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The Aging German Navy: Sea–Staff–School Workforce, Dynamics and Markov Projections to 2040

March 2026

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Prepared for the Naval Postgraduate School, Monterey, CA 93943.

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ABSTRACT

This thesis analyzes demographic age structure and personnel composition in the German Navy from 2015 to 2025, with a focus on sea, staff, and school assignments and their implications for operational readiness. Using two anonymized annual personnel datasets, it measures headcount and mean age by assignment type and ship type and estimates year-end-to-year-end transitions for four career tracks. Discrete-time Markov chain manpower models are calibrated and validated with backtesting and Monte Carlo uncertainty analysis to project inventory and age through 2040 under baseline and recruiting scenarios. From 2015 to 2025, total Navy strength declines 3.7%, while enlisted and junior noncommissioned officer inventories fall 19.7% and 30.1%, and senior noncommissioned officer and officer inventories rise 12.3% and 12.7%, indicating a more top-heavy force. Across assignments, sea billets remain younger than staff billets but age steadily, and platform-level patterns show distinct crewing structures and aging rates by ship type. Baseline projections to 2040 extend the top-heaviness: officers grow 14.1% to 4,129, senior noncommissioned officers remain near equilibrium, and junior noncommissioned officers and enlisted decline 11.7% to 2,496 and 7.4% to 2,271. Forecast uncertainty widens with horizon and differs by career track, implying that sustained accession and retention measures and post-reform model recalibration are necessary to manage sea-going manpower risk.

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"Zwei Jahre Leben und Studieren in Monterey—Once in a Lifetime!"

This thesis marks for me the completion of an additional academic education, and it would not have been possible without the great support of so many people.

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LIST OF ACRONYMS AND ABBREVIATIONS

COVID	coronavirus disease 2019
CV	coefficient of variation
EUROMIL	European Organization of Military Associations and Trade Unions
MAPE	mean absolute percentage error
NATO	North Atlantic Treaty Organization
NCO	noncommissioned officer
OLS	ordinary least squares
PID	person identifier
Q	quarter

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DISCLOSURES

AI-based tools were used to support parts of the writing and workflow for this thesis. Claude was used for coding support, ChatGPT for brainstorming and developing ideas, and Grammarly and DeepL for improving language, grammar, and clarity.

The intellectual content of the thesis, including the analysis, interpretation, and conclusions, remains the author’s own responsibility.

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I. INTRODUCTION

A. MOTIVATION AND PROBLEM STATEMENT

„Wir erleben eine Zeitenwende. Das bedeutet: Die Welt danach ist nicht mehr dieselbe wie die Welt davor” (Deutscher Bundestag, 2022).

„Wir müssen bis 2029 kriegstüchtig sein,” so der Minister. „Wir müssen Abschreckung leisten, um zu verhindern, dass es zum Äußersten kommt” (Deutscher Bundestag, 2024).

„Zwei Drittel unserer Schiffe, Boote und Luftfahrzeuge müssen einsatzbereit sein. Ein Schiff in der Werft schreckt nicht ab. ” (Kaack, 2026)

Germany’s post-2022 security debate is often framed as a “turning point” (“Zeitenwende”): The former German Chancellor Olaf Scholz (2022) called Russia’s attack on Ukraine a watershed and stated, “We are experiencing a turning point… the world afterwards is no longer the same as the world before.” That strategic break is now translated into a concrete requirement by Defense Minister Boris Pistorius, who set a planning deadline—”we must be war-capable by 2029”—and explicitly ties this to deterrence (“we must provide deterrence to prevent the worst”), anchored in the core pillars of personnel, materiel, and finance, as well as the ability to endure and scale up in crisis (Deutscher Bundestag, 2024).

For the German Navy, this “ability to grow” becomes a workforce pipeline problem: the Inspector of the Navy, Jan Christian Kaack, argues that young people must be recruited, trained, and inspired to join the Navy, and that regaining growth can only succeed as an all-hands effort—an investment in the future (Kaack, 2026). He links deterrence directly to measurable readiness output, stressing that a defined set of ships, boats, and aircraft must be operationally available, because a platform stuck in the shipyard does not deter (Kaack, 2026).

