



Research Report

JASON M. WARD, JEFFREY B. WENGER, IRINEO CABREROS, DANIEL SCHWAM,
CRAIG A. BOND, SAMUEL ABSHER

A Revised Recruiting Resource Model for Achieving the Army Personnel Strategy

Accounting for Digital Advertising

For more information on this publication, visit www.rand.org/t/RRA2108-1.

About RAND

The RAND Corporation is a research organization that develops solutions to public policy challenges to help make communities throughout the world safer and more secure, healthier and more prosperous. RAND is nonprofit, nonpartisan, and committed to the public interest. To learn more about RAND, visit www.rand.org.

Research Integrity

Our mission to help improve policy and decisionmaking through research and analysis is enabled through our core values of quality and objectivity and our unwavering commitment to the highest level of integrity and ethical behavior. To help ensure our research and analysis are rigorous, objective, and nonpartisan, we subject our research publications to a robust and exacting quality-assurance process; avoid both the appearance and reality of financial and other conflicts of interest through staff training, project screening, and a policy of mandatory disclosure; and pursue transparency in our research engagements through our commitment to the open publication of our research findings and recommendations, disclosure of the source of funding of published research, and policies to ensure intellectual independence. For more information, visit www.rand.org/about/research-integrity.

RAND's publications do not necessarily reflect the opinions of its research clients and sponsors.

Published by the RAND Corporation, Santa Monica, Calif.

© 2023 RAND Corporation

RAND® is a registered trademark.

Library of Congress Cataloging-in-Publication Data is available for this publication.

ISBN: 978-1-9774-1158-7

Limited Print and Electronic Distribution Rights

This publication and trademark(s) contained herein are protected by law. This representation of RAND intellectual property is provided for noncommercial use only. Unauthorized posting of this publication online is prohibited; linking directly to its webpage on rand.org is encouraged. Permission is required from RAND to reproduce, or reuse in another form, any of its research products for commercial purposes. For information on reprint and reuse permissions, please visit www.rand.org/pubs/permissions.

About This Report

This report documents research and analysis conducted as part of a project entitled *A Revised Recruiting Resource Model for Achieving the Army Personnel Strategy: Accounting for Digital Advertising*, sponsored by the Assistant Secretary of the Army for Manpower and Reserve Affairs (ASA [M&RA]). The purpose of the project was to provide ongoing analyses of the resources required through the project objective memorandum period to meet the goals of the U.S. Army People Strategy under alternative recruiting environments and recruit eligibility policies.

This research was conducted within RAND Arroyo Center's Personnel, Training, and Health Program. RAND Arroyo Center, part of the RAND Corporation, is a federally funded research and development center (FFRDC) sponsored by the United States Army.

RAND operates under a "Federal-Wide Assurance" (FWA00003425) and complies with the *Code of Federal Regulations for the Protection of Human Subjects Under United States Law* (45 CFR 46), also known as "the Common Rule," as well as with the implementation guidance set forth in U.S. Department of Defense (DoD) Instruction 3216.02. As applicable, this compliance includes reviews and approvals by RAND's Institutional Review Board (the Human Subjects Protection Committee) and by the U.S. Army. The views of sources utilized in this study are solely their own and do not represent the official policy or position of DoD or the U.S. Government.

Acknowledgments

We would like to thank our RAND colleagues Avery Calkins and Bruce Orvis for their keen insights and expert advice. We would also like to thank our initial action officer at the Army Enterprise Marketing Office, MAJ Dan Duplessis, and our continuing action officer MAJ Kevin Kumlien, as well as MAJ Reggie Cotton (Headquarters, Department of the Army, G-1) and COL Johnny Oliver (retired, ASA [M&RA]).

We would also like to thank our internal RAND reviewer, Jim Marrone, and our external reviewer, Mikhail Smirnov of the Institute for Defense Analyses, for their timely and thoughtful reviews and their careful attention to detail. This report benefited considerably from their input.

Summary

Introduction

This research provides ongoing analyses of the resources required to meet the goals of the U.S. Army People Strategy under alternative recruiting environments; recruit eligibility policies; and recruiting resources, such as bonuses, advertising, and recruiters. This research report presents results from an updated version of the RAND Corporation’s Recruiting Resource Model (RRM), a multi-part statistical model that explores how trade-offs between key recruiting resources affect the Army’s ability to achieve recruiting goals and the cost of doing so.

This project significantly updates and extends prior work on the RRM by Knapp et al. (2018) by examining the relationship between resource inputs and recruiting outcomes—particularly contracts and accessions—using the revised model and more-recent data. The updated model also incorporates digital advertising, which has become an increasingly important recruiting resource in recent years.

Consistent with previous iterations of the model, our results indicate that television advertising and recruiters have large, positive associations with contract production, and these inputs are more cost-effective than bonuses.

We tested the RRM’s predicted recruiting outcomes by comparing thousands of iterations of alternative levels of resource utilization. These optimization exercises consistently point to large increases in advertising (primarily television) and a significant reduction in bonus spending as a more effective use of financial resources than the baseline allocations of these resources. Across ten different scenarios to which we applied the model, the average recommendation was for an 80-percent increase in television advertising spending and a 40-percent decrease in bonus spending. The model generally recommends less spending on digital advertising, but because we were limited to less-than-optimal data, these results should be interpreted with caution. Furthermore, our study’s time span witnessed significant changes in the modes of digital advertising and the ways in which such advertising was consumed. Additionally, the model results suggest that shifting resource use modestly toward more recruiters is likely beneficial in more-difficult recruiting environments.

We are limited to using historical data on realized resource use and outcomes as opposed to data from truly experimental sources (for example, randomized trials of different levels of advertising spending, bonus use, or recruiter levels). For this reason, the results presented in this report cannot provide literal guidance for Army spending. Rather, they inform how the Army might move resources in different recruiting environments. Making marginal changes along these lines in a purposeful manner over time—either broadly or at a local level (as might be done in an experimental setting)—would be an appropriate first step in implementing the recommendations of our research.

Contract Production Model

The contract production model (CPM) is the foundation of the RRM. This econometric model relates both Army resource use and external economic factors to the production of enlistment contracts. This model is estimated at the recruiting company-by-month level using a standard fixed-effects panel estimator. Variables in the model include *high-quality* (HQ) *mission* (the number of high school graduates who score in the upper half of the Armed Forces Qualification Test that the Army prioritizes in recruiting), non-high-quality (NHQ) mission, U.S. Army Reserve (USAR) mission, number of recruiters, the local unemployment rate, local area minimum wages, the University of Michigan Consumer Sentiment Index (a well-regarded measure of expectations about the future state of the economy), military occupational specialty (MOS) and quick-ship (QS) bonuses, and spending on digital and television advertising. The estimated results all have conceptually predictable signs: USAR mission, consumer sentiment, and minimum wage are all negative. For example, this indicates that when the USAR recruiting mission increases, Regular Army (RA) contracts fall, suggesting that USAR and RA contracts are substitutes (increasing one mission negatively affects the ability to meet the other mission). As consumer sentiment improves and minimum wages increase, potential recruits have relatively better alternative employment options and fewer contracts are written. Conversely, a rise in the RA mission (both HQ and NHQ), an increase in the number of recruiters, a rising unemployment rate (indicating more-limited civilian employment options), bonus spending, and advertising all have positive associations with RA recruiting contracts. Overall, the model performed in a conceptually appropriate manner under a variety of alternate specifications.

We used the CPM to generate estimates of contract production separately by contract quality type (HQ and NHQ). While the results are often similar, there are notable differences, including in the estimated role of digital advertising, which appears to have a stronger association with HQ contract production. Additionally, macroeconomic factors vary in their associations with these two types of contracts: Changes in the minimum wage have a statistically meaningful, negative association with HQ contract production, while changes in the unemployment rate and Consumer Sentiment Index have a strong association with the production of NHQ contracts (we discuss these and other measures used in the model in more detail in Chapter 2 and Appendix B).

Role of the Delayed Entry Program

Once a recruit has gone through the Military Entrance Processing Station (MEPS)—which requires taking the Armed Services Vocational Aptitude Battery, passing a physical examination, and selecting an occupation—the recruit will take the Oath of Enlistment. While some recruits will *direct ship* (meaning that they will depart for basic combat training shortly after taking the oath), the majority will commit to enter basic training at some future date and wait

for their ship date in the Delayed Entry Program (DEP). Three things can happen to enlistees in the DEP:

1. While waiting for their ship date, they could change their mind about serving (this could be for a variety of reasons) and drop out of the DEP.
2. They could be offered a QS bonus to move their training date up.
3. They could complete their time in the DEP, return to the MEPS, indicate that they have had no new physical ailments, sign their final contract, and ship to basic training.

The RRM takes these three paths into account by modeling the assignment of QS bonuses to a certain share of contracts to speed some enlistees through the DEP and by assigning a probability of attrition to each contracted enlistee using historical rates of attrition for different types of contracts and lengths of time in the DEP. We assume that a fixed percentage of enlistees will fail to complete their terms, known as *DEP losses*. An excess of contracts will have to be written to account for DEP losses for the Army to reach its accession goal.

Cost-Optimization Function

With the contract production function estimates and the structure of the DEP in place, we turn our attention to optimizing costs. The goal is to determine whether the accession mission can be achieved in a more cost-effective manner than the current Army baseline budget. The optimizer searches for ways to achieve the accession mission by allowing resource parameters that are within the Army's control to vary. For example, perhaps the Army could have spent more on digital and television advertising and less on bonuses; the optimizer calculates the costs of this change and whether it is a lower-cost option. Another option could be to hire more recruiters or reduce bonus eligibility or amounts. These solutions are considered by the optimization algorithm until the lowest-cost mix of resources that meets a set of stopping criteria is found. The optimizer might stop searching before the mission is achieved because the optimizer assigns a penalty (denominated in dollars) to missing mission that is then weighed against spending more money on various resources to meet mission. Therefore, there may be scenarios where the total cost to missing mission is lower than the cost of continuing to increase resource use to meet mission.

In the optimization procedure, 11 parameters are allowed to vary across a 12-month period: the proportions of HQ eligible for MOS and QS bonuses, the proportions of NHQ eligible for MOS and QS bonuses, the MOS and QS average bonus amounts for both HQ and NHQ, digital and television advertising expenditures, and the number of on-production recruiters. Searching over this multi-dimensional space for the lowest-cost combination that achieves the accession mission is computationally demanding. To better represent both operational realities and historical practice, we impose bounds on how quickly parameters (including changes in the recruiter force, bonus eligibility, and bonus amounts) can vary in

each month. We also limit overall spending levels on bonuses and advertising to the minimum and maximum levels observed over all the months of the historical data we use.

In addition to finding the most cost-effective way to achieve an accession mission, the optimizer tool allows us to change the baseline scenario (the baseline is modeled as a mix of current Army policy and economic conditions that are modeled based on 2015 parameters). These input parameters can be varied for sensitivity analysis; runs are described in the Cost Excursions section below.

Cost Excursions

We estimate a series of cost excursions where we systematically alter one or more of the baseline conditions to demonstrate the optimization process. We compare both unoptimized and optimized spending and accession outcomes under these altered conditions with the baseline results. These excursions focus on policy-relevant or otherwise salient conditions with respect to recruiting outcomes (such as changes in the unemployment rate, minimum wage, HQ share of recruits, and advertising spending), estimate unoptimized model results, and then optimize the model under the given condition. These excursions include lowering the accession mission, decreasing the percentage of HQ recruits, increasing waivers, raising the minimum wage, and raising and lowering the unemployment rate. Additionally, we provide a series of excursions where we fix recruiters, bonuses, and advertising spending at baseline levels—either singly or in pairs—to assess how resources might be optimally varied in a more constrained environment.

Our main results focus on a few key excursions related to Army policy and economic conditions. Most of these excursions have the effect of making recruiting or the recruiting environment more difficult; the conditions of these excursions mirror aspects of the current recruiting environment. By lowering unemployment, raising minimum wages, or increasing the HQ share, the Army will incur higher costs to achieve the fiscal year 2022 accession mission.

Conclusions and Recommendations

Overall, the cost excursions show three main results:

1. Television advertising expenditures are currently too low; the optimized model regularly recommends approximately 80 percent greater spending on this resource.
2. Modest increases in spending on recruiters are generally recommended when the recruiting environment is difficult. Under less adverse recruiting conditions, advertising can substitute for recruiters and still achieve recruiting goals at lower cost.
3. Bonuses are a costly and inefficient way of achieving recruiting goals. The optimization model never solves for an increase in bonuses. Under all scenarios that we esti-

mate results for, the optimal solution reduces bonus spending. On average, the recommended reductions are between roughly 25 and 50 percent.

Consequently, we recommend that the Army increase advertising expenditures and, in the current difficult recruiting environment, consider an increase in recruiters. These additional costs might be at least partially offset by reducing QS bonus amounts (while preserving higher eligibility) and MOS bonuses (through both bonus eligibility and bonus amount). However, we acknowledge that MOS bonuses may play an additional and important role in the relative strength of occupation-specific end strength that we do not account for in our modeling.

There might be other policies, such as reducing recruit quality, that will save money in the short run. However, increasing accessions by lowering quality might have higher downstream costs, including increases in early attrition, lower performance, and lower reenlistment probabilities (we model these results in Appendix D). Because the RRM cannot fully capture these longer-range costs, we focus only on the costs of direct inputs to the recruiting enterprise.

Because the data used in the RRM did not arise from an experimental research setting, the associations between resources and contract production that our model estimates might not represent purely causal relationships despite our multiple approaches to minimize bias, drawn from econometric theory or institutional knowledge of Army recruiting operations. Thus, the RRM's quantitative results broadly reflect the relative effectiveness of resource use rather than give specific instructions for the future deployment of recruiting resources. Throughout the report, we highlight this and other specific limitations of the current iteration of the RRM. We emphasize that the Army should consider conducting a series of well-designed and rigorously implemented randomized controlled experiments to determine the true causal effect of Army advertising and other resources on contract production and enlistment.

Contents

About This Report	iii
Summary	v
Figures and Tables	xiii
CHAPTER 1	
Introduction	1
Background	1
What Is the Recruiting Resource Model?	3
Purpose of the Report	4
Organization of the Report	5
CHAPTER 2	
Contract Production Model	7
Conceptualization	7
Operationalization	9
Data	11
Estimates	12
Limitations	16
CHAPTER 3	
Role of the Delayed Entry Program	17
CHAPTER 4	
Cost-Optimization Function	19
Objective Function	19
Optimization Parameters	20
Excursions	21
Limitations	24
CHAPTER 5	
Cost Excursions	27
Recruiting Outcomes Under More-Challenging Economic Conditions	27
Recruiting Outcomes Under Differing Quality Goals	31
Recruiting Outcomes Under Constrained Advertising Spending	33
Summary of Findings	35
CHAPTER 6	
Conclusion and Recommendations	37
Summary of Findings	37

Recommendations	39
Recruiting Resource Model Limitations	42
Areas for Future Research	43
APPENDIXES	
A. Data Sources and Definitions	45
B. The Contract Production Model	55
C. The Optimization Process	71
D. Additional Tables and Figures	79
E. Documenting an Alternate Approach to Estimating Contract Production: Spatial First Differences	89
Abbreviations	97
References	99

Figures and Tables

Figures

2.1.	Estimates from the Contract Production Model by Contract Quality	13
4.1.	Comparing Baseline Spending with Optimized Spending on Advertising.....	24
4.2.	Comparing Baseline Spending with Optimized Spending on Advertising.....	25
C.1.	Graphical Overview of Optimization Model	72
D.1.	Probability of Dropping Out of Delayed Entry Program for Contracts with Different Delayed Entry Program Durations	79
D.2.	Comparing Unoptimized Spending with Optimized Spending on Advertising and Bonuses for Scenario 1 (Baseline)	80
E.1.	Map of Army Recruiting-Company Geography in the Continental United States	92
E.2.	Maps of Estimation Groups of Recruiting Companies by Rotation Angle	93

Tables

4.1.	Recruiting Resource Model Baseline Model Conditions.....	22
4.2.	Comparing Baseline with Optimized Results	23
5.1.	Unemployment Rate Declines by 25 Percent.....	28
5.2.	Federal Minimum Wage Increases to \$8.50.....	30
5.3.	Raise High-Quality Share Target to 61.75 Percent	32
5.4.	Lower High-Quality Share Target to 54 Percent	34
5.5.	Fix Ad Spending at Baseline Levels	35
5.6.	Summary of Recruiting Resource Model Recommendations for Changes in Resource Use Under Multiple Scenarios.....	36
A.1.	Available Contract Mission Subcategories by Service Type.....	46
A.2.	Total Contracts, Bonus Values and Eligibility, and Waiver Eligibility by Service.....	47
A.3.	Recruiters by Service Type	48
A.4.	Calendar Dates of Recruiting Contract Months for Fiscal Year 2017	51
B.1.	Contract Production Model Results	65
B.2.	Alternative Contract Production Model Results (with Fiscal Year Fixed Effects)	67
B.3.	Estimated Elasticities from Past Research on Recruitment.....	68
D.1.	Accession and Entry Pool Outcomes, Fiscal Years 2013–2018	81
D.2.	Recruiting Resource Model Excursion Scenarios	82
D.3.	Baseline Conditions (Scenario 1).....	83
D.4.	Lower Accession Mission to 60,000 (Scenario 2).....	83
D.5.	Prior-Year Entry Pool of 20 Percent (Scenario 3).....	83

D.6.	Decrease High-Quality Share to 54 Percent (Scenario 4)	84
D.7.	Increase High-Quality Share to 61.75 Percent (Scenario 5).....	84
D.8.	Increase Waivers to 15 Percent (Scenario 6)	84
D.9.	Federal Minimum Wage Increased to \$8.50 (Scenario 7).....	85
D.10.	Unemployment Rate Declines by 25 Percent (Scenario 8)	85
D.11.	Unemployment Rate Increases by 25 Percent (Scenario 9).....	85
D.12.	Fix Recruiters at Baseline Levels (Scenario 10)	86
D.13.	Fix Recruiters and Bonus Spending at Baseline Levels (Scenario 11).....	86
D.14.	Fix Recruiter and Ad Spending at Baseline Levels (Scenario 12)	87
D.15.	Fix Bonus Spending at Baseline Levels (Scenario 13).....	87
D.16.	Fix Ad Spending at Baseline Levels (Scenario 14).....	88
D.17.	Fix Ad and Bonus Spending at Baseline Levels (Scenario 15)	88
E.1.	Comparing Spatial First Difference Point Estimates with Recruiting Resource Model Contract Production Model Estimates	95

Introduction

Background

As the largest service branch in the U.S. Department of Defense (DoD), the Army seeks to enlist approximately 60,000 to 80,000 soldiers in the Regular Army (RA) each year. This number varies based on RA retention, missions, and operating environment. In addition to its RA mission, U.S. Army Recruiting Command (USAREC) seeks to enlist approximately 11,000 to 27,000 U.S. Army reservists. To accomplish this, the Army uses a wide array of recruiting resources, including national and local advertising and marketing campaigns, and more than 9,000 recruiters located at more than 1,300 recruiting stations throughout the United States. In addition to advertising and recruiting, the Army uses enlistment incentives (i.e., bonuses specific to high-demand occupations or willingness to ship on short notice). Historically, Army bonuses have been capped at \$45,000 and paid out over several years, but the maximum bonus level was recently raised to \$50,000 (Baldor, 2022). Bonus amounts and qualification requirements are managed at least quarterly by the Enlistment Incentive Review Board.

In fiscal year (FY) 2015, our data suggest recruiting cost the Army approximately \$1.6 billion, with approximately 62 percent of the budget spent on recruiters, 6 percent spent on advertising, and 32 percent spent on enlistment bonuses. While these outlays make up the direct financial costs of recruiting, the Army also self-imposes nonfinancial restraints on recruiting, such as requirements for recruit characteristics that have been shown to affect downstream costs in training and retention. This implies that the full stream of costs and benefits cannot be determined by the amount of money spent on recruiters, advertising, and bonuses (Orvis et al., 2018). In particular, the Army requires that at least 90 percent of enlisted personnel have graduated from high school with a diploma (not a General Educational Development) and that 60 percent of enlisted personnel score in the upper half of the Armed Forces Qualification Test (AFQT) distribution. These requirements are laid out in *Qualitative Distribution of Military Manpower* (Department of Defense Instruction [DoDI] 1145.01, 2018, p. 2). Recruits who achieve both of these benchmarks are referred to as *high quality* (HQ), while those who miss either benchmark or both benchmarks are referred to as *non-high quality* (NHQ). In addition to these educational and mental capacities, soldiers are required to be in good health, be in good social standing (i.e., have no history of convictions or incarceration), and have no evidence of current or prior drug or alcohol abuse. These

additional qualifications are established in DoDI 1304.26 (2005).¹ The goal of these quality requirements is to ensure that recruits can meet training requirements and reduce first-term attrition. However, these requirements also result in a smaller pool of qualified individuals that the Army can recruit from. This will raise immediate recruiting costs but will likely save money through more-efficient training, decreased attrition, and fewer issues due to conduct.

As this research shows, recruiting resources (e.g., recruiters, advertising, bonuses) differ in their effectiveness (cost per additional enlistment contract). However, they also differ in the amount of time it takes for the resource to be effective. While less cost-effective than other resources, enlistment bonuses can be “switched on” in a moment’s notice. Conversely, adding recruiters might require considerable lead time: New recruiters must be initiated, trained, and given time to learn the local area and the nature of the job. Similarly, advertising campaigns must be designed and tested, and then airtime or internet placements must be purchased. Additionally, advertising might require repeated exposure before the message begins to gain traction and alter choices.

While the Army has direct control over how it uses its resources and sets policy, the general recruiting environment can have a direct effect on recruitment and alter the effectiveness of recruiting resources. An extreme example occurred early in 2020 at the beginning of the coronavirus disease 2019 (COVID-19) pandemic. During that time, the Army stopped shipping to training—a clear case of external factors affecting the Army’s ability to recruit. Other periodic shifts in the economy can alter the Army’s ability to recruit. For example, when the unemployment rate declines significantly because of a robust national economy, as it did in the early 2000s and just prior to the Great Recession in 2007, there are fewer workers available to fill each job opening. Under such conditions, high school graduates might spend less time searching for a job, reducing the window for recruiting. Even those who have a predisposition to serve in the Army might find a more attractive civilian job offer. Importantly, many who sign a contract to enlist must wait months for a shipping date. If an attractive job offer comes their way during that time, they might not ship to training. Overall, a better economy for workers makes recruiting harder for the Army. We take these factors into account throughout this research. Finally, state and federal policy can have an impact on recruiting. For example, as states and localities raise their minimum wages, we find that Army contracts decline—suggesting that high school-aged students are taking jobs with higher pay instead of joining the Army.

In these different recruiting environments, recruiting resources and enlistment eligibility policies vary in their effectiveness to meet Army accession requirements. A tightening job market, such as the one the United States experienced over late 2021 and throughout 2022, will likely raise recruiting costs. There are other ways to increase the probability of meeting the mission, such as increasing the use of conduct waivers or reducing quality standards, that do not incur immediate costs. While these would likely reduce current recruiting costs, they

¹ There are gray areas (e.g., multiple traffic violations) where conduct or health waivers may be given.

could prove to have additional downstream costs because of first-term attrition and potentially affect Army readiness (Asch et al., 2021).

What Is the Recruiting Resource Model?

The Recruiting Resource Model (RRM) is a multi-part statistical model comprising three distinct sub-models: contract production, Delayed Entry Program (DEP) dynamics, and cost allocation. The contract production model (CPM) weighs trade-offs between recruiting conditions and the recruiting resources used to produce HQ and NHQ enlistment contracts. The DEP dynamics model assigns differential times in the DEP and rates of attrition according to contract characteristics (e.g., HQ or NHQ, prior service, and receipt of a quick-ship [QS] bonus), producing a stream of accessions based on the contracts that it receives as inputs. The third model, cost allocation, calculates costs per accession for a given FY.

The CPM reflects the Army's recruiting practices between FYs 2013 and 2018.² The CPM is estimated using Army and economic data that reflect the recruiting environment, spending on recruiting resources, and USAREC missioning by recruiting company and month. The model's regression parameters, estimated using detailed data, determine the extent to which resourcing, missioning, population, or the properties of recruiting companies are associated with greater or lesser levels of non-prior service (NPS) contract production.

The DEP model divides contracts by type—HQ and NHQ, prior service and NPS, and attachment of a QS bonus and no bonus incentive—and assigns a time in the DEP and a historical attrition parameter to each contract type. Because of these contract losses, meeting an accession goal requires the production of a higher number of contracts than the mission requires. For example, if historical attrition for those who are scheduled to ship in four months is 10 percent, then 100 contracts with a four-month ship date must be written to produce 90 accessions.

Finally, the cost allocation model generates costs per accession by allocating two key cost components to each realized accession: costs that are paid monthly or yearly (such as advertising and recruiter costs) and costs that are paid infrequently (typically during periods of difficult recruiting). By statute, these latter costs (typically enlistment incentives [bonuses]) are paid out over time if they exceed \$10,000. The cost allocation model counts bonus costs at the time they are incurred as a fiscal obligation by the Army. For example, though a recruit might not receive their first bonus installment until they complete their first year of service, the cost allocation model will assess the full bonus cost at the time of accession. This allows the RRM model to optimize total costs in real time by identifying cost-minimizing resource portfolios. The downside of this strategy is that it accounts for expenditures on bonuses each year in a way that might differ from the actual approach used by the Army.

² As will be discussed in Chapter 2 and Appendix B, we exclude FY 2016 because of limitations on the availability of digital advertising data.

The optimizer determines the cost-minimizing portfolio of recruiting resources; however, the solution is conditional on the baseline scenario used.³ All the scenarios we present use the same set of expenditures and resources as the baseline (detailed in Chapter 4) and economic conditions from FY 2015, which are then varied to demonstrate various alternative recruiting environments. The optimization algorithm aims to produce enough accessions to meet monthly and annual mission while minimizing total costs.

In addition to understanding how specific resources translate to contracts, the RRM can help Army leaders better understand the complex trade-offs involved in recruiting. The RRM can be refined and updated to reflect changes in the effectiveness and efficiency of individual recruiting resources, USAREC company structure or operations, and lessons learned from the results of changes in recruit eligibility policies.

Purpose of the Report

There are a nearly limitless number of combinations of resources, eligibility qualifications, and economic conditions that can go into planning and executing an Army recruiting mission. No single person can anticipate how all those combinations will play out. However, the RRM can contribute to making these complex decisions by simulating alternate spending plans and predicting which ones will improve results. We can also alter the conditions of the model to understand how a decline in unemployment, for example, will change the optimal mix of resources. Additionally, this research will help us understand how recruiting resources and recruit eligibility policies work together under varying accession requirements and recruiting environments. This is critical information for decisionmakers who must use limited resources efficiently and effectively to meet the Army's accession mission. This research builds on earlier research by Knapp et al. (2018), conducted by the RAND Arroyo Center, on the effectiveness of alternative recruiting resource use in generating enlistment contracts and accessions. The RRM developed in this report updates and extends the previous RRM by simplifying the structure of the CPM and updating the optimization algorithm; estimating new parameters; and incorporating more-recent data, including digital advertising. Despite these considerable changes, the purpose of the RRM is unchanged: to consider the associations among the monthly level and mix of recruiting resources, recruit eligibility policies, and overall recruiting environment and to assess the value of alternate combinations of these factors that could aid the Army in meeting its mission more efficiently. It models how these factors combine to produce monthly contracts, models the dynamics of the DEP, and produces estimates for the minimum resource requirements necessary to meet Army recruiting goals.

³ This is because the complexity of the model's parameter space and current computing power limits us to the use of a local optimization procedure that reaches a locally optimal solution rather than a global optimum. We discuss the optimizer in more detail in Appendix C.

Organization of the Report

Chapter 2 introduces the data and estimation strategy of the CPM and interprets its results. The CPM is the heart of the RRM in that it allows us to understand how recruiting resources, eligibility policies, and recruiting environment combine to generate contracts. Chapter 3 discusses the DEP model and DEP attrition. Chapter 4 discusses optimization and the search for the cost-minimizing portfolio of expenditures to achieve accession mission. Chapter 5 runs through multiple excursions in which we alter the mission, recruiting environment, eligibility policies, or some combination and examine the changes in the cost-minimized solution. Chapter 6 concludes with the main findings, provides recommendations, and discusses ways to improve the model in future iterations to make it more useful for senior decisionmakers. In Appendix A, we discuss our data in more detail. Appendix B provides a full derivation of the CPM and detailed results. Appendix C contains a detailed discussion of the optimization process. Appendix D contains additional tables and figures that complement those in the main text, and Appendix E contains a brief discussion of an alternative modeling approach that was explored in the interest of transparency about the research process.

Contract Production Model

Conceptualization

In their original work on the RRM, Knapp et al. (2018) lay out the theoretical and conceptual underpinnings of the CPM. They argue that recruiters are the essential component in generating contracts. This is true regardless of how the recruit found their way to the Army, be it through visiting GoArmy.com, attending an event, or walking into a recruiting center. Recruiters are responsible for getting the potential recruit to the Military Entrance Processing Station (MEPS), where they will receive their aptitude testing and a physical, and then working with them to select a suitable military occupational specialty (MOS).

We follow this conceptualization by using a model of NPS contract production that centers on recruiters and other variables that might affect their productivity. This is reflected in the CPM that we describe below, a linear regression model that is at the heart of the RRM. The full derivation of the CPM from a theoretical Cobb-Douglas production function based around recruiters and recruiter effort is provided in Appendix B.

Dependent Variables

Throughout the period of this study, recruiters used a team-based approach; consequently, the dependent variable in the CPM is the number of contracts generated by each company. As mentioned earlier, we separate recruits into two types: HQ and NHQ, where *HQ* is defined as high school diploma graduates with an AFQT score in the upper half of the scoring distribution (above the median, i.e., 50th percentile). We estimate separate company-level models for each contract quality type (HQ and NHQ). We do this for both theoretical and practical reasons. From a theory standpoint, it is likely that potential recruits of differing quality face different choices. That is, a high school diploma graduate who scores in the top half of the AFQT might have different civilian labor market opportunities than a high school graduate who scores in the bottom half of the AFQT. Potential recruits of differing quality might also be differentially affected by economic conditions or advertising. We show that this is generally the case: HQ and NHQ contract outcomes have differential associations with multiple measures of recruiting resources and the economic environment.

