018, to examine the effects of nearly two dozen experiments for four leading policy options (i.e., information emails, action steps, target contribution rates, active choice, and automatic enrollment) designed to increase retirement savings. Consistent with previous literature, we find sizable effects of savings interventions on participation and cumulative contributions that increase with the intensity of the intervention. We then exploit cost data to complete the first cost-effectiveness analysis in the literature. Our analysis suggests that active choice programs are the most cost-effective method to generate new program participation and contributions for small, medium, and large firms, while automatic enrollment is more cost-effective for very large firms.

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1. Evaluating the Relative Effectiveness of Retirement Savings Programs

A majority of Americans who are approaching retirement age have little to no money saved for retirement.[1] Over the past two decades, however, behavioral researchers have explored a variety of potential "nudges" designed to increase savings including active choice (Carroll et al., 2009), automatic enrollment (Madrian and Shea, 2001, Choi et al., 2006, 2004), automatic escalation (Thaler and Bernartzi, 2004), behaviorally informed messaging (Benartzi et al. 2017, Choi et al., 2017; Goda, Manchester and Sojourner, 2014), simplified enrollment options (Beshears et al. 2013), and actionable education (Skimmyhorn, 2016). This work has been at the forefront of the broader behavioral economic and financial literature (Madrian 2014, Madrian et al. 2017), and it has been especially influential on national-level policies (Beshears et al. 2009).[2]

Validating, comparing, and potentially selecting from among these different approaches is difficult for two reasons. First, existing studies differ significantly in their samples (e.g., demographics), firm characteristics, study periods, and outcomes—each of which can meaningfully alter the impact of the policy intervention. As a result, while extant research documents impactful policies in disparate samples, it remains unclear which policies are most effective. Ideally, a researcher could create direct comparisons between interventions by randomly assigning individuals from a large population to each of these approaches at the same time. In this study, we take advantage of a setting that nearly replicates this ideal framework.

Second, the existing literature has very little to say about the cost-effectiveness of various policies. Benartzi et al. (2017) note that despite relatively small absolute effects, "nudges" may be more cost-effective than traditional policies such as tax incentives in a variety of policy domains including retirement savings, but "more calculations are needed to determine the relative effectiveness of nudging." Yet to our knowledge, there is no evidence of the relative cost-effectiveness of widely varying behavioral policies to encourage retirement savings. We study leading policy options in a setting that affords the use of cost data to inform policy choices under budget constraints.

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[1] Morrissey (2016) finds that the medium U.S. family with a head of household aged 56-61 only has $17,000 in retirement account savings and that fewer than 50% of black and Hispanic households have any retirement account savings. Jeszeck et al. (2015) document similar statistics in their GAO report.

[2] See Beshears et al. (2018) for a review.

In this study, we examine the relative efficacy and cost-effectiveness of four leading policy options designed to promote retirement savings: behaviorally informed messaging, provision of target retirement savings rates, active choice enrollment, and automatic enrollment. We leverage two randomized field experiments and two natural experiments at one of the nation's largest employers (the U.S. Army) that exploit the largest samples to date (i.e., varying from approximately n=29,000 to n=164,000), that afford the use of high-quality administrative data and that rely on very similar workplace conditions. Without a doubt, our sample is unique relative to the full working population, both in firm and employee characteristics. However, both of these features may prove to be strengths. The relatively homogenous nature of the Army's locations and work requirements strengthen our ability to hold constant the institutional setting. Our sample is younger, with lower tenure, moderately educated, and with lower incomes than the full U.S. population, but these characteristics may reflect more closely the population of interest for retirement savings interventions (i.e., the lower tail of the savings distribution who are unlikely to save on their own, see e.g., Thaler and Benartzi (2004), Carroll et al. (2009), Madrian (2014)).[3] Taken together, these features enable us to hold constant the institutional setting and produce new and comparable estimates of program effects and cost-effectiveness.

In our main estimates that use a sample of new (i.e., first-term) service members, we find that light-touch email interventions (i.e., information, action steps, and contribution rate targets) increase employer-sponsored defined-contribution retirement plan participation by 0.5-0.8 percentage points (pp) relative to a control group (9-13% effect sizes), and the latter two behavioral interventions are sometimes distinguishable from information alone. Programs that involve additional individual interactions and personal selections (i.e., active choice) increase contributions by an additional order of magnitude, to 11pp (100%), and they are distinguishable from the control group and all of the light touch interventions. Automatic enrollment has much larger effects of 79pp (1000%), which are statistically different from all of the other programs. We observe similar effect sizes and patterns when we analyze the effects on contribution rates and cumulative contributions. In Appendix B, we analyze a larger sample that includes both new

[3] The military is also a sample of independent interest given the role of the all-volunteer force in the nation's security, its own federally mandated compensation and pension plans, and previous national-level commissions (e.g., the Hook Commission of 1948, the Zwick Commission of 1978, and the most recent Military Retirement and Modernization Commission of 2015) and programs (e.g., the Uniformed Services Retirement Modernization Act of 1974, policy changes in multiple National Defense Authorization Acts, and most recently, the Blended Retirement System) focused on military compensation and servicemember welfare.

and more tenured service members (i.e., those with more than three years of service) and find very similar results.[4] Overall, our results follow our intuition and validate the existing literature, which establishes that effect sizes grow in magnitude with the intensity of the intervention. Our detailed analysis of program efficacy by individual characteristics suggests that who benefits most from retirement interventions differs by treatment: light touch interventions are most effective for older individuals, active choice is most effective for whites and females, and automatic enrollment is most effective for young individuals, non-whites, males, non-married and those with no college. However, none of these differential effects overcomes the large differences in main effects – automatic enrollment induces larger effects for all groups than any other program for any subgroup.

Our cost-effectiveness analysis provides new and straightforward evidence on retirement savings policies for firms facing cost constraints or who wish to maximize the marginal effect of their policies. Our main results suggest that active choice programs are the most cost-effective method for small-sized firms to generate new program enrollments, at a cost of $10.70 for a new participant and $0.02 for a new dollar of contributions. Automatic enrollment, however, is the most cost-effective method for large and very large firms, including the organization we study (the Department of Defense), which can amortize the implementation costs over larger numbers (with estimates from $8 down to $0.01 for a new participant). The critical values for firm size when automatic enrollment becomes more cost-effective than active choice range from n=394 to n=1945) based on the outcome of interest and on assumptions about program costs.

Our paper proceeds as follows. In Section 2, we review the retirement savings literature and identify our contributions. We discuss our institutional setting and the four experiments we analyze in Section 3, and we summarize the data in Section 4. We present our results on program effectiveness in Section 5 and cost-effectiveness in Section 6. In Section 7, we conclude.

2. Literature Review

Our paper contributes primarily to the retirement savings literature, but also to the wider

[4] Since the Army implemented automatic enrollment for newly enlisted servicemembers, we can only estimate its effects for our first-term sample. We report the results from this sample in our main analysis of first-term soldiers and for completeness, in our expanded analysis of first-term and more tenured servicemembers (see Appendix B).

behavioral economics literature and the scientific literature on the value of replication. For simplicity, we focus our review of the retirement savings interventions primarily on new enrollments, and we classify these interventions into three categories: information nudges, active choice, and automatic enrollment.[5]

Information nudges include a large number of light-touch interventions that encourage retirement savings via information provision. These interventions might be traditional (e.g., a program benefits brochure or email) but are more frequently "behavioral" in leveraging psychological insights related to salience, simplification, reminders, and/or suggestions. The cues studied by Choi et al. (2017) have no statistically significant effect on participation or contributions, except for low target anchors reducing contribution rates (1.15pp, 41%) approximately six months after implementation. Bernartzi et al. (2017) study the effects of various messaging approaches including language related to framing, action steps, interest rate clarifications, and tax savings salience. Their interventions increased both program enrollment (0.72pp, 66% effect magnitude) and contribution amounts ($1.94), but the analysis only extends to one month after implementation. We study this same program and outcomes in a similar setting, and we are able to do so at longer horizons. In a slightly different program, Choi et al. (2009) and Beshears et al. (2013) study the effects of Quick Enrollment, which provides an employee with a pre-selected contribution rate and asset allocation. This program increased participation rates (15-20pp) and contribution rates (0.5pp). Similarly, Goldin et al. (2017) show that providing target contribution rates to military servicemembers increases enrollment (0.64pp, 33% effect magnitude) and contribution rates (0.05pp, 33% effect magnitude) after one month. We expand on their work by extending the analysis horizon in a similar setting. In related work, the Office of Evaluation Science (2017) find no effects of a 5% rate prompt on employee contributions at or above this rate for Department of Treasury employees.

Active choice programs promote retirement savings by encouraging (or requiring) employees to make retirement savings decisions related to contribution rate(s) and asset allocations, often during onboarding processes. Carroll et al. (2009) estimate large effects of these programs on the participation margin (23pp, 43% effect magnitudes) and contribution rates (1.3pp, 35% effect magnitudes) one year after implementation. In related work, Skimmyhorn (2016) shows that

[5] Some scholars use the term "nudge" to describe virtually all "behavioral" (or non-traditional) interventions. See, for example, Thaler and Sunstein (2008).

"actionable education," which combines financial education with enrollment assistance (e.g., distributing enrollment forms, answering questions, and collecting and submitting forms) has even larger effects on participation (15pp, 125% effect magnitude) and average monthly contributions ($19.93, 115% effect magnitude).

Finally, under automatic enrollment programs, an employer defaults individuals into participating in the firm's retirement savings plan. Studies on automatic enrollment document extremely large effects on individual decisions. Madrian and Shea (2001) find that automatic enrollment significantly increases participation (50pp, 135%) and contribution rates (1.14pp, 43% effect magnitude) for employees after 3-15 months. Choi et al. (2004) find very similar effects on participation (45-56pp, 90-144% effect magnitude) after 12 months but smaller effects on contribution rates (-0.19-0.55pp, -9-17% effect magnitudes) at the longer outcome horizons up to 35 months.

While there exists an impressive body of research on "behavioral" strategies to increase retirement savings, our review identifies some important limitations that the current research hopes to address. First, existing studies vary widely by firm type (e.g., technology to finance to military), participant demographics (e.g., gender imbalance, non-representative incomes), institutional features (e.g., matching), and time periods (i.e., from 1997-2016). These differences leave unanswered the generalizability of any specific study's findings to other settings. We are able to evaluate the effects of multiple interventions in a more constant setting.

Second, previous studies have estimated program effects on different outcomes (i.e., participation rates, contribution rates, and contribution amounts) and at different time horizons (e.g., 1 month through several years). We have attempted to mitigate some of the latter differences by reporting estimates from a reasonable and constant time horizon (6 months) in existing studies when possible. Nonetheless, assessing program effects across these outcomes proves difficult without better information on the full distribution of contribution rates (including non-participants) and incomes within each firm/study. Attempting to rank order the effectiveness of programs proves even more difficult as it requires detailed data on the precision of estimates throughout the distributions, which is often unavailable in published studies or supplementary results. In the present study, we will estimate program effects on the same outcomes for the maximum feasible horizon (6 months), and we will consistently test for differential effects across treatments.

Third, there is virtually no cost data or cost-effectiveness analysis in any of the published studies. One notable exception is Bernartzi et al. (2017) who provide the first rigorous cost-effectiveness analysis of traditional policies (e.g., tax incentives, information) vs. a single behavioral policy (e.g., nudges). They also conclude that more work should focus on the cost-effectiveness of different nudge policies. We include in our study a scientific replication of their results and additional cost-effectiveness analyses to provide more insight into optimal policy selection with respect to retirement savings.