This thesis addresses that strategy-to-implementation interface by documenting how German Navy personnel levels and age structure evolve across Sea/Staff/School assignment contexts and by projecting future trajectories using a Markov manpower modeling framework. The empirical focus is the observed evolution of personnel composition and age dynamics across the categories Enlisted, Junior noncommissioned officer (NCO[s]), Senior NCOs, and Officers, and across assignment contexts labeled Sea, Staff, and School, supplemented by residual categories used to preserve the full population. While the descriptive analysis does not directly measure readiness outcomes, it establishes the baseline personnel-structure patterns that are plausibly readiness-relevant because they describe how the workforce is distributed across operational versus non-operational contexts and how that workforce is aging over time.

B. RESEARCH OBJECTIVE AND QUESTIONS

The primary objective is to document how the Navy's workforce size, composition, and mean age evolved over the observation window. Later, I will project how inventories and age structure may evolve under alternative accession assumptions using a Markov manpower modeling framework. The thesis therefore combines descriptive demographic analysis with a personnel-flow-based Markov projection framework built from quarterly panel data.

- How did the German Navy's personnel composition and mean age change from 2015 to 2025, overall and by personnel category?
- How do age profiles differ across assignment contexts (Sea, Staff, School), and what platform-level differences appear within the Sea workforce?
- Under baseline and alternative recruiting scenarios, how do inventory and mean age evolve through 2040 for Officers, Senior NCOs, Junior NCOs, and Enlisted?

C. DATA AND METHODOLOGICAL APPROACH

The thesis uses two core datasets: an annual-slice dataset for demographic description (2015–2025) and a quarterly personnel flow dataset (2015–2025) used to estimate transition dynamics. In the Markov model, states are defined as the Cartesian combination of rank (Dienstgrad) and age class (Altersklasse), and separate transition matrices are estimated for four career tracks, with track membership enforced at each quarter (Q) IV snapshot. Forecasting uses the Q IV-to-Q IV time step and adds external inflows via destination-state-specific entry counts (r-vectors), allowing baseline projections and scenario comparisons.

D. SCOPE AND LIMITATIONS.

The descriptive chapters document structural patterns in age and distribution across Sea/Staff/School and ship types, but they do not claim to directly observe readiness as an outcome variable. The Markov approach provides a tractable framework for projecting inventories and age structure from empirically estimated transition probabilities, but the validity of long-horizon projections depends on the stability of underlying personnel processes and on the adequacy of post-reform data in segments where rank structures changed.

E. ORGANIZATION OF THE THESIS.

Chapter II reviews the literature on demographic constraints and security, readiness/operational tempo and retention, diversity and recruiting, and Markov manpower modeling approaches.

Chapter III describes the data sources and the Markov modeling methodology, including the transition estimation, matrix construction, and inflow specification.

Chapter IV presents descriptive findings for 2015–2025, including Sea–Staff–School comparisons, platform-level patterns, and female representation trends.

Chapters V and VI validate alternative Markov specifications and present baseline and scenario projection results through 2040, followed by conclusions and planning implications.

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II. LITERATURE REVIEW

A. MACRO DEMOGRAPHIC TRENDS AND SECURITY

Demographic research in security studies describes population change in advanced industrial democracies as historically unprecedented (Apt, 2014). This assessment reflects the combined effects of persistently low fertility, rising life expectancy, and rapid population aging. There are indicators that fertility and mortality rates and migration patterns represent the only structural elements which can be accurately forecasted for the next few decades, thus limiting security policy options (Leuprecht, 2016). With an aging society, public costs for pensions and healthcare increase, which reduce available defense spending and limits military personnel and technology development budgets.

The security demographics of Germany exist within a larger framework that shows how industrialized states with aging populations and declining numbers contrast with younger populations that grow quickly in other areas (Leuprecht, 2016). Against this backdrop of demographic divergence—aging and shrinking populations in industrialized states versus growth in younger regions—security challenges emerge as governments face tighter fiscal space and smaller recruitment cohorts. Older populations need to maintain expensive military forces with decreasing young adult numbers while dealing with immigration issues and security threats from younger nations (Leuprecht, 2016). Within this context, industrial ("aged") states have increased competition with the civil labor force for a shrinking pool of qualified young adults, especially in technically demanding occupations.