Independent Variables

Army Inputs

We start by incorporating the recruiting resources used by the Army to positively affect the number of contracts written, including recruiters, bonuses, and advertising. While care should be taken in how these inputs are modeled, the theoretical reason for including them is straightforward: They are the key direct inputs used to generate contracts. Apart from these recruiting resources, we also include the company-level recruiting mission, decomposed into HQ, NHQ, and a U.S. Army Reserve (USAR) mission. We include these measures that are not resources *per se* to account for recruitment effort, which is one of the missing variables that we would ideally have in the RRM. Recruiter effort is unobservable to quantitative researchers, and, even if it were observable, we do not have a measure of effort in our data. However, variation in recruiter effort should be proportional to variation in recruiting mission. In other words, we include HQ and NHQ RA contracts, as well as USAR contracts, as a proxy for effort: If recruiters know that they are expected to hit a higher-than-average mission, then they are likely to expend more effort. This is especially true if there is a distribution of effort across a company where some people work at capacity and others have excess capacity. With a larger mission, those with excess capacity will need to work harder. Second, effort might be expended toward different ends: Because these companies have a joint RA and USAR mission, if the RA mission goes up while the USAR mission remains constant, we should expect that recruiters will shift effort toward producing RA contracts.

Recruiting Environment (Economic)

There have been numerous studies showing that economic conditions influence the ease or difficulty of recruiting (see Asch et al., 2010; Asch, Hosek, and Warner, 2007; and Murray and McDonald, 1999). For example, Wenger et al. shows that

Successfully achieving a mission goal is tremendously more difficult when the national unemployment rate is lower rather than higher. Additionally, when casualty rates increase or operational difficulties mount, recruiting difficulty worsens. (2019, p. ix)

The first measure of economic conditions we introduce to the model is the unemployment rate. While the estimated association between the unemployment rate and contract production varies across past studies (see Table B.3 for a summary of these relationships), the association is invariably positive and often large in magnitude.

In this analysis, we use two additional measures of economic conditions. The first is the University of Michigan Consumer Sentiment Index (UMCSI) (FRED Economic Data, 2022). The UMCSI asks a nationally representative sample of U.S. households approximately 50 questions each month with a focus on three primary areas: how consumers view their own financial prospects, their expectations for the general economy over the near term, and their expectations for the economy over the long term. While the unemployment rate captures information about the current state of employment, the UMCSI allows us to measure

national expectations about future economic conditions. Since joining the military is a multiyear commitment, such a measure is conceptually relevant.

Our third measure of the recruiting environment is the minimum wage. The minimum wage essentially measures the lowest legal wage for employment (with narrow exceptions for tipped employees and others). Raising the minimum wage may make recruiting more difficult by effectively raising the floor on civilian earnings. Minimum wages vary significantly over time and across geography. While the federal minimum wage is binding in all states, many states have state minimum wages that exceed the federal minimum wage, and numerous localities (cities and counties) have raised their local minimum wages even further.

Increases in minimum wages are highly relevant for the population that the Army seeks to recruit—those in their late teens and early twenties. Using the Current Population Survey from 1979 to 2014, Allegretto et al. (2017) found that slightly more than 40 percent of working teens earned within 10 percent of the statutory minimum wage (higher than state or federal) while just 7.7 percent of workers overall earned that wage.

Therefore, a higher minimum wage might make it harder to successfully generate contracts among the population of young people targeted for recruitment. There is a countervailing force, however. Standard neoclassical economic theory suggests that in the absence of other market distortions, a binding statutory minimum wage should reduce employment (in particular, it should raise teen unemployment relative to overall unemployment). The argument suggests that employers will reduce hiring as wages increase, just as consumers drive less when gas prices go up. In the end, we find that minimum wage increases are associated with a decrease in the number of contracts written. But this association is stronger for HQ contract production, suggesting that minimum wage increases lead employers to shift toward hiring relatively more-skilled workers that would qualify as HQ recruits (Clemens, Kahn, and Meer, 2021).

Finally, we did not include measures of the operational environment, as was suggested by the quote from Wenger et al. (2019). However, casualty rates were low and did not vary significantly during the sample period used in this study (FYs 2013–2018), nor did the operational tempo.¹ Consequently, these factors were not likely to vary enough to be useful in explaining changes in the recruiting environment.

Operationalization

In this brief section, we discuss rescaling measures to better make comparisons, how certain variables were measured or specified to achieve a better fit, and how the overall model was estimated. The goal of this section is to explain the model's parameters.

¹ Overall active-duty military deaths, which reached highs near 2,000 per year from 2005 to 2007, fell to approximately 300 per year during this time (Defense Casualty Analysis System, 2011).

Scaling by Qualified Military Available

We divide company-level measures of recruiters, contracts, and mission by the number of qualified military available (QMA) in the company's recruiting area. QMA is DoD's estimate of the number of youth (ages 17–24) who are eligible and available to serve in the military. DoD considers seven potential types of disqualification: medical or physical, overweight, mental health, drugs, conduct, dependents, and aptitude. In 2013, DoD's Joint Advertising and Market Research Studies program—which is tasked with estimating the number of youth in the United States eligible for military service—estimated that 29 percent of youth ages 17–24 were eligible to serve but that nearly 40 percent were enrolled in college. This left only 17 percent of the overall youth population, or 5.8 million young people, considered to be QMA. By scaling the number of contracts by this number (the estimate of the pool of potential recruits in each geographic area in our analysis), we can better equalize the different recruiting companies for the sake of comparison. For example, the recruiting company in Boise, Idaho, which spans all of Idaho and far-eastern Oregon, can be compared with a recruiting company that covers part of the city of Houston, Texas, in terms of potential recruits. Consequently, the dependent variable is not a count of the number of contracts, but the number of contracts written per QMA. Other factors, including recruiters and advertising spending, are also scaled in this manner.

Advertising

One of the most critical variables in our analysis is advertising. Previous research (Dertouzos and Garber, 2003; Dertouzos and Garber, 2006) has postulated that the effect of advertising is a function of the amount of money spent and that this function (conceptualized as a graph with spending on the x-axis and contract production on the y-axis) is S-shaped. In other words, advertising has a minimal impact on contract production at low levels of spending, a more linear relationship over the middle range of spending, and minimal additional effects at extremely high levels of spending because the market is thought to be saturated. While this conceptualization is helpful for understanding the way that advertising might work, and while it might be empirically supported in prior data, it was not apparent in testing we performed with the recent, relatively short time span of advertising data that we had available.

The S-shaped function of advertising effects is informed by the idea that advertising has a cumulative effect (Leone, 1995). The initial exposure to an advertisement primes the viewer so that the second exposure is more impactful than the first. Repeated exposures can be increasingly effective up until a saturation point.

With the limited data we have, we consider advertising dynamics by using a basic, data-driven approach to generate a single *advertising stock* measure, which operationalizes the idea that both current and prior exposure contribute to the overall effect of advertising. Specifically, the reported estimates of the relationship between advertising and contract production represent an association between the outcome and the contemporaneous monthly advertis-

ing spending combined with the two prior months of advertising spending multiplied by scalars of 0.1 and 0.01, respectively.²

Data

In this study, we used the best available and most up-to-date data we could secure. It is important to note that our regression modeling approach requires a complete set of the included variables for every period to be used in the estimation of the model. Thus, our sample size was ultimately constrained by the most-sparsely populated of our variables, which was digital advertising. The data and these limitations are described in more detail in Appendix A.

Mission and recruiter data come from USAREC, and data are aggregated up from the station level to the company; in all cases, these source data are counts. Data on contracts, bonuses, and waivers come from Human Resources Command (HRC); like mission and recruiter data, these data are counts of the number of contracts that received all types of bonuses and all types of waivers.

Minimum wage data come from Vaghul and Zipperer (2021) and were cross-referenced against an independent dataset of state-level minimum wages (Neumark, undated). Consumer sentiment data, which are measured at the national level, come from the University of Michigan. Data on unemployment are from the U.S. Department of Labor Local Area Unemployment Statistics database. We used county-level, monthly unemployment rates and matched to the company level using zip codes.

As mentioned above, advertising data were the limiting factor in the length of our sample period because they were restricted to approximately seven years of data in the case of television and only around five of those years in the case of digital. For both television and digital advertising, our measure is spending in dollars. For television advertising, we have national expenditures on advertising by month. We distributed this spending to the company level based on area-level viewership shares provided by the Army Marketing and Research Group (AMRG). We have these data for FYs 2012–2018.

Digital advertising data were more difficult to obtain and had to be drawn from two sources. First, we were able to secure relatively detailed data on digital ad placements from DoubleClick (a distribution platform owned by Google that handles a high share of total digital advertising traffic) for January 2017 to January 2019. For FYs 2013–2015, we only had national monthly digital advertising expenditures. However, the national digital spending data did not have an analogous measure of area-level exposure, as was the case with television ad spending. To address this limitation, we created area-specific shares using the average distribution of spending by zip code for the two years of DoubleClick data and allocated this

² As discussed in more detail in Appendix B, the decay parameters and the lag structure were chosen to minimize the root mean squared error of the model, thereby incorporating both the magnitude and the precision of the estimated associations into the choice of how to formulate advertising stock.

earlier national advertising spending to companies using these shares in the same manner used for the television ad spending data.

Estimates

The derivation of our regression model from a theoretical recruiting production function and the full table of model results appear in Appendix B. However, we reproduce the final CPM here for convenience. The model is estimated at the company-by-recruiting month level (where the subscript s denotes company and the subscript t denotes recruiting months).

$$\begin{aligned} \log\left(\frac{C_{st}}{Q_{st}}\right) = & \beta_0 + \beta_1 \log\left(\frac{MISS\ RA\ HQ_{st}}{Q_{st}}\right) + \beta_2 \log\left(\frac{MISS\ RA\ NHQ_{st}}{Q_{st}}\right) + \beta_3 \log\left(\frac{MISS\ USAR_{st}}{Q_{st}}\right) + \beta_4 \log\left(\frac{R_{st}}{Q_{st}}\right) \\ & + \beta_5 \log(unemp_{st}) + \beta_6 \log(cons\ sent_{st}) + \beta_7 \log(min\ wage_{st}) \\ & + \beta_8 \log(bonus\ MOS_{st}) + \beta_9 \log(bonus\ QS_{st}) + \beta_{10} \log\left(\frac{TV\ ad\ stock_{st}}{Q_{st}}\right) \\ & + \beta_{11} \log\left(\frac{dig\ ad\ stock_{st}}{Q_{st}}\right) + \beta_{12} \log\left(\frac{TV\ ad\ stock_{st}}{Q_{st}} \times \frac{dig\ ad\ stock_{st}}{Q_{st}}\right) \\ & + \beta_{12} rcm_days_{st} + \pi_0 t + \pi_1 t^2 + \pi_2 t^3 + \gamma_s + \delta_t + \theta_t^{outlier} + \epsilon_{st}. \end{aligned}$$

For all the measures shown as the natural logarithm of a ratio, the respective ratios are the count data for the indicated measure divided by QMA population (Q), as mentioned above. This normalization is important because producing one contract in a recruiting company with an eligible military population of 20,000 is likely harder than producing a contract in a recruiting company with an eligible population of 80,000. All measures that represent Army resources or the economic environment are transformed by taking the natural log so that the resulting estimates have an elasticity interpretation. Elasticities are interpretable in the following way: A coefficient such as $\beta = 0.1$ represents a relationship of 1/10th, so a 10-percent change in the resource or condition is associated with a 1-percent change in contract production.

The model regresses NPS contracts per QMA population on the three mission measures we use to proxy for effort, as well as recruiters: unemployment, consumer sentiment, and the minimum-wage level; MOS bonus and QS bonus use;³ television and digital advertising spending; and the interaction of these two spending measures.⁴ These measures are all transformed by taking the natural log, with the key Army resource measures also scaled

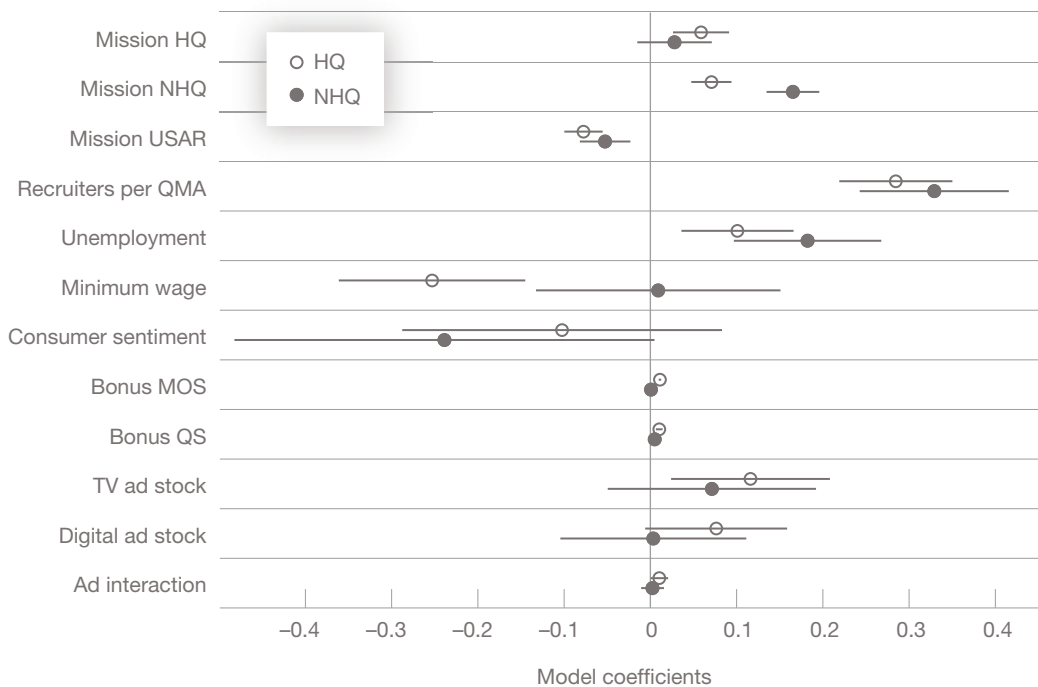
³ See Appendix B for how we define this measure.

⁴ The interaction between television and digital advertising spending flexibly allows for potential complementarity or substitution between them.

by QMA population, as mentioned above. The model also controls for a set of factors that we are not specifically interested in the parameters of but that are important to include in order to address potential biases that would otherwise arise. These include a control for the number of days in the recruiting month (which varies over time); a flexible control for linear time (a cubic term, to control for otherwise unobservable national trends that might influence recruiting); a set of month indicator variables for each month of the year (δ_p , to control for persistent seasonality in recruiting outcomes, such as the so-called bathtub months); and a single indicator variable, $\theta_t^{outlier}$, for one data point in our dependent variable (contracts) data that we believe represents an accounting error (contracts being shifted across adjacent recruiting months).

Figure 2.1 presents graphical results of the estimates from the CPM (see Table B.1 for all point estimates and standard errors). The point estimates for RA HQ mission are 0.06 for HQ contracts and 0.03 for NHQ contracts. Therefore, if we raised the HQ mission by 10 percent

FIGURE 2.1
Estimates from the Contract Production Model by Contract Quality



NOTE: A full table of these estimates appears in Appendix B. The 95-percent confidence interval for each estimate is shown by the line through the corresponding marker. All estimates are elasticities. For example, a 10-percent increase in the unemployment rate would result in a 1-percent increase in the share of HQ contracts.

while holding constant all other factors in the model, we would expect to see HQ contract production increase by 0.6 percent and NHQ contract production increase by 0.3 percent.⁵

Raising the NHQ mission has a similar relationship with contract production: It is associated with increases in the production of both types of contracts but has a much larger association with NHQ contract production (more than double the magnitude).⁶ Raising the USAR mission is associated with a reduction in RA contracts for both HR and NHR; it sends a message to recruiters to prioritize recruiting for this component. Raising the number of recruiters per QMA has the largest estimated impact on contracts in terms of elasticity.

A 10-percent increase in recruiters per QMA results in a 3.3-percent increase in the share of NHQ contracts and a 2.9-percent increase in the share of HQ contracts. As we will see in Chapter 4, this large magnitude does not imply that increasing the number of recruiters is necessarily more cost-effective because this measure is denominated in number of recruiters, not spending on recruiters (as is the case for advertising and bonuses).

Previous research has estimated that an increase in unemployment is associated with an increase in both types of contracts, but the relationship appears to be somewhat larger for NHQ contracts.⁷ A 10.0-percent increase in unemployment (for example, from 5.0 percent to 5.5 percent) is associated with a 1.0-percent increase in the share of HQ contracts and a 1.8-percent increase in the share of NHQ contracts. This seems plausible because HQ recruits might have more and better opportunities relative to NHQ candidates as the labor market worsens. Other economic variables tell a similar story. A 10.0-percent increase in the minimum wage (for example, from \$7.25 to \$7.97 per hour, considering only the federal minimum) is associated with virtually no change in NHQ contracts but with a decrease in HQ contracts of about 2.5 percent, suggesting that employers might become more discriminating in hiring when forced to offer higher wages. Finally, as consumer sentiment rises (the economy is expected to improve in both the near term and the longer term), the model estimates that fewer HQ and NHQ contracts will be produced but that the impact on NHQ contract production would be around 2.5 times the magnitude associated with HQ contract production.

The association between bonuses and contract production is relatively small in magnitude, with estimates ranging from 0.005 to 0.011 (focusing on three of the four total results that are statistically distinguishable from zero). One important reason for the low magni-

⁵ This latter estimate is not statistically distinguishable from zero at conventional levels of statistical significance (the 95-percent confidence level). However, leaving aside statistical precision, these point estimates represent our best estimation of the relationship in question, so they are used in the RRM as reported. In total, nine out of 28 total point estimates fail to be statistically distinguishable at the 95-percent confidence level, primarily because they are very close to zero. Two of these estimates that are not close to zero—the association between digital advertising and HQ contract production and the association between consumer sentiment and NHQ contract production—are both statistically significant at the 90-percent confidence level.

⁶ We discuss the conceptual relationship between these separate missions and contract production in more detail in Appendix B.

⁷ See Table B.3 for a comparison of our results to past research.

tude of these estimates is the deadweight loss associated with bonuses. Consider the following: An 18-year-old who is excited about the opportunity to become an infantryman walks into the recruiter's office. After going through the MEPS, the 18-year-old qualifies to be an infantryman, and the recruiter notes that there is a \$20,000 bonus associated with that MOS. Even though this payment had no influence on the soldier's decision to enlist, he will still receive it. This is the key reason for bonus inefficiency: A large portion of bonus spending is used to pay people for doing what they were already going to do. Additionally, bonuses cannot expand enlistment unless they are coupled with marketing activities that disseminate this information to potential recruits. In experimental research on the effect of enlistment bonuses conducted in the 1980s, the "market expansion effect" of increasing an enlistment bonus by 60 percent was estimated to be 4 percent (Polich, Dertouzos, and Press, 1986).⁸ This translates to an elasticity measure of 0.067, which is approximately equal to the estimate we calculate for MOS bonuses in our model that uses all contracts as the outcome.

Finally, we examine the effects of advertising spending. We include distinct measures for television advertising and digital advertising and their interaction, which allows for the possibility that these two modes of advertising can either reinforce each other (if their interaction is positive) or serve as substitutes for one another (if it is negative). In general, we find positive effects for both channels of advertising and a positive interaction, indicating complementarity between these channels (a reinforcing effect of television on digital and vice versa). Our estimates suggest that both television and digital advertising are more strongly associated with HQ contract production than with NHQ contract production (this difference is most pronounced with digital advertising). Comparing the estimated association between television advertising and HQ contract production with the association between MOS bonus spending and HQ contract production shows that an increase in television advertising spending is expected to produce around ten times the increase in contract production as the same increase in bonus spending.

Overall, the model's fit over the sample period is good, with an adjusted R2 of 0.37 for the model estimating HQ contracts and an adjusted R2 of 0.19 for the model estimating NHQ contracts.⁹ Thus, the model does a better job of explaining variation in HQ contract production than in NHQ contract production.

⁸ *Market expansion* is the extent to which bonuses increase enlistments overall, as opposed to two other conceptually important effects the researchers were concerned with: *skill channeling*—inducing enlistees to choose a certain MOS—and shifting the term of enlistment to a longer time horizon conditional on choosing to enlist.

⁹ An adjusted R2 of 0.37 means that the model explains 37 percent of the total variation in contract production, after discounting this measure of explanatory power according to the number of included variables and their individual predictive power (more variables or less relevant variables both lower this score, which ranges between 0 and 1).

Limitations

A primary limitation of the RRM (and of any model that uses historical data to predict future outcomes) is that past data might not help predict future outcomes or events. A case in point is the unemployment triggered by the COVID-19 pandemic, which resulted from a severe and unique combination of declining demand, explicit government policy, and international supply shocks occurring all at once. The rapid creation and deployment of multiple unprecedented income support policies for both individuals and businesses further affected the employment situation. In other words, the reasons for the unemployment crisis during the COVID-19 pandemic are entirely different from those that informed the estimated unemployment relationship in the sample data. Using our historical estimates of the relationship between the unemployment rate and recruiting outcomes would likely be ineffective in informing Army resource use during this unprecedented event.

Another key limitation is that this model uses observational—rather than experimental—data. Though we have taken several steps to minimize potential bias through the specification of the model and the inclusion and construction of our variables of interest, we cannot claim that these estimates represent purely causal relationships. The primary requirement for a causal claim is that changes in Army resource use meet two criteria: first, that resource use is not caused by recruiting outcomes (reverse causality) and, second, that unobserved external factors do not cause both recruiting outcomes and resource use (as might be the case if we did not control for the unemployment rate). However, basic facts about the way that Army recruiting activities are funded and coordinated, as well as informal institutional knowledge gleaned from our work on this and other related work, suggest that there might be less endogeneity in Army recruiting resource allocation than one might initially expect.

For example, Congress and the Secretary of Defense set several key constraints on Army recruiting goals and resource allocation, including quality mix, end strength, and overall budget. Different units within the Army must make competing cases for portions of this finite budget, and we are not aware of broad-based coordination of these efforts. Additionally, the annual marketing budget is set in ways that are, at least occasionally, unrelated to effectiveness or need. In 2019, for example, the Trump administration reduced the Army marketing budget by approximately 50 percent as a response to evidence of ineffective past spending (Cox, 2019). Furthermore, Army recruiting efforts rely on thousands of temporary recruiters, who are often reassigned staff sergeants. However, the Army recently limited these reassignments to a level 1,000 service members lower than the prior year because of operational needs unrelated to recruiting (Winkie, 2021).

We return to this issue in Chapter 6 and highlight how Army planners might benefit from conducting explicit experiments to derive more plausibly causal relationships between recruiting resources and enlistment contract production. We address other model-specific limitations in Appendix B.

Role of the Delayed Entry Program

Once a contract is signed, an enlistee must wait until there is a seat available in training. In some cases, they must wait until they have completed high school. Regardless of the reason, those who are waiting to ship to training wait in the DEP. Not everyone has a long wait in the DEP; some enlistees ship right away, and some ship earlier than planned with a cash incentive known as a *QS bonus*.

However, most enlistees will spend some time in the DEP. Modeling DEP dynamics is important because the hypothetical excursions we develop later in this research have implications for the DEP. Generally speaking, we rely on the DEP model developed by Knapp et al. (2018).¹ In this model, once the contract production function produces a contract, the enlistee is assigned an amount of time that they will wait in the DEP, which is determined by the number of training seats available. With each month that the enlistee spends in the DEP, the probability that the enlistee will cancel their contract increases. Empirically, the probability of contract cancellation is a function of quality; HQ enlistees (referred to below as *graduate alpha* [GA] for high school graduates scoring in the top half of the AFQT distribution and *senior alpha* [SA] for high school seniors scoring in this group) are more likely to cancel their contracts than NHQ enlistees.

Overall, we have five types of contracts in the DEP:

1. GA contracts with a QS bonus
2. GA contracts without a QS bonus
3. SA contracts without a QS bonus
4. NHQ contracts with a QS bonus
5. NHQ contracts without a QS bonus.

SA recruits typically have a long wait time in the DEP and are scheduled to ship on a particular date; therefore, they are not likely to receive a QS bonus.

Following Knapp et al. (2018), we assign length of time in the DEP based on historical training seat availability by type of contract. The average time spent in the DEP for a GA enlistee without a QS bonus is 2.9 months; for an NHQ enlistee without a QS bonus, it is 3.9

¹ For a detailed discussion of the construction of the DEP Retention Model, see Chapter 4, pp. 79–84.

months, and for an SA enlistee, it is 7.7 months.² Knapp et al. (2018) adjusts these downward, because it appears that ship times have shortened in recent years relative to historical data and assigns time in the DEP based on this new distribution for enlistees without a QS bonus. If training seats in a particular month are filled (overfilled, taking attrition into account), then the next contract will be extended to the first available month with a training seat. This implies that the size of the DEP can grow if recruiters are writing more contracts than there are available training seats in a particular accession month, and this growth will be due almost entirely to duration in the DEP. If training seats become available, the Army can draw down the DEP by shipping recruits.

Time in the DEP is assigned when the contract is written. Enlistees with a longer time in the DEP are more likely to drop out. It is not, however, predetermined who will drop out. After the enlistee is assigned a scheduled DEP duration, the enlistee progresses through the DEP. Again, following Knapp et al. (2018), in each month that an enlistee progresses toward the assigned ship date, the contracted enlistee is randomly assigned a probability of being canceled until the average historical share of DEP loss for the given calendar month relative to the ship date observed in the data is reached. The probability of dropping out of the DEP increases over time: On average, the probability of dropping out one month prior to ship date is greater than the probability of dropping out two months from ship date, and so on. We model this pattern, and Figure D.1 presents an example of the average probability of dropping out for contracted enlistees with nine months in the DEP and contracted enlistees with six months in the DEP.

Typically, QS bonuses are designed to move people out of the DEP in 30 days or less (a small number of people might have DEP lengths of 31–60 days). In keeping with Knapp et al. (2018), 90 percent of recruits with contracts that are offered a QS bonus will be in the DEP for 30 days or less, and 10 percent will be scheduled for a DEP duration of 31–60 days. No individuals with QS bonuses will be in the DEP for longer than 60 days. Additionally, we allow the number of individuals exiting the DEP (to enter training) to exceed the monthly accession mission within a modest range (up to 20 percent).

In summary, the DEP model takes the output from the CPM, a specified training seat distribution by contract type, accession mission, the target HQ accession percentage, the entry pool (last year's remaining DEP enlistees), the assigned DEP length, and DEP attrition rates and combines them to dynamically allocate enlistees to training seats. As stated in Knapp et al., "Variation in external economic conditions influences DEP retention because higher rates of contract production during particularly good recruiting conditions result in longer DEP lengths (and hence greater attrition)" (2018, p. 85). Additionally, because the CPM produces HQ and NHQ contracts at different rates under alternative scenarios, the quality mix in the DEP will change. However, there is no direct effect of external economic conditions on DEP attrition, something that should be investigated and modeled in future iterations of the RRM.

² See Knapp et al., 2018, Table 4.15, p. 82.

Cost-Optimization Function

With the contract production and the DEP models specified, we can now search for combinations of expenditures (conditional on recruiting conditions and eligibility) that would achieve the Army's accession mission at lower cost. This is done using an optimization approach known as *constrained optimization by linear approximation* (COBYLA), in which the user specifies the constraints, initialization parameters, and the objective function being optimized, and the optimizer searches for a locally optimal solution using approximate gradient descent, until a researcher-specified stopping criterion is reached (Powell, 1994).

Objective Function

Any optimization algorithm requires a function that formally describes what objective we are trying to achieve. Because our goal is to achieve the accession mission while minimizing spending on the portfolio of resources under the Army's control, our objective function incorporates information on both accessions and costs. We will specify the costs as the following objective function:

$$\text{Objective} = D + \sum_t (B_t + A_t + R_t + M_t)$$

In this equation, B , A , and R are the costs of bonuses, advertising, and recruiters, respectively, all indexed by t to denote monthly costs. D and M are penalty functions that convert bad outcomes (e.g., missing mission) into dollar costs (penalties) for the purposes of finding cost-minimizing solutions. M stands for the monthly accession penalty. This term creates a penalty whenever monthly accessions are too high or too low. We have quantified the penalty such that the amounts are similar in magnitude to Army bonuses. In the case of too few accessions, we generate a cost penalty such that an outcome of 100 too few accessions in a month incurs a cost of approximately \$800,000. An outcome with too many accessions also incurs a penalty (because this is also a misallocation of Army resources), but this penalty is lower: An outcome of 100 too many accessions in a month incurs a penalty of approximately \$300,000. D stands for the DEP penalty, which is defined similarly to the monthly accession penalty in that it monetizes how much it costs to miss the end-of-year DEP goal. In this case,

we are only concerned with the final DEP (not indexed by t , indicating that there is no penalty for missing intermediate monthly values) and there is no penalty for overshooting the end-of-year DEP goal, because contracted enlistees in the DEP at the end of the year reduce the necessary contract production in the next year. The DEP penalty was set such that the cost of a shortfall of 100 from the exit DEP was approximately \$630,000.

These relative penalty levels were settled on through experimentation using calibrated data from FY 2015 and by adjusting penalties to obtain results that most-closely matched the observed outcomes in terms of relative output of accessions and the exit DEP. As discussed elsewhere in this report, the use of uniformly higher penalties that preserved the relative ratios had the effect of driving costs beyond our constraints on maximum spending levels. Thus, the overall level of penalties was set so that, under a variety of conditions, solutions tended to produce spending results that had precedent in observed levels of Army spending over recent years.