Nonetheless, several review articles identify important themes from this line of research. Beshears et al. (2008) review the research related to default options and suggest that a combination of reduced complexity (defaults simplify and decouple decisions), procrastination, and an endorsement effect drive the large effects. Choi et al. (2004) review the effects of both behavioral and more traditional methods on 401(k) decisions and conclude that individuals often follow the 'path of least resistance.' In addition to their empirical results cited above, Carroll et al. (2009) develop a model of retirement savings plan enrollment decisions. Their results suggest that active choice may be optimal in settings with procrastination and/or heterogeneous savings preferences, while default enrollment may be optimal in settings with low financial literacy. This optimality relies on aggregated individual utility functions but ignores the effectiveness and cost-effectiveness of the policies. Madrian (2014) argues that behavioral findings related to the role of psychological biases (on retirement savings and elsewhere) motivate expanded thinking about market failures, and revised thinking about the effectiveness of traditional policy tools. She identifies one motivation for our current work, noting, "the academic literature has given little consideration to what constitutes an optimal default" (p.670). Similarly, Madrian et al. (2017) document the effects of "systematic psychological tendencies" and identify a number of behavioral approaches that have or may increase retirement savings (e.g., simplification, active decision-making, behaviorally informed messages), but the review leaves unanswered which approaches are the most effective and cost-effective. Their work highlights the value of research such as ours, noting that experiments and pilot programs within the federal government have significant potential to help our scientific understanding of the relative efficacy of different policies and to serve as a model for wider adoption in public and private employment settings. Given recent evidence on the failure of many behavioral "nudge" strategies to replicate at scale (DellaVigna and Linos 2022, Bird et al., 2021, Nudge Factor 2022, Hauser, Gino and Norton

2018), the research provides timely evidence on a mature and policy-relevant literature.

Finally, a growing body of research documents substantial inequality in retirement savings and wealth by race and ethnicity (Derenoncourt et al. 2022, Advisory Council on Employee Welfare and Pension Benefit Plans 2021, Smith 2020, Yoong et al. 2019, United States Office of Personnel Management [OPM] 2010, Ariel/Hewitt 2009), gender (Advisory Council on Employee Welfare and Pension Benefit Plans 2021, John 2010), and income (Hemel and Rosenthal 2021, Saad-Lessler, Ghilarducci, and Reznik 2018, Dushi and Iams 2015), but the role of prominent retirement savings enrollment programs in explaining these gaps or narrowing them has been relatively understudied. Existing research has identified a number of contributing factors to these disparities, but we focus our attention here on differences in savings behavior: racial and ethnic minorities, women, and low-income workers all have low defined contribution plan participation rates and, conditional on enrollment, low contribution rates (Choukhmane et al. 2022, Young et al. 2019, Dushi and Iams 2015, U.S. OPM 2010, Ariel/Hewitt 2009, John 2010).[6] Our large and demographically diverse sample enables us to provide new evidence on the differential effects of prominent behavioral strategies on enrollment and participation decisions of these important groups.[7]

We conclude our summary by noting that a common goal of much of this research is to improve policy design. We share this goal and believe that our ability to compare leading interventions quantitatively, both in their effectiveness and cost-effectiveness, can improve policy responses related to retirement savings.

3. Background on Retirement Savings Interventions

Our setting exploits experimental and quasi-experimental variation in enrollment policies generated by deliberate randomized controlled trials or differential policy exposure in the

[6] Other important factors in this literature include income (Saad-Lessler, Ghilarducci, and Reznik 2018, Dushi and Iams 2015), historical wealth conditions, income growth and capital returns (Derenoncourt et al. 2022), individual characteristics and liquidity needs (Choukhmane et al. 2022), and the tax code (Choukhmane et al. 2022, Hemel and Rosenthal 2021).

[7] Existing research on automatic enrollment (e.g., Madrian and Shea 2001) documents larger program effects for racial/ethnic minorities, women, and low-salaried individuals. Research on active choice suggests smaller effects for women (and no data by race/ethnicity) (Carroll et al. 2009). Neither of these studies can compare differential effects across programs. In related work, Young et al. (2019) find no differential effects of a default allocation by race/ethnicity in a hypothetical asset allocation problem, and John (2010) describes how automatic enrollment is differentially effective for racial/ethnic minorities without providing any new empirical evidence.

world's largest defined-contribution (DC) retirement savings plan.[8] From April 2015 through January 2018, the White House Social and Behavioral Sciences Team (WHSBST), the Department of Defense (DOD), and the Department of the Army (DA) implemented four experimental interventions designed to increase military servicemembers' contributions to their Thrift Savings Plan (TSP) retirement account- their employer-sponsored retirement account akin to a 401(k) for most employees.[9] The TSP offers tax-advantaged (traditional or Roth) savings in a variety of low-cost index investment funds (i.e., government securities, fixed-income, common stock, small-cap stock, international stock, and lifecycle target date funds that combine the five primary funds). Military servicemembers are also eligible for a defined benefit (DB) retirement, which was cliff-vested at 20 years of service prior to January 1, 2018 and has since expanded to a blended system with DC and DB components.[10]

Previous reports (Bernartzi et al. 2017, Goldin et al. 2017, Office of Evaluation Science 2015a, 2015b) suggest that these interventions can yield reliable estimates of the program effects, and we analyze the effects among active-duty military servicemembers in the U.S. Army.[11] In our primary analysis, we rely on a sample of new servicemembers (i.e., serving in their first voluntary enlistment term) to maximize the comparability of our estimates across programs. We describe each intervention below and summarize the combined samples in Table 1. The samples we study are young (mean age is 23), mostly male (85%), racially and ethnically diverse (e.g., approximately 22% black and 16% Hispanic), and moderately educated (e.g., a modal education level of high school graduate, but 17% with more than a high school degree). Their annual income is approximately $35,000 per year, and individual basic pay, used to compute retirement savings contributions, accounts for approximately 64% ($22,476) of the total.[12] We summarize the samples by control and treatment status for each intervention in Table

[8] As of December 31, 2018, the TSP had nearly $559B in assets under management. See the 2018 annual report at: https://www.frtib.gov/ReadingRoom/FinStmts/TSP-FS-Dec2018.pdf. For additional information on the TSP and its size, see: https://www.tsp.gov/thirty/.

[9] The TSP serves as the employer-provided defined contribution plan for federal employees, including military servicemembers. For more information, see https://www.tsp.gov/PDF/formspubs/tspbk08.pdf.

[10] For a summary of the new blended retirement system (BRS), see: https://militarypay.defense.gov/Portals/3/Documents/BlendedRetirementDocuments/A%20Guide%20to%20the%20Uniformed%20Services%20BRS%20December%202017.pdf?ver=2017-12-18-140805-343

[11] The first two interventions were conducted across all four military services (i.e., Air Force, Army, Navy, and Marine Corps), but we focus our analysis on the Army based on data limitations, and to ensure greater comparability of our estimates with interventions 3 and 4.

[12] Military compensation consists of several components including pay (basic, special, and incentive) and allowances. We observe and compute an estimated total pay (annual income) as the sum of the largest of these

2. We observe balance across characteristics within each intervention and similarity across interventions as well.

3.1 Intervention 1: Behavioral Messaging

The first of these interventions is a randomized controlled trial (RCT) conducted by the WHSBST, the DOD, and Benartzi et al. (2017). This study randomly assigned 806,861 servicemembers across the Air Force, Army, Marines, and Navy who were not contributing to their TSP retirement to one of 10 groups based on the last two digits of their social security number (SSN). These groups, as detailed in Appendix D, include (a) a control group that received no email, (b) a group that received a standard TSP information email with text from the TSP website and no explicit behavioral nudges (hereafter, the Information Email group),[13] (c) eight groups that received a behaviorally motivated email message that presents the contribution choice in three simple steps (hereafter, the Action Steps group).

These action steps include (1) logging into the linked military payroll website, (2) clicking on the link to "Traditional TSP and Roth TSP" contributions, and (3) Entering and submitting the percentage of pay that a servicemember wants to contribute to TSP. In seven of the action steps groups, action steps are paired with some combination of "fresh start" framing, "active choice" framing, "inertia" framing, and "interest rate clarification." In practice, we do not find any significant differences in savings outcomes across the different action step treatments in our sample.[14] We proceed by pooling the action-step treatments into one group in our primary analyses of first-term service members. Randomized treatment (confirmed in columns 3-4 of Table 2) enables straightforward ordinary least squares estimates of program effects.

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components: basic pay (which varies by rank and tenure), basic allowance for housing (BAH, which varies by rank, dependent status, and location), and basic allowance for subsistence (BAS, which varies by officer/enlisted status). See https://militarypay.defense.gov/Pay/ for more information.

[13] The Information Email group received an email (found in Appendix D, group B) that included a brief description of the TSP program, described where to sign up for the TSP, and provided a link for more information. Table 1 columns 1-2 compare the characteristics of those assigned to the control group and Information Email group. While a joint test across treatments is marginally significant (p=0.07), estimates of the effects of the Information Email (not shown) are unaffected by the inclusion of demographic controls. Furthermore, demographic characteristics in the full Army sample balance across control and Information Email treatments (p=0.49; Appendix B Table 1, columns 1 & 2), suggest that randomization was implemented correctly.

[14] One possible explanation for the lack of differences across all of these treatments is that the action steps appear to be the most visually distinct aspect of each of these email messages. As a result, the action steps may dominate a reader's attention in each version of the action steps email.

3.2 Intervention 2: Savings Rate Prompts

In January of 2016, the WHSBST and DOD conducted another large-scale email-based RCT that tested the effect of action-steps emails and *rate-prompt* emails: messages that informed servicemembers that other servicemembers were contributing a certain percentage or more of their basic pay to their TSP accounts.[15] Researchers randomly assigned 699,674 servicemembers across the Air Force, Army, Marines, and Navy who were not contributing to their TSP retirement to one of 10 groups based on the last two digits of their SSN. These groups, detailed in Appendix D, include (a) a control group that received no email, (b) an email with identical action steps to those sent in the April 2015 intervention, and (c) One of eight "rate prompt" emails. In each of the rate prompt emails, the servicemember received an email with action steps and the following message: "MANY SERVICEMEMBERS LIKE YOU START BY CONTRIBUTING AT LEAST *X*% OF THEIR BASIC PAY INTO A TRADITIONAL OR ROTH TSP ACCOUNT." In these emails, *X* takes on a value between 1 and 8, based on the last two digits of a servicemember's social security number. In our primary analysis, we pool all the rate prompt emails for simplicity and our estimates can be approximately interpreted as the effect of receiving an email with a target contribution rate equal to 4.5% compared to receiving no email.[16] As with the first intervention, we validate the random assignment (columns 5-6 of Table 2) and estimate program effects using ordinary least squares estimates.

3.3 Intervention 3: Active Choice

In the third intervention, the WHSBST, along with the DOD and US Army, conducted an active choice intervention in the spring of 2016, where newly arriving servicemembers at two military installations (Fort Bragg, NC and Fort Lewis, WA) were required to make a choice whether or not they would begin contributing to their TSP account. At Fort Lewis, all servicemembers arriving between March 14 and April 8 attended an inprocessing meeting in

[15] Goldin et al. (2017) and Goldin et al. (2019) analyze this experiment and document the effects of different contribution rate nudges on savings plan participation and contribution rates. We do not replicate their work here, and instead analyze the average effect of the contribution rate nudges to compare this policy with other behavioral approaches.