The NATO policy analysis from recent times indicates that these demographic changes have spread across the entire alliance. Drawing on recent demographic data, Palooma (2024) argues that fertility in all NATO countries has dropped below the replacement level of about 2.1 children per woman, with several allies already experiencing population decline when migration is excluded. At the same time, the median age in many member states is rising into the mid-40s and beyond. The result means that future armed forces will have to be recruited, trained, and paid for by societies with fewer young citizens and larger elderly populations (Palomaa, 2024). NATO will likely need to adopt compensatory measures—such as investing in advanced technologies, expanding training and upskilling programs, and implementing immigration policies that help offset shrinking recruitment cohorts—to sustain force readiness. (United Nations Department of Economic and Social Affairs, 2023); (Palomaa, 2024)

The research establishes demographic change as an active factor that determines military personnel availability and affects both military operations and funding requirements. This macro-level perspective provides the structural backdrop for the subsequent subsections, which narrow the focus to Germany's specific demographic trajectory and its implications for military recruitment and force planning.

1. German Demographic Constraints and Security Debate

Rzeszutko (2022) describes Germany widely as the European country where demographic decline and population aging are most acute, with negative natural growth recorded continuously since the 1970s. Projections by the Federal Statistical Office indicate that Germany remains on a long-term path of population contraction, despite several waves of immigration and the admission of around 1.5 million refugees and migrants between 2015 and 2017. The number of people aged 67 and older will reach more than 21.5 million by 2040. At the same time, its population will decrease from 83 million in 2019 to 67–74 million during the next forty years based on projected immigration rates (Rzeszutko, 2022).

The security sector needs to understand demographic changes because they impact the operational methods of military forces and all security organizations. The German Armed Forces (Bundeswehr) faces ongoing personnel shortages because Germany faces two major demographic challenges from an aging population and decreasing birth rates. At the same time, these trends increase public spending on pensions and healthcare, which narrows the fiscal space available for defense and internal security (Rzeszutko, 2022). An earlier analysis of European armed forces reached similar conclusions (Stemmer, 2005). Stemmer (2005) argues that Continental Europe must adapt its military capabilities amid shrinking workforces, rising social welfare costs, and persistent geopolitical uncertainty—pressures that place European militaries under ‘tense financial’ and demographic conditions.

In response to demographic decline, Germany has long relied on immigration as a partial remedy, encouraging the arrival of “guest workers” from the 1960s onward and, more recently, accepting large numbers of refugees and economic migrants. As a result of this policy, around 9–10 percent of Germany’s residents hold foreign citizenship, and more than one quarter of the population has a migration background. The share of people with migration ancestry increased from roughly 25 percent in 2018 to 27.2 percent in 2021 (Rzeszutko, 2022). While this diversified population base potentially broadens the pool of recruits, it also creates integration challenges and raises questions about social cohesion, value alignment, and political support for military engagements, which are central themes in the German security debate.

Analyses of the Microcensus and the coordinated population projections show that youth cohorts are shrinking in absolute terms. They also show particularly steep declines in several eastern federal states and pronounced east–west differences in the share of young people with German versus foreign citizenship (Apt, 2014). In western states such as North Rhine-Westphalia, Baden-Württemberg, and Hesse, the proportion of males aged 19–22 holding non-EU citizenship already exceeds 10 percent, whereas eastern states often have less than 3% non-EU youth, implying that the Bundeswehr’s target population is simultaneously smaller, more geographically uneven, and more ethnically heterogeneous than in previous decades (Apt, 2014).

Educational expansion further complicates recruitment prospects: since the 1970s, Germany has shifted toward higher secondary and tertiary education, increasing university enrollment and shrinking the pool of young adults with lower secondary qualifications—the traditional recruiting base for many military occupations. Apt (2014) argues that this shift both reduces the number of youths who consider military service and pulls a disproportionate share of high-achieving graduates into civilian education and careers, intensifying competition for qualified personnel.