Optimization Parameters

The contract production function produces estimates of the relationship between three key Army inputs—bonuses, advertising, and recruiting—and contracts. These are the choice parameters that the optimizer varies in finding an acceptable solution. The optimization can be thought of as having two parts: Part one chooses the resource mix, and part two accounts for the costs. The costs are all monetized in the objective function discussed earlier, along with the penalties expressed in monetary terms. In part one, we allow the optimizer to choose a potential bundle of Army inputs. There are 11 parameters that can be chosen, each of which can take many values. These include the following:

- MOS eligibility proportions (HQ and NHQ)
- MOS bonus amounts (HQ and NHQ)
- QS eligibility proportions (HQ and NHQ)
- QS bonus amounts (HQ and NHQ)
- television advertising amounts
- digital advertising amounts
- number of recruiters.

We initialize the optimizer by providing inputs that correspond to user-specified levels for bonus amounts, eligibility, advertising spending, and recruiters. Then we allow the optimizer to solve for different bundles of inputs with the search area constrained to the highest and lowest amounts of resources used in any month over our sample period (FYs 2013–2015 and FYs 2017–2018).¹ We also constrain the change in recruiters to be relatively small from

¹ These constraints are discussed in more detail in Appendix C.

month to month (a maximum increase of 1.6 percent or a maximum decrease of 1.0 percent) to reflect the difficulty of rapidly changing the size of this force. For each bundle, the objective function keeps account of the costs that are directly related to the inputs and those that are associated with the penalties of missing a monthly accession mission, the overall DEP, or the annual accession mission.²

Excursions

Baseline

The primary function of the optimizer is to solve for a given accession mission given baseline parameters. In Table 4.1, we introduce the baseline parameters to initialize the optimization, using 2015 inputs unless otherwise specified.³ We use an accession mission of 65,000 and an unemployment rate of 5.6 percent;⁴ the actual minimum wage by local area;⁵ waiver share; HQ share; entry pool;⁶ recruiters ranging in number from 8,597 to 8,954 per month; and advertising totaling \$55.3 million for the FY, allocated so that 60 percent is spent on television advertising and 40 percent is spent on digital advertising. For HQ contracts, QS and MOS bonus amounts are fixed at \$15,900 and \$16,400, respectively, while eligibility rates are set at 15 percent and 36 percent, again respectively for QS and MOS bonuses. NHQ eligibility rates for both MOS and QS bonuses are set at 0 percent.

These baseline inputs can be changed to run alternate scenarios where economic conditions are altered to make the recruiting environment easier or harder so that we can see what the optimal portfolio of spending would look like under those conditions (discussed in the next chapter). We can also change eligibility requirements, quality targets, accession mission, prior-year entry pool numbers, exit DEP numbers, and other inputs into the baseline scenario.

² We have chosen one additional parameter that is not allowed to vary: the share of recruits that must be HQ. This parameter is not varied as part of the optimization but is simply enforced, if necessary, by throwing out excess NHQ contracts to meet the target. In practice, this typically results in no more than 2 to 3 percent of NHQ contracts being discarded.

³ We chose FY 2015 because of the paucity of digital advertising data, discussed in more detail in Appendix A. FY 2015 is the most recent year for which we had a full 12 months of digital advertising data, required to initialize the optimization procedure.

⁴ This unemployment rate was the national average for FY 2015 in the data weighted by the company-level QMA.

⁵ The federal minimum wage was \$7.25, but with higher state and local minimum wages in many recruiting areas, the QMA-weighted average was \$8.03.

⁶ These data were provided to us by USAREC.

TABLE 4.1
Recruiting Resource Model Baseline Model Conditions

Parameter	Value
Accession mission	65,000
HQ share	58.9%
Prior-year entry pool	8.6%
Exit DEP goal	20.0%
Average HQ bonus eligibility	
QS	15.0%
MOS	36.0%
Average NHQ bonus eligibility	
QS	0.0%
MOS	0.0%
Average bonus amount	
QS	\$15,900
MOS	\$16,400
Recruiters	8,682/month (avg)
Total advertising	\$55.3 million
Average unemployment rate	5.6%
Average minimum wage	\$8.03

NOTE: Avg = average. HQ share, prior-year entry pool, exit DEP, and waivers are all expressed as percentages of the accession mission. For example, an exit DEP of 20 percent with an accession mission of 65,000 means an end-of-year target of 13,000 individuals in the DEP.

and searched over a set of possible values for bonuses, advertising, and recruiters constrained by the minimum and maximum values in the data over our sample period.

Before comparing optimized costs with non-optimized costs, it is worth noting that, under current conditions, the Army is unlikely to achieve its mission of 65,000 accessions (shown in Table 4.1). We estimate that baseline spending without optimization will achieve approximately 43,500 accessions, or roughly two-thirds of the annual accession goal, at a cost of around \$1.3 billion.

The optimized scenario tells a different story. To meet the accession mission, the spending mix would change meaningfully, resulting in an overall decline in recruiting costs of around \$145 million for a total cost of around \$1.15 billion, with the accession mission and the DEP target both achieved. As we see in column 3 of Table 4.2, the total recruiter costs have declined by \$55 million, while TV advertising has increased by about \$22 million and digital advertising has declined by about \$14 million. Bonus costs declined by more than

TABLE 4.2
Comparing Baseline with Optimized Results

Output	Unoptimized Result	Optimized Result	Difference
Recruiter costs (\$ millions)	1,005.6	950.6	-55.0
TV prospect ad costs (\$ millions)	33.2	55.4	22.2
Digital prospect ad costs (\$ millions)	22.1	8.5	-13.6
Bonus costs (\$ millions)	233.0	134.1	-98.8
Total costs (\$ millions)	1,293.9	1,148.7	-145.3
Accessions achieved (% achieved)	43,566 (67.0)	66,791 (103.0)	23,225
Exit DEP achieved (% achieved)	17,258 (133.0)	14,037 (108.0)	-3,221

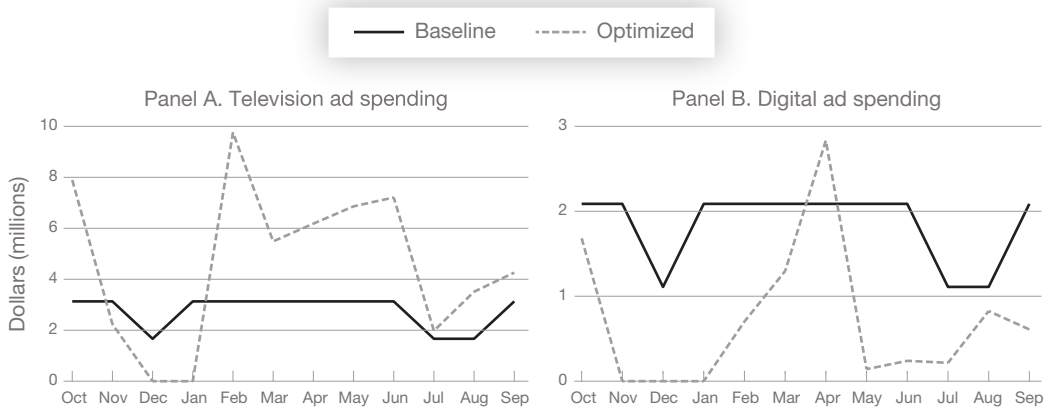
NOTE: All other values are set to the baseline values given in Table 4.1.

40 percent through cutting bonus spending by nearly \$100 million. The optimized conditions suggest that Army accessions will be approximately 66,800, or 103 percent of mission. We note that the mean standard error of prediction for the CPM (0.028) implies an approximate 95-percent confidence interval for the results of +/- 5.5 percent. For a baseline accession mission of 65,000, outcomes within +/- 3,500 accessions should be considered the statistical approximation of making mission.

To understand how the model is achieving better estimated outcomes, it is important to consider not only how annual spending on each recruiting resource changes but also how the pattern of spending on each resource changes. For example, the timing of spending on advertising might be more or less advantageous throughout the year depending on seasonality in recruiting and other factors. For bonus spending, the timing of spending, in addition to changes in eligibility and bonus amounts, might influence how accession goals are achieved beyond the overall level of spending. An example of how optimized advertising spending compares with baseline advertising spending is presented in Figure 4.1. At baseline, spending on advertising (the solid black line) is static across most months with declines in ad spending in December, and again in July and August of the FY. Optimized ad spending (the dashed line) shows greater month-to-month variation, with large increases in television advertising concentrated in November, April, and May; a large spike in digital advertising in October; and a smaller boost in March. Appendix D contains a set of figures that includes optimized versus unoptimized results for bonus spending and recruiters (Figure D.2).

Our main takeaway from modeling the baseline versus optimized scenario is that with an optimized portfolio of costs, the Army can achieve its accession mission and DEP goal at a savings of around 12 percent relative to the baseline level of expenditures. However, the baseline assumes a national unemployment rate of 5.6 percent, as compared with an actual unemployment rate of 3.6 percent (as of April 2022). In scenarios presented in the next chapter, we will allow the unemployment rate to fall by 25 percent (from 5.6 percent to 4.2 percent) to

FIGURE 4.1
Comparing Baseline Spending with Optimized Spending on Advertising



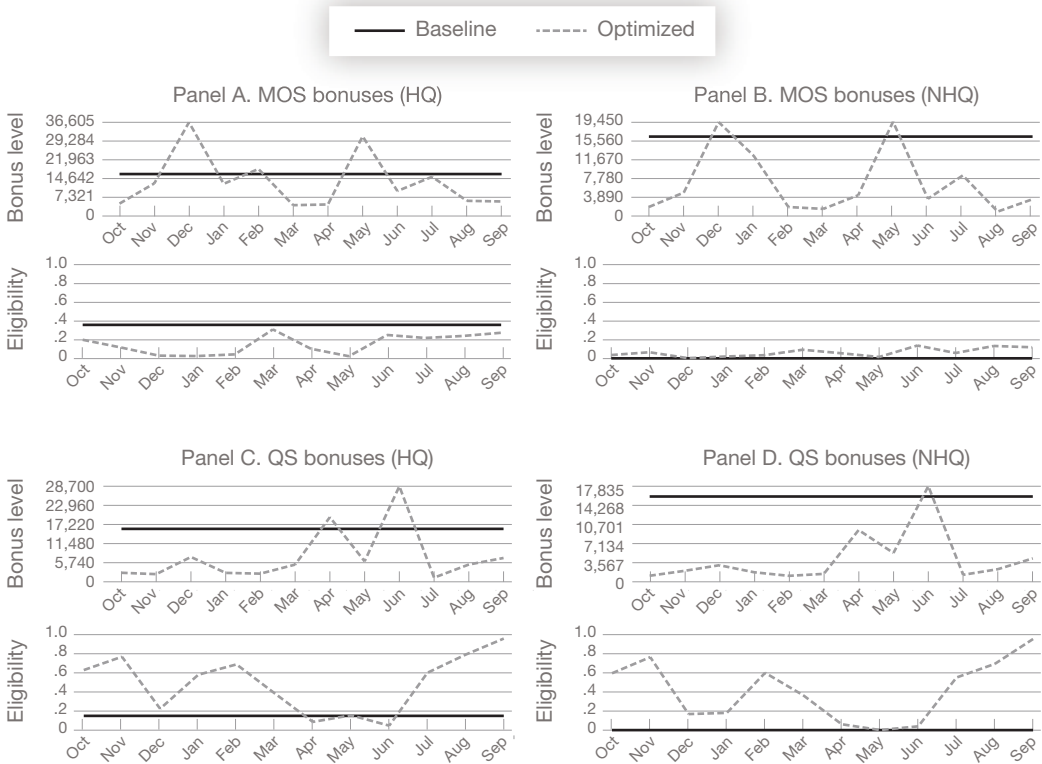
better understand how alternate recruiting environments will influence the optimal recruiting resource portfolio.

Figure 4.2 illustrates the effect of optimization on bonus amounts and eligibility. Panels A and C are more relevant, because HQ recruits are more likely to be eligible for bonuses. In general, for MOS bonuses, both eligibility and dollar amounts are considerably lower in the optimized results than at baseline. Additionally, their use is varied in a meaningful manner over the course of the year. In contrast, when considering optimized parameters for QS bonuses, the model recommendations are generally for higher eligibility on average, with eligibility reaching the (lower) baseline levels only in April, May, and June. Like the results for MOS bonuses, optimized results suggest using lower dollar amounts for QS bonuses, except in the lower-eligibility spring months, when the recommended amounts are higher (exceeding the baseline amount in the case of HQ and approximately matching the amount for NHQ). In general, the model trades off eligibility and bonus amounts throughout the year, and most of the optimized scenarios favor a greater use of QS bonuses at lower dollar amounts.

Limitations

There are several issues to keep in mind about the limitations of the RRM. First, the optimizer uses inputs from the CPM and DEP model. To the extent that these relationships are incorrect or that the assumptions do not hold, the optimizer will arrive at incorrect solutions. If the contract production function is incorrectly specified, the solutions that the optimizer finds are unlikely to reflect actual outcomes. While we have tested the contract production function for robustness and all our estimates are broadly confluent with previous estimates from the literature and economic theory (see Appendix B), we cannot rule out potential mis-

FIGURE 4.2
Comparing Baseline Spending with Optimized Spending on Advertising



specification, primarily because we are not using model parameters arrived at through true experimental variation in the use of Army resources.

It is also important to note that the COBYLA algorithm we use to minimize costs is a local optimizer. This means that the algorithm searches across the allowable set of potential resource expenditures in an iterative fashion. By performing approximate gradient descent, it moves in a direction that yields a better solution until it achieves an optimal solution that meets the stopping criteria. This solution will be a local optimum that may or may not be the globally optimal solution. Because of the large number of parameters being optimized for, it is computationally infeasible to use an optimization approach that could guarantee the solution to be a global optimum. While this approach guarantees that the solution is an improvement over the resource allocation specified by the initialization parameters, there might be other, superior solutions that the optimizer did not find. This implies that the precise amount of recommended spending in specific circumstances should be interpreted with significant caution.

We have greater confidence in the general direction of our recommendations: in particular, the model’s persistent preference for meaningful increases in television advertising

spending and sizable reductions in bonus spending. These general trends have remained present throughout many iterations and tests of the model's sensitivity to varying choices and parameters (such as penalties in the optimization function or alternate approaches to specifying a method of controlling for common time-varying characteristics in the CPM).

Finally, the model that we designed considers one FY at a time, which might affect the optimization. For example, when the baseline scenario misses the accession mission and overproduces the DEP, the optimizer tends to adjust resources to achieve both mission and the DEP. Such a solution could, for example, involve spending considerable money on advertising early in the year and then ramping these expenditures down significantly. But from an operational standpoint, the Army does not start over each FY. Additionally, the Army might prefer that accessions and the DEP are approximately aligned on a year-over-year basis so that it can plan for seasonal surges and shortfalls. One option would be to expand the optimization window from one year to two and then three. However, each year adds 12 times as many parameters to optimize over because all parameters would be allowed to change over the course of the year. Given the computational demands, each optimization could conceivably take many hours to solve.

Cost Excursions

In this chapter, we present a series of model simulations for cost excursions that allow us to explore several policy-relevant variations from the baseline and optimized results presented in Chapter 4. These excursions manipulate the baseline conditions (for example, changing the number of recruits in the DEP or varying the unemployment rate), estimate how these changes affect the unoptimized model results, and then optimize the model from each of these initial, unoptimized state outcomes. Each alteration of the baseline is referred to as an *excursion*. In what follows, we assess how results will change if, for example, the federal minimum wage is raised from \$7.25 to \$8.50 per hour. The results of all 16 excursions we modeled are available in Appendix D; Table D.2 outlines the characteristics of each excursion. These excursions include lowering the accession mission, decreasing the percentage of HQ recruits, increasing waivers, raising the minimum wage, and raising and lowering the unemployment rate. Additionally, we provide a series of excursions where we fix recruiters, bonuses, and advertising spending at baseline levels, either one at a time or in pairs, to assess how resources might be optimally varied in a more constrained environment.

While Appendix D shows the results of every excursion, here we take an in-depth look at a few key excursions. The excursions we present in the next three sections all work to make recruiting, or the recruiting environment, more difficult. By lowering unemployment, raising minimum wages, or increasing the HQ share, recruiting command and the Army Enterprise Marketing Office (AEMO) will incur higher costs to achieve the accession mission. We do this because the recruiting environment has become even more challenging than in 2015 (our baseline year) and is likely to remain challenging or become even more so in the current environment of increasing economic growth and low unemployment.

Recruiting Outcomes Under More-Challenging Economic Conditions

Excursion 1: Lowering Unemployment

In this excursion, we reduce the unemployment rate by 25 percent from baseline conditions, making the recruiting environment more challenging because of increased opportunities for potential recruits in the civilian labor market. Because we are using 2015 as a baseline, this implies lowering the QMA-weighted unemployment rate from approximately 5.6 percent to

4.2 percent. For the purpose of comparison, in April 2022, the national unemployment rate was 3.6 percent. While this excursion models an easier recruiting environment than in 2022, it still demonstrates how much more costly recruiting becomes as unemployment declines. Comparing the unoptimized results in panel A (baseline conditions) with those in panel B (lower unemployment) in Table 5.1, we see that the unoptimized results in a lower unemployment environment are somewhat worse than the unoptimized results under baseline conditions, yielding around 1,000 fewer accessions and around 500 fewer individuals in the DEP at the end of the year.

Like the results in panel A, optimizing resource use in panel B leads to the accession mission being approximately achieved and produces an exit DEP that is modestly larger than the exit DEP without optimization (133 percent of the target versus 129 percent). However, owing to the challenging recruiting environment, the optimized result does not save any notable amount of money in doing so, reducing overall spending by just \$5 million. But the resulting allocation is meaningfully changed from the unoptimized allocation, with an additional \$50 million spent on recruiters, almost \$28 million more spent on television advertising, a

TABLE 5.1
Unemployment Rate Declines by 25 Percent

Output	Unoptimized Result	Optimized Result	Difference
<i>Panel A: Baseline conditions (reproduced from Table 4.2)</i>			
Recruiter costs (\$ millions)	1,005.6	950.6	-55.0
TV prospect ad costs (\$ millions)	33.2	55.4	22.2
Digital prospect ad costs (\$ millions)	22.1	8.5	-13.6
Bonus costs (\$ millions)	233.0	134.1	-98.8
Total costs (\$ millions)	1,293.9	1,148.7	-145.3
Accessions achieved (%)	43,566 (67.0)	66,791 (103.0)	23,225
Exit DEP achieved (%)	17,258 (133.0)	14,037 (108.0)	-3,221
<i>Panel B: Unemployment rate 25 percent below baseline conditions</i>			
Recruiter costs (\$ millions)	1,005.6	1,055.7	50.0
TV prospect ad costs (\$ millions)	33.2	60.8	27.6
Digital prospect ad costs (\$ millions)	22.1	8.6	-13.5
Bonus costs (\$ millions)	226.3	157.1	-69.2
Total costs (\$ millions)	1,287.2	1,282.2	-5.0
Accessions achieved (% achieved)	42,528 (65.0)	62,950 (97.0)	20,422
Exit DEP achieved (% achieved)	16,792 (129.0)	18,706 (144.0)	1,914

NOTE: In panel B, all other values besides the unemployment rate are set to the baseline values given in Table 4.1.

reduction of around \$13 million in digital advertising, and a reduction of around \$69 million in bonus spending.

It is also worth comparing the optimized results in panel A with those in panel B. Overall optimized costs in panel A are \$1.1487 billion when unemployment is approximately 5.6 percent and \$1.2822 billion when unemployment is 4.2 percent. When the unemployment rate is 4.2 percent, the Army has to spend \$133.5 million more to achieve 97 percent of its accession mission. Thus, a 1.4-percentage-point reduction in the unemployment rate results in a 6-percent swing in accessions and a \$133 million increase in recruiting costs. It is worth noting that when we compare optimized results with optimized results across panels (A versus B) we see spending increase in all categories; the Army must effectively pull out all the stops to achieve mission.

Excursion 2: Raising the Minimum Wage

In this excursion, we explore how outcomes would change if the minimum wage were increased and assume that the federal minimum wage would increase from \$7.25 to \$8.50 per hour. Given that many states and substate jurisdictions (counties and cities) have higher minimum wages than the federal minimum, this has the effect of raising the national average minimum wage (weighted by QMA population) from \$8.03 to \$8.61 per hour in our baseline year. To be clear, this increase will be approximately 17 percent (an increase of \$1.25 per hour) in states where the federal minimum wage is binding (\$7.25 per hour), and it will be much smaller in states or localities that have local minimum wages above the federal minimum wages. (Alternatively, it could be completely nonbinding in places where the local minimum has already met or surpassed \$8.50 per hour). Nationally, the average increase would be approximately 7 percent. Recall that in the CPM, raising the minimum wage had a negative association with contracting HQ recruits, but almost no association (a small, statistically insignificant positive coefficient of 0.006) for those who are NHQ. The CPM estimates imply that the average minimum wage increase described above should reduce contract production by around 1.8 percent. This conforms nearly exactly with the results of Table 5.2, which show that the combined number of enlistees in terms of accessions and exit DEP is around 1,100 recruits less than the baseline combined total in panel A of Table 5.2.

Focusing on panel B, when we compare the unoptimized costs with optimized costs for the increased minimum wage excursion, unoptimized costs are \$1.29 billion, and only 66 percent of the accession mission is achieved, while the exit DEP goal is exceeded (130 percent). Optimization lowers costs by \$123 million and achieves 91 percent of the accession mission, also producing a slightly larger DEP. The total increase in recruits is 17,287 (16,115 additional accessions plus 1,172 additional enlistees in the exit DEP). Like the results of optimization under baseline conditions, the portfolio of expenditures calls for reductions in both recruiter costs and bonuses and for increases in TV advertising.

Consistent with the notion that raising civilian wages poses significant challenges for recruiting, the combined number of enlistees in terms of both accessions and exit DEP is

TABLE 5.2
Federal Minimum Wage Increases to \$8.50

Output	Unoptimized Result	Optimized Result	Difference
<i>Panel A: Baseline conditions (reproduced from Table 4.2)</i>			
Recruiter costs (\$ million)	1,005.6	950.6	-55.0
TV prospect ad costs (\$ million)	33.2	55.4	22.2
Digital prospect ad costs (\$ million)	22.1	8.5	-13.6
Bonus costs (\$ million)	233.0	134.1	-98.8
Total costs (\$ million)	1,293.9	1,148.7	-145.3
Accessions achieved (% achieved)	43,566 (67.0)	66,791 (103.0)	23,225
Exit DEP achieved (% achieved)	17,258 (133.0)	14,037 (108.0)	-3,221
<i>Panel B: Federal minimum wage raised to \$8.50 per hour (an increase of \$1.25 per hour)</i>			
Recruiter costs (\$ million)	1,005.6	944.5	-61.2
TV prospect ad costs (\$ million)	33.2	64.4	31.3
Digital prospect ad costs (\$ million)	22.1	16.1	-6.0
Bonus costs (\$ million)	228.0	141.2	-86.8
Total costs (\$ million)	1,288.9	1,166.3	-122.6
Accessions achieved (% achieved)	42,791 (66.0)	58,906 (91.0)	16,115
Exit DEP achieved (% achieved)	16,908 (130.0)	18,081 (139.0)	1,172

NOTE: In panel B, all other values besides the federal minimum wage are set to the baseline values given in Table 5.1.

3,841 fewer in panel B than in panel A. Comparing optimized results across panel A and panel B, we see that the overall costs increased from \$1.1487 billion to \$1.1663 billion, for a net increase of \$17.6 million.

Making Sense of Differences in Resource Allocation in the Lower Unemployment and Higher Minimum Wage Excursions

Although both a lower unemployment rate and a higher minimum wage make for a more difficult recruiting environment, the optimization results suggest higher spending on recruiters for a lower unemployment rate environment and lower utilization of recruiters in a higher minimum wage environment. Given our earlier recommendations to generally increase spending on recruiters in such environments, these findings might seem counterintuitive. However, this apparent discrepancy is expected: There is a static constraint on the minimum share of HQ recruits, and the CPM estimates meaningfully different associations with HQ and NHQ contract production for changes in the unemployment rate and the minimum wage.

In the case of an increase in the minimum wage (Table 5.1), this change is associated with a relatively large reduction in HQ contract production but has no association with NHQ contract production (see the coefficients in Table B.1). In these same results, recruiters are associated with lower productivity for HQ contract production relative to NHQ, while advertising is associated with greater productivity for HQ contract production relative to NHQ. In this scenario, if an increase in the minimum wage leads to relatively fewer HQ contracts, the optimization process can be expected to suggest the modest shifting of spending away from recruiters toward advertising.

On the other hand, a decline in the unemployment rate (Table 5.2) is associated with a relatively greater reduction in NHQ versus HQ contract production (the coefficients in Table B.1 are 0.18 versus 0.10). Recruiters are associated with lower productivity for HQ versus NHQ contract production, while advertising is associated with greater productivity for HQ contract production versus NHQ contract production. Thus, when lower unemployment is expected to lead to relatively fewer NHQ contracts, optimized spending levels will shift modestly toward recruiters and away from advertising; this is to say that the increase in recommended advertising spending levels is greater than in the case of a minimum wage increase.

Recruiting Outcomes Under Differing Quality Goals

Excursion 3: Raising the Target for High-Quality Recruits

The impact of variation in economic conditions on recruiting is of significant interest because it affects both outcomes and costs and it is not under the direct control of the Army. However, other factors affecting recruiting outcomes are set through policy either by the Army or, in some cases, through congressional mandates. One such important policy lever is the target for HQ recruits. The CPM shows that important external economic factors affect HQ and NHQ recruits differentially. Unemployment is less of a factor in driving HQ contract production, suggesting that higher-aptitude individuals are more likely to weather a poor labor market than others. Changes in the minimum wage only have a statistically distinguishable association with HQ contract production, consistent with the idea that employers discriminate on employee aptitude when required to pay higher entry-level wages. These and other factors mean that the Army's HQ share target might have important ramifications both for meeting accession goals and for the cost of doing so.

In this excursion, we consider recruiting outcomes under an alternative, higher target for the share of recruits who are high school diploma graduates who score in the top half of the distribution of AFQT scores. Panel A of Table 5.3 presents unoptimized and optimized results for the baseline scenario, where the HQ share target is set to 58.9 percent (this is a product of having 90 percent of recruits be high school graduates, with 65 percent I–IIIa scores for the AFQT, which represent scores in the top half of the distribution). As discussed in Chapter 4, in the unoptimized result, the Army misses the accession goal by around 21,500 recruits and has an exit DEP that is around 4,300 recruits more than the target. Under opti-

TABLE 5.3
Raise High-Quality Share Target to 61.75 Percent

Output	Unoptimized Result	Optimized Result	Difference
<i>Panel A: Baseline conditions (reproduced from Table 4.2)</i>			
Recruiter costs (\$ millions)	1,005.6	950.6	-55.0
TV prospect ad costs (\$ millions)	33.2	55.4	22.2
Digital prospect ad costs (\$ millions)	22.1	8.5	-13.6
Bonus costs (\$ millions)	233.0	134.1	-98.8
Total costs (\$ millions)	1,293.9	1,148.7	-145.3
Accessions achieved (%)	43,566 (67.0)	66,791 (103.0)	23,225
Exit DEP achieved (%)	17,258 (133.0)	14,037 (108.0)	-3,221
<i>Panel B: HQ share target raised to 61.75 percent</i>			
Recruiter costs (\$ millions)	1,005.6	1,074.0	68.3
TV prospect ad costs (\$ millions)	33.2	59.6	26.5
Digital prospect ad costs (\$ millions)	22.1	8.9	-13.2
Bonus costs (\$ millions)	232.8	217.1	-15.8
Total costs (\$ millions)	1,293.8	1,359.6	65.8
Accessions achieved (% achieved)	41,901 (64)	57,795 (89)	15,895
Exit DEP achieved (% achieved)	16,479 (127)	24,696 (190)	8,218

NOTE: In panel B, all values besides the HQ share target are set to the baseline values given in Table 5.1.

mized resource use, the model estimates that the Army will meet both goals while spending around \$145 million less.

Panel B of Table 5.3 presents estimates when the target for HQ share is raised to 61.75 percent.¹ In the unoptimized result, the combined accession and exit DEP outcome is lower by around 2,500 recruits. The optimized outcome in panel B suggests that improving on this outcome is considerably more difficult under the higher HQ target. Results are notably improved but still fall short, with only 89 percent of the accession goal achieved while the exit DEP is nearly double the target size even with bonus spending that is nearly as high as in the

¹ The formula used for overall HQ shares is the product of the percent of high school diploma graduates and the share of enlistees with an AFQT score in the top half of the score distribution (AFQT I-IIIa categories). For our baseline HQ share, we use 95 percent high school diploma graduates and 62 percent AFQT I-IIIa. For this higher share of HQ, we use 95 percent high school diploma graduates and 62 percent AFQT I-IIIa ($0.95 \times 0.65 = 61.75$). In the lower HQ share below, we use 90 percent high school diploma graduates and 60 percent AFQT I-IIIa ($0.9 \times 0.6 = .54$).

unoptimized scenario. Costs for achieving this outcome are nearly \$66 million higher than the unoptimized scenario and more than \$200 million higher than the optimized outcome in panel A (under the lower HQ share target), suggesting that implementing a meaningful increase in the HQ share target is likely to create substantial challenges for meeting accession goals.

Excursion 4: Lowering the Target for High-Quality Recruits

We also consider how moving the quality target in the opposite direction affects outcomes. In Table 5.4, we present results for lowering the target for HQ share to 54 percent. The differences in unoptimized outcomes are, predictably, the mirror image of the results considered above, with the lower HQ share resulting in a modestly better outcome in panel B relative to the baseline results in panel A (around 2,500 more total recruits in terms of both accessions and exit DEP). Under optimization, the accession mission is approximately achieved (at 91 percent) and the exit DEP goal is met. These outcomes are achieved at an estimated cost that is \$157 million lower than the unoptimized result and is around \$10 million lower than the optimized result in panel A.²

These results suggest that reducing the HQ share might be one tool that can be used to increase the number of accessions. However, there are potential downstream costs to having a lower proportion of recruits who are HQ, including higher first-term attrition and lower performance (Marrone, 2020; Putka et al., 2003). But in the current challenging recruiting environment, it might be worth weighing these costs and benefits in considering a suite of approaches to meeting overall manpower goals.