[16] In untabulated results, we replicate the findings of Goldin et al. (2017).

which servicemembers were asked to raise their hand if they wanted to begin contributing to the TSP. Those who raised their hands were immediately taken to computers where they were able to enroll in the TSP. At Fort Bragg, servicemembers were required to complete a modified TSP election form, which included a choice between three options: (1)“Yes, I choose to enroll and save," (2)"No I choose not to enroll and save," or (3)"I'm already enrolled." Although these two interventions implement active choice in slightly different ways, we combine both methods in our primary analyses.[17] We analyze this intervention using a difference-in-differences approach that compares the differences in contribution decisions for new service members at these two bases before and after the intervention compared to those of new service members at other bases before and after the intervention. We provide summary statistics for the control and treatment groups in Table 2 (columns 7-8) and note the similarity between groups in their demographic characteristics. We also document parallel trends in an event study for this program in Figure 1.[18]

3.4 Intervention 4: Automatic Enrollment

In January 2018, the Department of Defense (including the Army) implemented automatic enrollment in the TSP for all new servicemembers as part of a new military retirement system.[19] This program changed TSP participation from a default of no TSP contributions (i.e., opt-in) with no matching to a default contribution rate of 3% (i.e., opt-out) of their basic pay.[20] Additionally, BRS-eligible servicemembers receive a 1% agency automatic contribution regardless of whether they contribute.[21] An individual’s own contributions, and resulting

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[17] In untabulated results, we estimate the relative efficacy of the implementations at Fort Lewis and Fort Bragg.

[18] The results in Figure 1 suggest potential contamination of control group members in cohorts t=-5 through t=0. The graph plots program participation six months after arrival, so it is possible that spillovers from the policy change led to increases in contributions in the control group members who in-processed between t=-5 and t=0 and who were made aware of the subsequent changes. Such contamination would mean that our regression estimates are downward biased and therefore conservative.

[19] The military changed to a Blended Retirement System (BRS) that included a defined benefit pension (reduced relative to the legacy pension system), continuation pay (between 8 and 12 years of service), and a defined contribution component (DC) in the TSP. The default contribution rate in the TSP was 3% and applied only to basic pay, excluding special pay and other contributions. This DC plan structure is similar to what federal civilian employees receive. See Beshears et al. (2022) for an analysis of the effects of automatic enrollment on federal civilian employees’ TSP and debt balances.

[20] Basic pay is the standard pay servicemembers receive each month. Many servicemembers are also eligible for a variety of special pays and allowances, depending on location, housing, and occupation.

[21] Two years after entry, servicemembers become eligible for a 100% (i.e., dollar for dollar) match on their first 3% of basic pay contributed, and a 50% match on the next 2% of basic pay contributed. We assume that this future match does not significantly affect the decision to contribute within the first eight months of Army service, as servicemembers can change contribution levels at any time.

earnings vest immediately, but the agency-automatic contributions only vest after two years of service.

We exploit the sharp timing of the discontinuity at the implementation date (i.e., January 1, 2018) to estimate the effects of this program using a difference-in-difference approach. Specifically, we compare the changes in contributions for new servicemembers entering the Army immediately after the BRS system was implemented (January-March 2018) and those entering before the BRS (October-December of 2017) to the differences in contributions for new individuals between the same months in the previous year (January-March 2017 vs. October-December 2016). We note the similarity of demographic characteristics by treatment status in Table 2 (columns 9-10) and provide an event study in Figure 2 to support our identification assumptions of parallel trends.

4. Data

We exploit several, primarily administrative, data sources for our analysis. To estimate the effects of each program, we leverage administrative data from the Army and DOD. This data includes military personnel data (including demographics, location data, and relocation timing data), and DOD payroll data (including monthly TSP contribution amounts).[22]

To estimate the cost-effectiveness of each program, we leverage administrative cost data when possible. We combine the cost data and the program effect estimates to estimate the cost of each new enrollment, dividing total costs by the total number of new enrollments. To our knowledge, this enables the largest cost-effectiveness analysis to date in the retirement savings literature. See Appendix A for more details on our cost-effectiveness analysis (CEA), including sensitivity analysis.

The light-touch interventions (i.e., information, action steps, and target contribution rates) each had a fixed cost of $5,000, related primarily to developing new email content.[23] Cost data was unavailable for the active choice interventions, but we develop a model of total costs to support our cost-effectiveness analysis. Under reasonable assumptions (i.e., we include the labor

[22] We do not observe individual account balances. To the extent that individual accounts experience capital gains, our estimates might be downward biased. To the extent that individuals experience capital losses or make emergency withdrawals, our estimates might be upward biased.

[23] We obtained cost data from program administrators at the WHSBST and the Office of Evaluation Sciences. We validated the cost estimate with the former director of the Federal Retirement Thrift Investment Board, which manages the TSP and was familiar with these and similar programs.

costs for conducting briefings and collecting forms but omit any new costs for materials since the DOD had existing materials related to its retirement programs), the estimated cost is approximately 1.20 per person (one hour of labor at \$30/hour for each briefing to 25 people). We also estimate the costs to implement an automatic enrollment regime based on discussions with firms administering retirement plans.[24] We assume that firms are modifying an existing retirement savings plan to include a new default,[25] that they pay only a fixed cost of \$5,000 for the policy change.[26]

5. Results on Program Effectiveness

In this section, we present program effect estimates for three retirement savings outcomes. For the randomized controlled trials, we provide ordinary least squares estimates of equation 1:

$$y_i = \alpha + \beta Treatment_i + X_i\gamma + \varepsilon_i \tag{1}$$

Where y_i is an outcome of interest: participation in the TSP, the percentage of basic pay contributed to the TSP or the cumulative TSP contributions. We measure these outcomes six months after each intervention. X_i is the vector of covariates described in Table 2 including age, gender, race/ethnicity, marital status, number of dependents, education level, and military personnel category (officer or enlisted) and ε_i is our error term. $Treatment_i$ indicates assignment to one of the retirement savings interventions (i.e., information email, action steps, and target contribution rates). We document valid randomization in Table 2 and so β reflects the causal effect of each program.

[24] Our most reliable source for the \$5,000 estimate to implement automatic enrollment came from the former Director of the Federal Retirement Thrift Investment Board, which manages the TSP. This is our preferred estimate given his expertise and knowledge of the systems and organizations. In addition, during 2019 we contacted approximately half a dozen employee benefit provider firms to obtain their estimates for implementing automatic enrollment at a firm with an existing retirement plan. While there was some variation in their estimates, often due to considering matching costs, the \$5,000 seemed reasonable to most of them.

[25] Costs for establishing a new employer-provided plan would differ and could be significantly higher. Note that these are implementation costs, and do not affect any costs to the employer to match employee contributions.

[26] While firms might pass some or all of these costs on to employees via fees, we still consider them here as a marginal cost to an automatic enrollment regime. While the costs are likely to be small relative to the costs of the matching funds, they are non-negligible. We explore different combinations of these fees in our sensitivity analysis.

The active choice and automatic enrollment interventions generated differential exposure to treatment by location and time respectively. For these programs, we estimate difference-in-differences models:

$$y_i = \alpha + \beta_1 Treatment_i + \beta_2 Eligibility_i + \beta_3 Treatment_i \times Eligibility_i + X_i\gamma + \varepsilon_i \quad (2)$$

Here β_3 is our coefficient of interest and given parallel trends (see Figure 2 for the automatic enrollment intervention) it reflects the effect of each program.

TSP Participation

We analyze the effects of each intervention on plan participation and provide our results in Table 3. The light-touch email interventions providing information, action steps, and target contribution rates (columns 1-3) increase participation by 0.45 percentage points (pp), 0.57pp, and 0.77pp respectively, and these estimates are statistically significant ($p<0.10$ for information and $p<0.01$ for the latter two). These estimates represent moderate increases in participation rates (9-13%) relative to the control means (5.2%, 5.6%, and 5.9% respectively). These point estimates are not statistically distinguishable from one another, but the differences in their magnitudes are suggestive that the use of action steps or target contribution rates were the most effective of the light-touch interventions. Since this pattern holds for our other outcomes, we focus our attention on the action steps intervention when referring to the light-touch interventions in our effectiveness and cost-effectiveness analyses. Our action step estimates (95% CI [0.26pp, 0.88pp]) include the Bernartzi et al. (2017) estimates of 0.72pp, despite slightly different time horizons (1 month vs. 6 months for ours) and sample (all DOD servicemembers vs. Army members for ours). Our target contribution rate estimates (95% CI [0.38pp, 1.16pp]) include those of Goldin et al. (0.64pp) despite the same differences.

The active choice intervention (column 4) increases participation by an order of magnitude over these interventions, and by 11.22pp over the control group, a 100% effect size that is statistically significant ($p<0.01$). Our results are slightly smaller than Carroll et al. (2009), who estimate an effect of 23pp in a different sample (i.e., with more income, tenure, and female employees), and with matching contributions.

Automatic enrollment (column 5) increases participation even more, by 79.02pp relative to the control group, a roughly 1000% effect size that is an order of magnitude larger than active choice and statistically significant (p<0.01). Large effects are unsurprising given the existing literature on the power of defaults, however, our estimates stand out. Our results (95% CI is [78.10pp, 79.98pp]) are much larger than the effects found in Madrian and Shea (2001) and Choi et al. (2004), which range from 49pp-50pp. These larger effect sizes are driven by lower baseline contribution rates in our sample relative to the other studies (in which baseline participation rates are above 85%). These differences in baseline contribution rates across studies highlight important ways that our sample differs from most studies in which automatic enrollment has been studied. In particular, our sample is relatively younger, less educated, lower-earning, more racially diverse, and more likely to be male.

Taken together these results suggest that more intensive (and seemingly paternalistic) interventions increase TSP participation more. This relationship echoes previous findings in the rank orderings, though at slightly lower levels for nudges and active choice interventions and higher levels for defaults. These differences might arise from our younger samples, the absence of matching contributions, and/or the presence of the military's defined benefit pension.

TSP Contribution Rates

We estimate treatment effects on individual contribution rates in Table 4. The information email has a small positive effect of 0.01pp on contribution rates that is not statistically significant. Action steps and target contribution rates increase the percentage of pay contributed by 0.03pp (11%) and 0.04pp (15%) respectively, and these results are statistically different from the control group (p<0.01). We cannot rule out equal treatment effects across these light touch interventions. We forego benchmarking our action steps estimates, as few studies analyze this margin. The 95% CI for our target rate intervention [0.01pp, 0.07pp] includes the 0.05pp estimates of Goldin et al. (2017).

The active choice intervention increased contribution rates by 0.44pp (78%), and the estimate is statistically different from the control group and all three low-touch interventions (p<0.01). Our estimates (95% CI [0.22pp, 0.66pp]) are smaller than the 1.3pp estimate of Carroll et al. (2009) as they were for the participation analysis. Finally, we find that defaults increase contribution rates by 2.50 pp (873%, p<0.01). As with the participation margin, the program effect magnitudes for contribution rates increase with the intensity of the intervention.