Taken together, this literature frames Germany as a "demographic frontrunner" in Europe with its shrinking, aging, and increasingly diverse population. It poses a dual challenge for security policy: sustaining adequate force levels in the Bundeswehr and integrating national and ethnic minorities in ways that support internal and external security. These constraints form the national backdrop against which service-specific manpower issues—such as naval recruitment, retention, and age-structure management—must be understood in the remainder of the chapter.

2. Implications for the Bundeswehr and the German Navy

For the Bundeswehr, demographic change translates directly into a structural recruiting and retention challenge that is already visible in personnel numbers and planning documents. Since the suspension of conscription in 2011, the Bundeswehr has had to transform itself into a fully voluntary force while competing with the civilian economy in a "war for talent." Given declining cohort sizes and rising educational aspirations, the armed forces cannot currently recruit and retain enough suitable young men and women to meet quantitative and qualitative personnel requirements (Rümschüssel, 2015). Bundeswehr manpower planning was officially supposed to be "demography-proof," yet in practice suffers from a shortage of qualified applicants, high transformation pressure, and repeated structural reforms that make reliable long-term planning nearly impossible.

European Organization of Military Associations and Trade Unions' (EUROMIL) 2024 survey report, based on inputs from EUROMIL member associations rather than national authorities, indicates that these problems are not unique to Germany but are reported as particularly pronounced there (European Organisation of Military Associations and Trade Unions, 2024). However, because the findings reflect participating associations' assessments (not official administrative data and not necessarily a representative sample of all service members), the results should be interpreted as comparative stakeholder perceptions rather than definitive cross-national prevalence estimates (European Organisation of Military Associations and Trade Unions, 2024). Retention issues have become salient since around 2011, with total military personnel shrinking from roughly 206,000 to 180,000 between 2011 and 2024 despite political commitments to increase force levels considering the deteriorating European security environment (Statista, 2025). The Parliamentary Commissioner for the Armed Forces likewise stresses that the Bundeswehr is in direct competition with other employers on pay, long-term career prospects, and family-friendly working conditions, such as predictable postings and a sustainable work–life balance, which are crucial for both recruitment and retention (German Bundestag, 2023).

The Bundeswehr faces these pressures, which affect all military branches. Navy operations are particularly affected because they need extended training periods and skilled personnel, such as experienced leadership at all levels.

These findings, along with the demographic trends discussed, suggest that the Bundeswehr and the German Navy itself cannot simply rely on volume increases in recruitment to close personnel gaps. Instead, they need to change how they structure their forces, how they plan career models, and how they deploy troops to a long-term environment where skilled workers are hard to find and highly sought after (European Organisation of Military Associations and Trade Unions, 2024; Rümschüssel, 2015). This strategic constraint motivates the need for robust manpower forecasting tools and scenario analysis, including the Markov modeling approaches reviewed in the second part of this chapter.

3. Operational Tempo, Readiness, and Retention

The literature on operational tempo shows that deployment intensity affects readiness and retention in a non-linear way: some operational activity is necessary to keep people motivated and professionally satisfied, but very high and sustained deployment levels, especially when they exceed what personnel expected, undermine family stability and make reenlistment less likely (Hosek & Totten, 1998). Using service-specific logit regression models of reenlistment, they find that moving from no long/hostile duty to some exposure is associated with higher reenlistment, while additional exposure—especially hostile duty—reduces reenlistment probabilities, implying a non-linear effect of deployment intensity on retention (Hosek & Totten, 1998). At the same time, even small increases in average personnel tempo can greatly expand the share of service members who experience long or demanding tours.

Another research on U.S. Navy readiness between 2010 and 2017 extends this logic to a naval context by treating unsustainable operational tempo as a key indicator of a "hollow force" (Witwicki, 2019). The thesis draws on earlier research from the Army and Naval War College, which defines operational tempo as the combined rate of deployments, training exercises, garrison duties, and perceived role overload. The thesis argues that there is a level of tempo that maximizes unit performance and readiness, but that the early 2010s U.S. Navy operated well beyond this optimal range. As fleet size shrank while global presence requirements remained constant, individual ships and crews spent more time at sea, experienced extended deployments, and deferred maintenance, producing what analysts described as "doing more with less" and contributing to tragic at-sea mishaps in 2017 (Witwicki, 2019).