Recruiting Outcomes Under Constrained Advertising Spending

Excursion 5: Holding Advertising Spending Constant

Thus far, all our excursions have shown that one of the most important channels for achieving the accession mission is advertising. In the excursion that follows, we restrict advertising to the baseline amount and then optimize by allowing only recruiters and bonus use to fluctuate. We constrain annual advertising to be fixed at \$33.2 million for television advertising and \$22.2 million for digital advertising (see Figure D.2 for how this annual budget is deployed month by month over the year).

As a reminder, under optimization with baseline conditions where advertising is allowed to fluctuate, television advertising increases by around 67 percent, while digital advertising

² The fact that the accession goal is not quite met might be related to the local nature of our optimization algorithm, as discussed in Chapter 4 and Appendix C. In some cases, the optimizer might find a solution that satisfies the specified stopping rules even when there might exist another solution elsewhere in the space of all possible solutions that might have been found with a different set of initialization parameters than the baseline parameters that we used for all the excursions conducted in this report.

TABLE 5.4
Lower High-Quality Share Target to 54 Percent

Output	Unoptimized Result	Optimized Result	Difference
<i>Panel A: Baseline conditions (reproduced from Table 4.2)</i>			
Recruiter costs (\$ millions)	1,005.6	950.6	-55.0
TV prospect ad costs (\$ millions)	33.2	55.4	22.2
Digital prospect ad costs (\$ millions)	22.1	8.5	-13.6
Bonus costs (\$ millions)	233.0	134.1	-98.8
Total costs (\$ millions)	1,293.9	1,148.7	-145.3
Accessions achieved (% achieved)	43,566 (67.0)	66,791 (103.0)	23,225
Exit DEP achieved (% achieved)	17,258 (133.0)	14,037 (108.0)	-3,221
<i>Panel B: HQ share target lowered to 54 percent</i>			
Recruiter costs (\$ millions)	1,005.6	943.2	-62.4
TV prospect ad costs (\$ millions)	33.2	67.7	34.5
Digital prospect ad costs (\$ millions)	22.1	9.8	-12.3
Bonus costs (\$ millions)	233.0	116.0	-117.1
Total costs (\$ millions)	1,294.0	1,136.7	-157.3
Accessions achieved (% achieved)	45,085 (69.0)	58,890 (91.0)	13,805
Exit DEP achieved (% achieved)	17,976 (138.0)	13,198 (102.0)	-4,778

NOTE: In panel B, all values besides the HQ share target are set to the baseline values given in Table 5.1.

declines by around the same amount, for a total increase in advertising spending of roughly 20 percent. Under this unconstrained optimization, the Army achieves both accession mission and the DEP goal at a cost savings of \$145 million relative to the unoptimized results.

Turning to the results in Table 5.5, we see that advertising plays a key role in the optimized results in panel A. In panel B, with constrained advertising spending and an optimized portfolio, the Army can only improve accession outcomes from 67 percent to 77 percent of the mission, and the DEP goal is also just missed (in contrast to most other scenarios, where the DEP goal is either met or, often, significantly exceeded). These results are achieved at an estimated cost savings that is only half the magnitude of the cost savings when advertising is allowed to vary (\$73 million versus \$145 million). The optimizer relies much more heavily on recruiters when advertising cannot vary, increasing spending on this resource by nearly \$100 million. It is also worth noting that even in this less flexible environment, the model still eschews bonus increases, cutting spending on this resource by around 75 percent from baseline levels.

TABLE 5.5
Fix Ad Spending at Baseline Levels

Output	Unoptimized Result	Optimized Result	Difference
<i>Panel A: Baseline conditions (reproduced from Table 4.2)</i>			
Recruiter costs (\$ millions)	1,005.6	950.6	-55.0
TV prospect ad costs (\$ millions)	33.2	55.4	22.2
Digital prospect ad costs (\$ millions)	22.1	8.5	-13.6
Bonus costs (\$ millions)	233.0	134.1	-98.8
Total costs (\$ millions)	1,293.9	1,148.7	-145.3
Accessions achieved (% achieved)	43,566 (67.0)	66,791 (103.0)	23,225
Exit DEP achieved (% achieved)	17,258 (133.0)	14,037 (108.0)	-3,221
<i>Panel B: Advertising spending constrained to baseline level</i>			
Recruiter costs (\$ millions)	1,005.6	1,103.4	97.8
TV prospect ad costs (\$ millions)	33.2	33.2	0.0
Digital prospect ad costs (\$ millions)	22.1	22.1	0.0
Bonus costs (\$ millions)	233.0	61.9	-171.1
Total costs (\$ millions)	1,293.9	1,220.6	-73.3
Accessions achieved (% achieved)	43,566 (67)	50,040 (77)	6,473
Exit DEP achieved (% achieved)	17,258 (133)	12,153 (93)	-5,105

NOTE: In panel B, advertising levels are constrained to remain fixed at baseline levels while recruiters and bonuses are allowed to vary.

Summary of Findings

The main takeaway from this analysis is that the Army will struggle to make its accession mission given the baseline resource allocations considered here. Unoptimized results designed to reflect the current reality relative to baseline, such as the lower unemployment results presented above, perform even worse. However, in all cases, optimization leads to significant improvement in estimated outcomes, and it often does so at significant cost savings relative to baseline resource use.

The common factor in virtually all these scenarios is that the optimization process suggests that the Army should rely less on bonus expenditures and more on television advertising. In a simplified fashion, Table 5.6 summarizes the model’s recommendations for the direction and magnitude of spending changes for our key resource categories under each of the scenarios considered above and additional scenarios presented in Appendix D.

Importantly, this research was conducted on data collected prior to the COVID-19 pandemic. Not only are the associations between economic conditions and military service likely

to change, but the operational environment has as well. In the current labor market, there are many potential workers waiting on the sidelines—workers who are characterized as not being in the labor force because they are not currently employed or searching for employment, conditions that exclude them from entering into the unemployment rate, which only counts those nonworkers who are actively searching for employment. The civilian labor force participation rate (i.e., the proportion of Americans who are employed or looking for work) was 62.3 percent in February 2022; it has not been that low since 1977, when many women had not yet entered the labor force.³ One consequence of this low level of labor market participation is that a massive reentry into the labor market could significantly shift the recruiting environment. Given these unprecedented times, estimates and predictions should be interpreted with caution.

TABLE 5.6
Summary of Recruiting Resource Model Recommendations for Changes in Resource Use Under Multiple Scenarios

Spending Category and Approximate Amount at Baseline	Recruiter Spending (\$1,005 Million)	Television Advertising (\$22 Million)	Digital Advertising (\$22 Million)	Bonus Spending (\$233 Million)
Baseline scenario	↓	↑↑↑↑↑	↓↓↓↓	↓↓↓↓
Lower mission (60,000)	–	↑↑↑↑↑	↓↓↓↓↓	↓↓↓↓↓
Higher entry pool (20%)	↓↓	↑↑↑↑↑	–	↓↓↓↓↓
Lower HQ share (54%)	↓	↑↑↑↑↑	↓↓↓↓↓	↓↓↓↓↓
Higher HQ share (61.75%)	↑	↑↑↑↑	↓↓↓↓↓	↓
Higher waivers level (15%)	–	↑↑↑↑	↓↓↓↓↓	↓↓↓↓↓
Federal minimum wage increase (\$8.50)	↓	↑↑↑↑↑	↓↓↓	↓↓↓↓
Unemployment rate decline (–25%)	↑	↑↑↑↑↑	↓↓↓↓↓	↓↓↓
Unemployment rate increase (25%)	↓	↑↑↑↑↑	↓↓↓↓↓	↓↓

NOTE: Each arrow represents an approximately 10-percent change (for example, a single arrow represents a roughly 5-percent to 15-percent change) in the resource allocation up to a maximum of 50 percent or higher (all of which we indicate with five arrows for visual simplicity).

³ U.S. Bureau of Labor Statistics, “The Employment Situation—February 2022,” news release, USDL-22-0344, March 4, 2022.

Conclusion and Recommendations

Summary of Findings

The RRM is a comprehensive model that estimates how the factors of recruitment production translate into enlistment contracts, how those contracts evolve in the DEP, and how the Army could reprogram resources to achieve its accession goal.

Contract Production Function

We define the *factors of production* as those resources under the Army's control: the number of recruiters, spending on digital and television advertising, and QS and MOS bonuses. Of course, these are not the only factors that determine whether an Army prospect signs an enlistment contract. Current and future labor market expectations play an important role in whether a person is likely to enlist in the Army. When civilian labor market prospects are good (i.e., declining unemployment, rising minimum wages, and improving consumer sentiment), the willingness to enlist declines (for those who are marginally interested in serving in the Army). This is reflected in the estimates from the contract production function discussed in Chapter 2.

Delayed Entry Program

The DEP model mediates the process of turning contract production into accessions by queuing contracts produced by the CPM for a specified period and assigning related probabilities of attrition to each contract based on various factors: HQ and NHQ contracts, those with and without QS bonuses, and time spent in the DEP. Individuals with HQ contracts have higher DEP attrition, as do individuals who wait longer for a shipping date.

Optimization

The optimization function performs a highly complex task and does most of the heavy lifting for the RRM. Essentially, the optimization is initialized by giving baseline parameters that mimic the actual staffing and spending by USAREC and AEMO. The optimization routine solves for the lowest-cost combination of inputs that will achieve the mission relative to these baseline inputs. There are times, however, when the mission is higher than the resources can

achieve. In those cases, the optimizer strikes a balance between missing the mission and minimizing total costs. As we show in several excursions, there are times when the recruiting environment becomes so difficult that the optimizer chooses a solution that misses the mission at a “reasonable” cost.¹

Baseline Scenario

The baseline scenario estimates that current total recruiting costs are \$1.294 billion. The current level and allocation of spending allows for only 67 percent of the 65,000 accessions to be achieved (around 44,000). Optimizing the expenditure portfolio results in a reduction in total spending to \$1.149 billion (a savings of \$145 million) while effectively achieving both the accession mission and the DEP goal. Importantly—and this is a consistent message throughout this analysis—the mission is made through an increase in spending on television advertising, coupled with a modest decline in the number of recruiters and a large decline in MOS and QS bonus spending.

Excursion Scenarios

The baseline scenario takes the existing budget and spending allocation as given, but it also takes the current recruiting environment as predetermined. In the baseline scenarios, we set the recruiting environment conditions to be those in 2015—prior to the COVID-19 pandemic with a modest level of economic expansion and moderate unemployment rate. The excursions allow us to impose alternate recruiting environment conditions and see how the model responds. For example, in one excursion, we lower the average unemployment rate from 5.6 percent to 4.2 percent (a 25-percent decline). In another, we raise the federal minimum wage by \$1.25 per hour. The recruiting environment becomes more challenging in each of these scenarios, which manifest in the unoptimized level of expenditures achieving a smaller fraction of the accession mission. Even under these most-challenging conditions, an optimized spending portfolio persistently calls for increased spending on television and digital advertising and a large decline in MOS and QS bonus spending. Under the most-challenging economic conditions, or when advertising expenditures are constrained, the optimized solution also involves putting more recruiters into the field.

¹ It is possible to raise the penalty on missing accession mission in the optimization function so that it is never “optimal” to miss mission. When we implemented such a penalty, costs increased enough in some scenarios to raise questions about the usefulness and validity of the estimated outcomes in guiding policy (e.g., doubling total recruiting costs from \$1.3 to \$2.6 billion). Consequently, we tested multiple penalty levels and opted for a level that expresses more “real-world” trade-offs between meeting recruiting goals and staying within financial constraints.

Recommendations

Spend More on Advertising

One consistent takeaway from the RRM results is that the Army should spend more money on advertising—in particular, television advertising. Our average estimate of the association between television advertising and contract production is an elasticity of approximately 0.1, indicating that a 10-percentage-point increase in advertising would yield a 1-percent increase in contracts. On an annual base of 75,000 contracts (note that the quantity of accessions is lower than the quantity of contracts because of DEP attrition), this implies that a 10-percent increase in television advertising from the baseline (a change of approximately \$3.3 million) would yield about 750 more contracts at a cost of approximately \$4,400 per contract. This amount is less than recruiter costs per contract and typical bonus costs (for example, at baseline conditions for MOS bonuses—36-percent eligibility and \$16,400 per bonus—the cost in MOS bonuses per HQ contract is \$5,904).

Put another way, the optimized scenario in Table 4.2 recommends increasing spending from \$33 million to \$55 million, which represents a \$22 million increase in advertising spending (a 67-percent increase). Using the elasticity estimates from the CPM, this would yield a 6.7-percent increase in contract production. In a hypothetical example of a recruiting year in which 60,000 accessions would be produced with a \$33 million budget for television advertising, increasing this budget to \$55 million would be expected to produce more than 64,000 accessions.

Overall, we observe this general pattern in nearly every excursion we estimated that did not constrain advertising spending; the model calls for substantive increases in Army television advertising. Previous iterations of the RRM have pointed to the same recommendation to spend more on advertising. Because we recognize that such a programming shift would take some time to enact, we recommend that the Army start laying the groundwork for this spending shift now so that a reinvigorated advertising campaign can be undertaken in FYs 2023 and 2024.

As mentioned earlier, our advertising data are not experimental in nature; therefore, the associations we estimate here might not reflect purely causal relationships. Even with the assumption that our estimated elasticity represents a causal relationship, the validity of this estimate also hinges on the historical conditions present in the data we used. If the pandemic, technology, or even the passage of time (and maybe all three) have affected the responsiveness of the target population to television advertising, this recommendation might bear out different results.

Further Discussion of Our Findings on Advertising

The CPM estimates an association between digital advertising spending and contract production that is around half the magnitude of the association between television advertising and contracts. Consequently, our optimizations often recommend decreasing digital advertising spending. We feel that a few points regarding this result are worth briefly discussing.

First, as noted throughout this report, we were not able to obtain complete digital advertising data for the period we were considering and the data we did obtain had some quality issues that we had to address through unconventional means. These data issues might have affected our estimates.

Second, there is a limited body of evidence on the effects of digital advertising that have a reasonable claim to represent causal effects, but this evidence generally points to limited or zero effects of such advertising (Blake, Nosko, and Tadelis, 2015; Gordon et al., 2019). Thus, the relatively lower estimated effectiveness of digital advertising might be correct. Indeed, the modest positive associations that we estimate might be incorrectly large. We strongly urge the Army to generate experimental evidence on advertising effectiveness across media types.

Additionally, prior research has suggested that parents and other influencers play a large role in youth decisionmaking around military service (Johnson, Dawes, and Iacono, 2017; Cave, 2005). This is consistent with our finding that TV advertising has a stronger association with recruiting than digital advertising, because the patterns of media consumption by mode (digital versus television) have changed far less among adults than among youth (Nielsen, 2016; Rainie, 2017).

Finally, media consumption habits and technology use among youth have changed significantly over the period of our historical data. For example, between calendar years 2015 and 2019, the number of teens saying that they watch online videos every day increased from 34 percent to 69 percent. Over the same period, the share of lower-income youth with smartphones increased from 51 percent to 74 percent (Rideout and Robb, 2019).

Continue to Use Recruiters, Especially When Recruiting Is Difficult

While the first policy recommendation is to increase advertising spending when the recruiting environment is challenging (as it is now), the Army must deploy more of its recruiting resources to achieve the accession mission. While the optimized baseline scenario in Table 4.2 calls for fewer recruiters, this outcome is partially a result of the RRM being fully resourced to achieve the accession mission. That is, under the baseline scenario, the recruiting mission can be achieved for less than the current budget when resource allocation is adjusted toward more advertising spending, modestly reduced recruiting spending, and significantly reduced spending on bonuses.

When a declining unemployment rate makes recruiting more difficult, we estimate that a significant increase in both advertising and recruiters in the field is preferable. In fact, under this scenario, optimization increases recruiter spending more than advertising spending (\$50 million versus \$27 million relative to the baseline). Consequently, the Army's decision to reduce recruiters during this difficult recruiting period might have exacerbated the accession shortfalls that USAREC is currently experiencing. To summarize, when adequately resourced in a less difficult recruiting environment, the Army tends to overspend on recruiters. However, when recruiting becomes more difficult and the Army is limited in recruiting

resources, the model suggests that spending on recruiters is consistently more productive than spending on bonuses.

Reduce Bonus Spending

The RRM produces a consistent set of results and recommendations on bonuses. In all scenarios, even when we fix advertising at the baseline level, we find that the optimal bonus amount is lower than the Army is currently spending (see Table 5.5). Overall, we find that while QS bonus eligibility should increase (this helps with shipping to training seats and reduces the number of enlistees waiting in the DEP, which likely leads to lower attrition), the model suggests that QS bonus dollar amounts should generally be reduced. Additionally, the results suggest that both eligibility levels and spending on MOS bonuses should be reduced.

Why Is Bonus Spending So Disfavored by the Model?

Bonus spending is highly inefficient because of the deadweight loss associated with providing bonuses to recruits who would already engage in the behavior the Army wishes to incentivize. For example, the Army pays a bonus of \$40,000 to a recruit who would like to be a cryptologic linguist and has the required language skills even if the recruit would have selected this MOS without the incentive.² This is true for all MOS bonuses, and the problem becomes worse as more and more recruits are eligible and the choice set gets larger.

Additionally, in experimental research on the effect of enlistment bonuses conducted in the 1980s, the ability of MOS bonuses to attract new individuals to enlist in the Army—referred to by the authors as the “market expansion effect”—was found to be low, consistent with our estimates (Polich, Dertouzos, and Press, 1986). This might be driven in large part by the fact that high bonus levels must be advertised to be effective; they cannot lead individuals to a recruiting station simply because they exist.

The need to meet end-strength requirements is not a factor of MOS bonuses that we consider in this work, so we note that MOS bonuses play an additional role apart from moving a marginal recruit to enlist in the Army. However, evidence from experiments with a bid-based system for reenlistment assignments in the Navy suggests that the Army could explore using an auction-based system for enlistment bonuses to meet these specific manning needs while reducing the number of unnecessary bonuses paid out to enlistees who would have chosen a given MOS without a bonus (Golfin, Lien, and Gregory, 2004).

² U.S. Army, “Bonuses—Regular Army: Active Duty Benefit Fact Sheet,” 2022.

Recruiting Resource Model Limitations

Throughout this report, we detail limitations specific to key components of the model. Here, we summarize these issues to provide a clear outline of the limits of the RRM in its current incarnation.

Perhaps the most important limitation of this or any model is that past relationships, even if modeled accurately using past data, might not hold in the future. Consider the recent COVID-19 pandemic. This event had no historical precedent in existing data that would have allowed it to be accurately modeled. Taken together, the unique confluence of factors the COVID-19 pandemic represented often confounded the typical relationships estimated in the RRM. For example, the pandemic induced a severe shock to the civilian labor market, which triggered unemployment rates that have not been experienced in modern times. The RRM would suggest that high unemployment would create an easier recruiting environment. However, this spike in unemployment was driven by a simultaneous shock to consumer demand, a shock to international supply chains, and multiple policies requiring that businesses cease normal activities and individuals shelter in place. Additionally, public health concerns dictated a temporary cessation of shipping recruits to basic training, limiting the ability of the Army to meet accession goals even though high unemployment led to an easier recruiting environment.

Other potential future changes to historical relationships require this same caveat. For example, the landscape of media and advertising is rapidly evolving: The line between television and digital advertising is being increasingly blurred by streaming media content and specialty media content apps developed by both new and legacy media companies (e.g., YouTube TV, Hulu, Peacock). This might require a reconsideration of how television and digital advertising should be defined and how their effectiveness should be measured. Additionally, this evolution might have implications for how recruiters interact with potential recruits and how their recruiting methods might change.

None of the variation in the historical data we use to estimate the associations between either Army resource use or macroeconomic factors and contract production was derived from an experimental setting. Therefore, the estimates we use in this model do not have a strong claim to represent strictly causal relationships. Addressing this shortcoming would require that the Army conduct purposeful experiments to generate causal estimates of the effects of recruiters, bonus use, and advertising. Large-scale efforts along these lines have not been conducted since the 1980s (see, for example, Dertouzos, 1989; and Polich, Dertouzos, and Press, 1986).

Because of significant constraints on available advertising data, the CPM uses a relatively short period (roughly five years out of the six years from FY 2013 to FY 2018), which might affect our ability to accurately estimate the relationships of interest. We discuss this issue and other minor specific issues relating to the CPM in more detail in Appendix B.

Finally, the CPM is what is referred to as a *reduced-form model*. This means that we model associations between Army inputs, such as recruiters and advertising, and recruiting out-

comes as a “black box” where spending on these inputs goes in and contracts come out. In using such a model, we make an implicit assumption that the underlying relationships driving these associations are stable over time. For example, this assumption would not hold if the Army’s advertising agency made unusually effective or ineffective use of advertising spending resources in our study period compared with other times. A similar caveat applies to recruiters: Their effectiveness could be shifted by factors such as the use of individual versus station-level mission goals, new approaches to recruiter training, or MOS bonuses (where we must assume a consistent level of accurate—or inaccurate—targeting of bonuses to needed occupations).

Additionally, despite substantial improvements to the optimization process relative to the prior version of the RRM, there are still important limitations to this component of the model. The optimization algorithm we use is a local optimizer, meaning that it searches in an iterative fashion across the allowable set of potential resource expenditures, moving in a direction that yields a better solution until it achieves a solution that is optimal enough to meet its stopping criteria (discussed in more detail in Appendix C). This solution might or might not be the globally optimal solution. Because we optimize over a large number of parameters, it is computationally infeasible to use an optimization approach that could guarantee a global solution to the optimization problem. Therefore, although we have significant confidence in broad patterns common to multiple optimizations, the precise amounts of recommended spending in specific circumstances should be interpreted with significant caution.

Finally, the current RRM models one year at a time, which might affect the optimization directly. For example, when the baseline scenario misses the accession mission but overproduces the DEP, the optimizer tends to adjust resources to achieve both the mission and DEP as exactly as possible. Such a solution could involve spending considerable money on advertising early in the year and then ramping these expenditures down significantly. However, because the Army does not start over from an operational standpoint each FY, a larger exit DEP might be desirable in some scenarios. The current RRM design only considers about one FY at a time. One option to address this limitation would be to expand the optimization window from one year to two and then three years. However, each additional year would add 132 more parameters to optimize over because all 11 parameters would be allowed to change monthly over the course of the year. This would dramatically increase the computational complexity of the model.

Areas for Future Research

Current experimental evidence is sorely needed to provide a conclusive evidence base for the efficacy of Army recruiting resources (advertising, recruiters, and bonus use). Whether such decisions are ultimately guided by a model like the RRM or not, experimental evidence could help the Army better use its limited financial resources. Experiments conducted in the 1980s (Dertouzos, 1989; Polich, Dertouzos, and Press, 1986) show that such research is feasible.

The nature of digital and television advertising, which has become increasingly targeted both geographically and demographically over time, suggests that such experimentation on advertising effectiveness could be undertaken at a relatively small scale. For example, the level of digital or television advertising to a given digital marketing area could be varied. This manner of research would be unlikely to risk Army recruiting outcomes significantly, regardless of the results.

Additionally, the fact that there are more than 200 recruiting companies across the United States suggests that it is possible to vary the size of the recruiting workforce and the structure of the endeavor (for example, individual versus station-level recruiting goals) at a highly local level, generating substantial variation in resource use in a relatively small number of areas without generating significant concern over negatively affecting the overall recruiting enterprise. A similar caveat applies to bonus utilization.

Finally, the current RRM does not model USAR recruiting, which is an important aspect of overall Army readiness and operational capabilities. Recent research presents the results of a reserve RRM that is highly analogous to the model presented here (see Orvis et al., 2022). Modeling both RA and USAR recruiting jointly and capturing the trade-offs represented by attempting to meet these two goals simultaneously would likely increase the value of the RRM to Army planners.

We also note that a paucity of high-quality historical data on Army advertising spending affected both the feasibility and timeliness of our study. We recommend that AEMO ensure that a comprehensive system to measure television and digital advertising expenditures at the Designated Market Area level is in place going forward. Furthermore, a regular query of digital advertising spending should be implemented to generate a consistent stream of data using a platform like DoubleClick, which can generate zip code-level measurements of digital advertising spending. These data are essential to future modeling work on the efficacy of advertising, whether or not explicit experiments are conducted.

Data Sources and Definitions

This appendix describes in detail the major sources of data used in the RRM, as well as the structure and generation of high-level variable components (e.g., mission, contracts, and recruiters). There are some important notes about data inclusion that should be kept in mind while reviewing the sources on mission, contracts, and recruiters. Specifically, only recruiting stations with a positive contract mission and positive number of recruiters are included in the analysis. This is done to control for the opening and closing of recruiting centers, which can affect monthly contract mission levels (Knapp et al., 2018). Additionally, we restrict our analysis to stations within the 50 states and the District of Columbia.

Contract Mission

Data on contract missions come from USAREC and are available monthly at the station level. The data include contract mission for both the RA and the USAR and for various subcategorizations, such as GAs, SAs, graduate bravos, senior bravos, prior service, and all other.¹ Table A.1 provides a list of available mission categories for the RA and USAR.

Station-level data are aggregated to the company level. Stations are identified by a four-digit identifier called a *recruiting station ID* (RSID). The first digit of the RSID refers to the brigade, the second to the battalion within the brigade, and the third to the company within the battalion. Therefore, we aggregate the contract mission data by the first three digits of the RSID and obtain company month-level contract missions.

Contracts, Bonuses, and Waivers

Data on signed contracts for the RA and the USAR come from HRC datasets titled RA-Analyst and USAR-Analyst, respectively. Both datasets include detailed demographic and enlistment characteristics for the individual signing the contract. Demographic characteristics include age, date of birth, and whether the enlistee graduated high school. Enlistment

¹ *Graduate* refers to high school graduates, while *senior* refers to students in grade 12. High school diploma graduates who score in the lower half of the AFQT distribution are classified as “bravos.”

TABLE A.1
Available Contract Mission Subcategories by Service Type

Definition	Availability	Unit of Observation
Total PS contract mission	RA and USAR	Station-month
Total NPS contract mission	RA and USAR	Station-month
Total contract mission for NPS GAs	RA and USAR	Station-month
Total contract mission for NPS SAs	RA and USAR	Station-month
Total contract mission for all other NPS recruits	RA and USAR	Station-month
Total contract mission for NPS graduate bravos	RA only	Station-month
Total contract mission for NPS senior bravos	RA only	Station-month

NOTE: PS = prior service. Station-month refers to recruiting stations, which are the smallest unit in the recruiting ecosystem. The recruiting companies that we focus on in our main analysis comprise multiple recruiting stations.

characteristics include AFQT test scores, HQ status (i.e., GA or SA), whether the enlistee has previously served, if the enlistee was granted any waivers (i.e., medical waiver, conduct waiver), the enlistee's military occupation specialty, enlistment bonus types and total value (both MOS and QS incentives), the date the contract was signed, where the contract was signed, and projected and actual accession dates.

The detailed enlistment characteristics, particularly when and where the contract was signed, enable us to calculate the total number of contracts (mainly NPS contracts) by type at each company over time. Moreover, we can calculate the number of recruits that receive MOS bonuses, QS bonuses, medical waivers, and conduct waivers. Table A.2 provides a detailed list of the contract variables we generate for each service. Given that we can calculate these totals, we can also calculate variables for the average bonus received (conditional on receiving a bonus), the proportion of contracts that receive at least one bonus, and the proportion of contracts that receive at least one waiver.

Recruiters

Data on recruiters come from USAREC administrative records. This dataset provides demographic and enlistment characteristics for recruiters over time. Demographic characteristics include sex, race and ethnicity, and marital status. Enlistment characteristics consist of recruiting station, personnel class code, service (RA versus USAR), job class, rank, grade, MOS, and a unique identifier.

Furthermore, we consider the total number of RA and USAR recruiters at each company rather than include these as individual variables. The reason for this is because RA recruiters can write contracts for the USAR and USAR recruiters can write contracts for the RA. Finally, recall our data inclusion notes from the beginning of the appendix: We only con-

TABLE A.2
Total Contracts, Bonus Values and Eligibility, and Waiver Eligibility by Service

Definition	Availability	Unit of Observation
<i>Contracts (i.e., recruits)</i>		
Total prior service contracts	RA and USAR	Contract level with station identifier
Total NPS GA contracts	RA and USAR	Contract level with station identifier
Total NPS SA contracts	RA and USAR	Contract level with station identifier
All other NPS contracts	RA and USAR	Contract level with station identifier
Total NPS contracts	RA and USAR	Contract level with station identifier
<i>Bonuses</i>		
Percentage of all NPS contracts that received at least one QS bonus	RA only	Station-month
Percentage of all NPS contracts that received at least one MOS bonus	RA and USAR	Station-month
Percentage of NPS GA contracts that received at least one QS bonus	RA only	Station-month
Percentage of NPS GA contracts that received at least one MOS bonus	RA and USAR	Station-month
Average MOS bonus value for all NPS contracts conditional on receiving at least one MOS bonus	RA and USAR	Station-month
Average QS bonus value for all NPS contracts conditional on receiving at least one QS bonus	RA only	Station-month
Average MOS bonus value for GA NPS contracts conditional on receiving at least one MOS bonus	RA and USAR	Station-month
Average QS bonus value for GA NPS contracts conditional on receiving at least one QS bonus	RA only	Station-month
Average MOS bonus value for all other NPS contracts conditional on receiving at least one MOS bonus	RA and USAR	Station-month
Average QS bonus value for all other NPS contracts conditional on receiving at least one QS bonus	RA only	Station-month
<i>Waivers</i>		
Percentage of all NPS contracts that received at least one medical waiver	RA and USAR	Station-month
Percentage of all NPS contracts that received at least one conduct waiver	RA and USAR	Station-month

Table A.2—Continued

Definition	Availability	Unit of Observation
Percentage of all NPS contracts that received at least one medical or conduct waiver, or both	RA and USAR	Station-month
Percentage of NPS GA contracts that received at least one medical bonus	RA and USAR	Station-month
Percentage of NPS GA contracts that received at least one conduct bonus	RA and USAR	Station-month
Percentage of NPS GA contracts that received at least one medical or conduct bonus, or both	RA and USAR	Station-month

NOTE: PS = prior service.

sider recruiters in the 50 states and the District of Columbia and only consider recruiters at stations with a positive mission and a positive number of recruiters (RA mission for RA recruiters, USAR mission for USAR recruiters). Table A.3 provides the definitions of our recruiter variables.

