

How do behavioral approaches to increase savings compare?

Evidence from multiple interventions in the U.S. Army

Richard W. Patterson,
United States Military
Academy at West Point

William L. Skimmyhorn,
William & Mary

1. Expanding our understanding of the effectiveness of retirement savings policies

Most Americans approaching retirement age have insufficient savings to fund their retirement.¹ This fact defies a large academic literature on behavioral economic approaches (“nudges”) proven to increase individual retirement savings. These programs include active choice (Carroll et al., 2009), automatic enrollment (Madrian and Shea, 2001, Choi et al., 2006, 2004), automatic escalation (Thaler and Benartzi, 2004), behaviorally informed messaging (Benartzi et al. 2017, Choi et al., 2017; Goda, Manchester and Sojourner, 2014), simplified enrollment options (Beshears et al., 2013, Choi et al., 2009), and actionable education (Skimmyhorn, 2016). Beshears et al. (2018) provide a helpful review. This line of research has been at the forefront of the wider behavioral economic and financial literature (Madrian 2014, Madrian et al. 2017) and it has influenced national level policies (Beshears et al. 2009).

A lesser explored topic in the research is how to best choose from these promising approaches. As it turns out, such choices, which require validation/replication, standardization and comparison, and then selection from among these approaches is difficult for at least two reasons. First, these studies differ significantly in their samples (e.g., participant demographics), firm characteristics, study periods, and their analyzed outcomes. In an ideal situation, a researcher could generate direct comparisons between programs of interest by randomly assigning individuals from a large population to each of these approaches at the same time. Our study capitalizes on a setting that nearly replicates this ideal framework.

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.

Any opinions expressed herein are those of the authors, and do not necessarily represent the views of TIAA, the TIAA Institute or any other organization with which the authors are affiliated.

Second, we know very little about the costs or cost-effectiveness of these different policies. Benartzi et al. (2017) show that “nudges” are relatively cost-effective compared to traditional approaches like tax incentives, but they also note that “more calculations are needed to determine the relative effectiveness of nudging.” We concur with their assessment and note that, to our knowledge, there is no evidence on the cost-effectiveness of different behavioral policies designed to encourage retirement savings. Our study occurs in a government setting where costs are available through administrative data or straightforward estimates, and our cost-effectiveness measures can inform the academic literature on retirement savings and firm decisions on which program to select when faced with budget constraints.

In this study, we examine the relative efficacy and cost-effectiveness of four leading retirement savings policies: 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 in settings with very similar workplace conditions, the largest study samples to date (i.e., approximately $n=29,000$ to $n=164,000$), and high-quality administrative data. We recognize that our study sample is unique relative to the full working population of interest in designing retirement savings programs, both in the nature of the firm and the employees’ characteristics. However, this uniqueness may be a strength. Army installations and working conditions are relatively homogenous and strengthen our ability to hold constant the institutional setting when evaluating different programs. In terms of the sample characteristics, our sample is younger, lower tenure, moderately educated, and with lower incomes than the U.S. working population, but it also more closely represents the population for which retirement savings interventions are generally designed (i.e., the lower tail of the savings distribution, in terms of participation and contributions, as documented by e.g., Carroll et

al. (2009), Madrian (2014)).² Our main analysis uses a sample of new servicemembers and we document that our findings hold in a larger and more demographically representative sample of higher-tenure military members.

To preview our findings, our main estimates suggest that light touch email interventions (i.e., information, action steps, and contribution rate targets) increase TSP contributions by 0.2-0.7 percentage points (pp) relative to a control group (6-9% effect sizes). Programs with more individual interactions (i.e., active choice) increase contributions by an order of magnitude, nearly 11pp (104%). Automatic enrollment even larger effects of 37pp (208%). We find similar effect sizes and patterns when we analyze contribution rates and cumulative contributions. These results follow our intuition and validate the existing literature, which establishes that effect sizes grow in magnitude with the intensity of the intervention.