TSP Contributions

We present estimates for cumulative contributions after six months in Table 5. Providing information increases the average total contributions after six months by a statistically insignificant \$2.16 (an 8% effect size). Providing action steps and target rates increase cumulative contributions by \$3.60 (12%) and \$4.75 (15%) respectively ($p<0.01$ for both). Action steps and target rates are statistically distinguishable from the information email and from one another. We are unable to compare these estimates to previous studies, as they do not include estimates on this outcome. Our action step estimates (95% CI [\$1.56, \$5.62]) are smaller than our adaptation of the Bernartzi et al. (2017) estimates (\$11.64).[27]

The active choice intervention increases total contributions by \$49.76 after six months, an 86% effect size that is distinguishable from the control group ($p<0.01$) and the behavioral email interventions ($p<0.01$). We forego benchmarking these results to Carroll et al. (2009), who do not analyze balances. Finally, automatic enrollment increases accumulated dollars by \$213, a 705% effect size that is significantly different from the control group ($p<0.01$) and from all other treatments ($p<0.01$). Madrian and Shea (2001) and Choi et al. (2004) do not estimate program effects on unconditional balances and so we are unable to benchmark these results. Overall, these results follow the patterns for the participation and contribution rates, with increasing effect magnitudes based on the intensity of the intervention.

Extension1: Heterogeneity of Treatment Effects

We analyze whether each of our treatment effects on TSP participation differs by age, race/ethnicity, sex, marital status, and education in Table 6. Our results suggest several important patterns in treatment effectiveness. First, in columns 1 and 2, we divide our entire sample in half by age. Panels A-C suggest that information email nudges are most effective among older individuals in our sample (with point estimates at least twice as large for the older participants as the younger participants).[28] This may be because young people spend less time on

[27] Benartzi et al. (2017) estimate an effect of \$1.94 after 1 month. \$1.94 x 6 months = \$11.64.

[28] Differences in participation by younger and older are statistically insignificant for the baseline treatment and action steps, but significant for rate prompts ($p<0.10$).

email than older people do.[29] In contrast, active choice has similar efficacy across age groups and automatic enrollment is more effective for younger individuals ($p<0.01$).

In columns 3 and 4 of Table 6, we estimate the efficacy of each treatment for both non-white and white individuals in our sample. Among non-white individuals, we find that automatic enrollment is significantly more effective (about 2pp or 3%, $p<0.05$). Active choice appears to be less effective for non-whites relative to whites, though the difference is not statistically significant. Otherwise, while the effects of the light touch interventions (action steps and rate prompts) appear to be larger for non-white individuals, the differences are not statistically significant.

While we do not find any differences in treatment effects by sex for any of the information nudges, we do find differences in the effects of active choice and default treatments by sex in columns 5 and 6 of Table 6. Although statistically insignificant, the active choice effects are nearly twice as large for women as they are for men. In contrast, men are more affected by automatic enrollment treatment than women (about 8pp or 12%, $p<0.01$).[30]

In columns 7 and 8 of Table 6, we examine how the effect of each behavioral intervention varies by marital status. In general, we find similar patterns in our divisions by age, which may be unsurprising given the correlation between age and marital status in our sample (older individuals in our sample are nearly three times as likely to be married as younger individuals). However, the differences by marital status are only significant in the default treatment.

Finally, in columns 9 and 10 of Table 6, we compare the responsiveness to treatments by education status. In each of our email nudge treatments, we find that those with at least some college experience are much more likely to respond. The baseline treatment effects for those with more education are large but statistically insignificant, but the Action Steps and Target Rate treatments increase participation by approximately an order of magnitude for these individuals ($p<0.10$ and $p<0.01$ respectively). Active Choice also has a much larger effect for those with more education (about 16pp or 180%, $p<0.01$). In contrast, we find that those with no college experience are much more likely to participate under defaults than those with at least some college experience about 10pp or 13%, $p<0.01$).

[29] See, for example, Perez (2016), NTIA (2018), and Pew (2010).
[30] Our differential effects for active choice among women are opposite of those found in Carroll et al. (2009).

The differences we observe across programs by age, race/ethnicity, sex, and education highlight how the effectiveness of behavioral interventions might vary by research setting. They also demonstrate the importance of holding the context and population constant when comparing the efficacy of different programs designed to increase retirement savings. Our evidence suggests that automatic enrollment is the most efficacious enrollment program in reducing retirement savings disparities by gender and racial/ethnic minority status.[31]

Extension 2: Alternative Sample Including New and More Experienced Servicemembers

In Appendix B, we analyze an alternative group of enlisted Army members that includes all first-term servicemembers (as above) and more tenured service members (i.e., those serving in second or higher terms of service). This increases our sample sizes and the demographic representativeness of our sample, but might reduce the comparability across settings, since the more tenured individuals were negatively selected into treatment as previous non-savers.[32] Our summary statistics (Table B2) demonstrate valid experimental variation and the results are quantitatively and qualitatively very similar to our main estimates. Specifically, all of our estimates from the larger sample fall within the 95% confidence intervals from our main estimates. Note that the estimates for active choice are slightly smaller than in the full sample and that the effect sizes for all interventions are slightly larger since the control group means are typically smaller for the sample that includes more individuals who had previously chosen not to save in the TSP.

Extension 3: Treatment Effects on the Distribution of Contribution Rates

Our data enable a detailed analysis of the effects of each program on the contribution rate distribution. In Figure 3 we plot the fraction of the total participation effect (y-axis) that occurs at each payroll contribution rate (P%, on the x-axis).[33] The results suggest that the rate prompts

[31] The direction of these differential effects for automatic enrollment follows the evidence from Madrian and Shea (2001) and the comments from John (2010).

[32] The selection criteria for the WHSBST and DOD interventions was previous non-participation in the TSP. These individuals are likely to be less receptive to any given retirement savings intervention, and they may have received multiple treatments during their service. This concern does not apply to our main analysis of first-term servicemembers. In untabulated results, we augment our main regression specifications with controls for any previous treatment(s). We find very similar results to our main effects, which reassures us about any selection bias.

[33] Specifically, we estimate the effect of the treatment on the probability of contributing exactly P percent of base income to a TSP fund, where P takes on values 1%,2%,…,10%,11+%.

(which varied from 1-8%) induced participation at values corresponding to lower percentage prompts (1-5%). Active choice participation is widely distributed around 5%, whereas automatic enrollment is narrowly distributed at the default contribution rate of 3%.

6. Results on Cost Effectiveness

We estimate the cost-effectiveness for each policy j using the total program costs and total new enrollments according to equation 3:

$$CE_j = \frac{Cost_j}{\#\ Enrolled} = \frac{FC_j + VC_j}{\widehat{\beta_j} \times n_j} \tag{3}$$

Where the total cost to implement the program $(Cost_j)$ is a function of fixed (e.g., content development costs) and variable (e.g., per person administrative fees) costs. $\widehat{\beta_j}$ is the point estimate for intervention j on TSP participation, and n_j is the respective sample size. In our main specifications, the light touch email interventions and automatic enrollment have fixed costs equal to $5,000. Active choice costs are variable, but the cost-effectiveness proves to be a constant value. In Appendix A, we derive the cost-effectiveness functions for each intervention, which enable us to determine the most cost-effective programs (i.e., minimum cost per new enrollment or minimum cost per dollar of new contributions) for any firm size. We estimate these measures for four different firm sizes: small (n=25), medium (n=750),[34] large (n=1000) and the Department of Defense (n=800,000) and present our results in Table 7.

Cost Per New Enrollment

Our Panel A results depict the estimated costs for each new enrollment in the TSP for each of the interventions. For example, automatic enrollment (column 5) costs $5,000 to implement and it increases enrollment by 0.7902pp. For a small firm (n=25), this generates 19.76 new enrollments and the average cost per new enrollment is, therefore, $5,000/19.76 = $253. Note also that the nature of the program costs simplifies our comparisons significantly. Since automatic enrollment has the same total costs ($5,000) as the light-touch interventions

[34] According to the Census Longitudinal Business Database in 2014, the median employee works at a firm with 500-999 employees. We use the midpoint of this range (n=750) as our medium firm size.

(information emails, action steps, and target contribution rates) but much larger effects on enrollment (see Table 2), it is always more cost-effective than these interventions.[35] Specifically, the estimates in column 5 are always lower than the estimates in columns 1-3. This enables us to focus primarily on comparing the cost-effectiveness measures for automatic enrollment and active choice.

Our main estimates suggest that active choice is more cost-effective than automatic enrollment for small firms, at a cost of about $10.70 per new enrollment. However, automatic enrollment becomes more effective for medium, large, and very large firms that can amortize the fixed costs over a large number of employees. For very large firms (including the Department of Defense), automatic enrollment generates a new enrollment for approximately 1 cent. We compute the critical value for the firm size by equating the cost functions for these two programs and estimate that active choice is the most cost-effective policy for firms smaller than n*=592 employees and automatic enrollment is more cost-effective for firms larger than this size.[36] [37] It is also worth noting that the light-touch interventions also become more cost-effective than active choice for very large firms, but they never outperform automatic enrollment given our data on costs.

Cost Per Dollar Contributed

In Panel B of Table 7, we complete a similar cost-effectiveness analysis for the average individual cumulative TSP contributions after six months. Qualitatively our results for new contributions are similar to those for new enrollments. In our baseline scenario, active choice (column 4) remains the most cost-effective for small firms, as well as medium firms, who can generate a dollar of contributions for $0.02 each.[38] Automatic enrollment (column 5) is more cost effective for large and very large firms, which can generate a dollar of contributions for

[35] This result would hold for any level of equal fixed costs or equal marginal costs (e.g., an outreach fee) across these programs. For the light touch interventions to be more cost-effective, one or both of these costs would have to be significantly higher for automatic enrollment.

[36] $CE_{AC} = \frac{\$1.20}{\hat{\beta}_{AC}} = \frac{\$1.20}{0.1122} = 10.70 = \frac{\$5{,}000}{0.7902 \times n^*} = \frac{\$5{,}000}{\hat{\beta}_{AE} \times n^*} = CE_{AE}\,; n^* = 591.6.$

[37] Census data from the Longitudinal Business Database in 2014 suggests that there are 10,869 firms with more than 1,000 employees, and this is a reasonable estimate for the number of firms that might prefer active choice to target contribution rates given the critical value for firm size, n*=592. This applies to approximately 0.21% of firms and 46.3% of employees.

[38] Our main effect and cost-effectiveness estimates for the action steps intervention are very similar to those in Benartzi et al. (2017), suggesting that results from the Army sample can generalize to all DOD military services.

$0.00003. Here the critical value for firm size is n*=973 employees, which is slightly larger but qualitatively similar to the threshold from the enrollment analysis above.[39]

Sensitivity Analysis

We conduct a number of alternative analyses to determine how sensitive the main cost-effectiveness results are to our assumptions about the nature and level of costs in Appendix Tables A2 and A3. Given that automatic enrollment dominates the light-touch interventions, these analyses focus on changes to the costs of automatic enrollment and active choice programs. We adjust the underlying costs to the active choice upwards and downwards by 50% to account for changes to program capacity and/or labor costs. Increasing the capacity for active choice meetings by 50% (or reducing the costs by this amount) increases its cost-effectiveness and makes it cost-effective for more firms at $5.35 per new enrollment and $0.01 per dollar of contributions (with critical values of n*=1,183 and n*=1,945 respectively). Conversely, reducing the capacity for active choice by 50% (or increasing the costs by this amount) decreases the cost-effectiveness of active choice and makes it cost-effective for more firms at $16.04 per new enrollment and $0.04 per dollar of contributions (with critical values of n*=394 and n*=648 respectively). Finally, since automatic enrollment might require additional individual notifications or other marginal costs to implement, we add individual marginal costs ($30) to automatic enrollment, which makes active choice more cost-effective for firms of any size for both outcomes.[40] Overall, our analysis suggests that active choice is typically the most cost-effective policy for small and medium-sized firms and that automatic enrollment is the most cost-effective choice for large and very large firms, with the critical values ranging from n=394 to n=1,945 depending on cost assumptions. To the extent that our automatic enrollment estimates are slightly conservative (based on the estimates from the larger and more tenured sample in Appendix D), it could be more cost-effective for even smaller-sized firms.