Minimum Wage

Minimum wage data are from Vaghul and Zipperer (2021) and are measured at state and substate levels (e.g., county or municipality). The minimum wage dataset is available at the monthly level for the 50 states and the District of Columbia from May 1974 through Decem-

**TABLE A.3
Recruiters by Service Type**

Definition	Availability	Unit of Observation
Total number of RA recruiters at companies with nonzero RA contract mission	RA	Recruiter level with station identifier
Total number of USAR recruiters at companies with nonzero USAR contract mission	USAR	Recruiter level with station identifier
Total number of RA and USAR recruiters at companies with nonzero contract mission	RA and USAR	Recruiter level with station identifier

Substate Localities with Distinct Minimum Wages

Flagstaff, AZ	Redwood City, CA	Louisville, KY
Alameda, CA	Richmond, CA	Montgomery County, MD
Belmont, CA	San Diego, CA	Prince George's County, MD
Berkeley, CA	San Francisco, CA	Portland, ME
Cupertino, CA	San Jose, CA	Minneapolis, MN
East Palo Alto, CA	San Leandro, CA	St. Paul, MN
El Cerrito, CA	San Mateo, CA	Albuquerque, NM
Emeryville, CA	Santa Clara, CA	Bernalillo County, NM
Fremont, CA	Santa Monica, CA	Las Cruces, NM
Hayward, CA	Santa Rosa, CA	Santa Fe, NM
Los Altos, CA	Sonoma, CA	Santa Fe County, NM
Los Angeles, CA	Sunnyvale, CA	Long Island and Westchester, NY
Los Angeles County, CA	Denver, CO	New York City, NY
Malibu, CA	Washington, DC	Remainder of New York State, NY
Milpitas, CA	Johnson County, IA	Nonurban counties, OR
Mountain View, CA	Linn County, IA	Portland, OR
Novato, CA	Wapello County, IA	Remainder of Oregon, OR
Oakland, CA	Chicago, IL	SeaTac, WA
Palo Alto, CA	Cook County, IL	Seattle, WA
Pasadena, CA	Lexington, KY	Tacoma, WA
Petaluma, CA		

ber 2021, while data for the 61 substate localities begin in January 2004 and end in December 2021.² The 61 localities with minimum wages are presented below.

The unit of analysis for the RRM is the recruiting company-recruit contract month. Our general rule for creating a minimum wage variable is to use the local minimum wage when

² We convert the calendar months to FY months, where the FY starts in October and ends the following September.

available; otherwise, we assign the state's minimum wage. To do so, we need to know if a recruiting company is within a locality with its own minimum wage. Fortunately, we know the zip codes that fall within each recruiting company. To map companies to localities, we create our own crosswalks of zip codes to localities by using geographic information system (GIS) shapefiles for zip code tabulation areas (ZCTAs), which are essentially time-consistent, and overlaying locality boundaries, which are commonly available for most localities. We combine these GIS overlays with some manual zip code lookups to generate a crosswalk of zip codes to localities. This allows us to map the zip codes within companies to a locality, thereby generating a company-to-locality crosswalk. If a company spans multiple localities, we take a simple average of the minimum wages.

Workers might consider potential jobs that fall outside the recruiting areas we consider. In other words, we might attribute the wrong potential minimum wage to someone who enlisted when they could have taken a civilian job at a wage different from the prevailing rate in their area. From a regression modeling standpoint, this would amount to measurement error in our minimum wage variable and would have the effect of biasing downward (in magnitude) the minimum wage coefficient.

Days in Recruit Contract Month

An important variable in the RRM is the length of the recruit contract month, as the more days in a month that recruiting stations are open, the greater the opportunity recruiters have to sign contracts. We use available recruiting calendars from USAREC and manually tally the number of days recruiting stations are open in each recruiting contract month (RCM).

There is an important caveat when working with RCMs: RCMs do not align with standard calendar months. Typically, RCMs extend from midway through the prior calendar month to midway through the current calendar month. For example, the first RCM of FY 2019 (October 2018 in calendar year terms) began on September 14, 2018, and ended on October 11, 2018.³ Table A.4 provides details on some example RCMs, including the original calendar dates, the start and end dates, and the total number of days that recruiting stations were open.

Advertising Data

Television Advertising

For information on television advertising, we refer the reader to Knapp et al. (2018). Data on television advertising are extended through FY 2018 and reflect spending at the national

³ For a brief time in our sample period, roughly between October 2014 and September 2015, RCMs were well aligned with standard month start and end dates, i.e., starting around the 1st of the calendar month and ending on the 30th or 31st, depending on the month.

TABLE A.4
Calendar Dates of Recruiting Contract Months for
Fiscal Year 2017

Recruit Contract Month	Start	End	Days in RCM
September 2016	9/16/16	10/13/16	18
October 2016	10/14/16	11/10/16	20
November 2016	11/11/16	12/15/16	20
December 2016	12/16/16	1/12/17	16
January 2017	1/13/17	2/16/17	23
February 2017	2/17/17	3/17/17	18
March 2017	3/18/17	4/13/17	19
April 2017	4/14/17	5/11/17	20
May 2017	5/12/17	6/15/17	22
June 2017	6/16/17	7/13/17	18
July 2017	7/14/17	8/17/17	24
August 2017	8/18/17	9/14/17	18

level. We follow the approach outlined in Knapp et al. (2018) to allocate national-level spending to companies on the basis of each company's share of national ad impressions. We used data on Designated Market Area shares of national ad impressions, which were provided by a third-party media analytics firm employed by AMRG. These shares were derived from an annual, area-specific measure of viewership from some combination of electronic and manual viewer measurements. These area-specific levels of viewership were used as weights to distribute national ad impressions to local areas, and then national spending was distributed according to these area-specific weights.

In total, we had approximately six years of data on prospect television advertising spending (ranging from FY 2013 to FY 2018) to use in our analyses. Because of constraints on the digital advertising data described below, we only ended up using approximately five of these years in the final analysis sample.

Digital Advertising

A primary aim of this study was to credibly incorporate digital advertising into the mix of resources that the RRM could optimize over. First and foremost, accomplishing this required a reasonable source of advertising data. Fulfilling this need proved to be one of the most challenging aspects of this study.

One reason for this difficulty was the lack of a formalized data-provision mechanism from the Army's ad agency, McCann, to AMRG. This was among the issues identified in a

report by the Government Accountability Office, which outlined multiple inefficiencies in Army marketing operations and steps that were being taken to address them (Field, 2019). An additional data limitation resulted from the simultaneous dissolution of AMRG and its replacement with a new organization, AEMO, and the shifting of the Army’s marketing contract from McCann to Doyle Dane Bernbach (Cox, 2019). This shift made it impossible to retrospectively obtain any systematic data on digital marketing spending for multiple time periods between 2016 and 2019.

To make progress despite these challenges, we took a novel approach to synthesizing two data sources, which allowed us to construct a usable set of digital advertising data covering approximately five of the six years for which we had television advertising data. These are most of FYs 2013–2015 and FY 2017 through most of FY 2018. We describe the process we used to construct this set of digital advertising spending data below.

A portion of our digital advertising comes from data queries performed by AMRG on the behalf of the research team from the original RRM study using DoubleClick, an ad-buying tool and data product owned by Google (Knapp et al., 2018). The variables that were available to use from these queries included clicks, impressions, and total costs at the zip code–by-day level from January 2017 through January 2019. Using a zip code–to-company crosswalk, we aggregated the DoubleClick data to the company-RCM level.

These data provided us with *realized spending* on ads—in other words, the ad spending that resulted from auction-based processes that place ads into the content accessed by users. Our spending measure summed the multiple ad categories that were included in the DoubleClick query to a single measure in dollars at the company-RCM level. We then expressed this spending in thousands of dollars and took the log of this measure.⁴

The advertising activity in the DoubleClick data does not represent all digital marketing activities conducted by the Army. However, DoubleClick captures all ad traffic handled by Google, which is estimated to control up to 90 percent of the publisher ad server market (Morton and Dinielli, 2020). For the purposes of this study, we treat these data as an approximation of total advertising activities.

National data on digital spending were the only measure we had for FYs 2013–2015. To incorporate these data in a manner that would yield company-by-RCM-level data that could be reasonably analyzed along with the years of DoubleClick data, we used a weighting approach like the one used to allocate national TV spending data. Specifically, we used the highly detailed data from FY 2017 to FY 2018 to impute how digital spending was allocated

⁴ As in other instances described in this report, we added \$1 to any cells with spending equal to \$0 so that this logarithmic measure would be defined and would not create missing cells in our dataset that would lead to dropped company months in estimation. In terms of how likely it is that we created any bias through this procedure (i.e., whether ad spending of \$1 has any meaningful actual analog in the actual spending data such that this procedure could bias estimates), the lower nonzero cell in the data was \$61, the median spending was \$494, and the mean spending level was \$876, so we believe this was a thoroughly benign adjustment in terms of any impact on the analysis.

across recruiting companies in these earlier years.⁵ We generated an average share over the two-year period for each company and used these shares as weights to distribute national spending. There were no digital ad spending data available to us for FY 2016, so the limited availability of digital advertising data ultimately defined our overall sample period, which comprised month seven of FY 2013 through the end of FY 2015 and also month three of FY 2017 through month ten of FY 2018 (for a total of 50 recruiting months).

Unemployment Rate

For information on the unemployment rate variable, see Knapp et al. (2018). Specifically, unemployment rates come from the U.S. Bureau of Labor Statistics' Local Area Unemployment Statistics database. We use county-level, monthly unemployment rates and allocate these to recruiting companies. First, we disaggregate county-level unemployment rates to zip codes using zip populations as weights from the 2000 and 2010 decennial U.S. censuses, then we use a zip-to-company crosswalk and aggregate to the company level.

Consumer Sentiment

We use Consumer Sentiment Index data from the UMCSI downloaded from the St. Louis Federal Reserve Bank's "FRED" website (FRED Economic Data, 2022). The survey asks a nationally representative group of respondents approximately 50 questions each month concerning three key topics: how consumers view their own financial prospects, their expectations for the general economy over the near term, and their expectations for the economy over the long term. These survey data are provided only at the national level, so they do not vary across recruiting companies (this is the only national measure we incorporate).

⁵ To provide evidence that this imputation was reasonable, we first tested the level of variation in digital ad spending within companies in these two years. We found that there was relatively little variation in spending levels across companies over this period; the coefficient of variation of monthly spending in thousands of dollars (the mean over the standard deviation) was 0.25 with a minimum of 0.11 and a maximum of 0.58.

The Contract Production Model

A key aspect of our updating of the RRM was a significant revision of the CPM used to estimate how Army resources and economic conditions affect contract production. In this appendix, we discuss the structure of the previous CPM and the procedure used to estimate it and then detail how we revised and simplified the model for the updated RRM.

The model used in Knapp et al. (2018) was a nonlinear least squares (NLS) model using company-level panel data from FY 2012 to FY 2015. However, a subset of parameters in this model (measures of bonus use and recruiting difficulty) were first estimated using a linear fixed effects model over a longer time (FY 2003–FY 2015) that omitted the nonlinear portion of the model. Specifically, advertising was the one component modeled nonlinearly and for which data were unavailable from FY 2003 to FY 2011. The coefficients from this linear model were then fixed at their estimated values in the NLS model, and this model was estimated using these fixed parameter values.¹

A primary motivation for our efforts to update the CPM was evidence of the original model's sensitivity to the addition of newer data. The original NLS CPM used an unconventional process that took a set of starting values for key parameters in the nonlinear model specification of advertising effectiveness, generated an estimate (using maximum likelihood), discarded the residual variation in the dependent variable, and reestimated the model repeatedly until the parameter estimates reached a user-specified level of stability from one model run to the next. When additional data from FY 2016 to FY 2018 were added to the model, it failed to converge using this process, necessitating a reevaluation of key features of the model. We felt that this obstacle signaled an opportunity to see whether a simpler CPM that followed more-traditional theoretical and econometric approaches could be identified and validated.

Our approach to modeling the relationship between contract production and Army resources was constrained by a lack of truly experimental variation in the deployment of recruiting resources, leading to well-understood but difficult-to-address issues of potential bias from factors including omitted variables and reverse causality (see the discussion below on bonuses). However, because we had data that took on a panel structure (following the same units of observation over a given time period), we followed Knapp et al. (2018) by focusing

¹ Chapter 4 of Knapp et al. (2018) contains some detailed discussion about various subjective decisions related to the estimation of the CPM, including this unorthodox approach of first estimating a linear model and using a subset of these estimated coefficients as fixed parameters in a nonlinear model.

on an approach that leveraged this structure through the use of *fixed effects modeling* (see Wooldridge, 2010). In this way, permanent, unobservable differences across areas in recruiting productivity are accounted for by a series of indicator variables for geographic units. This allows the model to account for permanent differences in historical recruiting productivity of different geographic areas without explicitly modeling why they differ.² But we first had to assess the appropriate level of geographic aggregation to use in such an analysis. The primary data on contracts, recruiters, and mission were available at the recruiting station-by-recruiting month level for a period of several years. Other variables of potential interest, such as unemployment and minimum wage, were at higher levels of aggregation (county or state). We experimented with estimating the relationship between recruiting and other inputs and contract production at the national, recruiting battalion, and recruiting-company levels.³ The results of this process led us to maintain the approach used in Knapp et al. (2018) of conducting estimation at the recruiting-company level; using a fixed effects model at the recruiting-company level is a feasible way to plausibly address factors such as omitted variable bias and reverse causality that are more likely to arise from estimating a model at the national level.⁴ Generally, this is a common approach for reducing the bias in estimated empirical relationships in the absence of experimental variation in resource use.⁵

Deriving the Model

We adopt a slightly modified version of the Cobb-Douglas-style contract production function used in Knapp et al. (2018) that assumes that contract production, C , in recruiting company s at time t is a function of recruiters, R ; recruiter effort (which we proxy for with mis-

² We also pursued one alternative approach, “spatial first differences” modeling that uses only cross-sectional data, or data from a single period, but this approach proved unsatisfactory for the task at hand. Details of this exploration are presented in Appendix E.

³ We did not spend significant time exploring estimation at the recruiting station level because these units were excessively small, with zero mission or contracts in one or more categories and time periods being a fairly frequent event. Recruiting stations were also shuttered or assigned to different geographies with some frequency.

⁴ See Chapter 4, “Identifying Model Parameters,” in Knapp et al. (2018).

⁵ Our approach differs in one notable way. In the original CPM, companies that changed geographic boundaries outside a very small tolerance were treated as if an old company ended and a new company was “born.” Empirically, this splitting of companies has the effect of reducing the total variation contributing to each within-company estimate for these split companies. This approach might be reasonable if a change in geography were accompanied by a complete change in the administration, personnel, and culture of a given company. However, if a company is viewed as an administrative unit that services a generally fixed area, then it would seem more appropriate to consider a company as a continuous entity, even conditional on relatively significant changes in geography (much as one might view a farming operation that ranges over a somewhat flexible—but generally fixed—plot of land). We use a set of constant company definitions across our analysis, tolerating some small to moderate changes in the geography of a subset of companies over time.

sion, M); and QMA population, Q . These primary factors are scaled by Army advertising, A ; bonus use, B ; a vector, X , of macroeconomic factors (e.g., unemployment, minimum wage); and a vector of other potentially important factors, Z , such as seasonality in recruiting across months correlated with the school year, other time-dependent but unobservable economic factors affecting all companies in a common fashion, and permanent differences in the recruiting productivity of local areas. We normalize the model in terms of contract production per QMA by dividing company-level contracts, recruiters, and mission by company-level QMA rather than including this eligible population resource as a distinct parameter of the model. In formal terms, we assume that

$$\frac{C_{st}}{Q_{st}} = \left(\frac{M_{st}^{\beta_m} R_{st}^{\beta_r}}{Q_{st}} \right) \times e^{(f_1(A_{st}) + f_2(B_{st}) + f_3(X_{st}) + f_4(Z_{st}))}. \quad (\text{B.1})$$

Because recruiter effort might be driven differentially by distinct mission goals related to both active-duty or reserve service and recruit quality, we further decompose overall mission for each company into RA HQ, meaning recruits who are both Tier 1 and AFQT I–IIIa, RA NHQ, and USAR.

$$\frac{C_{st}}{Q_{st}} = \left(\frac{M(\text{HQ})_{st}^{\beta_{m1}} M(\text{nonHQ})_{st}^{\beta_{m2}} M(\text{USAR})_{st}^{\beta_{m3}} R_{st}^{\beta_r}}{Q_{st}} \right) \times e^{(f_1(A_{st}) + f_2(B_{st}) + f_3(X_{st}) + f_4(Z_{st}))}. \quad (\text{B.2})$$

We assume that RA and USAR mission goals are substitutes such that an increase in USAR mission will negatively affect RA contract production, while we assume that HQ and NHQ mission goals are partial complements.⁶

We follow Knapp et al. (2018) in viewing certain aspects of recruiting resources as multipliers that increase the effectiveness of recruiters. These include advertising and bonuses. These factors are indicated, respectively, in Equation B.2 as $f_1(A_{st})$ and $f_2(B_{st})$.

Modeling Advertising

In defining the function $f_1(A_{st})$, we diverge from the Knapp et al. (2018) approach to estimating the effects of advertising. Knapp et al. (2018) focused specifically on television prospect advertising only and used a nonlinear estimation approach based around the a priori assumption that the functional form of advertising efficacy is represented by an S-shape that was

⁶ For the RA, there are three mission recruiting categories: *GA* (referring to Tier 1 graduates with AFQT scores of I–IIIa), *SA* (referring to Tier 1 high school seniors with AFQT scores of I–IIIa), and *other NPS*. Our measure of HQ mission combines GA and SA mission goals. Conceptually, HQ mission numbers are the constraining factor because there are specific limits on the quality level of recruits. The Army would presumably take up to 100 percent of HQ recruits, but meeting the residual NHQ goal (mechanically) requires lower recruiter effort because a contract satisfying it might be either HQ or NHQ. Another way of stating this is that the pool of QMA is larger for the NHQ mission goal because it includes the pool of QMA satisfying the requirements for HQ contracts, but the converse is not true. Our empirical results are consistent with this intuition.

first explicated in Dertouzos and Garber (2003). Described simply, this approach stipulates that the relationship between contract production and advertising spending is symmetrical around a single, user-specified inflection point such that there is little to no effect of advertising at very low levels of spending, and then there are increasing returns to scale associated with moving from low levels of advertising to the inflection point. As spending increases, there are symmetrically decreasing returns to scale associated with moving from the inflection point to higher levels of advertising until a saturation point is reached, where additional advertising has approximately no further effect. The model assumes that the inflection point is located at exactly half the distance (in spending) between zero and this saturation point.

In addition to being the single factor in the prior CPM that required the use of a nonlinear estimator, the highly restrictive nature of this functional form assumption gave us pause. We were also concerned about using this specification given that the original work on this model was supported by analyses of television and print media data that predated the introduction of the internet, the widespread adoption of cable TV, and other potentially paradigm-shifting developments in advertising.

For the updated CPM, we incorporate spending for prospect advertising both on television and across a variety of digital platforms. We follow a relatively simple linear modeling approach that has been used in past work and was recently employed by Shapiro, Hitsch, and Tuchman (2020): We construct a linear “advertising stock” measure that allows advertising to have a persistent effect by generating a blended measure of contemporaneous and lagged advertising, with the number of lags and the (constant) rate of decay selected through a data-driven process that minimizes root mean square error. Specifically, we form the ad stock variable using the following model:

$$ad\ stock_{st} = \sum_{t=0}^T \delta^t ad\ spend_{st}. \quad (B.3)$$

This model assumes that the ad stock for company s in recruiting month t is a cumulative function of advertising spending in the contemporaneous month and the effects of past months of ad spending, which decay at rate δ . Using the log of this measure, we allowed the ad stock measure to enter the model as a single linear parameter or as a cubic parameter, which allows for the possibility that the association between advertising and contract production follows an S-shaped pattern, as was assumed in Knapp et al. (2018). We found that a linear parameter was interpretable in a straightforward manner, was more stable, and had greater precision. Thus, we adopted this approach.

Our testing of models using between one and three lags and decay values between zero and one in 0.1 increments identified two lags with a decay value of 0.1 as the most efficient combination of values. Our choice to constrain lags at three or fewer was informed by recent and credible research using truly experimental advertising variation that suggests relatively short-lived advertising effects (Gerber et al., 2011; Hill et al., 2013). Additionally, this con-

straint limited the discarding of relatively scarce sample data because for each lag we introduced, we reduced the start of the sample period by one month.

Because we are considering two discrete advertising platforms, television and digital (see Appendix A for a description of the advertising data we employed), and it seems plausible that they would interact with one another in contributing to contract production, we also introduce a linear interaction term between them. Although our expectation was that these two channels of advertising would complement each other in enhancing the effectiveness of recruiters at contract production, this approach allows them to act as complements to each other (so that the interaction coefficient would have a positive sign) or as substitutes (where the interaction would have a negative sign).

Modeling Bonus Use

The prior CPM modeled $f_2(B_{st})$ by aggregating national bonus measures in a factor model approach that entered the factor model's first component as a squared term into the main model. While the coefficients on these variables took on conceptually correct signs in Knapp et al. (2018), they had no clear economic interpretation; thus, they were not comparable with any other findings in the literature. This approach also conflated MOS-specific and QS bonuses, which serve different purposes and target different types of recruits. Furthermore, they might have differing levels of effectiveness and endogeneity with respect to otherwise unobservable or difficult-to-model aspects of the recruiting environment. Our view is that QS bonuses, which often relate to the idiosyncratic variation in available training seats, might exhibit less endogeneity in the timing and magnitude of their use than do MOS bonuses. These occupation-specific enlistment incentives might reflect the contemporaneous civilian opportunities for both recruits with higher cognitive skills and those with lower cognitive skills (e.g., those on the margin between college attendance and service versus those on the margin between entry-level employment and service). They also might reflect differential levels of exit by current service members, such that bonus use might exhibit characteristics of “reverse causality.” In other words, increased bonuses “cause” more positive recruiting outcomes—suggesting a positive statistical relationship between the two—but it might be that poor recruiting outcomes “cause” increased bonuses, leading to a biased statistical relationship that could be lower in magnitude or that could even have a negative sign.

For this reason, we allow these two bonus types to enter the updated CPM separately and linearly. We calculate company-by-month measures that are the product of the share of actual contracted enlistees that received a bonus and the average amount for bonuses given and multiply this by the monthly ratio of company-level (overall RA) mission to QMA. The company-level approach (as opposed to using national bonus policy) incorporates exogenous geographic variation in economic factors that might help to address the confounding influence of national macroeconomic factors on bonus use. Furthermore, scaling realized bonus use by mission introduces a measure of the propensity to use bonuses in relation to the magnitude of a company's mission goal that is less endogenous than simply using realized bonus

levels. Allowing for the separate estimation of QS and MOS bonuses also provides a chance to assess endogeneity because we expect QS bonus use to be less subject to the reverse causality of MOS bonuses discussed above.⁷

Economic Factors Affecting Contract Production

Contract production is also affected by economic considerations of potential recruits. In the revised CPM, we model $f_3(X_{st})$ using three factors that we believe capture important and distinct aspects of the economic environment:

- *Unemployment rate.* We compute monthly employment rates at the recruiting-company level using county-level local area unemployment statistics from the U.S. Bureau of Labor Statistics. We view this factor as reflecting the contemporaneous civilian employment climate faced by a potential recruit at the time of the decision to enlist.
- *Consumer Sentiment Index.* We use a monthly measure of national consumer sentiment collected since the 1940s by the University of Michigan. This index is generated using the responses to a series of questions about respondents' beliefs concerning future economic conditions in the near term (in one year) and in the more distant future (five years). It is intended to measure how the attitudes and expectations of consumers influence economic activity (e.g., high expectations of future inflation will lead consumers to spend today if they believe incomes will not keep up with prices). We believe that this forward-looking attitude toward the economy relates importantly to the multiyear commitment represented by enlistment.
- *Minimum wage policy.* We include this measure because the variation in local wage floors might be an important marginal factor in young people's decisions to enter military service. We believe this might provide a more salient measure than the civilian military wage ratio used in numerous past studies (see, for example, Asch et al., 2010; Murray and McDonald, 1999; and Warner, Simon, and Payne, 2003). On the one hand, the minimum wage level represents a policy-based measure of wages that is exogenous to recruiting needs. On the other, the ratio of civilian to military wages is an equilibrium measure that might be more endogenous to aspects of the recruiting environment (e.g., military pay raises might be related to the probability of more-arduous duty). Wages are also inevitably measured with error on the civilian side unless they truly represent area-specific wages among the QMA population. Additionally, there was little variation in the relative measures of civilian and military pay during the period we focus on (Asch et al., 2020), while there was considerable variation in minimum wage policy

⁷ The interacting of company-level mission and national bonus spending and eligibility introduces additional variation into this variable over time that appears to have led to smaller standard errors that would otherwise be obtained using only national-level variation. However, because we only make use of point estimates in operationalizing the output of the CPM, we decided that the potential reduction in endogeneity discussed above warranted the potential that confidence intervals would be artificially narrow.

across states and counties. Furthermore, even though the number of workers earning minimum wage has declined significantly over time—from around 13 percent in 1979 to under 3 percent in 2018, the last year of our data—over 8 percent of workers ages 16–19 earned the minimum (U.S. Bureau of Labor Statistics, 2019). Recent evidence also shows that changes in the minimum wage affect the structure of wages more broadly as employers attempt to preserve wage differentials across a pool of employees (Ashenfelter and Jurajda, 2021).

We exclude a measure of educational benefits, a factor that has been included in multiple past studies of recruiting outcomes (Murray and McDonald, 1999; Warner, Simon, and Payne, 2003), because all service members were fully eligible for the Post-9/11 GI Bill during the period we focus on. Within relatively generous limits, this program pays the full cost of college tuition for up to 36 months, along with a monthly housing allowance and a stipend for supplies for those completing at least three years of active-duty service (U.S. Department of Veterans Affairs, 2022). Thus, we view this aspect of the recruiting environment as being essentially held fixed over our brief sample period by this flexible and generous benefit program.

Other Factors Affecting Contract Production

Other factors, including unobservable differences across geographies, seasonality in recruiting, and temporal variation in how recruiting data are grouped, might affect model estimates of contract production. We employ multiple control variables aimed at addressing these factors in the portmanteau function $f_4(Z_{st})$. These controls are

- A set of month indicator variables that control for persistent seasonality in recruiting outcomes related to, for example, the timing of the school year and seasonal variation in the labor market.
- A single indicator variable for one outlier period in the contract data (recruiting month 12 of FY 2015) that appears to be related to an end-of-FY accounting issue rather than an extreme change in national recruiting outcomes.
- A third-degree polynomial function of time (expressed as a sequential count of months in the data) that provides a flexible way to control for any unobserved factors that vary only in the time dimension and affect each company in the same way, such as the national economic climate. We also estimated model results using single-FY fixed effects rather than this polynomial function of time. These estimates are presented below in Table B.2. Our estimates were very similar when using this alternate approach

to controlling for otherwise unobservable temporal factors affecting the national recruiting environment.⁸

The Updated Contract Production Model

To obtain a model that can be estimated using linear regression techniques, we take logs of the production function in Equation B.2. To address the problem of using logged values when there are occasional zero contracts, mission goals, or bonuses at the company-month level (because the log of zero is negative infinity), we implement a common approach that adds one to the value of a given measure before taking the log, because the log of one is zero. The number of zeroes among contracts and mission goals is minimal in the data, affecting only 203 total company-months out of 11,315 (1.8 percent). We tested the potential for this modification of the data to affect our estimates (because, for example, adding a “1” to data primarily comprising numbers close to one could have a meaningful effect on estimates using such transformed variables). However, few observations have values close to one (the closest is the USAR mission variable, but the mean mission level in the data is 6.3, and, even at the 25th percentile of the data, the value is 4) and estimates that dropped company months with zero values yielded very similar results to those using this approach.⁹ After substituting for the various $f_i(\cdot)$ functions in Equation B.2 as described above and renumbering our model parameter subscripts for simplicity, we obtain the following regression model:

⁸ The one exception is the coefficient for consumer sentiment, which is the only of our control variables that is only measured at the national level. This estimate increases by roughly a factor of three when using single-year fixed effects.