Our cost-effectiveness analysis suggests that active choice programs are the most cost-effective method for small, medium, and large firms in generating new program participation (approximately \$11 for each new participant) or savings (approximately \$0.01 for a new dollar of contributions). Automatic enrollment, however, is the most cost-effective for very large firms, including the organization we study (the Department of Defense), who can distribute the program costs over more employees. We estimate the critical values for firm size, where automatic enrollment becomes more cost-effective than active choice, and find that these sizes vary based on the outcome of interest and on assumptions about program costs.

2. Our approach: New experiments to replicate and extend existing research

In this paper, we leverage differential policy exposure and deliberate randomized controlled trials designed to increase U.S. military members’ participation in the Thrift

² The military is a sample of independent interest given its size, the role of the all-volunteer force in the nation’s security, its own federally mandated compensation and pension plans, and persistent attention from national-level commissions (e.g., most recent Military Retirement and Modernization Commission of 2015).

Savings Plan (TSP), along with administrative data on individual decisions. The TSP is an employer-sponsored retirement account for federal workers, akin to most employees' 401(k). 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 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. The military pension has since expanded to a blended system with DC and DB components.³

From April 2015 through January 2018, the White House Social and Behavioral Sciences Team (WHSBST), along with the Departments of Defense (DOD) and Army (DA) completed four separate experimental interventions designed to increase military servicemembers' contributions to TSP accounts. We couple these programs with military personnel data (including demographics, location data, and relocation timing data), DOD payroll data (including monthly TSP contribution amounts), and TSP account data (including quarterly TSP contributions and account balances). We also use administrative data on program costs, or estimates of these costs, to support our cost-effectiveness analysis. Below we briefly describe each intervention as they apply to our sample (U.S. Army servicemembers who were not contributing the TSP at the time of each intervention), and review their companion findings in the current literature.

Intervention 1: Behavioral messaging

Information nudges include a large number of light-touch interventions that encourage retirement savings via carefully designed provision of information. These

interventions might be traditional (e.g., a program benefits brochure or email) but are often “behavioral” in their application of psychological insights related to salience, simplification, reminders, and/or suggestions. Choi et al. (2017) find that savings cues have no statistically significant effect on participation or contributions, except for low target anchors that reduce contribution rates approximately six months after implementation. Benartzi et al. (2017) study the effects of various messaging approaches including language related to framing, action steps, interest rate clarifications, and tax savings salience and find that these programs increased enrollment and contribution amounts, but the analysis only extends to one month after implementation.

The WHSBST, the DOD, and Benartzi et al. (2017) conducted a randomized controlled trial (RCT) of several messaging strategies informed by previous psychological studies (e.g., framing, action steps). The study randomly assigned servicemembers across the Air Force, Army, Marines, and Navy who were not contributing to their TSP, to one of 10 groups based on the last two digits of their Social Security number (SSN). The groups 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), and (c) eight groups that received a behaviorally motivated email message that presents the contribution choice in three simple steps (hereafter, the Action Steps group).⁴ We find no significant differences in the various strategies and thus pool the action-steps treatments into one group in our primary analyses of first-term servicemembers.

³ For a summary of the 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>

⁴ 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 steps treatments in our sample.

Intervention 2: Savings rate prompts

Choi et al. (2009) and Beshears et al. (2013) study the effects of Quick Enrollment, which simplifies the enrollment process by providing an employee with a pre-selected contribution rate and asset allocation. This program increased both participation and contribution rates. Similarly, Goldin et al. (2017) show that providing target contribution rates to military servicemembers similarly increases enrollment and contribution rates after one month. However, in related work, the Office of Evaluation Science (2017) finds no effects of a 5% rate prompt on employee contributions at or above this rate for Department of Treasury employees.

The WHSBST and DOD conducted another large-scale email-based RCT to evaluate the effect of action-steps emails and *rate-prompt* emails in January of 2016. These messages informed servicemembers that other servicemembers were contributing a certain percentage or more (e.g., 1%, 2%,...8%) of their basic pay to their TSP accounts. Researchers randomly assigned servicemembers across the Air Force, Army, Marines, and Navy who were not contributing to their TSP to one of 10 groups based on the last two digits of their SSN. These groups 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,” where *X* takes on a value between 1 and 8. For simplicity, in our primary analysis, we pool all the rate prompt emails 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.