7. Discussion

[39] $CE_{AC} = \frac{\$1.20}{\hat{\beta}_{AC}} = \frac{\$1.20}{\$49.76} = 0.0241 = \frac{\$5{,}000}{213.16\times n^*} = \frac{\$5{,}000}{\hat{\beta}_{AE}\times n^*} = CE_{AE}\,; n^* = 972.7$

[40] Given the cost functions, automatic enrollment will only be more cost-effective than active choice for very large firms when the marginal costs remain less than $10.81 (for new enrollments) and $0.01 (for new contributions).

We analyze the relative efficacy of leading policies designed to increase retirement savings in employer-provided plans. While there exists a large literature on potential strategies, choosing from these approaches is hard since the studies have differed significantly in their settings. In this study, we hold the institutional setting constant and study several leading programs in the U.S. Army. We find sizable effects on participation for emails with action steps or target contribution rates (around 9-13%), larger effect sizes for active choice enrollment (99%), and even larger effect sizes for automatic enrollment (over 360%). Our results on contribution rates and cumulative contributions are similar in their magnitudes and positive relationship between the intensity of the behavioral intervention and the observed effects. Together, our results provide several lessons. First, they provide large-scale rigorous validation of existing estimates, which arose from widely disparate settings. In this way they serve as a large-scale scientific replication of much of the existing literature on retirement savings interventions, a unique contribution in economics (Hammermesh 2007) despite the established value of such efforts (Nichols 2017, Hammermesh 2016).

Second, taken together, our estimates suggest that behavioral interventions, even light touch emails, generally outperform traditional information provision. In addition, in all cases, our estimated effect magnitudes appear to increase with the “behavioral” intensity of the intervention: automatic enrollment generates markedly larger effects than active choice, which generates larger effects than behavioral messaging. These lessons, developed while holding the institutional setting constant, further validate policy approaches designed to leverage lessons from psychology.

Our detailed analysis of program efficacy by individual characteristics suggests the importance of analyzing programs in a constant setting since the programs have varying effects on different groups. Equally notable, automatic enrollment has the largest effects on several groups previously documented as experiencing disparities in retirement savings and wealth accumulation: the young, the non-White, the non-married, and those with no college.

The reasons for non-savings are varied (e.g., procrastination, limited attention), they may interact, and they may require different policies to address them (Carroll et al. 2009). Identifying these mechanisms is another line of research worthy of study to develop optimal policy responses, though our setting is not well suited to evaluate the impact of any specific mechanisms. Instead, our setting enables a unique and experimental comparison of several leading policy choices, and we document the importance of considering program costs in addition to program effects.

Our cost-effectiveness analysis provides unique evidence to the existing literature. Our results suggest that active choice is the most cost-effective program for small and sometimes for medium-sized firms and that automatic enrollment is the most cost effective for large and very large firms, including the Department of Defense, the organization from which our study derives. Firms with around 600-970 employees appear to have comparable cost-effectiveness estimates for active choice and automatic enrollment. In addition to our main estimates, we conduct a variety of sensitivity analyses that support this conclusion, and we demonstrate a method (following and extending Bernartzi et al. 2017) for firms or other organizations to estimate their own cost-effectiveness measures in support of retirement savings plan design. Firms might reasonably interpret these employee numbers as cumulative as opposed to a current stock, and thus any firm that expects to have or eventually hire and onboard 600 or more employees will likely find automatic enrollment the most cost-effective program.

Our sample of first-term uniformed servicemembers differs from the full working population in several ways. Most notably, members are younger, more often male, and they have a narrower distribution of education levels. While we control for these observable characteristics and conduct heterogeneous treatment analyses, our sample may still differ from the population of interest in unobservable ways. To expand our analysis to a more representative sample, we analyze a second sample in Appendix B that includes servicemembers of all tenure levels. Our results are very similar to the main analysis, all with the same signs and with point estimates that fall within the original 95% confidence intervals. This analysis leverages a larger and more demographically representative sample, though it is still non-representative. To further address this concern, we completed detailed benchmarking of our results to the current literature and note that in most cases, our effect estimates are comparable to those from non-military settings. Those studies also took place in very unique settings with variability in firm types, sample demographics (e.g., gender imbalance, high salary firms), and over a two-decade period. Relative to this literature, we are able to estimate causal program effects for several leading policies while holding the institutional setting nearly constant and for low and moderate income and education levels, arguably the most policy-relevant group in light of the documented relationships between income and retirement savings decisions (Smith 2020, Saad-Lessler, Ghilarducci and Reznike 2018, Dushi and Iams 2015). Given that a primary objective of this research is a relative comparison of policies, we know of no reason that the relative rankings of these policies should vary in different samples even if the effect levels might. While we have extended and replicated a robust literature on choice architecture, further study is required to estimate the full effects of enrollment policies (e.g., active choice, automatic enrollment), financial incentives (e.g., matching, tax considerations), and their interactions.