As a conclusion, planners need to monitor not only the overall level of deployments but also how unevenly they are distributed across units and career fields, because pockets of extreme workload tend to push out exactly the experienced people needed most for readiness.

Together, these studies underscore that operational tempo is not only a readiness issue but also a long-term retention risk, particularly for high-skill communities that bear a disproportionate share of deployments. For a navy such as Germany's, which must maintain readiness and presence under tight personnel constraints, several policy measures appear essential. These include efforts to mitigate personnel tempo, distribute deployment burdens more evenly, and support affected families—all of which are likely to be critical for sustaining both readiness and reenlistment over time.

4. Diversity and Recruitment

The integration of women and broader diversity has become a core element of personnel policy in aging, all-volunteer forces, including the Bundeswehr. This shift reflects the fact that shrinking male cohorts and tight labor markets make traditional recruitment pools increasingly insufficient.

Using nationally representative German survey data from 2019 and multivariate ordinary least squares (OLS) regression, (Graf & Kuemmel, 2022) show that women who perceive higher levels of gender equality in the Bundeswehr are more likely to rate it as an attractive potential employer. Another case study illustrates that incidents of right-wing extremism, experiences of sexual harassment and a persistent "combat-masculine warrior paradigm" can seriously damage the perceived credibility of the Bundeswehr's official diversity and equality agenda, especially among younger women and minority groups (Spindler, 2021). Spindler (2021) argues that credible action against extremism, effective protection from harassment, and more inclusive career structures are therefore not symbolic gestures but practical preconditions for attracting and retaining a broader and more highly qualified pool of recruits.

5. Summary

Taken together, the reviewed studies suggest that the German Navy faces a predictable but binding demographic constraint. Smaller, older, and regionally uneven youth cohorts limit the pool of potential sailors at the same time as political commitments and operational demands point toward higher force levels.

Because demographic trends unfold slowly but can be projected with reasonable confidence, a Navy-specific analysis of current age structure and career flows is one of the few tools that can reveal looming retirement waves, rank imbalances, and skill bottlenecks early enough to adjust accessions, training, and career patterns. Projecting the force to 2030 and beyond under alternative recruitment and retention assumptions therefore does more than describe the status quo; it translates abstract demographic constraints into concrete personnel risks and policy levers and provides the analytical foundation for both the Markov modeling and for practical manpower planning in the fleet.

B. OVERVIEW OF MARKOV MANPOWER MODELING APPROACHES

Markov manpower models describe personnel systems as a finite set of states (such as rank and contract categories) and use empirically estimated transition probabilities to capture how individuals move between these states over time. In a discrete-time Markov chain, the distribution of personnel in the next period depends solely on the current distribution and the transition matrix, which makes it possible to project future force size and structure under different recruitment, promotion, and retention assumptions without modeling each individual decision. General stochastic frameworks and subsequent workforce applications show that such models remain computationally tractable even for relatively complex grade structures and provide closed-form or numerically stable solutions for quantities like expected time in state and long-run distributions (Guerry & De Feyter, 2009; Ross, 2010).

Existing applications demonstrate that this kind of Markov modeling is both feasible and policy-relevant for large military organizations. Gass et al. (1988) describe how the U.S. Army's Manpower Long-Range Planning System uses discrete-time Markov chains combined with goal-programming techniques to manage hundreds of thousands of soldiers across multiple grades and specialties. This approach improves the accuracy of long-term strength and grade forecasts compared with simple trend-based methods. More recent studies apply similar Markov frameworks to Marine Corps Reserve officers and Australian Navy technicians, using them to forecast end strength and test alternative policy scenarios, which underpins the decision to adopt a Markov approach for analyzing the German Navy's demographic future (Grossi, 2016; Licari, 2013).

III. DATA AND METHODOLOGY

This chapter describes the two core datasets used in the thesis and documents all preparation steps that transform raw personnel records into a Markov-ready yearly panel.

The output of this pipeline is a cleaned dataset that remains deliberately "wide" (many variables retained) so that later analyses can apply focused filters without re-running the entire preparation process.