Intervention 3: Active choice

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 for these programs on the participation margin and contribution rates one year after implementation.

In our third intervention, we analyze the effects of a Spring 2016 program from the WHSBST, along with the DOD and US Army, to implement active choice for newly arriving servicemembers at two military installations (Fort Bragg, NC, and Fort Lewis, WA). Individuals arriving at these bases were required to choose whether or not they would begin contributing to their TSP account.⁵ We analyze this intervention using a difference-in-differences approach that compares the differences in contribution decisions for new servicemembers at these two bases before and after the intervention compared to those of new servicemembers at other Army bases during the same time periods.

Intervention 4: Automatic enrollment

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 and contribution rates for employees after 3-15 months. Choi et al. (2004) find very similar effects on participation after 12 months but smaller effects on contribution rates at the longer outcome horizons up to 35 months.

In January of 2018, the Department of Defense (including the Army) implemented automatic enrollment in the TSP for all new servicemembers as part of a new military

⁵ At Fort Lewis, WA, soldiers were asked to self-identify if they were not saving in the TSP and then taken to nearby computers and given the choice to enroll. At Fort Bragg, NC, servicemembers were required to complete a modified enrollment form that elicited an active choice. We pool these two programs together in our analysis.

retirement system. The program changed the default participation from no contributions to a contribution rate of 3% of their basic pay. Eligible servicemembers receive a 1% agency automatic contribution (which vests after two years) regardless of whether they contribute, and they become eligible for matching contributions after two years, past the time horizon we analyze.

Here we exploit the timing of the eligibility change at the implementation date (i.e., January 1, 2018) to estimate the effects of this program using a difference-in-difference approach. We compare the changes in contributions for new Army servicemembers joining immediately after the BRS system was implemented (January-March 2018) to those entering before the BRS (October-December of 2017) relative to the differences in contributions for new individuals between the same months in the previous year (January-March 2017 vs. October-December 2016).

Summarizing our analytic approach

Previous reports (e.g., Benartzi et al. 2017, Office of Evaluation Science 2015) suggest that all four of these interventions can yield reliable estimates of program effects, and we build on existing studies here to analyze the effects in a common institutional setting: active-duty military servicemembers in the U.S. Army. In our primary analysis, we rely on a sample of new members (i.e., serving in their first voluntary enlistment term) to maximize the comparability of our estimates across programs. We summarize the samples by intervention in Table 1. Overall, our sample members are young (mean age is 23), predominantly male (85%), diverse in their race and ethnicity (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, of which approximately 64% (\$22,476) derives from individual basic pay, used to compute retirement savings contributions. In comparing the groups by control and treatment status, we observe

balance across characteristics within each intervention and similarity across interventions as well. In our full analysis, for the active choice and automatic enrollment interventions, we also provide evidence of parallel trends for our comparison groups in the time periods preceding the interventions.⁶ Our evidence suggests valid experiments which enable us to measure the causal effects of the programs.

3. Estimating and interpreting program effects and cost-effectiveness

In this section, we analyze the effects and cost-effectiveness of each retirement savings intervention. For the information emails, action steps, and target rates experiments, we estimate straightforward ordinary least squares regression models that also control for age, sex, race/ethnicity, marital status, children, education level, and rank. For the active choice and automatic enrollment interventions, we implement difference-in-difference models that estimate the average differences for eligible and ineligible servicemembers before and after the policy change, controlling for the same characteristics. We analyze outcomes related to TSP participation, contribution rates, and contributions six months after program implementation, and we present effect estimates in percentage points (for participation) and dollars (for contributions) as well as effect magnitudes (%) comparing each estimate to the control group mean.