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Figures and Tables

Figure 1. Active Choice Event Study

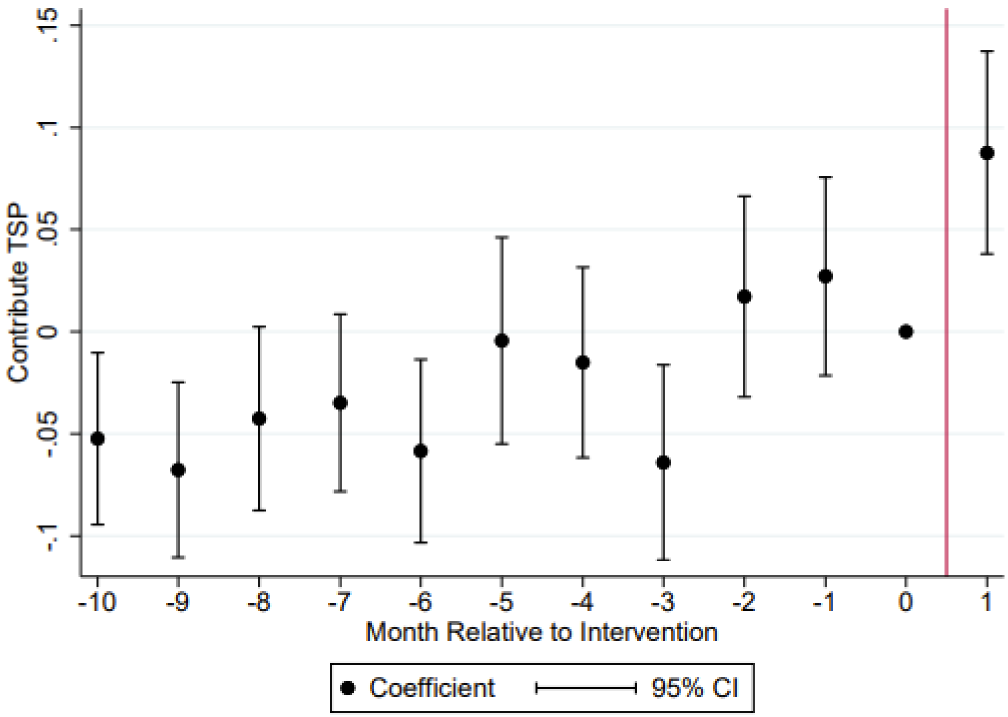

Figure 2. Automatic Enrollment Event Study

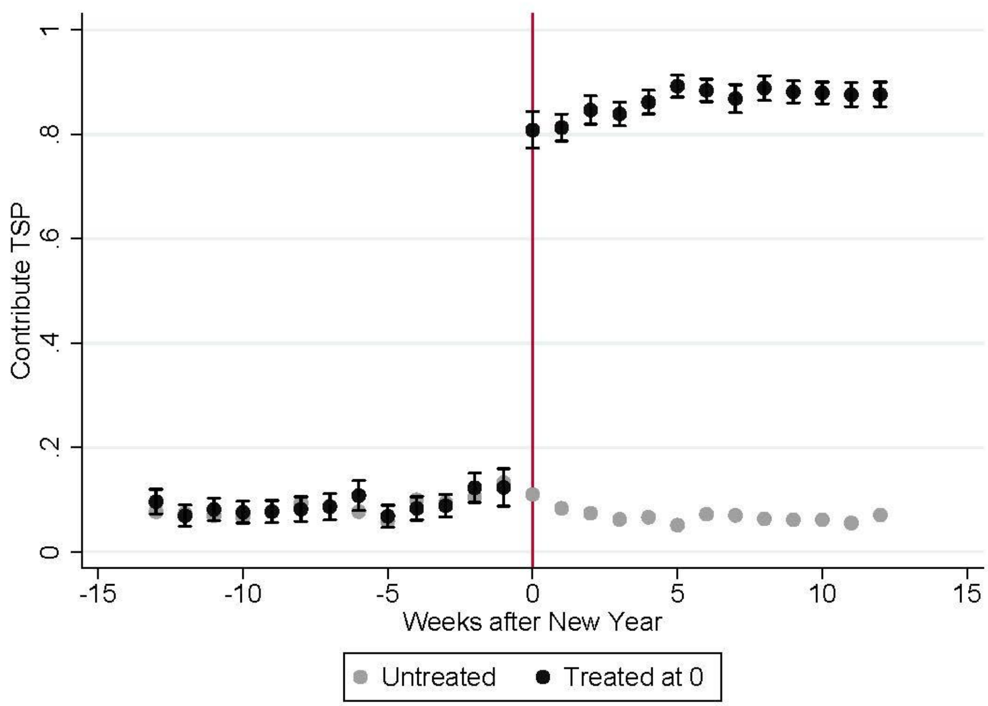

Figure 3. Distribution of Intervention Effects by Contribution Rates

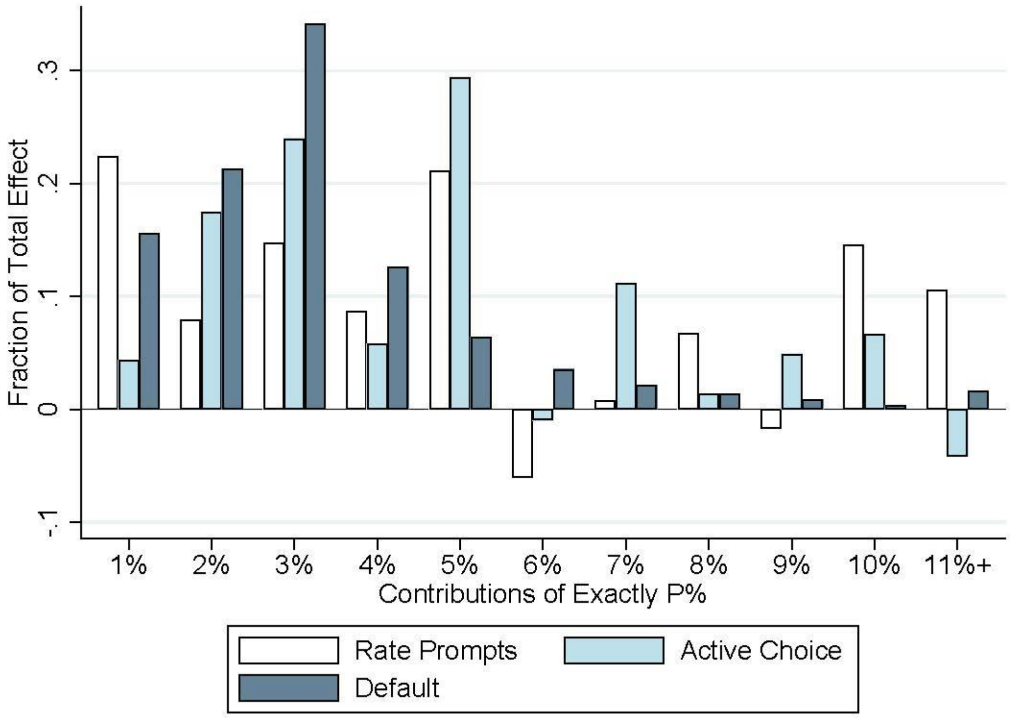

Table 1: Summary Statistics

Variable	Mean	Standard Deviation	N
Age	22.584	3.490	421,305
Female	0.153	0.360	421,305
Black	0.219	0.413	421,305
Hispanic	0.158	0.365	421,305
Other race/ethnicity	0.068	0.252	421,305
Married	0.260	0.439	421,305
Children	0.351	0.710	269,791
High school/GED	0.830	0.376	421,305
Some college	0.057	0.232	421,305
Bachelors or more	0.111	0.314	421,305
Enlisted	0.929	0.258	421,305
Officer	0.060	0.238	421,305
Total monthly pay	2,907	1,312	384,899
Total basic pay	1,979	551	413,016

Note. DOD data. This table displays the means and standard deviations (in parentheses) for the first-term servicemember sample. For observations with any missing data (e.g., children or pay) we use a missing indicator in all regressions.

Table 2: Summary Characteristics by Intervention

	Information Email		Action Steps		Target Rates		Active Choice		Default Choice	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Age	23.207	23.244	22.774	23.112	22.350	22.330	22.103	21.164	21.833	22.000
Female	0.153	0.146	0.154	0.149	0.155	0.151	0.150	0.169	0.169	0.169
Black	0.220	0.213	0.220	0.220	0.219	0.220	0.221	0.177	0.212	0.212
Hispanic	0.147	0.151	0.151	0.150	0.154	0.158	0.157	0.188	0.185	0.185
Other race/ethnicity	0.070	0.065	0.072	0.068	0.074	0.070	0.073	0.084	0.058	0.059
Married	0.288	0.286	0.282	0.287	0.275	0.276	0.296	0.271	0.125	0.125
Children	0.519	0.515	0.447	0.500	0.394	0.386	0.285	0.234	0.114	0.114
High school/GED	0.815	0.816	0.817	0.816	0.819	0.823	0.808	0.848	0.900	0.902
Some college	0.062	0.063	0.059	0.063	0.057	0.058	0.058	0.071	0.038	0.037
Bachelors or more	0.121	0.118	0.121	0.118	0.121	0.116	0.133	0.082	0.062	0.061
Enlisted	0.916	0.917	0.916	0.918	0.917	0.920	0.909	0.955	0.994	0.994
Officer	0.070	0.068	0.069	0.068	0.067	0.066	0.090	0.045	0.006	0.006
N	14,810	14,551	29,936	134,044	15,126	120,779	31,365	538	44,841	15,315
P-value of joint significance	0.07	–	0.63	–	0.33	–	–	–	–	–

Note. DOD data. This table displays the means and standard deviations (in parentheses) for the full samples used in each analysis. The p-values at the bottom of select columns reflect the tests of joint significance of the listed variables in predicting treatment assignment.

Table 3: Main Effects of Interventions on TSP Participation

	Information Email	Action Steps	Target Rates	Active Choice	Default
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0045*	0.0057***	0.0077***	0.1122***	0.7902***
	(0.0026)	(0.0016)	(0.0020)	(0.0189)	(0.0047)
N	29,361	163,980	135,905	31,903	60,156
R2	0.0073	0.0069	0.0102	0.0135	0.5873
Control Group Mean	0.052	0.056	0.059	0.112	0.079
Control Variables	Y	Y	Y	Y	Y
RCT	Y	Y	Y	N	N
Difference in Difference	N	N	N	Y	Y
P-values for equality of treatment effects					
Information Email	-	0.601	0.338	0.000	0.000
Action Steps		-	0.445	0.000	0.000
Target Rates			-	0.000	0.000
Active Choice				-	0.000

* p < 0.10, ** p < 0.05, *** p < 0.01. Estimates from column 1 are pooled from two separate RCTs with identical informational emails. Standard errors in Column 1 are clustered at the individual level.

Table 4: Main Effects of Interventions on Percentage of Salary Contributed

	Information Email	Action Steps	Target Rates	Active Choice	Default
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0106	0.0318***	0.0441***	0.4406***	2.5052***
	(0.0207)	(0.0123)	(0.0150)	(0.1132)	(0.0470)
N	28,748	160,606	132,899	31,587	59,514
R2	0.0058	0.0081	0.0133	0.0213	0.1462
Control Group Mean	0.271	0.287	0.304	0.563	0.287
Control Variables	Y	Y	Y	Y	Y
RCT	Y	Y	Y	N	N
Difference in Difference	N	N	N	Y	Y
P-values for equality of treatment effects					
Information Email	-	0.233	0.189	0.000	0.000
Action Steps		-	0.528	0.000	0.000
Target Rates			-	0.001	0.000
Active Choice				-	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates from column 1 are pooled from two separate RCTs with identical informational emails. Standard errors in Column 1 are clustered at the individual level.

Table 5: Main Effects of Interventions on Cumulative TSP Contributions at 6 Months

	Information Email	Action Steps	Target Rates	Active Choice	Default
	(1)	(2)	(3)	(4)	(5)
Treatment	2.1642	3.5973***	4.7468***	49.7619***	213.1699***
	(1.6826)	(1.0368)	(1.3581)	(12.0367)	(2.5181)
N	29,361	163,980	135,905	31,903	60,156
R2	0.011	0.0132	0.021	0.0293	0.2998
Control Group Mean	26.89	29.62	32.30	57.89	30.22
Control Variables	Y	Y	Y	Y	Y
RCT	Y	Y	Y	N	N
Difference in Difference	N	N	N	Y	Y
P-values for equality of treatment effects					
Information Email	-	0.233	0.189	0.000	0.000
Action Steps		-	0.528	0.000	0.000
Target Rates			-	0.001	0.000
Active Choice				-	0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates from column 1 are pooled from two separate RCTs with identical informational emails. Standard errors in Column 1 are clustered at the individual level.

Table 6: Heterogeneous Treatment Results for TSP Participation

	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Baseline Treatment										
Treatment	0.0017	0.0063*	0.0032	0.0046	0.0028	0.0043	0.0032	0.0058	0.0023	0.0119
	(0.0037)	(0.0038)	(0.0042)	(0.0034)	(0.0075)	(0.0028)	(0.0033)	(0.0044)	(0.0028)	(0.0074)
N	14,978	14,383	12,712	16,649	4,389	24,972	20,924	8,437	24,026	5,335
Control Group Mean	0.053	0.051	0.057	0.049	0.065	0.050	0.058	0.039	0.048	0.073
P-value	0.394		0.789		0.852		0.631		0.224	
Panel B: Action Steps	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.0037*	0.0074***	0.0064**	0.0046**	0.0087*	0.0049***	0.0038*	0.0093***	0.0034**	0.0149***
	(0.0022)	(0.0024)	(0.0025)	(0.0021)	(0.0046)	(0.0017)	(0.0020)	(0.0027)	(0.0017)	(0.0045)
N	87,183	76,797	71,881	92,099	24,524	139,456	117,126	46,854	134,337	29,643
Control Group Mean	0.056	0.055	0.059	0.053	0.071	0.053	0.060	0.044	0.051	0.078
P-value	0.373		0.191		0.771		0.119		0.056	
Panel C: Rate Prompts	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.0042	0.0121***	0.0081***	0.0065**	0.0106*	0.0067***	0.0059**	0.0108***	0.0036*	0.0252***
	(0.0026)	(0.0033)	(0.0031)	(0.0027)	(0.0059)	(0.0022)	(0.0025)	(0.0036)	(0.0022)	(0.0057)
N	83,565	52,340	60,896	75,009	20,623	115,282	98,452	37,453	112,200	23,705
Control Group Mean	0.058	0.060	0.061	0.057	0.078	0.056	0.063	0.049	0.054	0.083
P-value	0.063		0.709		0.531		0.257		0.000	
Panel D: Active Choice	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.1096***	0.1045***	0.0888***	0.1299***	0.1754***	0.0980***	0.1228***	0.0771**	0.0850***	0.2407***
	(0.0220)	(0.0364)	(0.0283)	(0.0254)	(0.0511)	(0.0202)	(0.0227)	(0.0337)	(0.0197)	(0.0557)
N	20,416	11,486	14,385	17,517	4,783	27,119	22,418	9,484	25,822	6,080
Control Group Mean	0.106	0.121	0.114	0.110	0.133	0.108	0.117	0.100	0.099	0.165
P-value	0.904		0.280		0.158		0.260		0.008	
Panel E: Default	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.4840***	0.4310***	0.4982***	0.4376***	0.4005***	0.4780***	0.4700***	0.4406***	0.4826***	0.3540***
	(0.0080)	(0.0110)	(0.0095)	(0.0090)	(0.0157)	(0.0072)	(0.0070)	(0.0173)	(0.0068)	(0.0208)
N	31,171	22,014	24,944	28,241	8,829	44,356	44,886	8,299	45,724	7,461
Control Group Mean	0.102	0.162	0.123	0.132	0.122	0.129	0.125	0.145	0.107	0.254
P-value	0.000		0.000		0.000		0.114		0.000	

Table 7: Cost-Effectiveness Estimates

Firm	N	Info Email (1)	Action Steps (2)	Target Rates (3)	Active Choice (4)	Auto Enrollment (5)
Panel A. Thrift Savings Plan Participation ($ Per New Enrollment)						
Small	25	$44,444	$35,088	$25,974	$10.70	$253
Medium	750	$1,481	$1,170	$866	$10.70	$8
Large	1,000	$1,111	$877	$649	$10.70	$6.33
Dept of Defense	800,000	$1.39	$1.10	$0.81	$10.70	$0.01
Panel B. Thrift Savings Plan Cumulative Contributions ($ Per New $ of Contributions)						
Small	25	$92	$56	$42	$0.02	$1
Medium	750	$3	$2	$1	$0.02	$0.03
Large	1,000	$2	$1	$1	$0.02	$0.02
Dept of Defense	800,000	$0.003	$0.002	$0.001	$0.02	$0.00003

Note. Author calculations using cost data and program effect estimates from Tables 3 and 5. We report the cost of each new enrollment (Panel A) and the cost of each new dollar of contributions (Panel B) in the TSP for each program (Columns) for firms of various sizes (Rows). See Appendix A for details on our methodology.