A. DATA

1. Demographic Analysis

The dataset for the demographic analysis is organized in annual slices (2015–2025) and covers all Navy uniformed personnel including those serving outside the Navy organizational area with more than 250,000 entries.

Three assignment-type dummies are created to distinguish operational Sea assignments ("Sea"), staff/headquarters assignments ("Staff"), and education/training assignments ("School").

- Variable 1 ("Sea") includes all records assigned to personnel employed operationally within the Navy, especially in particular ships and boats, naval aviation, as well as technical support units.
- Variable 2 ("Staff") comprises all records assigned to personnel serving in Navy staff organizations.
- Variable 3 ("School") comprises all records assigned to personnel serving at education and training institutions, including schools, universities, and fleet-affiliated training and continuing-education centers.

For descriptive comparisons over time, the transcript also defines period groupings such as pre-COVID years, COVID years, and "Zeitenwende" years.

a. Existing Variables

(1) Jahr

Identifies the annual slice (2015–2025 Demographic Analysis and 2016–2025 for the Personnel Flow Dataset) in which a given personnel record is observed.

(2) PID

Is an anonymized person identifier (PID) that allows records to be linked to the same individual across years without using personally identifiable information.

(3) Dienstposten

Post/assignment information records the posting or assignment context for the individual in the respective observation period.

(4) Tätigkeit

Defines the type of billet where the person is currently booked in the Manpower System, such as, Education for Career Track, deployed etc.

(5) Bündelung

Identifies the billet's paygrade possibilities, e.g., can be filled from E5 to E8.

(6) PersKat

The personnel category specifies the personnel category to which the individual belongs in the respective observation period.

(7) Laufbahn

Career track indicates the individual's career track classification as stored in the dataset.

(8) Verpflichtungszeit

Obligated service time captures obligated service time for the individual as recorded in the personnel data.

(9) Geburtsjahr

Birth year records the individual's year of birth as contained in the source records.

(10) Geschlecht

Gender records the individual's gender as stored in the personnel records.

(11) VwdgR _lang

The career field captures the individual's career field classification in the dataset

(12) OrgBereich

Organizational area records the organizational area associated with the individual, including cases where personnel serve outside the Navy organizational area.

(13) Dienststellenbezeichnung

Identifies the unit designation associated with the individual in the dataset.

b. Created Variables

(1) Sea

The dummy variable "Sea" equals 1 for records classified as operational assignments and includes boats and ships, naval aviation, and technical support units; otherwise, it equals 0.

(2) Staff

The dummy variable "Staff" equals 1 for records classified as staff/headquarters assignments within Navy staff organizations; otherwise, it equals 0.

(3) School

The dummy variable "School" equals 1 for records classified as education/ training assignments, including schools, universities, and fleet-affiliated training and continuing-education centers; otherwise, it equals 0.

2. Markov Modelling

The second dataset is a personnel flow-based dataset. It includes quarterly panel data from 2016 to 2025 and has almost similar variables with additional information for the previous state values (VG-Variables) to support flow-style comparisons. It comprises 984452 observations for the period.

a. Cleaning and panel construction

Variables are renamed into a standardized schema (e.g., pid , jahr , quartal , alter , perskat , laufbahn , dienstgrad), and corresponding VG variables are harmonized where present. Observations missing a PID are removed, duplicates on (pid, quartal, jahr) are detected and dropped, and a quarterly time index date_q = yq (jahr, quartal) is created to order observations within person careers. A within-person running index t is generated after sorting by (pid, date_q) to represent the sequence of observed quarterly periods for everyone.

Personnel category flags are created for "full" categories (e.g., is_uop, is_ump, is_offz) and for candidate tracks ("Anwärter") such as is_ump_anw, is_uop_anw, and is_offz_anw, with "exit status" captured when perskat is empty. Parallel "previous period" flags (was_uop, was_ump, etc.) are created using vg_perskat to enable transition logic later without repeatedly referencing raw string fields.

Career-track flags are constructed (is_trd, is_fachd) and used to define analysis populations such as is_ump_trd_fachd, is_offz_trd. Rank (paygrade) is mapped into numeric grade variables by career track (e.g., dg_ump, dg_uop, dg_offz_trd) using the pay scale labels.