⁹ We use this same approach for our final formulation of the bonus variables because there are a fairly large number of company months with zero bonus values. The incidence of zero values is 19 percent of company months for QS bonuses and 13 percent of company months for MOS bonuses. To test the mathematical sensitivity of estimates to this fix, we compared estimates for the subsample of company months with positive bonus use both with and without adding one and confirmed that they were identical. Overall, these subsample estimates are higher in positive magnitude for HQ contract production but are negative for NHQ production. We believe this is related to the fact that bonuses are generally deployed to aid in meeting HQ mission, so that bonus use shifts contract production toward HQ contracts and away from NHQ. By including company months that reflect more positive recruiting outcomes, the use of the +1 approach has the effect of averaging the association between bonus use and contract production across company months that did and did not rely on bonuses, resulting in nonnegative estimates that are smaller in magnitude than those derived from the subsample of company months with only positive bonus use. Given that we use this model to generate predictions of optimal bonus use at the national level, we feel that this is the more appropriate approach to take.

$$\begin{aligned}
 \log\left(\frac{C_{st}}{Q_{st}}\right) = & \beta_0 + \beta_1 \log\left(\frac{HQ M_{st}}{Q_{st}}\right) + \beta_2 \log\left(\frac{nonHQ M_{st}}{Q_{st}}\right) + \beta_3 \log\left(\frac{USAR M_{st}}{Q_{st}}\right) + \beta_4 \log\left(\frac{R_{st}}{Q_{st}}\right) \\
 & + \beta_5 \log(unemp_{st}) + \beta_6 \log(cons sent_t) + \beta_7 \log(min wage_{st}) \\
 & + \beta_8 \log(bonus MOS_{st}) + \beta_9 \log(bonus QS_{st}) + \beta_{10} \log\left(\frac{TV ad stock_{st}}{Q_{st}}\right) \\
 & + \beta_{11} \log\left(\frac{dig ad stock_{st}}{Q_{st}}\right) + \beta_{12} \log\left(\frac{TV ad stock_{st}}{Q_{st}} \times \frac{dig ad stock_{st}}{Q_{st}}\right) \\
 & + \beta_{12} rcm_days_t + \pi_0 t + \pi_1 t^2 + \pi_2 t^3 + \gamma_s + \delta_i + \theta_t^{outlier} + \epsilon_{st}.
 \end{aligned} \tag{B.4}$$

To allow the RRM to more realistically model actual recruiting outcomes, we estimate the CPM using two distinct dependent variables: HQ RA contracts and NHQ RA contracts. This distinction is important not only to disentangle recruiter effort levels that we proxy for but also to allow for the potential that other factors, such as bonuses and unemployment, might have differential associations with HQ or NHQ contract production.¹⁰

Limitations of the Contract Production Model

Specific to the RRM, the complex nature of the Army recruiting enterprise necessarily means that any model of this endeavor will have significant limitations that might affect its usefulness as a planning tool in important ways. Below, we discuss a few important points in this regard:

- As discussed in more detail above, none of the variation in the historical data we use to estimate the associations between either Army resource use or macroeconomic factors and recruiting outcomes was truly experimental or quasi-experimental. Therefore, the estimates we use in this model do not have a strong claim to represent entirely causal relationships, despite our efforts to understand and effectively address foreseeable sources of bias.
- Because of constraints on the available advertising data, the CPM uses a relatively short period of time to estimate the relationships we are interested in. Broadly, this period was characterized by relatively low levels of variation in unemployment, relatively consistent

¹⁰ Although it was not explicitly derived from the CPM, we explored modeling the relationship between recruiters and unemployment using simple linear interactions. The results led us to conclude that these sorts of interactions are, in general, more complex than a linear term can account for: Unusually large changes in the main coefficients (in the case of the association between unemployment and recruiting) moved the estimates quite far from the magnitudes seen across several prior studies. For this reason, we opted to refrain from including any interactions except in the case of digital and TV advertising (where the literal duplication of key elements of an ad campaign across these mediums suggested inclusion of a straightforward linear interaction).

mission levels, and other factors that might affect the amount of variation in the input factors to the model. Our testing of data from other time periods (when we excluded advertising data) revealed a moderate level of sensitivity to the period chosen. This sensitivity might be related to actual changes in the underlying relationships over time, but it also might be related to limitations in the amount of variation in the model inputs over the period we were limited to employing. In the latter case, our associations might be inaccurate with respect to an underlying “true” association between any such inputs and contract production.

- One important model input is mission; as discussed above, we use this measure as a proxy for recruiter effort. However, mission is sometimes revised downward over the course of more difficult recruiting years, and, to the best of our knowledge, the data we incorporate into the model reflect the inclusion of any such adjustments. To the extent that recruiters might have been motivated to exert greater effort under original, higher mission numbers than they would have if the revised numbers had been used initially, our estimates of these model parameters might be upwardly biased. In other words, we might be attributing more motivation to mission than is appropriate if actual mission in a given month was higher than was ultimately recorded in the data we used.
- The CPM is a reduced-form model. What this means is that we model relationships between Army inputs, such as recruiters and advertising, and recruiting outcomes as a “black box” where spending on these inputs goes in and contracts come out. This approach might be sufficient if there are not large changes to the underlying mechanisms by which spending on a factor is converted into contract production. We make an implicit assumption that this is not the case by using such a model. Counterexamples to this assumption might include, for example, if the Army’s advertising agency made unusually effective or ineffective use of advertising spending resources in our study period versus at other times. For example, if the Army had an unusually effective ad campaign for some initial period of three years and an unusually ineffective ad campaign for the following three years, then the model’s estimate for advertising effectiveness over these six years would represent the mean level of effectiveness over these two periods. A similar caveat applies to recruiters; their effectiveness could be shifted by factors including using individual versus station-level mission goals or using new approaches to recruiter training. This is also the case for MOS bonuses; we cannot provide insight on whether the Army used a bonus structure that accurately targeted individuals who required a bonus to enlist versus a structure that paid bonuses to many individuals who would have enlisted without a bonus.

Model Results

Table B.1 presents results from the CPM for three outcome variables: the log of all NPS contracts (we use this outcome as a benchmark to consider the average relationship between

TABLE B.1
Contract Production Model Results

	(1) Log NPS Contracts	(2) Log HQ NPS Contracts	(3) Log NHQ NPS Contracts
Log (RA HQ mission per QMA population)	0.031 [*] (0.013)	0.059 ^{***} (0.017)	0.028 (0.022)
Log (RA NHQ mission per QMA population)	0.094 ^{***} (0.010)	0.071 ^{***} (0.012)	0.165 ^{***} (0.016)
Log (USAR mission per QMA population)	-0.071 ^{***} (0.009)	-0.078 ^{***} (0.011)	-0.053 ^{***} (0.015)
Log (recruiters per QMA population)	0.322 ^{***} (0.027)	0.285 ^{***} (0.033)	0.329 ^{***} (0.044)
Log unemployment rate	0.139 ^{***} (0.027)	0.101 ^{**} (0.033)	0.182 ^{***} (0.044)
Log minimum wage	-0.128 ^{**} (0.045)	-0.253 ^{***} (0.055)	0.009 (0.072)
Log Consumer Sentiment Index	-0.110 (0.076)	-0.102 (0.095)	-0.239 (0.124)
Log MOS bonus	0.007 ^{***} (0.001)	0.011 ^{***} (0.001)	0.001 (0.001)
Log QS bonus	0.010 ^{***} (0.002)	0.010 ^{***} (0.002)	0.005 [*] (0.003)
Log TV advertising	0.114 ^{**} (0.038)	0.116 [*] (0.047)	0.071 (0.062)
Log digital advertising	0.060 (0.034)	0.076 (0.042)	0.003 (0.055)
Interaction of log TV and digital advertising	0.009 [*] (0.004)	0.011 [*] (0.005)	0.003 (0.007)
Days in recruiting month	0.030 ^{***} (0.001)	0.034 ^{***} (0.001)	0.023 ^{***} (0.002)
<i>N</i>	11,315	11,290	11,193
Adjusted R ²	0.48	0.36	0.19

NOTE: Standard errors in parentheses are clustered at the company level. The model includes company-level fixed effects and a cubic term in time. We omit these coefficients from the results above.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

contracts and the resources and other factors we model) and the two outcomes entered in the RRM optimization procedure, which are the log of HQ NPS contracts (GA and SA) and the log of NHQ NPS contracts. A few points are worth highlighting in these results: There appears to be meaningful substitution between RA contracts and USAR contracts but some level of complementarity between HQ mission and NHQ mission. This is perhaps not sur-

prising because these missions are tightly linked because the number of HQ accessions is set as a share of the overall mission. We estimate an average elasticity of recruiters to contract production of 0.32 in column 1, with the contract-type-specific models in columns 2 and 3 suggesting that NHQ contract production is slightly more responsive than HQ contract production to increased recruiter levels. This is consistent with the notion of HQ contracts being generally more difficult to produce.

In terms of the relationship between economic factors and contract production, we see evidence of contrasting associations between HQ and NHQ contract production and our three measures of the macroeconomic environment that are consistent with economic theory. Specifically, we see a greater responsiveness to the minimum wage for HQ contract production. This is consistent with evidence showing that employers shift to hiring or retaining higher-productivity employees as wages increase (Modestino, Shoag, and Ballance, 2020), leading to relatively greater difficulty recruiting HQ individuals away from civilian employment when the wage floor is raised. Relatedly, we see stronger associations between the unemployment rate (positive) and consumer sentiment (negative) and NHQ contract production, suggesting that NHQ recruits are more likely to encounter more difficulty in the labor market than their HQ peers when there is a general downturn in the economy, leading to an easier recruiting environment for these individuals.

We estimate a significantly greater responsiveness to MOS-specific bonuses among HQ recruits, reflecting the fact that these individuals are broadly more suitable for MOSs that are likely to have bonuses associated with them. In contrast, QS bonuses appear to be equally effective across both contract types.

Our estimates of the association between television advertising and contract production, using all contracts as the outcome, suggest that a 10.0-percent increase in television ad spending is associated with a 1.1-percent increase in contract production, while the same increase in digital ad spending is associated with a 0.6-percent increase in contract production, or a magnitude of roughly half of the television estimate. The interaction term between these two primary advertising channels that we include indicates that there is a complementarity between them and suggests that increasing both TV and digital advertising by 10.0 percent is associated with an additional increase in contract production of approximately 0.1 percent.

Considering how these estimates enter the actual RRM, columns 2 and 3 indicate that the positive association between both television and digital ad spending and contract production is primarily related to HQ contract production, though the relationship is still positive for NHQ contract production. We note that, except for TV ad spending in column 2, none of these other estimates are statistically significant at the 95-percent confidence level, though the digital ad spending estimate is statistically significant at the 90-percent confidence level. Both the relatively short period for which we were able to obtain digital advertising data and the potential measurement error related to the way advertising data were distributed at the company level might have reduced the precision of these estimates.

To assess how our use of a cubic term in time controlled for otherwise unobservable trends influencing the national recruiting environment, we also tested a model that uses a set of FY

fixed effects. This nonparametric approach is less restrictive than the assumptions underlying the cubic approach. These results are presented in Table B.2. Few of the model parameters change in a meaningful fashion because of this change. One exception is the coefficient on consumer sentiment, which is approximately 3.5 times the magnitude of the estimate in Table B.1. Notably, this is the only input to the model that is defined only at the national level. Ultimately, we decided that the cubic term was a more appropriate way to address unobserv-

TABLE B.2
Alternative Contract Production Model Results (with Fiscal Year Fixed Effects)

	(1) Log NPS Contracts	(2) Log HQ NPS Contracts	(3) Log NHQ NPS Contracts
Log (HQ mission per QMA population)	0.032 [*] (0.013)	0.052 ^{**} (0.017)	0.038 (0.022)
Log (NHQ mission per QMA population)	0.090 ^{***} (0.010)	0.075 ^{***} (0.012)	0.151 ^{***} (0.016)
Log (USAR mission per QMA population)	-0.078 ^{***} (0.009)	-0.087 ^{***} (0.011)	-0.056 ^{***} (0.015)
Log (recruiters per QMA population)	0.322 ^{***} (0.027)	0.285 ^{***} (0.033)	0.332 ^{***} (0.044)
Log unemployment rate	0.146 ^{***} (0.027)	0.107 ^{**} (0.033)	0.187 ^{***} (0.044)
Log minimum wage	-0.139 ^{**} (0.045)	-0.258 ^{***} (0.055)	-0.009 (0.072)
Log Consumer Sentiment Index	-0.378 ^{***} (0.104)	-0.239 (0.128)	-0.558 ^{***} (0.168)
Log MOS-specific bonus	0.007 ^{***} (0.001)	0.011 ^{***} (0.001)	0.001 (0.001)
Log QS bonus	0.012 ^{***} (0.002)	0.012 ^{***} (0.002)	0.009 ^{***} (0.002)
Log TV advertising	0.085 [*] (0.038)	0.124 ^{**} (0.048)	-0.012 (0.062)
Log digital advertising	0.042 (0.034)	0.082 (0.042)	-0.050 (0.055)
Interaction of log TV and digital advertising	0.006 (0.004)	0.011 [*] (0.005)	-0.006 (0.007)
Days in recruiting month	0.031 ^{***} (0.001)	0.034 ^{***} (0.001)	0.026 ^{***} (0.002)
<i>N</i>	11,315	11,290	11,193
Adjusted R ²	0.48	0.36	0.19

NOTE: Standard errors in parentheses are clustered at the company level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

able, time-varying national factors, in part because the lower resulting value of consumer sentiment was more conceptually plausible and broadly in line with the magnitudes of the estimates for the other macroeconomic factors of the model.

Comparability with Results from Existing Research

We briefly compare our results with those from past studies on the association between contract production and both recruiting resources and measures of the recruiting environment. To do so, we consider results from six studies conducted within the past 25 years that used an elasticity-based modeling approach. These results for four key variables—recruiters, mission, advertising, and the unemployment rate—are presented in Table B.3.¹¹ We note that these models vary meaningfully in important aspects of the modeling approach (the use of differing levels of geographic aggregation, implementation of fixed effects, etc.), in what covari-

TABLE B.3
Estimated Elasticities from Past Research on Recruitment

	Recruiters	Mission	Advertising (National)	Unemployment Rate
Asch et al. (2010)	0.57	–	–	0.10
Warner and Simon (2005)	0.41	–	–	0.49
Warner, Simon, and Payne (2001)	0.50	0.15	0.16	0.26
Bohn and Schmitz (1996)	0.14	–	–	0.19
Hogan et al. (1996)	0.29	–	0.03	0.18
Murray and McDonald (1999)	0.48	0.11	0.23	0.23
Average elasticity estimate	0.40	0.13	0.14	0.24
RRM CPM	0.32	0.06 (HQ) 0.17 (NHQ)	0.11	0.14

NOTE: – indicates that the past research does not offer an estimated elasticity for the category. All the results reported except for Asch et al. (2010) and Murray and McDonald (1999) are reproduced from Asch, Hosek, and Warner (2007). Asch et al. (2010) results are for their model with time fixed effects. Warner and Simon (2005) results are for an increase in recruiters (they estimated an approximately 30 percent larger association for a decrease in recruiters). The advertising estimate for Hogan et al. (1996) is for television advertising (they also generated an estimate for radio) and uses their median estimates for the Navy. Results from Bohn and Schmitz (1996) are for their model with recruiting area and month dummy variables. Results from Murray and McDonald (1999) use the log-log model (“Disaggregated Data”) they estimate in Appendix C and represent estimates for the later of the two data periods they considered (FYs 1990–1993). The mission goal in Murray and McDonald (1999) is for HQ contracts. The RRM CPM estimates for recruiters, unemployment, and (television) advertising coefficients are for the overall contract production outcome. The mission estimates are for each “own contract type” outcome.

¹¹ We do not include bonus estimates. The studies that included this factor used some representation of the average dollar amount of bonuses without conditioning on eligibility, as we do, so their estimated associations were generally larger than ours by an order of magnitude or more.

ates they included, and in the sample period and military services considered. Despite these potentially important differences, we believe that the variety of such estimates and their average can still provide useful context for consideration of the results of the CPM we estimate.

Our estimate of the association between recruiters and contract production (0.32 for overall contract production) is lower than the largest of the estimates in this literature (0.57) but is around twice the magnitude of the smallest estimate (0.14) and is similar to the simple average of these estimates (0.40). Our HQ mission estimate is meaningfully smaller than the result from Murray and McDonald (1999), while the NHQ estimate is closer to these past results on mission. Our estimates of the association between advertising spending and recruiting (we use the estimate for television spending because these studies all predated the widespread use of digital advertising) are only slightly smaller than the average of the three estimates presented here.

The estimate for the association between the unemployment rate and contract production is smaller than nearly all the estimates presented here except for the most recent one (Asch et al., 2010). Asch and Warner (2018) discuss the possibility that the sensitivity of recruiting to unemployment has declined over time but do not suggest a causal mechanism.¹²

Additionally, we have one particularly useful measure of the efficacy of MOS bonuses in recruiting to compare with our estimates. In experimental research on the effect of enlistment bonuses conducted in the 1980s, Polich, Dertouzos, and Press (1986) estimated the effect of increasing an MOS enlistment bonus by 60 percent on three different aspects of Army manning: “market expansion” (or the extent to which bonuses actually increase enlistments overall), skill channeling (inducing enlistees to choose a certain MOS), and shifting the term of enlistment to a longer time horizon conditional on choosing to enlist. The market expansion effect is the component that is relevant to this project. The authors found the estimated effect of a 60-percent increase in the amount of the bonus to be 4 percent. This translates to an elasticity measure of 0.0067, which is approximately equal to the estimate we calculate for MOS bonuses in our model that uses all contracts as the outcome (0.007).

¹² Other recent related research has attempted to explore reasons behind the failure of the labor supply of young adult males to rebound in the years after the Great Recession; some research has concluded that this pattern remains difficult to explain (Pérez-Arce and Prados, 2021), while one novel study suggests that increases in the quality of “leisure technology” (specifically recreational computing or video gaming) are a potential causal factor (Aguiar et al., 2021).

The Optimization Process

Overview of the Optimization Model

In this appendix, we summarize the basic approach of the current optimization model, emphasizing differences between the preexisting approach and the current methodology. Figure C.1 provides a graphical representation of the optimization model. This figure details how input parameters influence contract production (identified by the node labeled “CP”), the output of which enters into the DEP simulation (identified by the node labeled “DEP”), the output of which enters the objective function.

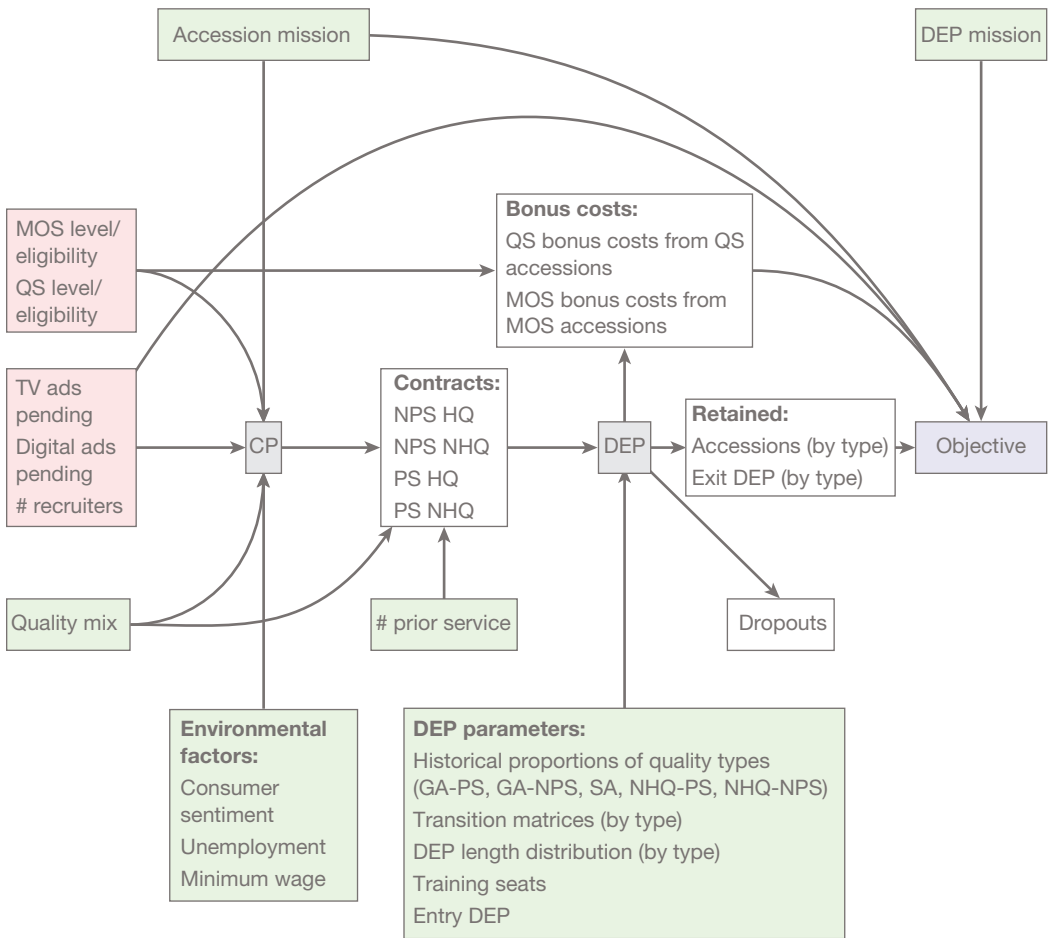
Nodes in Figure C.1 for which there are no incoming arrows are inputs into the optimization model. There are two different types of inputs: excursion parameters (highlighted in green) and optimization parameters (highlighted in pink). Excursion parameters are set by the user upstream of the entire optimization process and remain fixed throughout. How optimization output reacts to variation in excursion parameters might be of interest. For instance, the user might run the optimizer once under one assumption about unemployment (for example, high unemployment rates) and again under another assumption about unemployment (for example, low unemployment rates). By contrast, the optimization parameters are initialized by the user at the beginning of the optimization but are varied throughout the optimization process.

Ultimately, the goal of the optimizer is to find optimization parameters that minimize the objective function, which is indicated by the purple node to the far right of Figure C.1. The objective function is defined as follows:

$$\text{Objective} = D + \sum_t (B_t + A_t + R_t + M_t).$$

First, we discuss the set of terms defined at the monthly level (indexed by t), which enter the objective function summed across the entire year. The first three terms, B_t , A_t , and R_t , are bonus, advertising, and recruiter spending, respectively. Monthly bonus costs B_t are incurred only for accessions and are determined by the four optimization parameters defining the MOS bonus level, MOS bonus eligibility, QS bonus level, and QS bonus eligibility per month. Monthly television and digital advertising spending, A_t , are themselves optimization parameters that enter directly into the objective function. Monthly recruiter spending R_t is deter-

FIGURE C.1
Graphical Overview of Optimization Model



NOTE: PS = prior service. Pink-shaded nodes indicate variables that are optimized over. Green-shaded nodes indicate variables that are set by the user and define an excursion.

mined by multiplying the monthly number of recruiters (an optimization parameter) by a fixed per-recruiter cost (set to \$115,830, per a recent estimate provided to us by USAREC).

The next term in the objective function is the monthly accession mission costs, M_t . If we define the monthly accession mission to be m_t^* and actual accessions to be m_t , and the indicator function as I , then the monthly accession mission penalty is defined as follows:

$$M_t = \gamma_{\text{surplus}} I(m_t^* < m_t) (m_t - m_t^*)^{1.75} + \gamma_{\text{shortfall}} I(m_t^* > m_t) (m_t^* - m_t)^{1.75}.$$

In other words, the term M_t encodes two types of penalties, one penalty for monthly surpluses in attained accessions and one penalty for monthly shortfalls in attained accessions.

The parameters γ_{surplus} and $\gamma_{\text{shortfall}}$ determine the relative sizes of these penalties and are set to 100 and 250, respectively. While the terms B , A , and R_i are naturally in units of dollars, the parameters γ_{surplus} and $\gamma_{\text{shortfall}}$ induce implicit monetary values on mission shortfalls and surpluses. For instance, a shortfall of 100 accessions incurs a penalty equivalent to \$790,569. The larger penalty for shortfalls relative to surpluses reflects the view that shortfalls are considerably less desirable than surpluses.¹

The term D denotes the DEP term and is defined as follows (here, d^* denotes the annual DEP mission and d denotes the actual final DEP size):

$$D_i = \delta I(d^* > d)(d^* - d)^{1.75}.$$

The DEP penalty is defined similarly to the monthly accession penalty, except that (1) only the final DEP is of concern (rather than the intermediate monthly values) and (2) there are only penalties incurred for DEP shortfalls (and no penalties incurred for DEP surpluses). We have set the coefficient δ to 200 and the exponent to 1.75 to reflect the preference that shortfalls in the DEP are penalized to a lesser extent than (and are therefore preferred to) shortfalls in accessions.

Bonus Spending

The contract production function incorporates bonus spending through the following variables:

$$l = \log(b_{\text{MOS}}^{\text{all}} e_{\text{MOS}}^{\text{all}} m^{\text{all}} + 1) lD_{\text{QS}} = \log(b_{\text{QS}}^{\text{all}} e_{\text{QS}}^{\text{all}} m^{\text{all}} + 1),$$

where $b_{\text{MOS}}^{\text{all}}$ is the average MOS bonus offered to all those receiving a bonus, $e_{\text{MOS}}^{\text{all}}$ is the proportion eligible to receive an MOS bonus, and m^{all} is the overall mission. The QS variables are analogously defined. While the bonus variables entering the CPM are defined for the overall population, we optimize bonus amounts and eligibility separately for the HQ and NHQ subpopulations. This introduces a slight complication in coercing quality-specific bonuses and eligibilities into overall bonuses and eligibilities. We therefore redefine the bonus variables lD_{MOS} and lD_{QS} in terms of the subpopulation parameters:

- $b_{\text{MOS}}^{\text{HQ}}$: Average bonus received among HQ recruits receiving an MOS bonus
- $b_{\text{MOS}}^{\text{LQ}}$: Average bonus received among NHQ recruits receiving an MOS bonus
- $b_{\text{QS}}^{\text{HQ}}$: Average bonus received among HQ recruits receiving a QS bonus
- $b_{\text{QS}}^{\text{LQ}}$: Average bonus received among NHQ recruits receiving a QS bonus
- $e_{\text{MOS}}^{\text{HQ}}$: proportion of HQ contracts eligible to receive an MOS bonus

¹ We chose to use 1.75 as the exponent value in our penalty functions so that the implicit dollar value for missing a marginal recruit in a situation where there is a significant shortfall relative to mission was approximately equal to the cost of one recruiter year.

- e_{MOS}^{LQ} : proportion of NHQ contracts eligible to receive an MOS bonus
- e_{QS}^{HQ} : proportion of HQ contracts eligible to receive a QS bonus
- e_{QS}^{LQ} : proportion of NHQ contracts eligible to receive a QS bonus.

First, we define the overall eligibility parameter in terms of the subpopulation eligibility parameters by noting that, among the population receiving contracts,

$$P(MOS | Contract) = P(MOS | HQ, Contract)P(HQ | Contract) + P(MOS | LQ, Contract)P(LQ | Contract)$$

and identifying the probability of receiving an MOS bonus for HQ contract recipients as e_{MOS}^{HQ} and the probability of receiving an MOS bonus for NHQ recruits as e_{MOS}^{LQ} . Therefore, we define the following parameters:

$$\begin{aligned}\tilde{e}_{MOS}^{all} &= e_{MOS}^{HQ} p^{HQ} + e_{MOS}^{LQ} (1 - p^{HQ}) \\ \tilde{e}_{QS}^{all} &= e_{QS}^{HQ} p^{HQ} + e_{QS}^{LQ} (1 - p^{HQ}).\end{aligned}$$

Next, we need to define b_{MOS}^{all} and b_{QS}^{all} in terms of the available subpopulation parameters. We note that

$$\begin{aligned}b_{MOS}^{all} &= E[B_{MOS} | MOS, Contract] \\ &= E_{Quality}[E[B_{MOS} | Quality, MOS, Contract]] \\ &= E[B_{MOS} | HQ, MOS, Contract] P(HQ | MOS, Contract) \\ &\quad + E[B_{MOS} | LQ, MOS, Contract] P(LQ | MOS, Contract) \\ &= b_{MOS}^{HQ} P(HQ | MOS, Contract) + b_{MOS}^{LQ} P(LQ | MOS, Contract),\end{aligned}$$

where B_{MOS} is the MOS bonus amount in dollars. To compute the probabilities $P(HQ | MOS, Contract)$ and $P(LQ | MOS, Contract)$, we use Bayes' Rule. For example,

$$\begin{aligned}P(HQ | MOS, Contract) &= \frac{P(MOS | HQ, Contract) P(HQ | Contract)}{P(MOS | Contract)} \\ &= \frac{e_{MOS}^{HQ} P(HQ | Contract)}{P(MOS | Contract)} \\ &\approx \frac{e_{MOS}^{HQ} p^{HQ}}{\tilde{e}_{MOS}^{all}}.\end{aligned}$$

In the last line, we make the same substitution $P(\text{HQ} \mid \text{Contract}) \rightarrow p^{\text{HQ}}$ mentioned earlier and substitute $P(\text{MOS} \mid \text{Contract}) \rightarrow \tilde{e}_{\text{MOS}}^{\text{all}}$. Finally, we define the following quantities:

$$\begin{aligned}\tilde{b}_{\text{MOS}}^{\text{all}} &= b_{\text{MOS}}^{\text{HQ}} \frac{e_{\text{MOS}}^{\text{HQ}} p^{\text{HQ}}}{\tilde{e}_{\text{MOS}}^{\text{all}}} + b_{\text{MOS}}^{\text{LQ}} \frac{e_{\text{MOS}}^{\text{LQ}} (1 - p^{\text{HQ}})}{\tilde{e}_{\text{MOS}}^{\text{all}}} \\ \tilde{b}_{\text{QS}}^{\text{all}} &= b_{\text{QS}}^{\text{HQ}} \frac{e_{\text{QS}}^{\text{HQ}} p^{\text{HQ}}}{\tilde{e}_{\text{QS}}^{\text{all}}} + b_{\text{MOS}}^{\text{LQ}} \frac{e_{\text{QS}}^{\text{LQ}} (1 - p^{\text{HQ}})}{\tilde{e}_{\text{QS}}^{\text{all}}}.\end{aligned}$$

In our optimization, we input the following quantities into our bonus variables:

$$\begin{aligned}\widetilde{D}_{\text{MOS}} &= \log\left(\tilde{b}_{\text{MOS}}^{\text{all}} \tilde{e}_{\text{MOS}}^{\text{all}} m^{\text{all}} + 1\right) \\ \widetilde{D}_{\text{QS}} &= \log\left(\tilde{b}_{\text{QS}}^{\text{all}} \tilde{e}_{\text{QS}}^{\text{all}} m^{\text{all}} + 1\right).\end{aligned}$$

Optimization is now possible because all \tilde{b}^{all} and \tilde{e}^{all} quantities are defined by optimization parameters $b^{\text{HQ}}, b^{\text{LQ}}, e^{\text{HQ}}, e^{\text{LQ}}$, and p^{HQ} .