Appendix A
Cost Effectiveness Analysis

1. Cost Effectiveness Method

We estimate the cost-effectiveness for each intervention (j) as follows:

$$CE_j = \frac{TotalCost_j}{\#\ Enrolled_j} = \frac{FC_j + VC_j}{\widehat{\beta_j} \times n}$$

Total costs are a function of the fixed and variable costs for each intervention, and the number enrolled is the extensive margin program effect $(\widehat{\beta_j})$ multiplied by the sample (or firm) size (n).

A. Light Touch Email Interventions

As discussed in Section 4, the total costs for the light-touch interventions (i.e., information, actions steps, and target contribution rates) were simply the fixed costs of \$5,000. We use this as the total costs for our main analysis and consider adding marginal costs (e.g., a per person administrative account fee) in robustness checks. The total costs for these policies is therefore:

$$TotalCost_{Info} = TotalCost_{ActionSteps} = TotalCost_{Targets} = \$5{,}000$$

The number of individuals who enroll $(\#\ Enrolled)$ based on each program is the product of the causal effect of the program $(\widehat{\beta_j})$ and the number of individuals exposed to the treatment (n). In sensitivity analysis, we add marginal costs to each program, by multiplying the assumed cost by the number of enrollees. Combining these facts, the cost effectiveness equations are:

Baseline Estimate	**Add Marginal Costs**
(A1) $CE_{Info} = \frac{\$5{,}000}{\widehat{\beta}_{Info} \times n}$	(A1A) $CE_{Info} = \frac{\$5{,}000 + MC(\widehat{\beta}_{Info} \times n)}{\widehat{\beta}_{Info} \times n}$
(A2) $CE_{ActionSteps} = \frac{\$5{,}000}{\widehat{\beta}_{ActionSteps} \times n}$	(A2A) $CE_{ActionSteps} = \frac{\$5{,}000 + MC(\widehat{\beta}_{ActionSteps} \times n)}{\widehat{\beta}_{ActionSteps} \times n}$
(A3) $CE_{Targets} = \frac{\$5{,}000}{\widehat{\beta}_{Targets} \times n}$	(A3A) $CE_{Targets} = \frac{\$5{,}000 + MC(\widehat{\beta}_{Targets} \times n)}{\widehat{\beta}_{Targets} \times n}$

B. Active choice

We develop a cost model for the active choice intervention. The total cost of the intervention $(TotalCost_{AC})$ arises from the variable costs: the cost per briefing and the number of briefings.

$$CE_{AC} = \frac{\frac{Cost}{Briefing} \times \#Briefings}{\hat{\beta}_{AC} \times n}$$

The number of briefings required is dictated by the number of new employees (n) and the capacity of the briefing facilities. We estimate the number of briefings required for any number of new employees by assuming that employers hold monthly sessions (though this is not critical) and use rooms that support approximately $X = 25$ people. The cost-effectiveness simplifies to:

$$CE_{AC} = \frac{\frac{Cost}{Briefing} \times \frac{1\ Briefing}{25\ People\ per\ Briefing} \times n}{\hat{\beta}_{AC} \times n} = \frac{\frac{Cost}{25}}{\hat{\beta}_{AC}} = \frac{Cost}{25 \times \hat{\beta}_{AC}}$$

We estimate the briefing has a marginal cost of one hour of labor ($30 in our setting) [41] and so:

$$\text{(A4)} CE_{AC} = \frac{\$30}{25 \times \hat{\beta}_{AC}} = \frac{\$1.20}{\hat{\beta}_{AC}}$$

Note that this estimate is constant with respect to the program sample size and the number of new enrollees. Firms might differ from our setting in their cost and we conduct sensitivity analysis that varies the numerator from $0.60 to $1.80 (see Appendix Table A1). [42]

C. Automatic Enrollment

We estimate the total costs for automatic enrollment based on interviews with several firms providing payroll and retirement plan services.[43] In our main analysis, we assume that a firm would face a one-time fixed cost of $5,000 to implement automatic enrollment. However, these fixed cost estimates may be too low for at least two reasons. First, they reflect estimates from firms with existing plans (without automatic enrollment), and a firm implementing a new plan might face costs as much as

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[41] We assume the briefing was conducted by an individual with paygrade E-6 with greater than 8 years of service at the intervention locations (Fort Bragg) which is also one of the Army's largest and most representative installations. The annual salary estimate using DOD pay data is $59,560. Glassdoor estimates the average salary for "Human Resources" as $59,385 (https://www.glassdoor.com/Salaries/human-resources-salary-SRCH_KO0,15.htm accessed August 6, 2019) and so the estimates should generalize well, but could adjust to any specific firm's hourly wage.

[42] We can vary the numerator to account for different briefing costs and/or the capacity of the briefing room. Cost differences could arise due to several factors, including: differing labor costs for the employee conducting the briefing, differing marginal costs (e.g., HR personnel have slack in their schedules vs. no slack), or a firm's need to develop new materials (e.g., we assumed no costs for firms with existing materials vs. some that have to develop materials). Firms might also differ in their capacity per briefing based on preferences for session size (e.g., efficient vs. intimate), the geographic distribution of new personnel or human resources personnel (e.g., concentrated vs. dispersed), the frequency of briefings (e.g., quarterly vs. daily), or the sizes of available of rooms. Table A1 presents our primary assumptions (bold) and sensitivity analysis values (italics), which account for many scenarios.

[43] These interviews included multiple private firms and one former government agency official.

twenty times higher.[44] Second, the costs might not be entirely fixed as an employer might need to notify its employees about automatic enrollment. Such notifications can vary significantly based on whether a firm can complete the notifications by email (with a fixed cost around \$5,000 for content development) or by letter (\$1-\$2 per employee). As a result, the total cost and cost-effectiveness equations are similar to those for the light-touch interventions:

Baseline Estimate	**Add Marginal Costs**
(A5) $CE_{AE} = \frac{\$5{,}000}{\widehat{\beta}_{AE} \times n}$	(A5A) $CE_{AE} = \frac{\$5{,}000 + MC(\widehat{\beta}_{AE} \times n)}{\widehat{\beta}_{AE} \times n}$

Table A1: Sensitivity Analysis for Active Choice Intervention Costs

Cost per briefing (\$)	Capacity per briefing (number of people) 2	10	**25**	50	100	200
15	7.5	*1.5*	*0.6*	0.3	0.15	0.075
20	10	2	*0.8*	0.4	0.2	0.1
25	12.5	2.5	*1*	0.5	0.25	0.125
30	15	3	***1.20***	*0.6*	0.3	0.15
35	17.5	3.5	*1.4*	*0.7*	0.35	0.175
40	20	4	*1.6*	*0.8*	0.4	0.2
45	22.5	4.5	*1.8*	*0.9*	0.45	0.225

[44] Multiple employee benefit firms confirmed the multiplier of 20 for implementing a new plan.

Table A2
Sensitivity Analysis for Cost-Effectiveness Estimates for TSP Participation

Firm	N	Info Email	Action Steps	Target Rates	Active Choice	Auto Enrollment
		(1)	(2)	(3)	(4)	(5)
Panel A. Baseline Estimates						
Small	25	$44,444	$35,088	$25,974	**$10.70**	$253
Medium	750	$1,481	$1,170	$866	**$10.70**	$8
Large	1,000	$1,111	$877	$649	$10.70	**$6.33**
Dept of Defense	800,000	$1.39	$1.10	$0.81	$10.70	**$0.01**
Panel B. Reduce Active Choice Ratio from 1.2 to 0.6						
Small	25	$44,444	$35,088	$25,974	**$5.35**	$253
Medium	750	$1,481	$1,170	$866	**$5.35**	$8
Large	1,000	$1,111	$877	$649	**$5.35**	$6
Dept of Defense	800,000	$1	$1	$1	$5.35	**$0.01**
Panel C. Increase Active Choice Ratio from 1.2 to 1.8						
Small	25	$44,444	$35,088	$25,974	**$16.04**	$253
Medium	750	$1,481	$1,170	$866	$16.04	**$8**
Large	1,000	$1,111	$877	$649	$16.04	**$6**
Dept of Defense	800,000	$1	$1	$1	$16.04	**$0.01**
Panel D. Add Variable Costs of $30 Per Person to Automatic Enrollment						
Small	25	$44,444	$35,088	$25,974	**$10.70**	$283
Medium	750	$1,481	$1,170	$866	**$10.70**	$38
Large	1,000	$1,111	$877	$649	**$10.70**	$36
Dept of Defense	800,000	$1	$1	$1	**$10.70**	$30

Note. Author calculations using cost data and program effect estimates from Tables 3 and 4. We report the cost of each new enrollment in the TSP for each program (Columns) for firms of various sizes (Rows). See Appendix A for details on our methodology.

Appendix B
All Servicemember Sample

Table B1: Summary Statistics, Full Sample

Variable	Mean	Standard Deviation	Obs
Age	27.364	7.606	768,400
Female	0.134	0.341	768,400
Black	0.210	0.407	768,400
Hispanic	0.146	0.353	768,400
Other race/ethnicity	0.070	0.255	768,400
Married	0.492	0.500	768,400
Children	0.928	1.161	599,314
High school/GED	0.702	0.457	768,400
Some college	0.123	0.329	768,400
Bachelors or more	0.172	0.377	768,400
Enlisted	0.856	0.351	768,400
Officer	0.113	0.316	768,400
Total monthly pay	$4,358	$2,507	720,622
Total basic pay	$2,862	$1,551	748,744

Notes: DOD Data.

Table B2: Summary Statistics by Intervention, Full Sample

	Information Email		Action Steps		Target Rates		Active Choice		Default	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Age	28.534	28.575	28.010	28.370	27.475	27.426	25.981	24.210	21.833	22.000
Female	0.130	0.127	0.132	0.130	0.133	0.132	0.136	0.153	0.169	0.169
Black	0.209	0.206	0.209	0.210	0.209	0.210	0.214	0.171	0.212	0.212
Hispanic	0.139	0.141	0.142	0.139	0.144	0.145	0.147	0.168	0.185	0.185
Other race/ethnicity	0.072	0.068	0.073	0.070	0.074	0.071	0.074	0.088	0.058	0.059
Married	0.536	0.542	0.526	0.533	0.516	0.517	0.475	0.429	0.125	0.125
Children	1.136	1.138	1.065	1.111	0.998	0.990	0.629	0.533	0.114	0.114
High school/GED	0.683	0.685	0.685	0.683	0.686	0.687	0.691	0.760	0.900	0.902
Some college	0.132	0.133	0.130	0.134	0.127	0.130	0.116	0.123	0.038	0.037
Bachelors or more	0.182	0.179	0.183	0.180	0.183	0.180	0.191	0.117	0.062	0.061
Enlisted	0.843	0.844	0.844	0.843	0.844	0.846	0.847	0.920	0.994	0.994
Officer	0.122	0.119	0.120	0.121	0.119	0.120	0.137	0.065	0.006	0.006
N	30,141	30,193	59,688	272,595	29,547	236,561	48,782	737	44,841	15,315
P-value of joint significance	0.48	–	0.71	–	0.33	–	–	–	–	–

Note. DOD data. This table displays the means and standard deviations (in parentheses) for the full samples used in each analysis. The p-values at the bottom of select columns reflect the tests of joint significance of the listed variables in predicting treatment assignment.