Age is discretized into ten five-year bins (age_class) from 17–21 through 63–65, providing a stable age dimension for later state definitions.

b. Descriptive stock/flow outputs used for validation

After the Markov-ready panel is created, annual end-to-end (Quarter (Q) IV to Q IV) stock changes are computed for each main population (Officers, Senior NCOs, Junior NCOs, and Enlisted) to produce beginning and end inventory, exits, inflows, and an exit rate, and these summaries are exported to Excel. In addition, state-level stocks per year are computed at Q IV by counting personnel in each defined state index for the relevant track-specific state space.

For interpretability, mean observed ages are calculated within age classes (baseline Q IV 2024) and average age by year (Q IV only) is produced for multiple tracks including counts, with exports in both long and wide formats. These tables support descriptive discussion of demographic shifts without changing the discrete state definitions used later in the Markov model.

B. METHODOLOGY

A Markov manpower model is a simplified way of representing how a personnel system evolves from one year to the next. Instead of tracking each career decision separately, the model groups personnel into recurring categories and uses the observed movement between those categories to estimate how the force structure changes over time. In this thesis, the model is estimated from Q IV-to-Q IV observations so that each step represents one annual transition in the Navy workforce.

A state in the model represents one cell in the personnel structure, defined by the combination of rank and age class. At any Q IV snapshot, each person belongs to exactly one such state, and the transition matrix records the probabilities of where personnel in that state are found one year later, including staying in place, aging into the next class, promoting, or exiting the track.

Inflows and exits are handled explicitly. Exits are treated as outflows from the starting state, while new entrants are added separately through destination-state-specific inflow vectors that specify where accessions enter the system. Starting from an observed stock vector, the model applies the transition matrix and then adds inflows to generate the next year's projected distribution. The main forecast outputs are therefore the projected state distribution, total inventory, and average age for each career track under different inflow assumptions.

1. Markov Model Setup

For the purposes of this thesis, the Markov model is specified as a discrete-time model aligned to the observation interval, and the primary object of interest is the evolution of the personnel distribution across the defined states from one period to the next. Forecasts are generated by applying empirically estimated transition probabilities to the observed stock vector and then adding external inflows through destination-state-specific entry vectors. This framework allows career-track inventories and age structures to evolve endogenously under baseline and alternative recruiting scenarios.

2. State Space and Tracks

Markov states are defined as the Cartesian combination of rank (Dienstgrad) and age class (Altersklasse), i.e., everyone occupies exactly one Dienstgrad × Altersklasse state at each snapshot. Separate transition matrices are estimated for the four career tracks. Track membership is enforced by restricting the snapshot samples to individuals flagged as belonging to the respective track at the snapshot date. For matrix construction, the state set is restricted to valid observed states to avoid artificial gaps introduced by the numeric coding of rank-age combinations; thus, only states that occur in the data enter the transition matrix (Figure 1).

state		Maat 17-21 T1	Maat 22-26 T2	Maat 27-31 T3	Maat 32-36 T4	Maat 37-41 T5	Maat 42-46 T6	Maat 47-51 T7	Maat 52-56 T8	Maat 57-61 T9	Obermaat 17-21 T11	Obermaat 22-26 T12
Maat	1	0.052	0.059	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.385	0.393
Maat	2	0.000	0.100	0.011	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.577
Maat	3	0.000	0.000	0.074	0.022	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maat	4	0.000	0.000	0.000	0.067	0.013	0.000	0.000	0.000	0.000	0.000	0.000
Maat	5	0.000	0.000	0.000	0.000	0.056	0.000	0.000	0.000	0.000	0.000	0.000
Maat	6	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maat	7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maat	8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maat	9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obermaat	11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.281	0.640
Obermaat	12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.575
Obermaat	13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obermaat	14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obermaat	15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obermaat	16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obermaat	17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Obermaat	18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Figure 1. Example: Portion of the Transition Matrix Junior NCO

3. Transition Estimation (Q IV to Q IV)

For each transition year, two track-specific cross-sectional snapshots are constructed: a start snapshot at Q IV of the year and an end snapshot at Q IV of the next year. Each snapshot is restricted to individuals observed in the respective track at the snapshot date and retains PID together with the state definition (Dienstgrad × Altersklasse).