An additional complication with the bonus parameters is that, while we are optimizing them at the national level, they are supplied to the CPM at the company level. To reflect the company-level heterogeneity in realized bonus levels and eligibilities in the data, we perform the following association between national parameters and historical baseline parameters from FY 2015. First, let the number of FY 2015 contracts written by company i in month t be X_{it} and the corresponding number of bonus contracts be Y_{it} . (The procedure for MOS and QS bonus eligibilities is identical, so we describe the procedure here for a generic bonus type.) The company-level eligibility is $e_{it} = X_{it}/Y_{it}$, the total number of contracts written across all companies is $X_t = \sum_i X_{it}$, and the corresponding number of bonus contracts is $Y_t = \sum_i Y_{it}$. To translate the desired national eligibility, e_t^* , into company-level eligibilities, we first denote the number of FY 2015 contracts that would have been written under the counterfactual national eligibility as $Y_t^* = e_t^* X_t$. We then allocate $Y_{it}^* = Y_t^* (Y_{it}/Y_t)$ hypothetical contracts to company i and define the new company-level eligibility as $e_{it}^* = Y_{it}^*/X_{it}$. For bonus levels, we perform a similar operation. We denote the total number of bonus dollars spent in company i in month t in FY 2015 as D_{it} and the total number of bonus dollars spent in month t across all companies as $D_t = \sum_i D_{it}$. If the desired national bonus level is b_t^* , then the corresponding total bonus spending would be $D_t^* = b_t^* Y_t$. We then allocate $D_{it}^* = D_t^* (D_{it}/D_t)$ total bonus dollars to each company and define the new company-level eligibility as $b_{it}^* = D_{it}^*/Y_{it}$.

Optimization Procedures

We emphasize that the described objective function summarizes the performance of the optimizer over the entire year. The optimizer therefore seeks a set of optimization parameters that maximize a single annual objective function. This is distinct from the strategy used

in the previous iteration of the RRM, in which optimal parameters were sought month by month, using a greedy algorithm. By contrast, the current iteration of the optimizer jointly optimizes over the entire set of annual optimization parameters. In particular, the optimizer is jointly optimizing a set of 132 total parameters, corresponding to

1. monthly HQ/NHQ MOS eligibility proportions
2. monthly HQ/NHQ MOS bonus levels
3. monthly HQ/NHQ QS eligibility proportions
4. monthly HQ/NHQ QS bonus levels
5. monthly TV advertising spending
6. monthly digital advertising spending
7. monthly quantity of recruiters.

The first four items of this list each encode two different sets of parameters (one for HQ and another for NHQ). Because each quantity is allowed to vary for each month, this yields $(4 \times 2 + 3) \times 12 = 11 \times 12 = 132$ total parameters.

There are several important constraints imposed on the optimization procedure to ensure that the recommended output optimization parameters correspond to realistic and actionable recruitment strategies. First, because of the logistical difficulties of drastically changing the recruiter numbers, we impose a maximum increase and decrease in monthly changes to the recruiter population. In particular, the recruiter population in month $t + 1$ cannot exceed the recruiter population in month t by more than 1.6 percent. Likewise, the recruiter population in month $t + 1$ cannot be less than the recruiter population in month t by more than 1.0 percent. This is to reflect the reality that recruiter numbers cannot drastically increase in magnitude at the start of a new FY. Another important constraint is that NHQ bonus levels and eligibilities cannot exceed those corresponding to HQ. We also impose the following absolute bounds on all parameters:

1. TV ad spending does not exceed \$1 billion in any month.
2. The number of recruiters does not exceed 25,000 or fall below 2,000 in any month.
3. MOS and QS eligibility (for both HQ and NHQ) does not exceed 90 percent.
4. MOS and QS bonus levels (for both HQ and NHQ) do not exceed \$30,000 or fall below \$5,000 in any month.

One additional parameter that is chosen by the researcher but is not allowed to vary is the share of recruits that must be HQ. This parameter is not varied as part of the optimization but is simply enforced by, if necessary, throwing out excess NHQ contracts to meet the target. In practice, this typically results in no more than 2 to 3 percent of NHQ contracts being discarded.

In a previous version of this project (Knapp et al., 2018), referred to as Version 1.0, a customized algorithm was developed to determine optimal resource allocation. This algorithm looped through each month in an FY, searching for optimal resource allocation month by

month. For each month t , an objective function based on the costs in month t and the accessions and DEP in months t and $t + 1$ is minimized by iteratively increasing resource allocation by prespecified increments until the objective function stops decreasing. At this point, the algorithm decreases the increment size to 10 percent of its original values and performs a second round of iterative increases starting with the values found in the previous step. Finally, a third round is performed using increments at 1 percent of their original value.

While Version 1.0 of the optimization is attractive in its simplicity, it has several shortcomings that we attempted to address in this current version of the optimization algorithm. First, the previous approach is based on optimizing month-by-month objective functions. However, the dynamics of the DEP mean that resource allocation decisions in month t can have significant downstream effects in later months. For this reason, our current optimization approach, which we refer to as Version 2.0, is based on optimizing a single objective function that incorporates information about costs, accession, and DEP across all fiscal months. Intuitively, this will allow the optimizer to discover strategies that involve longer-term planning of resource allocation than the previous, month-by-month approach did. Version 1.0's second shortcoming was that it searched across resource allocation strategies using predefined incremental increases. This ad hoc approach was used in lieu of more-advanced algorithmic approaches because of the complexity of the optimization problem posed by the RRM. A significant barrier to the application of many optimization approaches is the need to analytically compute the gradient of the objective function. This gradient is intractable in the present application due to the complicated connection between the resourcing parameters (e.g., bonus parameters, recruiters, advertising costs) and the inputs to the objective function (e.g., accessions, DEP size, and bonus costs).

To overcome this difficulty, in Version 2.0, we use an algorithm known as *COBYLA* (Powell, 1994). This algorithm is particularly useful for our application because it does not require analytic computation of the gradient of the objective function. The *COBYLA* algorithm operates by first generating a linear approximation of the objective function, centered around the initialization. This linear approximation is then optimized over a trust region (defined below) in the space of parameters. This process continues, decreasing the volume of the trust region in each iteration, until convergence.

The *COBYLA* algorithm can be thought of as an extension of the simplex algorithm. Let θ denote the n -vector of parameters and $O(\theta)$ the value of the objective function at the point θ in parameter space. Here, n denotes the dimension of the parameter space, which is 132 in this application. In each iteration, the *COBYLA* algorithm computes the unique linear interpolation of the objective function computed on $n + 1$ points in the parameter space $(\theta_0, \theta_1, \dots, \theta_n)$. Note that the linear interpolation of the values of the objective function at these points $(O(\theta_0), O(\theta_1), \dots, O(\theta_n))$ is unique because, in general, there is a unique linear interpolation between $n + 1$ points in n dimensions. The $n + 1$ points are ordered such that $O(\theta_0) \leq O(\theta_1) \leq \dots \leq O(\theta_n)$. While the gradient of the true objective function is not tractable, the gradient of the linear interpolation is trivial. Using this approximate gradient, the *COBYLA* algorithm computes a minimizer $\hat{\theta}$ of the linear interpolation of $O(\theta)$ using

conventional gradient descent within a specified radius Δ of the point θ_0 . The set of points over which the linearly interpolated objective is optimized $\{\theta: \|\theta_0 - \theta\| < \Delta\}$ is called the *trust region*. The trust region radius Δ decreases in each iteration as the optimizer converges. At the end of each iteration, the minimizer $\hat{\theta}$ replaces the point in the θ_n with the highest objective value, the new set of $n + 1$ points are reordered in ascending order according to their objective values, and the process continues with the new set of $n + 1$ points. (An important subtlety is that the algorithm does not make this replacement if the convex hull of the resulting $n + 1$ points is degenerate.) The algorithm is initialized with a starting guess θ_0 , and the n required remaining points are defined as $\theta_i = \theta_0 + \rho e_k$, where ρ is a small, pre-specified constant and e_k are the coordinate axes in parameters space. Note that after many iterations, the original initialization θ_0 is typically replaced from the set of $n + 1$ points governing an iteration.

The COBYLA algorithm is a local optimization algorithm. While solutions improve upon the initialized parameters, they are not guaranteed to converge on a globally optimal solution. For instance, if the algorithm is initialized near a local minimum of the objective function, it will likely converge to that local minimum, missing any global optimums that are far from this initialization. When small increases (relative to the initialization) in a particular recruiting resource increase the objective function, this approach might miss an optimal solution that involves large increases in that same resource.

While we believe that Version 2.0 improves upon several shortcomings of Version 1.0, we think that it can be improved in several regards in future iterations of this work. Under our current implementation, excursion optimizations converge in approximately two hours. This is primarily because of the large number of variables (132) that are simultaneously being optimized. A potential future avenue for improving the computational speed of the optimizer is to optimize over subsets of the parameter space in a modular fashion. For instance, an alternative algorithm might cycle through optimization of single resource categories (e.g., TV ad spending, digital ad spending, recruiter resources), keeping all others fixed. By optimizing 12-month spending strategies separately for each resource category, we might be able to retain the advantage of identifying complex allocation strategies while increasing computational efficiency.

Additional Tables and Figures

This appendix collects miscellaneous figures and tables referenced in the body of the report that offer more details about the study and its findings.

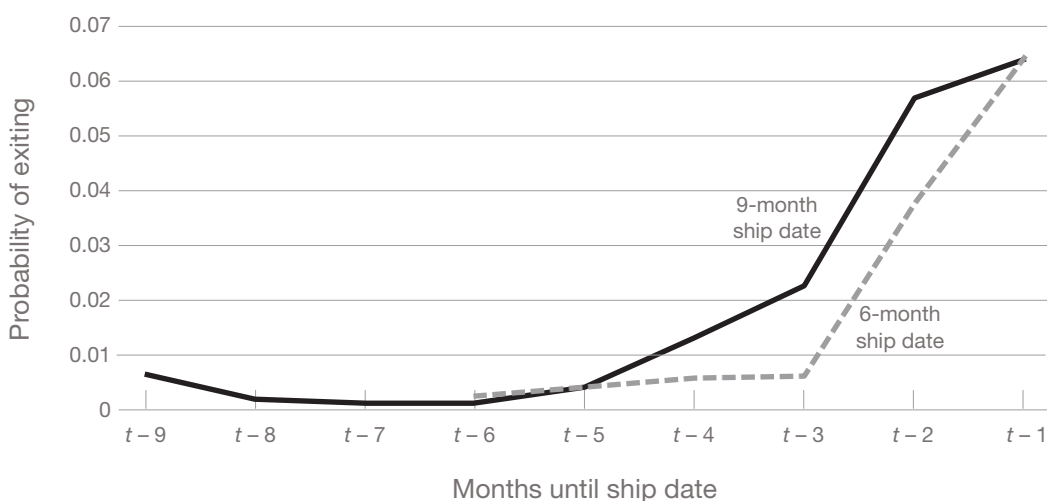
Figure D.1 presents two examples of the monthly probabilities of attrition from the DEP that are used in our DEP model. The figure’s intent is to give a sense of the amount of variation that the model introduces in terms of attrition probability depending on the length of time an enlistee spends in the DEP.

Figure D.2 presents graphical representations of month-by-month model results for resource use. In each case, the solid black lines show monthly resource use prior to optimization (baseline) and the dashed lines show optimized resource use.

Table D.1 presents data on historical accession goals, achieved accessions and DEP outcomes, and share of accessions in the top half of the AFQT distribution over the sample period.

Table D.2 lays out all the excursion scenarios we model and is followed by 15 tables (Tables D.3–D.17) detailing the unoptimized and optimized spending results for each excursion.

FIGURE D.1
Probability of Dropping Out of Delayed Entry Program for Contracts with Different Delayed Entry Program Durations



NOTE: Probabilities on the y-axis are on a 0 to 1 scale.

FIGURE D.2
Comparing Unoptimized Spending with Optimized Spending on Advertising and Bonuses for Scenario 1 (Baseline)

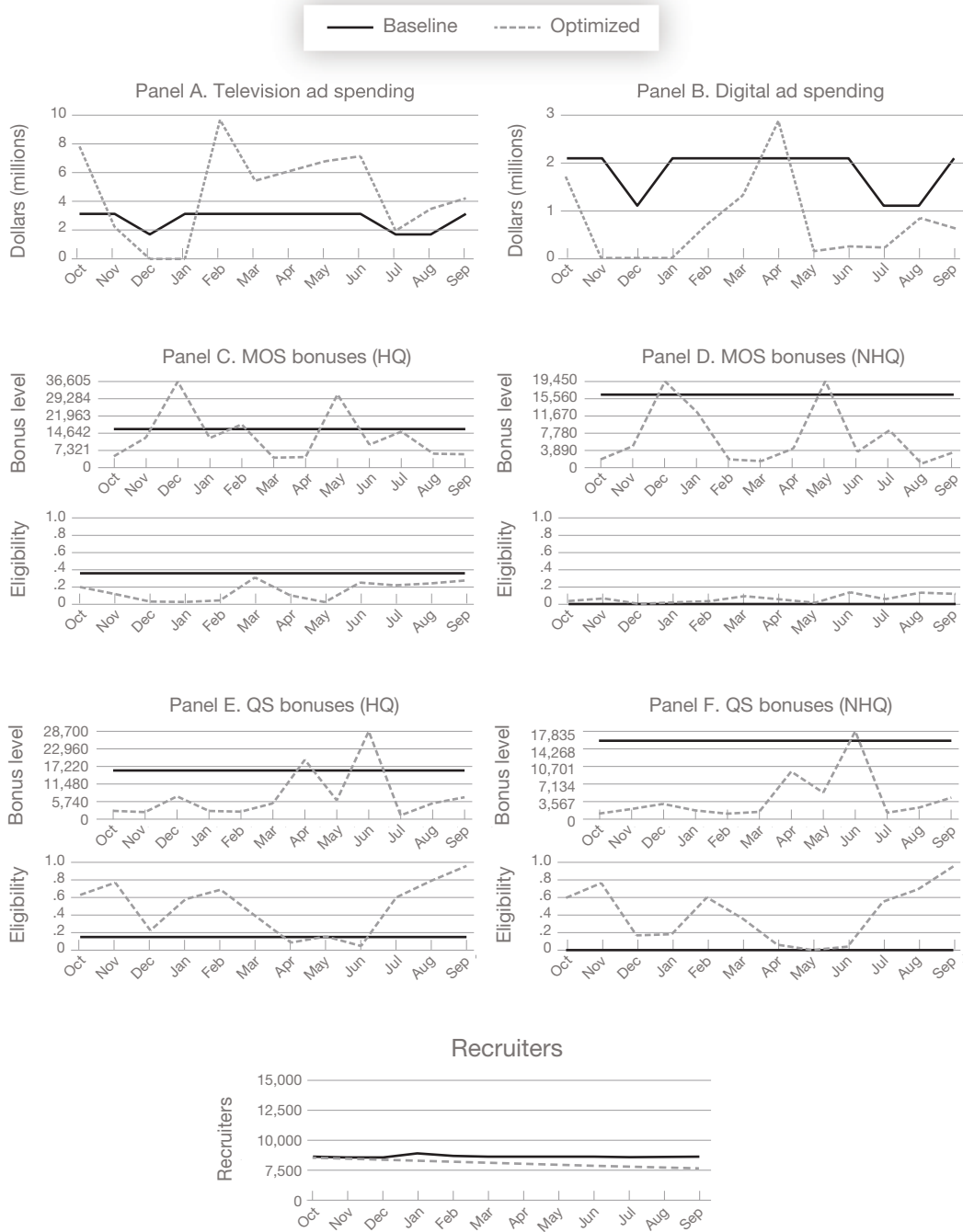


TABLE D.1
Accession and Entry Pool Outcomes, Fiscal Years 2013–2018

Year	NPS Objective	NPS Achieved	Categories I–IIIa (%)	Entry Pool
2013	69,000	69,154	62.2	27,992
2014	57,000	57,101	61.7	18,816
2015	59,000	59,177	60.2	16,479
2016	62,500	62,681	60.3	15,207
2017	68,500	68,862	60.4	16,522
2018	76,500	69,972	63.9	21,657

SOURCE: Army recruiting data provided through Headquarters, Department of the Army G-1.

NOTE: We include 2016 even though it is not in our sample period because of a lack of digital advertising spending data.

The following tables present unoptimized and optimized results for excursions listed in Table D.2. Each table heading lists the condition being implemented relative to the baseline excursion followed by the model excursion scenario numbers in Table D.2 in parentheses. As indicated, all dollar amounts are shown in millions. For accessions and exit DEP, the estimated outcome is accompanied by a percentage measure that indicates the ratio of the achieved outcome relative to the goal (65,000 accessions unless otherwise indicated and 20 percent of the accession goal for the exit DEP).

TABLE D.2
Recruiting Resource Model Excursion Scenarios

Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Accession mission (thousands)	65	60	65	65	65	65	65	65	65	65	65	65	65	65	65
Unemployment rate (% change)	0	0	0	0	0	0	0	-25	25	0	0	0	0	0	0
Federal minimum wage (\$)	7.25	7.25	7.25	7.25	7.25	7.25	8.50	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Waivers (%)	12.10	12.10	12.10	12.10	12.10	15.00	12.10	12.10	12.10	12.10	12.10	12.10	12.10	12.10	12.10
HQ share (%)	58.90	58.90	58.90	54.00	61.75	58.90	58.90	58.90	58.90	58.90	58.90	58.90	58.90	58.90	58.90
Entry pool (% of current mission)	8.46	8.46	20.00	8.46	8.46	8.46	8.46	8.46	8.46	8.46	8.46	8.46	8.46	8.46	8.46
Fix recruiters										X	X	X			
Fix ad spending												X		X	X
Fix bonus spending											X		X		X
Results table	D.3	D.4	D.5	D.6	D.7	D.8	D.9	D.10	D.11	D.12	D.13	D.14	D.15	D.16	D.17

NOTE: Measures in bold type indicate the condition that is being varied for a given excursion. An "X" indicates that the indicated spending condition is implemented.

TABLE D.3
Baseline Conditions (Scenario 1)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	950.6	-55.0
TV prospect ad costs (\$ millions)	33.2	55.4	22.2
Digital prospect ad costs (\$ millions)	22.1	8.5	-13.6
Bonus costs (\$ millions)	233.0	134.0	-99.0
Total costs (\$ millions)	1,293.9	1,148.5	-145.4
Accessions achieved (% achieved)	43,566 (67)	66,752 (103)	23,185
Exit DEP achieved (% achieved)	17,258 (133)	13,968 (107)	-3,290

TABLE D.4
Lower Accession Mission to 60,000 (Scenario 2)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,020.0	14.3
TV prospect ad costs (\$ millions)	33.2	53.2	20.0
Digital prospect ad costs (\$ millions)	22.1	3.0	-19.1
Bonus costs (\$ millions)	230.7	73.1	-157.6
Total costs (\$ millions)	1,291.6	1,149.3	-142.4
Accessions achieved (% achieved)	42,847 (71)	51,014 (85)	8,168
Exit DEP achieved (% achieved)	17,086 (131)	12,587 (97)	-4,499

TABLE D.5
Prior-Year Entry Pool of 20 Percent (Scenario 3)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	942.2	-63.5
TV prospect ad costs (\$ millions)	33.2	68.6	35.4
Digital prospect ad costs (\$ millions)	22.1	22.1	0.0
Bonus costs (\$ millions)	232.9	110.7	-122.2
Total costs (\$ millions)	1,293.8	1,143.6	-150.2
Accessions achieved (% achieved)	50,256 (77)	63,077 (97)	12,821
Exit DEP achieved (% achieved)	17,291 (133)	15,203 (117)	-2,088

TABLE D.6
Decrease High-Quality Share to 54 Percent (Scenario 4)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	943.2	-62.4
TV prospect ad costs (\$ millions)	33.2	67.7	34.5
Digital prospect ad costs (\$ millions)	22.1	9.8	-12.3
Bonus costs (\$ millions)	233.0	116.0	-117.1
Total costs (\$ millions)	1,294.0	1,136.7	-157.3
Accessions achieved (% achieved)	45,085 (69)	58,890 (91)	13,805
Exit DEP achieved (% achieved)	17,976 (138)	13,198 (102)	-4,778

TABLE D.7
Increase High-Quality Share to 61.75 Percent (Scenario 5)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,074.0	68.3
TV prospect ad costs (\$ millions)	33.2	59.6	26.5
Digital prospect ad costs (\$ millions)	22.1	8.9	-13.2
Bonus costs (\$ millions)	232.8	217.1	-15.8
Total costs (\$ millions)	1,293.8	1,359.6	65.8
Accessions achieved (% achieved)	41,901 (64)	57,795 (89)	15,895
Exit DEP achieved (% achieved)	16,479 (127)	24,696 (190)	8,218

TABLE D.8
Increase Waivers to 15 Percent (Scenario 6)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,043.9	38.3
TV prospect ad costs (\$ millions)	33.2	48.0	14.8
Digital prospect ad costs (\$ millions)	22.1	10.3	-11.8
Bonus costs (\$ millions)	240.9	113.1	-127.9
Total costs (\$ millions)	1,301.9	1,215.3	-86.6
Accessions achieved (% achieved)	44,804 (69)	65,185 (100)	20,381
Exit DEP achieved (% achieved)	17,814 (137)	15,974 (123)	-1,840

TABLE D.9
Federal Minimum Wage Increased to \$8.50 (Scenario 7)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	944.5	-61.2
TV prospect ad costs (\$ millions)	33.2	64.4	31.3
Digital prospect ad costs (\$ millions)	22.1	16.1	-6.0
Bonus costs (\$ millions)	228.0	141.2	-86.8
Total costs (\$ millions)	1,288.9	1,166.3	-122.6
Accessions achieved (% achieved)	42,791 (66)	58,906 (91)	16,115
Exit DEP achieved (% achieved)	16,908 (130)	18,081 (139)	1,172

TABLE D.10
Unemployment Rate Declines by 25 Percent (Scenario 8)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,055.7	50.0
TV prospect ad costs (\$ millions)	33.2	60.8	27.6
Digital prospect ad costs (\$ millions)	22.1	8.6	-13.5
Bonus costs (\$ millions)	226.3	157.1	-69.2
Total costs (\$ millions)	1,287.2	1,282.2	-5.0
Accessions achieved (% achieved)	42,528 (65)	62,950 (97)	20,422
Exit DEP achieved (% achieved)	16,792 (129)	18,706 (144)	1,914

TABLE D.11
Unemployment Rate Increases by 25 Percent (Scenario 9)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	943.4	-62.2
TV prospect ad costs (\$ millions)	33.2	59.4	26.3
Digital prospect ad costs (\$ millions)	22.1	9.8	-12.3
Bonus costs (\$ millions)	238.3	199.0	-39.3
Total costs (\$ millions)	1,299.2	1,211.7	-87.6
Accessions achieved (% achieved)	44,393 (68)	64,521 (99)	20,128
Exit DEP achieved (% achieved)	17,629 (136)	15,795 (122)	-1,834

TABLE D.12
Fix Recruiters at Baseline Levels (Scenario 10)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,005.7	0.1
TV prospect ad costs (\$ millions)	33.2	81.2	48.0
Digital prospect ad costs (\$ millions)	22.1	12.0	-10.2
Bonus costs (\$ millions)	233.0	91.1	-141.9
Total costs (\$ millions)	1,293.9	1,190.0	-104.0
Accessions achieved (% achieved)	43,566 (67)	56,757 (87)	13,190
Exit DEP achieved (% achieved)	17,258 (133)	13,207 (102)	-4,051

TABLE D.13
Fix Recruiters and Bonus Spending at Baseline Levels (Scenario 11)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,005.7	0.0
TV prospect ad costs (\$ millions)	33.2	78.6	45.4
Digital prospect ad costs (\$ millions)	22.1	10.6	-11.5
Bonus costs (\$ millions)	233.0	354.3	121.3
Total costs (\$ millions)	1,293.9	1,449.2	155.2
Accessions achieved (% achieved)	43,566 (67)	64,237 (99)	20,670
Exit DEP achieved (% achieved)	17,258 (133)	21,708 (167)	4,450

NOTE: Bonus spending is fixed by not allowing eligibility and bonus amounts to change. However, overall bonus spending fluctuates proportionally with contract production at fixed levels of eligibility and bonus amounts.

TABLE D.14**Fix Recruiter and Ad Spending at Baseline Levels (Scenario 12)**

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,005.6	0.0
TV prospect ad costs (\$ millions)	33.2	33.2	0.0
Digital prospect ad costs (\$ millions)	22.1	22.1	0.0
Bonus costs (\$ millions)	233.0	62.4	-170.6
Total costs (\$ millions)	1,293.9	1,123.3	-170.6
Accessions achieved (% achieved)	43,566 (67)	48,848 (75)	5,281
Exit DEP achieved (% achieved)	17,258 (133)	11,915 (92)	-5,344

TABLE D.15**Fix Bonus Spending at Baseline Levels (Scenario 13)**

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,013.7	8.1
TV prospect ad costs (\$ millions)	33.2	54.9	21.7
Digital prospect ad costs (\$ millions)	22.1	5.4	-16.7
Bonus costs (\$ millions)	233.0	397.6	164.6
Total costs (\$ millions)	1,293.9	1,471.6	177.7
Accessions achieved (% achieved)	43,566 (67)	55,407 (85)	11,840
Exit DEP achieved (% achieved)	17,258 (133)	42,982 (331)	25,723

NOTE: Bonus spending is "fixed" by not allowing eligibility and bonus amounts to change. However, overall bonus spending fluctuates proportionally with contract production at fixed levels of eligibility and bonus amounts.

TABLE D.16
Fix Ad Spending at Baseline Levels (Scenario 14)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,103.4	97.8
TV prospect ad costs (\$ millions)	33.2	33.2	0.0
Digital prospect ad costs (\$ millions)	22.1	22.1	0.0
Bonus costs (\$ millions)	233.0	61.9	-171.1
Total costs (\$ millions)	1,293.9	1,220.6	-73.3
Accessions achieved (% achieved)	43,566 (67)	50,040 (77)	6,473
Exit DEP achieved (% achieved)	17,258 (133)	12,153 (93)	-5,105

TABLE D.17
Fix Ad and Bonus Spending at Baseline Levels (Scenario 15)

Output	Baseline Scenario	Optimized Scenario	Difference
Recruiter costs (\$ millions)	1,005.6	1,024.7	19.1
TV prospect ad costs (\$ millions)	33.2	33.2	0.0
Digital prospect ad costs (\$ millions)	22.1	22.1	0.0
Bonus costs (\$ millions)	233.0	235.4	2.4
Total costs (\$ millions)	1,293.9	1,315.4	21.5
Accessions achieved (% achieved)	43,566 (67)	43,872 (68)	306
Exit DEP achieved (% achieved)	17,258 (133)	17,453 (134)	195

NOTE: Bonus spending is fixed by not allowing eligibility and bonus amounts to change. However, overall bonus spending fluctuates proportionally with contract production at fixed levels of eligibility and bonus amounts.

Documenting an Alternate Approach to Estimating Contract Production: Spatial First Differences

In this appendix, we present results from an alternative estimation strategy we explored using a recently developed modeling approach called *spatial first differences* (SFD) (Druckemiller and Hsiang, 2018). SFD, as its name suggests, is an identification strategy that exploits spatial—rather than temporal—variation and requires a different set of identifying assumptions that, if satisfied, can produce estimated relationships that might have a more credible claim to be causal in nature.

Because SFD does not require variation in inputs over time, we can estimate the effects of the inputs using only data from a single point in time, greatly reducing the model’s data needs. SFD also uses a different counterfactual to estimate effects: Rather than comparing a company’s performance to itself under other conditions at different points in time, SFD compares a company’s performance at a point in time to the performance of that company’s neighbors. These neighbors might use a different mix of recruiting resources but—because they are presumably subject to many otherwise unobservable factors related to their spatial proximity—might be considered a good counterfactual for the company of interest. In this appendix, we explain the SFD method and its identifying assumptions, describe changes made to the data here that are different from the data used in the main report, and summarize our findings.

Spatial First Differences: Intuition and Assumptions

The intuition underlying SFD is straightforward: Neighboring units of observation (whether they be U.S. counties, individual residences, or Army companies) can make for good counterfactuals. We borrow the language of the “potential outcomes framework” (Rubin, 2005) from randomized drug trials in which there are “treated” and “untreated” individuals or units. In other words, if neighbor A is subject to some treatment and neighbor B is not, comparing the differences in their outcomes is likely a better way to estimate the effect of the treatment than comparing neighbor A with some faraway, untreated unit. The identifying assumptions in

SFD are comparable to those employed in the *regression discontinuity research design* (Thistlethwaite and Campbell, 1960). The SFD approach is mathematically identical to the better-known first-differences estimator “where the key alteration is to exchange the time index of observations to an index describing the position of observations in space” (Druckenmiller and Hsiang, 2018, p. 1).

Formally, the identifying assumption is that units are conditionally independent with respect to their local neighbors, which Druckenmiller and Hsiang call the “local conditional independence assumption” (2018). The equation describing this assumption is

$$E[y_i|x_{i-1}] = E[y_{i-1}|x_{i-1}] \forall \{i, i - 1\}.$$

In laymen’s terms, the equation means that we assume that two neighbors, i and $i - 1$, will have the same outcome if their treatment, x_{i-1} , is also the same. This differs from the assumption needed for causal identification in a standard cross-section regression, which is the conditional independence assumption:

$$E[y_i|x_j] = E[y_j|x_j] \forall i \neq j.$$

This requires that outcomes must be the same for any two observations, given the same x ’s. But the existence of unobserved heterogeneity or omitted variable bias violates this assumption and makes identification of causal effects unlikely. The use of spatial neighbors, which are subject to most or all of the same types of unobservable factors as the focal unit, is a potentially effective approach to addressing omitted variable bias. The SFD design is like the better-known geographic regression discontinuity, an approach where observations on either side of a geographic treatment cutoff are compared with each another. SFD extends this intuition, considering every two neighbors as observations on either side of a cutoff.

Despite the promising approach offered by SFD, in our exploration, we found that estimates of the effects of the Army recruiting inputs were, in many cases, implausible. We suspect this issue might be related to the size of the recruiting companies’ geographies, which are relatively large. Larger geographies weaken the feasibility of the Local Conditional Independence Assumption, because, across larger geographies, unobservable factors might be more likely to vary across units than would be the case for very small geographies. Druckenmiller and Hsiang (2018) illustrate SFD using census tracts and counties as the level of observation and geography in their two examples. These areas are much smaller than the typical areas that Army recruiting companies serve.

For completeness and as a potential aid to future researchers, the remainder of this appendix documents the process we used to generate CPM estimates using SFD.