Table B3: Main Effects of Interventions on TSP Participation, Full Sample

	Information Email	Action Steps	Target Rates	Active Choice	Default
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0038***	0.0060***	0.0075***	0.0906***	0.7902***
	0.0015	0.0010	(0.0013)	0.0146	0.0047
N	60,334	332,283	266,108	49,519	60,156
R^2	0.0103	0.0097	0.0108	0.0215	0.5873
Control Group Mean	0.036	0.040	0.043	0.086	0.079
Control Variables	Y	Y	Y	Y	Y
RCT	Y	Y	Y	N	N
Difference in Difference	N	N	N	Y	Y
P-values for equality of treatment effects					
Information Email	–	0.102	0.066	0.000	0.000
Action Steps		–	0.363	0.000	0.000
Target Rates			–	0.000	0.000
Active Choice				–	0.000

*p<0.10, **p<0.05, ***p<0.01. Estimates from column 1 are pooled from two separate RCTs with identical informational emails. Standard errors in column 1 are clustered at the individual level.

Table B4: Main Effects of Interventions on Percentage of Salary Contributed, Full Sample

	Information Email	Action Steps	Target Rates	Active Choice	Default
	(1)	(2)	(3)	(4)	(5)
Treatment	0.0181	0.0361***	0.0426***	0.3757***	2.5052***
	0.0123	0.0075	0.0095	0.0873	0.0470
N	58,717	323,428	258,778	48,863	59,514
R^2	0.0068	0.0073	0.0097	0.0209	0.1462
Control Group Mean	0.180	0.198	0.216	0.424	0.198
Control Variables	Y	Y	Y	Y	Y
RCT	Y	Y	Y	N	N
Difference in Difference	N	N	N	Y	Y
P-values for equality of treatment effects					
Information Email	–	0.091	0.113	0.000	0.000
Action Steps		–	0.585	0.000	0.000
Target Rates			–	0.000	0.000
Active Choice				–	0.000

*p<0.10, **p<0.05, ***p<0.01. Estimates from column 1 are pooled from two separate RCTs with identical informational emails. Standard errors in column 1 are clustered at the individual level.

Table B5: Main Effects of Interventions on Cumulative Contributions at 6 Months, Full Sample

	Information Email	Action Steps	Target Rates	Active Choice	Default
	(1)	(2)	(3)	(4)	(5)
Treatment	2.5245*	4.4455***	5.7344***	40.7232**	213.16994***
	(1.0573)	(0.6618)	(0.8880)	(9.4231)	(2.5181)
N	60,334	332,283	266,108	49,519	60,156
R^2	0.0083	0.0095	0.0122	0.0245	0.2998
Control Group Mean	19.92	22.44	25.01	46.98	30.22
Control Variables	Y	Y	Y	Y	Y
RCT	Y	Y	Y	N	N
Difference in Difference	N	N	N	Y	Y
P-values for equality of treatment effects					
Information Email	–	0.041	0.020	0.000	0.000
Action Steps		–	0.244	0.000	0.000
Target Rates			–	0.000	0.000
Active Choice				–	0.000

*p<0.10, **p<0.05, ***p<0.01. Estimates from column 1 are pooled from two separate RCTs with identical informational emails. Standard errors in column 1 are clustered at the individual level.

Table B6: Heterogeneous Treatment Effects of Interventions on TSP Participation, Full Sample

	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Panel A: Baseline Treatment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	0.0010	0.0056***	0.0032	0.0037*	0.0034	0.0035**	0.0041	0.0032*	0.0016	0.0075***
	(0.0026)	(0.0018)	(0.0025)	(0.0020)	(0.0050)	(0.0016)	(0.0026)	(0.0018)	(0.0018)	(0.0029)
N	27,260	33,074	25,195	35,139	7,759	52,575	27,796	32,538	41,449	18,885
Control Group Mean	0.048	0.026	0.039	0.034	0.050	0.034	0.049	0.025	0.036	0.036
P-value	0.152		0.895		0.976		0.760		0.085	
Panel B: Action Steps	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.0043***	0.0075***	0.0082***	0.0045***	0.0104***	0.0054***	0.0045***	0.0074***	0.0044***	0.0097***
	(0.0016)	(0.0011)	(0.0015)	(0.0012)	(0.0031)	(0.0010)	(0.0016)	(0.0011)	(0.0011)	(0.0018)
N	154,839	177,444	139,566	192,717	43,170	289,113	155,471	176,812	228,147	104,136
Control Group Mean	0.051	0.029	0.042	0.038	0.055	0.037	0.052	0.028	0.039	0.040
P-value	0.080		0.015		0.101		0.216		0.010	
Panel C: Rate Prompts	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.0057***	0.0092***	0.0100***	0.0056***	0.0140***	0.0065***	0.0062***	0.0087***	0.0046***	0.0139***
	(0.0019)	(0.0016)	(0.0020)	(0.0016)	(0.0040)	(0.0013)	(0.0020)	(0.0015)	(0.0015)	(0.0023)
N	137,411	128,697	113,565	152,543	35,129	230,979	128,542	137,566	183,698	82,410
Control Group Mean	0.054	0.032	0.045	0.042	0.059	0.041	0.056	0.032	0.043	0.045
P-value	0.165		0.090		0.076		0.311		0.001	
Panel D: Active Choice	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.1055***	0.0504**	0.0710***	0.1060***	0.1525***	0.0799***	0.1103***	0.0609***	0.0785***	0.1211***
	(0.0190)	(0.0209)	(0.0224)	(0.0193)	(0.0435)	(0.0153)	(0.0210)	(0.0194)	(0.0166)	(0.0306)
N	29,474	20,045	21,563	27,956	6,736	42,783	26,044	23,475	34,337	15,182
Control Group Mean	0.103	0.061	0.090	0.083	0.111	0.082	0.107	0.063	0.083	0.094
P-value	0.051		0.237		0.115		0.083		0.220	
Panel E: Default	Young	Old	Non-White	White	Female	Male	Non-Married	Married	No College	Some College+
Treatment	0.7988***	0.7249***	0.8035***	0.7809***	0.7354***	0.8010***	0.7958***	0.7477***	0.7999***	0.7046***
	(0.0049)	(0.0157)	(0.0069)	(0.0065)	(0.0116)	(0.0052)	(0.0050)	(0.0149)	(0.0048)	(0.0188)
N	52,109	8,047	27,313	32,843	10,166	49,990	52,629	7,527	54,129	6,027
Control Group Mean	0.069	0.141	0.078	0.080	0.065	0.082	0.075	0.109	0.069	0.170
P-value	0.000		0.017		0.000		0.002		0.000	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Estimates from column 1 are pooled from two separate RCTs with identical informational emails. Standard errors in Column 1 are clustered at the individual level

Appendix D
Randomized Controlled Trial Details & Materials

GROUP A: SSNs ending in 00-09

No Email Sent

GROUP B: SSNs ending in 10-19

Subject: Contribute to TSP to Invest in Your Future

You are eligible to invest in the Thrift Savings Plan (TSP). The TSP is similar to the 401K plan or a deductible Individual Retirement Account (IRA) offered by many private corporations - we encourage you to consider the benefits of TSP. You may want to choose to enroll today by logging onto MyPay and selecting a contribution percentage.

You may start, change or stop your contributions at any time. If you are enrolling for the first time, select a contribution percentage of at least 1% equivalent of your basic pay.

Your elections may be submitted quickly and securely using MyPay. You may also use a TSP-U-1 form available at www.tsp.gov; this website also has information about Traditional vs. Roth TSP. Forms must be submitted to your servicing finance office.

For more information about the TSP visit the tsp website (above), http://www.dfas.mil/militarymembers/tspformilitary/tspac.html/, or speak to your installation personal financial manager.

GROUP C: SSNs ending in 20-29

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

With tax season over and spring beginning, now is the perfect time to take action and make a choice to ensure you don't lose out on a secure future by investing with a Thrift Savings Plan (TSP). TSP is like a 401k or a deductible Individual Retirement Account.

DO YOU WANT TO SIGN UP TO SAVE?

CHOICE 1: 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, press submit and you're done!

CHOICE 2: NO, I DON'T WANT TO SAVE THROUGH TSP.

* 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.

PS. With tax day behind you and spring beginning, it is the perfect time to start fresh: Go to mypay.dfas.mil and make your choice to start saving today!

GROUP D: SSNs ending in 30-39

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

With tax season over and spring beginning, now is the perfect time to take action and make a choice to ensure you don't lose out on a secure future by investing with a Thrift Savings Plan (TSP). TSP is like a 401k or a deductible Individual Retirement Account.

DO YOU WANT TO SIGN UP TO SAVE?

CHOICE 1: 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, press submit and you're done!

CHOICE 2: NO, I DON'T WANT TO SAVE THROUGH TSP. Go to mypay.dfas.mil and follow steps (2) and (3) if you want to invest in your future or make changes down the line.

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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.

PS. With tax day behind you and spring beginning, it is the perfect time to start fresh: Go to mypay.dfas.mil and make your choice to start saving today!

<u>GROUP E: SSNs ending in 40-49</u>

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

With tax season over and spring beginning, now is the perfect time 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 or a deductible Individual Retirement Account.

DO YOU WANT TO 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, press 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.

PS. With tax day behind you and spring beginning, it is the perfect time to start fresh: Go to mypay.dfas.mil and start saving today!

GROUP F: SSNs ending in 50-59

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

Now is the perfect time to take action and make a choice to ensure you don't lose out on a secure future by investing with a Thrift Savings Plan (TSP). TSP is like a 401k or a deductible Individual Retirement Account.

DO YOU WANT TO SIGN UP TO SAVE?

CHOICE 1: 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, press submit and you're done!

CHOICE 2: NO, I DON'T WANT TO SAVE THROUGH TSP.

* 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.

PS. Go to mypay.dfas.mil and make your choice to start saving today!

GROUP G: SSNs ending in 60-69

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

Now is the perfect time to take action and make a choice to ensure you don't lose out on a secure future by investing with a Thrift Savings Plan (TSP). TSP is like a 401k or a deductible Individual Retirement Account.

DO YOU WANT TO SIGN UP TO SAVE?

CHOICE 1: 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, press submit and you're done!

CHOICE 2: NO, I DON'T WANT TO SAVE THROUGH TSP. Go to mypay.dfas.mil and follow steps (2) and (3) if you want to invest in your future or make changes down the line.

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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.

PS. Go to mypay.dfas.mil and make your choice to start saving today!

GROUP H: SSNs ending in 70-79

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

Now is the perfect time 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 or a deductible Individual Retirement Account.

DO YOU WANT TO 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, press 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.

PS. Go to mypay.dfas.mil and start saving today!

<u>GROUP I: SSNs ending in 80-89</u>

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

Now is the perfect time 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 or a deductible Individual Retirement Account – you can invest in your future – if you'd put away just $25 a month starting in 1980, it'd be worth over $66,700 today.

DO YOU WANT TO 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, press submit and you're done!

* 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.

PS. Go to mypay.dfas.mil and start saving today!

GROUP J: SSNs ending in 90-99

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

Now is the perfect time 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 or a deductible Individual Retirement Account: save on taxes today while investing for the future.

DO YOU WANT TO 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, press 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.

PS. Go to mypay.dfas.mil and start saving today!