Estimating program effectiveness

We present our estimates of program effects on TSP participation in Table 2. Providing information, action steps, and target rates increases participation by 0.20 percentage points (pp), 0.41pp (7.2%) and 0.69pp (7.6%), respectively, and the latter two estimates are statistically significant ($p < 0.05$ and $p < 0.01$, respectively). These point estimates are not statistically distinguishable from one another, but they suggest that using action steps or target contribution rates were the most effective of the

⁶ In further analyses, we include more tenured servicemembers, which increases our sample sizes and the demographic representativeness of our sample. However, this alternative sample also reduces the comparability across settings slightly, since these more tenured individuals were selected based on previous non-participation. Our results are quantitatively and qualitatively similar.

light-touch interventions. Given this pattern, we focus on the action steps intervention when referring to the light-touch interventions in our effectiveness and cost-effectiveness analyses.⁷

The active choice intervention increases participation by an order of magnitude over these interventions, by 10.68pp (104%) and the effect that is statistically significant ($p < 0.01$). Automatic enrollment increases participation by 37.28pp (208%) relative to the control group, and the result is also statistically significant ($p < 0.01$). The larger effects are unsurprising given the existing literature on the power of defaults.

We observe a similar pattern of results for effects on individual contribution rates. The information email has a small positive effect of 0.0036pp (0.74%) on contribution rates that is not statistically significant. Action steps and target contribution rates increase the percentage of pay contributed by 0.03pp (10%) and 0.04pp (12%), respectively, and these results are statistically significant ($p < 0.01$). The active choice intervention increased contribution rates by 0.61pp (281%), and the estimate is statistically significant ($p < 0.01$).

Finally, we provide comparable estimates for cumulative TSP contributions after six months. Information increases the average contributions after six months by a statistically insignificant \$2.30 (5%), but providing action steps and target rates increase cumulative contributions by \$8.88 (18%) and \$10.91 (21%), respectively ($p < 0.01$ for both). The active choice intervention increases contribution amounts by \$82.61 after six months (81%) and the result is statistically significant ($p < 0.05$). Automatic enrollment increases accumulated dollars by \$138, a 197% effect that is significantly different from the control group ($p < 0.01$) and from all other groups ($p < 0.01$ for the email interventions and $p < 0.01$

from active choice). Overall, our results suggest that program effect sizes increase in economically and statistically significant ways based on the intensity of the intervention.

Estimating program cost-effectiveness

We next turn to estimating the cost-effectiveness of each program. We compute two measures: the cost per new enrollment, and the cost per dollar of cumulative contributions. The costs for the light touch email interventions and for automatic enrollment are \$5,000 per program.⁸ Active choice costs vary based on assumptions about personnel costs and the number of employees in a session. We compute our cost-effectiveness measures for four firm sizes: small ($n = 25$ employees), medium ($n = 750$ employees),⁹ large ($n = 1,000$ employees), and the Department of Defense ($n = 800,000$ employees).¹⁰

In Table 3 we present the results from our cost-effectiveness analysis. Panel A depicts the results for the estimated cost for each new enrollment in the TSP. Automatic enrollment costs \$5,000 to implement and it increases enrollment by 0.3728pp. For a small firm ($n = 25$), this generates 9.32 enrollments and the cost per new enrollment is, therefore, $\$5,000 / 9.32 = \536 . Since automatic enrollment has the same total costs as the light touch interventions but much larger effects on enrollment, it is always more cost-effective than these interventions. We thus focus on comparing the cost-effectiveness measures for automatic enrollment and active choice.

Our main estimates suggest that active choice, at a cost of \$11.24 per new enrollment, is more cost-effective than automatic enrollment for small, medium,

⁷ On our full analysis, we analyze program effects by age, sex, race/ethnicity, marital status, and education level.

⁸ The email intervention costs come from the Department of Defense, and the automatic enrollment costs are based on these same costs, validated by former TSP personnel.

⁹ According to the Census Longitudinal Business Database in 2014, the medium employee works at a firm with 500-999 employees. We use the midpoint of this range ($n = 750$) as our medium firm size.

¹⁰ In our full report, we conduct a number of sensitivity analyses related to our estimates for active choice ($\pm 50\%$), adding marginal costs to our automatic enrollment costs. Active choice remains the most cost-effective program for small, medium, and large firms under all scenarios.

and large firms. However, automatic enrollment is more cost-effective for very large firms like the Department of Defense who can amortize the fixed costs over a larger number of employees and generate a new enrollment for approximately 4 cents. The critical value of firm size where the costs for active choice and automatic enrollment are equal, is $n=1,194$. Light-touch interventions also become more cost-effective than active choice for very large firms, but they never outperform automatic enrollment given the costs in our setting.