Data

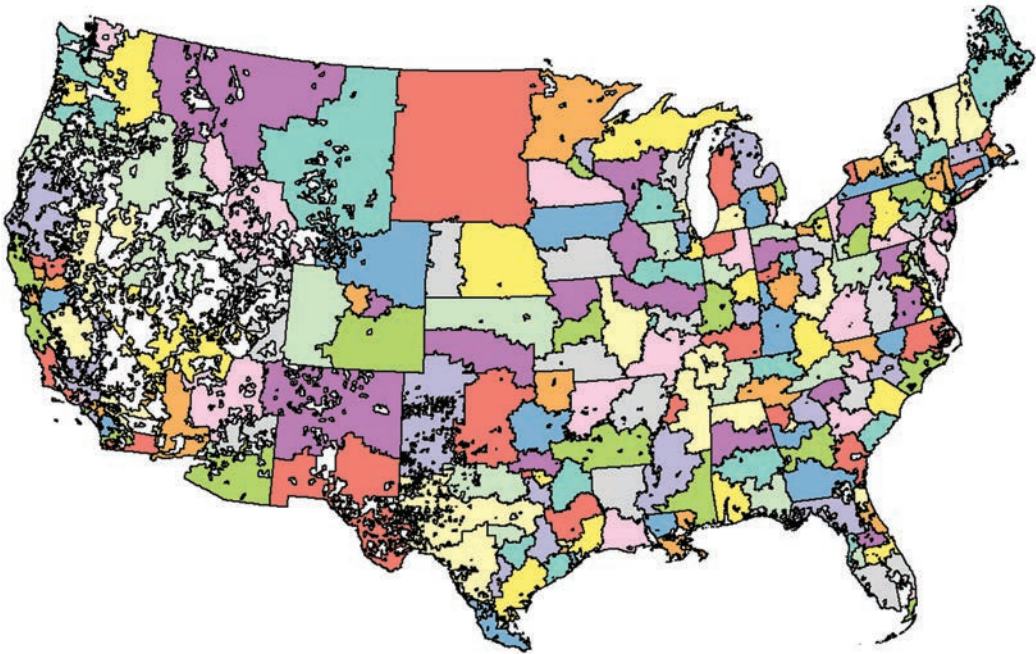
The data on the model's inputs and outputs used in this analysis are described in the main body of this report. We use those data again in this analysis, with one main alteration. Because SFD compares the performance of neighbors, a spatial feature, we must add spatial information into the data. Incorporating this information is a surprisingly complex process, which we explain below. We tested the SFD approach using the averaged data for the third and fourth quarters of FY 2017.

Unfortunately, there is no map of Army recruiting companies, so we constructed our own. While companies do not directly have geographies, they are composed of smaller units, *stations*, which link to zip codes. To make matters more complex, zip codes are also not geographic areas per se. They are a collection of addresses and mail delivery routes. The U.S. Census Bureau created ZCTAs as a means of explicitly defining their geography in the 2000 census and have done so for the 2010 and 2020 censuses. The process involves looking at each census block and calculating the most frequent zip code therein. The blocks are then aggregated up to the ZCTA level. Not all zip codes are represented as a ZCTA. In some cases, the zip codes define only a single home or residence and thus cover an insufficient area to make their way into the ZCTA map. The gaps in the map represent uninhabited regions, which the postal office does not serve. Additional information on zip codes, ZCTAs, and the ZCTA shapefile can be found on the Census Bureau's website (U.S. Census Bureau, 2021).

We merge our station-level data with the ZCTA shapefile using company zip codes, but not all stations are successfully matched to ZCTA geographies. We begin with 1,382 unique stations and successfully merge 1,374 (99.4 percent) to ZCTA polygons. The eight unmatched stations belong to just two companies, 1A8 and 6K3, of the 242 total (0.8 percent). We are forced to omit these from the SFD analysis, but they are included in the data sample for the CPM used in the main report. After the matching, we aggregate the station geographies to the company level, where each company is represented by the ZCTAs of its station subunits. A map describing the data is plotted in Figure E.1, where a total of 240 Army companies span the United States.

The SFD method compares Army companies that have one resource mix and set of contract production outcomes with immediate neighbors that have a different resource mix and set of contract production outcomes. The difference in their outcomes is assumed to be a result of their different inputs or, using the terminology from our brief theory section, the x 's. But systematically identifying neighbors is difficult. We use an algorithm designed by Druckmiller and Hsiang (2018) and Tanutama (undated) and available at GitHub. To understand how the algorithm functions, imagine creating an unbroken string of neighbors in any set of polygons moving left to right in the top "row" of polygons. The algorithm then moves to the second row and repeats the exercise, attempting to create another string of unbroken neighbors. Sometimes the idiosyncrasies of the polygon shapes leave a region (i.e., Army company) unmatched, while all its neighbors are occupied with another pairing. This is a failure of the algorithm that weakens the estimation process by effectively removing an observation when

FIGURE E.1

Map of Army Recruiting-Company Geography in the Continental United States

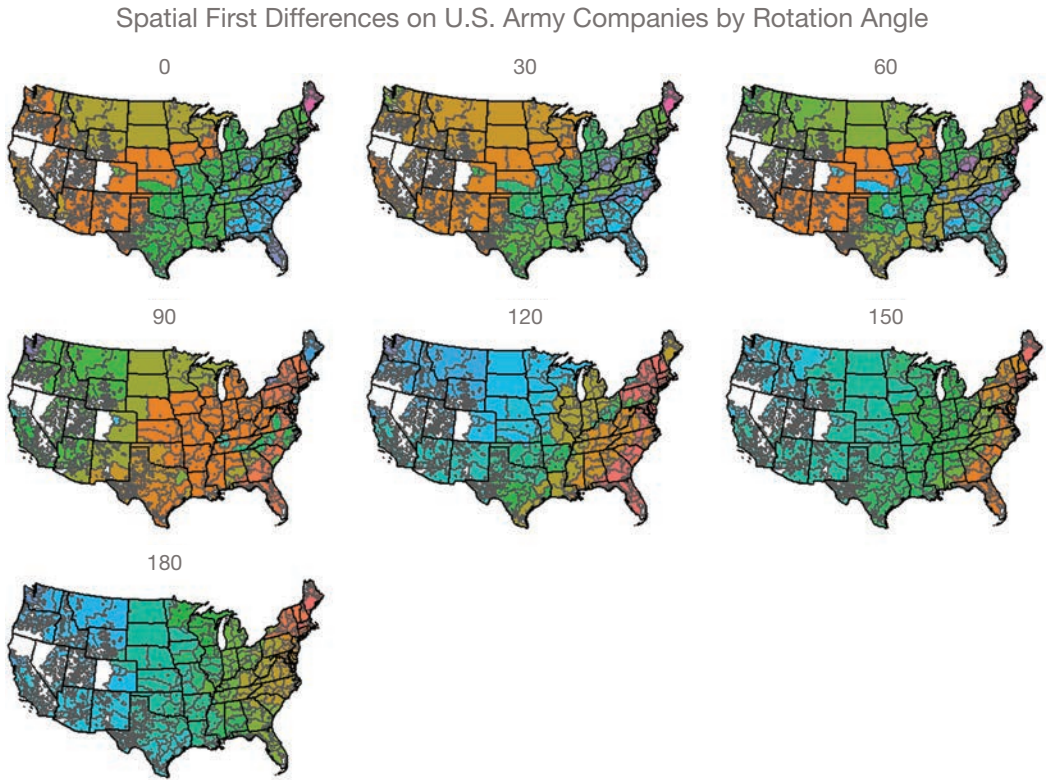
SOURCE: RAND analysis.

no neighbors can be generated for it. The algorithm attempts to minimize this occurrence. In an ideal setting, the algorithm would match all the polygons as neighbors in a single, unbroken string. Each string of unbroken neighbors corresponds to the observations from a single unit in panel data. In first differences, neighboring times are differenced. In SFD, neighboring polygons are differenced.

For robustness, Druckenmiller and Hsiang (2018) suggest attempting the process multiple times by “rotating” the polygons and finding neighbors again. Unique estimates will be produced for each “rotation angle” and the estimates combined in a process that we explain below. In our analysis, we rotate the map of Army companies and employ the neighbor-matching algorithm seven times (0, 30, 60, 90, 120, 150, and 180 degrees). Figure E.2 plots each of those rotations and their corresponding neighbors in seven different panels. Each group or string of neighbors is highlighted in a different color.

A final difference between these data and the data used in the main body of the report is that we use a panel at the company-quarter level rather than the company-month level. We chose this approach to address any potential month-to-month measurement error in our variables that might relate to, for example, differences in the timing of recruiting months and calendar months, which we have mentioned elsewhere in this report. The influence of this issue is likely to be attenuated when time periods under consideration are longer (i.e., fiscal quarters). We use two time periods in our analysis: FY 2017 Quarter 3 and FY 2017 Quarter 4.

FIGURE E.2
Maps of Estimation Groups of Recruiting Companies by Rotation Angle



SOURCE: RAND analysis.

Empirical Strategy and Estimation

Once the data are created, we estimate the effects of the various portfolio inputs. Here, we again diverge from the analytic approach used in the main body of the report because of the idiosyncrasies of the SFD model. Because SFD uses spatial rather than temporal variation, it cannot estimate the effects of parameters that do not vary spatially. For example, “days in RCM,” a variable used in the original specification, applies to all Army companies equally in the same period. Because it varies across time, the main model using time-based variation within companies can estimate its effect on the dependent variable (i.e., contracts), but SFD does not share this feature. The model employed is

$$\Delta \log(C_s) = \alpha_1 + \beta_1 \Delta \log(M RA HQ_s) + \beta_2 \Delta \log(M RA other_s) + \beta_3 \Delta \log(M USA R_s) + \beta_4 \Delta \log(R_s) + \beta_5 \Delta f_1(A_s) + \beta_6 \Delta f_2(B_s) + \beta_7 \Delta f_3(X_s) + \epsilon_s.$$

We estimate the coefficients using ordinary least squares and the spatially first-differenced data. To estimate the standard errors, we follow Druckenmiller and Hsiang (2018) and use Conley standard errors that account for spatial correlation (Düben et al., 2022). Recall that, for robustness, we run the neighbor-matching algorithm seven different times. Each piece of data requires estimation, resulting in seven unique parameter estimates—one for each angle.

We face the problem of combining these seven estimates into a single effect estimate for the portfolio optimization process—a process which Druckenmiller and Hsiang do not attempt in their work (2018). We use Rubin’s rules, a method of pooling estimates and standard errors with multiple imputed data, as a blueprint for the parameters estimates. While we are not dealing with missing data and imputation, we are pooling estimates from multiple datasets (i.e., different angles used in the neighbor-matching algorithm). Calculating the pooled coefficients is simple: The individual coefficients, denoted by $\bar{\theta}$, are simply averaged. However, the processes behind calculating the pooled standard errors, p -values, and significance testing are more complex. To calculate pooled standard errors, two intermediary variances must be calculated: the within variance, V_W , and the between variance, V_B . Their equations are

$$V_W = \frac{1}{m} \sum_{i=1}^m SE_i^2$$

$$V_B = \frac{\sum_{i=1}^m (\theta_i - \bar{\theta})^2}{m - 1}.$$

Here, m is the number of imputed datasets, which in our case is seven, and SE_i is the standard error for the coefficient estimate. θ_i is the coefficient estimate, and $\bar{\theta}$ is the average coefficient estimate. Once these two variances are calculated, the total variance, V_T , is calculated using the following formula:

$$V_T = V_W + V_B + \frac{V_B}{m}.$$

The pooled standard error is simply its square root. We depart from Rubin’s rules here and assume a normal distribution of the pooled estimates rather than a t -distribution for computational simplicity. The consequence is that our estimates are insufficiently conservative (the t -distribution has fatter tails than its normal counterpart), but the differences in the distributions are relatively small and, because the objective of this process is to estimate the inputs for the RRM, it is the parameters estimates, not statistical inference, that are the primary concern.

Results

The estimates here differ substantially from those in the main CPM, and their implausibility in some areas prohibits their use in balancing the Army’s recruitment portfolio. Table E.1

TABLE E.1

Comparing Spatial First Difference Point Estimates with Recruiting Resource Model Contract Production Model Estimates

Recruiting Input	SFD Estimate (FY 2017 Q3)	SFD Estimate (FY 2017 Q4)	Main Contract Production Model Estimate
Log(HQ mission + 1/QMA pop)	0.584 (0.0934)	0.340 (0.115)	0.022 (0.013)
Log(NHQ mission + 1/QMA pop)	0.204 (0.090)	0.343 (0.136)	0.086 (0.009)
Log(USAR mission + 1/QMA pop)	0.046 (0.056)	0.079 (0.084)	-0.072 (0.009)
Log (recruiters/QMA pop)	0.293 (0.108)	0.342 (0.178)	0.325 (0.027)
Log unemployment rate	0.071 (0.103)	-0.039 (0.145)	0.138 (0.027)
Log minimum wage	-0.467 (0.162)	-0.169 (0.248)	-0.148 (0.044)
Log MOS-specific bonus	-0.040 (0.043)	0.070 (0.059)	0.011 (0.001)
Log QS bonus	0.045 (0.063)	-0.033 (0.101)	0.013 (0.001)
Log TV advertising	0.020 (0.099)	-0.050 (0.075)	0.119 (0.038)
Log digital advertising	-0.066 (0.112)	-0.112 (0.065)	0.067 (0.042)
Interaction of log TV/digital advertising	-0.004 (0.010)	-0.008 (0.007)	0.008 (0.005)

NOTE: pop = population. This table compares the estimates from the SFD model and the main CPM. The dependent variable is *Log NPS contracts*.

plots coefficients from both the main CPM and SFD models and shows that, in many cases, there are large differences between the two estimation strategies. Because we estimate the parameters at two different cross sections (i.e., FY 2017 Quarters 3 and 4), we post their results separately.

As can be seen, most of these estimates differ significantly from both the main CPM estimates and the collection of estimates from past research sampled in Table B.3. Multiple estimates, including USAR mission and all advertising measures, have the opposite sign from what theory suggests should hold. Unemployment has a near-zero association with contract production, despite significant variation across geography in the data.

Ultimately, we were unable to address whether the departure of these estimates from both historical estimates in other studies and the estimates in the main version of the CPM was due primarily to the overly large geography or to data issues or other factors. We believe that

the SFD approach might still warrant further investigation in the future, but we decided to use a more time-tested approach based on our exploratory work with it for this iteration of the RRM.

Abbreviations

AEMO	Army Enterprise Marketing Office
AFQT	Armed Forces Qualification Test
AMRG	Army Marketing and Research Group
COBYLA	constrained optimization by linear approximation
COVID-19	coronavirus disease 2019
CPM	contract production model
DEP	Delayed Entry Program
DoD	U.S. Department of Defense
DoDI	Department of Defense Instruction
FY	fiscal year
GA	graduate alpha
GIS	geographic information system
HQ	high quality
HRC	Human Resources Command
MEPS	Military Entrance Processing Station
MOS	military occupational specialty
NHQ	non-high quality
NLS	nonlinear least squares
NPS	non-prior service
QMA	qualified military available
QS	quick-ship
RA	Regular Army
RCM	recruiting contract month
RRM	Recruiting Resource Model
RSID	recruiting station ID
SA	senior alpha
SFD	spatial first differences
UMCSI	University of Michigan Consumer Sentiment Index
USAR	U.S. Army Reserve
USAREC	U.S. Army Recruiting Command
ZCTA	zip code tabulation areas

References

Aguiar, Mark, Mark Bills, Kerwin Kofi Charles, and Erik Hurst, “Leisure Luxuries and the Labor Supply of Young Men,” *Journal of Political Economy*, Vol. 129, No. 2, 2021.

Allegretto, Sylvia, Arindrajit Dube, Michael Reich, and Ben Zipperer, “Credible Research Designs for Minimum Wage Studies: A Response to Neumark, Salas, and Wascher,” *ILR Review*, Vol. 70, No. 3, 2017.

Asch, Beth J., Michael L. Hansen, Rosanna Smart, David Knapp, and Daniel Schwam, *An Empirical Assessment of the U.S. Army’s Enlistment Waiver Policies: An Examination in Light of Emerging Societal Trends in Behavioral Health and the Legalization of Marijuana*, RAND Corporation, RR-4431-A, 2021. As of September 1, 2022:
https://www.rand.org/pubs/research_reports/RR4431.html

Asch, Beth J., Paul Heaton, James Hosek, Francisco Martorell, Curtis Simon, and John T. Warner, *Cash Incentives and Military Enlistment, Attrition, and Reenlistment*, RAND Corporation, MG-950-OSD, 2010. As of March 25, 2022:
<https://www.rand.org/pubs/monographs/MG950.html>

Asch, Beth J., James R. Hosek, and John T. Warner, “New Economics of Manpower in the Post-Cold War Era,” in Todd Sandler and Keith Hartley, eds., *Handbook of Defense Economics: Defense in a Globalized World*, Elsevier, 2007.

Asch, Beth J., Michael G. Mattock, Troy D. Smith, and Jason M. Ward, *Setting the Level and Annual Adjustment of Military Pay*, RAND Corporation, RR-A368-1, 2020. As of March 25, 2022:
https://www.rand.org/pubs/research_reports/RRA368-1.html

Asch, Beth J., and John T. Warner, “Recruiting and Retention to Sustain a Volunteer Military Force,” in David J. Galbreath and John R. Deni, eds., *Routledge Handbook of Defence Studies*, Routledge, 2018.

Ashenfelter, Orley C., and Štěpán Jurajda, *Wages, Minimum Wages, and Price Pass-Through: The Case of McDonald’s Restaurants*, National Bureau of Economic Research, working paper 28506, February 2021.

Baldor, Lolita C., “Army Offers Recruits Up to \$50K Bonus as Pandemic Takes Toll,” *Army Times*, January 12, 2022.

Blake, Thomas, Chris Nosko, and Steven Tadelis, “Consumer Heterogeneity and Paid Search Effectiveness: A Large-Scale Field Experiment,” *Econometrica*, Vol. 83, No. 1, 2015.

Bohn, Donald, and Edward Schmitz, *The Expansion of the Navy College Fund: An Evaluation of the FY 1995 Program Impacts*, Navy Recruiting Command, 1996.

Cave, Damien, “Growing Problem for Military Recruiters: Parents,” *New York Times*, June 3, 2005.

Clemens, Jeffrey, Lisa B. Kahn, and Jonathan Meer, “Dropouts Need Not Apply? The Minimum Wage and Skill Upgrading,” *Journal of Labor Economics*, Vol. 39, No. S1, January 2021.

Cox, Matthew, “In a Shake-Up, Army Relocates Marketing Operation to Chicago,” *Military.com*, June 6, 2019.

Defense Casualty Analysis System, “Active Duty Military Deaths by Year and Manner, 1980–2021,” webpage, Defense Manpower Data Center, 2011. As of September 1, 2022: <https://dcas.dmdc.osd.mil/dcas/app/summaryData/deaths/byYearManner>

Department of Defense Instruction 1145.01, *Qualitative Distribution of Military Manpower*, U.S. Department of Defense, updated October 26, 2018.

Department of Defense Instruction 1304.26, *Qualification Standards for Enlistment, Appointment, and Induction*, U.S. Department of Defense, September 20, 2005.

Dertouzos, James N., *The Effects of Military Advertising: Evidence from the Advertising Mix Test*, RAND Corporation, N-2907-FMP, 1989. As of May 11, 2022: <https://www.rand.org/pubs/notes/N2907.html>

Dertouzos, James N., and Steven Garber, *Is Military Advertising Effective? An Estimation Methodology and Applications to Recruiting in the 1980s and 90s*, RAND Corporation, MR-1591-OSD, 2003. As of March 24, 2022: https://www.rand.org/pubs/monograph_reports/MR1591.html

Dertouzos, James N., and Steven Garber, “Effectiveness of Advertising in Different Media: The Case of U.S. Army Recruiting,” *Journal of Advertising*, Vol. 35, No. 2, 2006.

DoDI—See Department of Defense Instruction.

Druckenmiller, Hannah, and Solomon Hsiang, *Accounting for Unobservable Heterogeneity in Cross Section Using Spatial First Differences*, working paper 25177, National Bureau of Economic Research, October 2018.

Düben, Christian, Richard Bluhm, Luis Calderon, Darin Christensen, Timothy Conley, Thiemo Fetzer, and Leander Heldring, “Estimations Using Conley Standard Errors,” version 0.1.7, March 4, 2022.

Field, Elizabeth, *Army Marketing: The Army Has Taken Recent Actions That Could Improve Program Oversight, Effectiveness, and Workforce Practices*, United States Government Accountability Office, GAO-20-93, 2019.

FRED Economic Data, “University of Michigan: Consumer Sentiment,” webpage, Federal Reserve Bank of St. Louis, 2022. As of March 25, 2022: <https://fred.stlouisfed.org/series/UMCSENT/>

Gerber, Alan S., James G. Gimpel, Donald P. Green, and Daron R. Shaw, “How Large and Long-Lasting Are the Persuasive Effects of Televised Campaign Ads? Results from a Randomized Field Experiment,” *American Political Science Review*, Vol. 105, No. 1, February 2011.

Golfin, Peggy A., Diana S. Lien, and David Gregory, “Evaluation of the Assignment Incentive Pay (AIP) System,” *Center for Naval Analyses*, CAB D0010240.A2/Final, June 2004.

Gordon, Brett R., Florian Zettelmeyer, Neva Bhargava, and Dan Chapsky, “A Comparison of Approaches to Advertising Measurement: Evidence from Big Field Experiments at Facebook,” *Marketing Science*, Vol. 38, No. 2, 2019.

Hill, Seth J., James Lo, Lynn Vavreck, and John Zaller, “How Quickly We Forget: The Duration of Persuasion Effects from Mass Communication,” *Political Communication*, Vol. 30, No. 4, 2013.

Hogan, Paul, Timothy Dali, Pat Mackin, and Chris Mackie, *An Econometric Analysis of Navy Television Advertising Effectiveness*, Systems Analytic Group, 1996.

- Johnson, Tim, Christopher T. Dawes, and William G. Iacono, “Numbers Assigned in the Vietnam-Era Selective Service Lotteries Influence the Military Service Decisions of Children Born to Draft-Eligible Men: A Research Note,” *Armed Forces & Society*, Vol. 44, No. 2, June 2017.
- Knapp, David, Bruce R. Orvis, Christopher E. Maerzluft, and Tiffany Tsai, *Resources Required to Meet the U.S. Army’s Enlisted Recruiting Requirements Under Alternative Recruiting Goals, Conditions, and Eligibility Policies*, RAND Corporation, RR-2364-A, 2018. As of March 24, 2022: https://www.rand.org/pubs/research_reports/RR2364.html
- Leone, Robert P., “Generalizing What Is Known About Temporal Aggregation and Advertising Carryover,” *Marketing Science*, Vol. 14, No. 3, supplement, August 1995.
- Marrone, James V., *Predicting 36-Month Attrition in the U.S. Military: A Comparison Across Service Branches*, RAND Corporation, RR-4258-OSD, 2020. As of September 1, 2022: https://www.rand.org/pubs/research_reports/RR4258.html
- Modestino, Alicia Sasser, Daniel Shoag, and Joshua Ballance, “Upskilling: Do Employers Demand Greater Skill When Workers Are Plentiful?” *Review of Economics and Statistics*, Vol. 102, No. 4, 2020.
- Morton, Fiona M. Scott, and David C. Dinielli, *Roadmap for a Digital Advertising Monopolization Case Against Google*, Omidyar Network, May 2020.
- Murray, Michael, and Laurie L. McDonald, *Recent Recruiting Trends and Their Implications for Models of Enlistment Supply*, RAND Corporation, MR-847-OSD/A, 1999. As of March 25, 2022: https://www.rand.org/pubs/monograph_reports/MR847.html
- Neumark, David, “State Minimum Wage Data Set Through Sept. 2019,” undated. As of March 29, 2020: <http://www.economics.uci.edu/~dneumark/datasets.html>
- Nielsen, “Television Is Still Top Brass, but Viewing Differences Vary with Age,” July 2016.
- Orvis, Bruce R., Craig A. Bond, Daniel Schwam, and Irineo Cabrerros, *Resources Required to Meet the U.S. Army Reserve’s Enlisted Recruiting Requirements Under Alternative Recruiting Goals, Conditions, and Eligibility Policies*, RAND Corporation, RR-A1304-1, 2022. As of September 1, 2022: https://www.rand.org/pubs/research_reports/RRA1304-1.html
- Orvis, Bruce R., Christopher E. Maerzluft, Sung-Bou Kim, Michael G. Shanley, and Heather Krull, *Prospective Outcome Assessment for Alternative Recruit Selection Policies*, RAND Corporation, RR-2267-A, 2018. As of May 31, 2022: https://www.rand.org/pubs/research_reports/RR2267.html
- Pérez-Arce, Francisco, and María J. Prados, “The Decline in the U.S. Labor Force Participation Rate: A Literature Review,” *Journal of Economic Surveys*, Vol. 35, No. 2, 2021.
- Polich, J. Michael, James N. Dertouzos, and S. James Press, *The Enlistment Bonus Experiment*, RAND Corporation, R-3353-FMP, 1986. As of May 31, 2022: <https://www.rand.org/pubs/reports/R3353.html>
- Powell, M. J. D., “A Direct Search Optimization Method That Models the Objective and Constraint Functions by Linear Interpolation,” in S. Gomez and J. P. Hennart, eds., *Advances in Optimization and Numerical Analysis: Mathematics and Its Applications*, Springer, 1994.
- Putka, D. J., C. L. Noble, D. E. Becker, and P. F. Ramsberger, *Evaluating Moral Character Waiver Policy Against Servicemember Attrition and In-Service Deviance Through the First 18 Months of Service*, FR-03-96, Human Resources Research Organization, 2003.

- Rainie, Lee, “About 6 in 10 Young Adults in the U.S. Primarily Use Online Streaming to Watch TV,” Pew Research Center, September 13, 2017.
- Rideout, Victoria, and Michael Robb, *The Common Sense Census: Media Use by Tweens and Teens, 2019*, Common Sense Media, October 28, 2019.
- Rubin, Donald B., “Causal Inference Using Potential Outcomes: Design, Modeling, Decisions,” *Journal of the American Statistical Association*, Vol. 100, No. 469, 2005.
- Shapiro, Bradley, Günter J. Hitsch, and Anna Tuchman, “Generalizable and Robust TV Advertising Effects,” working paper 27684, National Bureau of Economic Research, 2020.
- Tanutama, Vincent, “sfd-algo Codes,” website, undated. As of May 31, 2022:
<https://github.com/vincentanutama/sfd-algo>
- Thistlethwaite, Donald L., and Donald T. Campbell, “Regression-Discontinuity Analysis: An Alternative to the Ex Post Facto Experiment,” *Journal of Educational Psychology*, Vol. 51, No. 6, 1960.
- U.S. Army, “Bonuses—Regular Army: Active Duty Benefit Fact Sheet,” 2022.
- U.S. Bureau of Labor Statistics, “The Employment Situation—February 2022,” news release, USDL-22-0344, March 4, 2022.
- U.S. Bureau of Labor Statistics, *Characteristics of Minimum Wage Workers, 2018*, report 1078, March 2019.
- U.S. Census Bureau, “ZIP Code Tabulation Areas (ZCTAs),” webpage, 2021. As of March 30, 2022:
<https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html>
- U.S. Department of Veterans Affairs, “Post-9/11 GI Bill (Chapter 33),” February 11, 2022.
- Vaghul, Kavya, and Ben Zipperer, “Historical State and Sub-State Minimum Wages,” Version 1.3.0, 2021. As of March 25, 2022:
<https://github.com/benzipperer/historicalminwage/releases/tag/v1.3.0>
- Warner, John T., and Curtis J. Simon, “Estimates of Army Enlistment Supply 1988–2005,” briefing to the military recruiting summit, Clemson University, November 2, 2005.
- Warner, John T., Curtis J. Simon, and Deborah M. Payne, *Enlistment Supply in the 1990s: A Study of the Navy College Fund and Other Enlistment Incentive Programs*, DMDC Report No. 2000–015, Defense Manpower Data Center, 2001.
- Warner, John T., Curtis J. Simon, and Deborah M. Payne, “The Military Recruiting Productivity Slowdown: The Roles of Resources, Opportunity Cost and the Tastes of Youth,” *Defence and Peace Economics*, Vol. 14, No. 5, 2003.
- Wenger, Jeffrey B., David Knapp, Parag Mahajan, Bruce R. Orvis, and Tiffany Berglund, *Developing a National Recruiting Difficulty Index*, RAND Corporation, RR-2637-A, 2019. As of March 24, 2022:
https://www.rand.org/pubs/research_reports/RR2637.html
- Winkie, Davis, “Fewer Recruiters, Individual Quotas: How the Army Is ‘Modernizing’ Recruiting,” *Army Times*, November 7, 2021.
- Wooldridge, Jeffrey M., *Econometric Analysis of Cross Section and Panel Data*, 2nd ed., MIT Press, 2010.



The U.S. Army uses a variety of resources and tools to achieve its recruiting mission each year. In this report, the authors present results from an updated version of RAND Corporation’s Recruiting Resource Model (RRM), a multipart statistical model that explores how trade-offs between key recruiting resources (bonuses, advertising, and recruiters) affect the Army’s ability to achieve recruiting goals and the cost of doing so. They use the RRM to analyze the mix and level of resources required to meet the recruiting mission under alternative recruiting environments and recruit eligibility policies.

The RRM was updated to include more recent data to analyze the relationship between resource inputs and recruiting outcomes while incorporating the use of digital advertising, which has become an increasingly important recruiting resource in recent years. Consistent with previous iterations of the model, the results indicate that television advertising and, to a lesser extent, recruiters have positive associations with contract production and that these inputs are relatively more cost-effective than bonuses.

This research can help inform how the Army might move resources in a variety of recruiting environments. Making marginal changes along these lines in a purposeful manner over time—either broadly or at a more local level (as might be done in an experimental setting)—would be an appropriate first step in implementing the recommendations that arose from this research.

\$29.00

www.rand.org

ISBN-10 1-9774-1158-4
ISBN-13 978-1-9774-1158-7



9 781977 411587

52900