In Panel B of Table 3, we complete a similar analysis for the cost to generate a dollar of new cumulative TSP contributions after six months. Qualitatively these results are similar to those for new enrollments. Active choice remains the most cost-effective for small, medium, and large firms, who can generate a dollar of contributions for \$0.01. Automatic enrollment is more cost-effective for very large firms like the Department of Defense, which can generate a dollar of contributions for \$0.0001. The critical firm size is $n=2,490$ employees.

4. Effectiveness measures appear valid and active choice appears most cost-effective

In this study, we analyze the relative efficacy of leading policies designed to increase retirement savings in employer-provided plans. Relative to the existing literature, in which study settings vary significantly, we study several leading programs in a constant institutional setting. We find sizable effects on participation for light-

touch interventions such as emails with action steps or target contribution rates (around 6-9%), much larger effects for active choice enrollment (91%), and even larger effects for automatic enrollment (over 200%). We document a similar pattern of results when we analyze contribution rates and cumulative contributions.

These results provide a large-scale and rigorous validation of existing estimates, serving as a meaningful scientific replication of much of the existing literature on retirement savings interventions. In addition, our estimates suggest that behavioral interventions, even light touch emails, generally outperform traditional approaches that provide information alone, and the effect magnitudes appear to increase with the “behavioral” intensity of the intervention: defaults generate larger effects than active choice, which generates larger effects than behavioral messaging. These lessons further validate policy approaches designed to leverage lessons from psychology.

Our cost-effectiveness analysis provides unique evidence that active choice is the most cost-effective program for small, medium, and large firms and that automatic enrollment is the most cost-effective for very large firms, including the Department of Defense, the organization from which our study derives. We demonstrate a method (following and extending Benartzi et al. (2017)) for other organizations to estimate their own cost-effectiveness measures in support of retirement savings plan design.

References

- Benartzi, Shlomo, John Beshears, Katherine L. Milkman, Cass R. Sunstein, Richard H. Thaler, Maya Shankar, Will Tucker-Ray, William J. Congdon, and Steven Galing. (2017). Should governments invest more in nudging? *Psychological science*, 28 (8), 1041–1055.
- Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C. (2009). The importance of default options for retirement saving outcomes: Evidence from the United States. In *Social security policy in a changing environment* (pp. 167-195). University of Chicago Press.
- Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C. (2013). “Simplification and Saving.” *Journal of Economic Behavior and Organizations*, 95:130-145.
- Beshears, J., Choi, J. J., Laibson, D., & Madrian, B. C. (2018). “Behavioral Household Finance.” In *Handbook of Behavioral Economics: Foundations and Applications 1*, edited by B. Douglas Bernheim, Stefano DellaVigna, and David Laibson, 177–276. Amsterdam: Elsevier.
- Beshears, J., Choi, J. J., Laibson, D., Madrian, B. C., & Skimmyhorn, W.L. (2020). Borrowing to Save? The Impact of Automatic Enrollment on Debt. Forthcoming, *Journal of Finance*.
- Carroll, Gabriel D. James J. Choi, David Laibson, Brigitte C. Madrian, Andrew Metrick; (2009) Optimal Defaults and Active Decisions, *The Quarterly Journal of Economics*, Volume 124, Issue 4, 1 November, Pages 1639–674.
- Choi, J. J., Laibson, D., Madrian, B. C., & Metrick, A. (2004). For better or for worse: Default effects and 401 (k) savings behavior. In *Perspectives on the Economics of Aging* (pp. 81-126). University of Chicago Press.
- Choi, James J., David Laibson, Brigitte C. Madrian, and Andrew Metrick. “Saving for Retirement on the Path of Least Resistance.” (2006). In Edward J. McCaffrey and Joel Slemrod, editors, *Behavioral Public Finance: Toward a New Agenda*, New York: Russell Sage Foundation, pp. 304-351
- Choi, J.J., Laibson, D., Madrian, B.C. (2009). Reducing the complexity costs of 401(k) participation: the case of quick enrollment. In: Wise, D.A. (Ed.), *Developments in the Economics of Aging*. University of Chicago Press, Chicago, pp. 57–82.
- Choi, J.J., Haisley, E., Kurkoski, J., and Massey, C. (2017). Small cues change savings choices, *Journal of Economic Behavior & Organization*, 142(C), 378-395.
- Goda, G. S., Manchester, C. F., & Sojourner, A. J. (2014). What will my account really be worth? Experimental evidence on how retirement income projections affect saving. *Journal of Public Economics*, 119, 80-92.
- Madrian, Brigitte C. (2014). Applying Insights from Behavioral Economics to Policy Design, *Annual Review of Economics*, 6:1, 663-688.
- Madrian, Brigitte C. and Dennis F. Shea. (2001) The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior, *The Quarterly Journal of Economics*, Volume 116, Issue 4, 1 November, Pages 1149-1187.
- Madrian Brigitte C., Hal E. Hershfield, Abigail B. Sussman, Saurabh Bhargava, Jeremy Burke, Scott A. Huettel, Julian Jamison, Eric J. Johnson, John G. Lynch, Stephan Meier, Scott Rick and Suzanne B. Shu. Behaviorally Informed Policies for Household Financial Decision-making.” *Behavioral Science and Policy*. 2017;3 (1) :26-40.
- Morrissey, Monique. (2016). The State of American Retirement. *Economic Policy Institute, Washington, DC*.
- Office of Evaluation Sciences. (2015). On-Base Servicemember TSP Enrollment. Available: <https://oes.gsa.gov/assets/abstracts/1506-On-Base-Servicemember-TSP-Enrollment.pdf>



Office of Evaluation Sciences. (2017). Prompting Decisions on Retirement Saving. Available: <https://oes.gsa.gov/assets/abstracts/1703-prompting-tsp.pdf>

Skimmyhorn, William. (2016). "Assessing Financial Education: Evidence From Boot Camp." *American Economic Journal: Economic Policy*, 8(2): 322-343.

Thaler, Richard H. and Shlomo Benartzi. 2004. Save More Tomorrow™: Using Behavioral Economics to Increase Employee Saving. *Journal of Political Economy*, 112:S1, S164-S187

Table 1. Summary statistics by intervention

| Variable | Information Email | | Action Steps | | Target Rates | | Active Choice | | Default Choice | |
|-------------------------------|-------------------|-----------|--------------|-----------|--------------|-----------|---------------|-----------|----------------|-----------|
| | Control | Treatment | Control | Treatment | Control | Treatment | Control | Treatment | Control | Treatment |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Age | 23.207 | 23.244 | 22.774 | 23.112 | 22.350 | 22.330 | 21.939 | 21.237 | 22.723 | 22.934 |
| Female | 0.153 | 0.146 | 0.154 | 0.149 | 0.155 | 0.151 | 0.143 | 0.175 | 0.164 | 0.163 |
| Black | 0.220 | 0.213 | 0.220 | 0.220 | 0.219 | 0.220 | 0.223 | 0.177 | 0.224 | 0.229 |
| Hispanic | 0.147 | 0.151 | 0.151 | 0.150 | 0.154 | 0.158 | 0.160 | 0.185 | 0.179 | 0.179 |
| Other race | 0.070 | 0.065 | 0.072 | 0.068 | 0.074 | 0.070 | 0.073 | 0.076 | 0.063 | 0.065 |
| Married | 0.288 | 0.286 | 0.282 | 0.287 | 0.275 | 0.276 | 0.266 | 0.282 | 0.155 | 0.156 |
| Children | 0.519 | 0.515 | 0.447 | 0.500 | 0.394 | 0.386 | 0.405 | 0.274 | 0.330 | 0.331 |
| High school/GED | 0.815 | 0.816 | 0.817 | 0.816 | 0.819 | 0.823 | 0.831 | 0.845 | 0.860 | 0.864 |
| Some college | 0.062 | 0.063 | 0.059 | 0.063 | 0.057 | 0.058 | 0.054 | 0.074 | 0.045 | 0.045 |
| Bachelors or more | 0.121 | 0.118 | 0.121 | 0.118 | 0.121 | 0.116 | 0.114 | 0.080 | 0.094 | 0.090 |
| Enlisted | 0.916 | 0.917 | 0.916 | 0.918 | 0.917 | 0.920 | 0.927 | 0.948 | 0.969 | 0.971 |
| Officer | 0.070 | 0.068 | 0.069 | 0.068 | 0.067 | 0.066 | 0.072 | 0.052 | 0.031 | 0.029 |
| N | 14,810 | 14,551 | 29,936 | 134,044 | 15,126 | 120,779 | 48,040 | 497 | 37,133 | 14,409 |
| 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 2. Main effects of interventions on TSP participation

| | Information Email | Action Steps | Target Rates | Active Choice | Default |
|--|-------------------|--------------|--------------|---------------|-----------|
| | (1) | (2) | (3) | (4) | (5) |
| Treatment | 0.0020 | 0.0041** | 0.0069*** | 0.1068*** | 0.3728*** |
| | (0.0030) | (0.0018) | (0.0023) | (0.0191) | (0.0070) |
| N | 29,361 | 163,980 | 135,905 | 31,906 | 51,542 |
| R ² | 0.0083 | 0.0091 | 0.0134 | 0.0134 | 0.2112 |
| Control Group Mean | 0.069 | 0.072 | 0.076 | 0.103 | 0.179 |
| 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 | - | 0.419 | 0.185 | 0.000 | 0.000 |
| Action Steps | | - | 0.33 | 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 3. 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 | \$100,000 | \$48,780 | \$28,986 | \$11 | \$536 |
| Medium | 750 | \$3,333 | \$1,626 | \$966 | \$11 | \$18 |
| Large | 1,000 | \$2,500 | \$1,220 | \$725 | \$11 | \$13 |
| Dept of Defense | 800,000 | \$3 | \$2 | \$0.91 | \$11 | \$0.02 |
| Panel B. Thrift Savings Plan Cumulative Contributions (\$ Per New \$ of Contributions) | | | | | | |
| Small | 25 | \$87 | \$23 | \$18 | \$0.01 | \$1 |
| Medium | 750 | \$3 | \$1 | \$1 | \$0.01 | \$0.05 |
| Large | 1,000 | \$2 | \$1 | \$0.46 | \$0.01 | \$0.04 |
| Dept of Defense | 800,000 | \$0.003 | \$0.001 | \$0.001 | \$0.01 | \$0.00005 |

Note. Author calculations using cost data and program effect estimates from Tables 3 and 4. 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).

About the authors

Richard Patterson is an Assistant Professor of Economics at the United States Military Academy at West Point, Long-Term Research Coordinator at the U.S. Army Office of Economic and Manpower Analysis, IZA Research Affiliate, and CESifo Research Affiliate. He received his Ph.D. in Policy Analysis and Management from Cornell University in 2015. His research interests are primarily in the areas of behavioral economics, economics of education, household finance, and labor economics. His work has examined the impact of technology in the classroom, the effects of behavioral interventions in higher education and household finance, and behavioral factors influencing college major decisions.

William Skimmyhorn is an Assistant Professor of Economics and Finance at the Raymond A. Mason School of Business at William and Mary. His research interests include household finance, human capital acquisition, behavioral economics and finance, and national security. He holds a Ph.D. in Public Policy from Harvard University, an M.S. in Management Science and Engineering from Stanford University, an M.A. in International Policy Studies from Stanford University, and a B.S. in Economics from West Point. He has published or forthcoming research at the *Review of Economics and Statistics*, the *Journal of Finance*, and the *American Economic Journal: Economic Policy* and his research has been featured in the *Wall Street Journal* and the *New York Times*. He previously served as a career officer in the U.S. Army with worldwide assignments including as an attack helicopter platoon leader and the Long-Term Research Coordinator at the U.S. Army Office of Economic and Manpower Analysis.