The start and end snapshots are matched 1:1 by PID to classify personnel movements into three mutually exclusive categories: (i) exits (present at start, absent at end), (ii) external inflows (absent at start, present at end), and (iii) internal transitions (present at both snapshots). Internal transitions are aggregated as counts by year and by start/end state; for diagnostic purposes, movements can additionally be labeled as “Stay,” “Aging,” “Promotion,” “Promotion with aging,” and rare “Demotion” cases based on changes in Dienstgrad and/or age class. Exits are recorded as outflows from the originating start state, while external inflows are recorded as destination-state-specific entry counts into the end snapshot; both are stored alongside internal transitions to support subsequent matrix construction and forecasting.

4. Building the Markov Transition Matrix

To construct the Markov transition matrix, the long transition dataset is restricted to internal transitions and exits, while external inflows are excluded from the matrix itself. Transition counts are then aggregated by start and end state and row-normalized by the total number of departures from each starting state, yielding estimated transition probabilities. Exits are represented as a dedicated destination category by recoding missing end states accordingly and retaining the resulting probability as an Exit_Rate.

To ensure a rectangular matrix in each estimation window, the full set of allowed starting states is imposed as a template; unobserved transitions are assigned zero probability, and states with no observed outgoing transitions are assigned Exit_Rate = 1.0. After reshaping to wide format, destination columns are standardized across tracks and row totals are checked as a diagnostic to confirm that each row sums to one.

External inflows are estimated separately as individuals who are absent from the track at Q IV of year but present in the track at Q IV of year. Each inflow is assigned to the destination state observed at entry, and annual inflows are aggregated by destination state. These counts are then converted into destination-state shares, yielding the r-vectors used in Markov forecasting.

IV. DESCRIPTIVE ANALYSIS

This section presents aggregate personnel trends across the German Navy from 2015 to 2025, drawing on annual cross-sections of uniformed personnel linked by PID. Each year reflects unique individuals observed in that year; personnel appearing in multiple years contribute one observation per year. The analysis uses four personnel categories—Enlisted, Junior NCO, Senior NCO, and Officers—corresponding to the persk_cat grouping in the demographic dataset. These descriptive statistics establish the baseline for subsequent disaggregation by assignment type (Sea, Staff, School) and operational context.

A. WORKFORCE SIZE AND COMPOSITION

Total Navy personnel declined modestly from 20,936 in 2015 to 20,155 in 2025, a reduction of 781 individuals or 3.7 percent (Table 1). Within this aggregate stability, personnel composition shifted substantially. Enlisted ranks fell from 4,556 to 3,658 (−19.7 percent), while Junior NCO inventory decreased from 4,524 to 3,162 (−30.1 percent). In contrast, Senior NCO positions grew from 6,400 to 7,184 (+12.3 percent), and Officer strength increased from 5,456 to 6,151 (+12.7 percent). Measured as shares of total personnel, Enlisted representation declined from 21.76 percent in 2015 to 18.15 percent in 2025, and Junior NCO share fell from 21.61 percent to 15.69 percent. Over the same period, Senior NCO share rose from 30.57 percent to 35.64 percent, and Officer share increased from 26.06 percent to 30.52 percent (Table 1). Figure 2 visualizes these trajectories, highlighting the structural rebalancing toward more senior career stages.

B. MEAN AGE DYNAMICS

Figure 3 shows mean age over time for the total workforce. The trend reflects the compositional shifts documented in Table 1: as the share of junior personnel declines and the share of senior personnel rises, aggregate mean age increases mechanically. Figure 3 disaggregates mean age by personnel category, revealing that each category maintains a distinct age profile throughout the observation period. Officers and Senior NCOs exhibit consistently higher mean ages than Junior NCOs and Enlisted personnel, with the four categories following largely parallel trajectories. These patterns establish that the overall aging trend derives primarily from changes in workforce composition rather than uniform aging within each category.

The next sections examine whether these aggregate patterns differ systematically across assignment types (Sea, Staff, School) and explore how demographic structure varies by operational context.

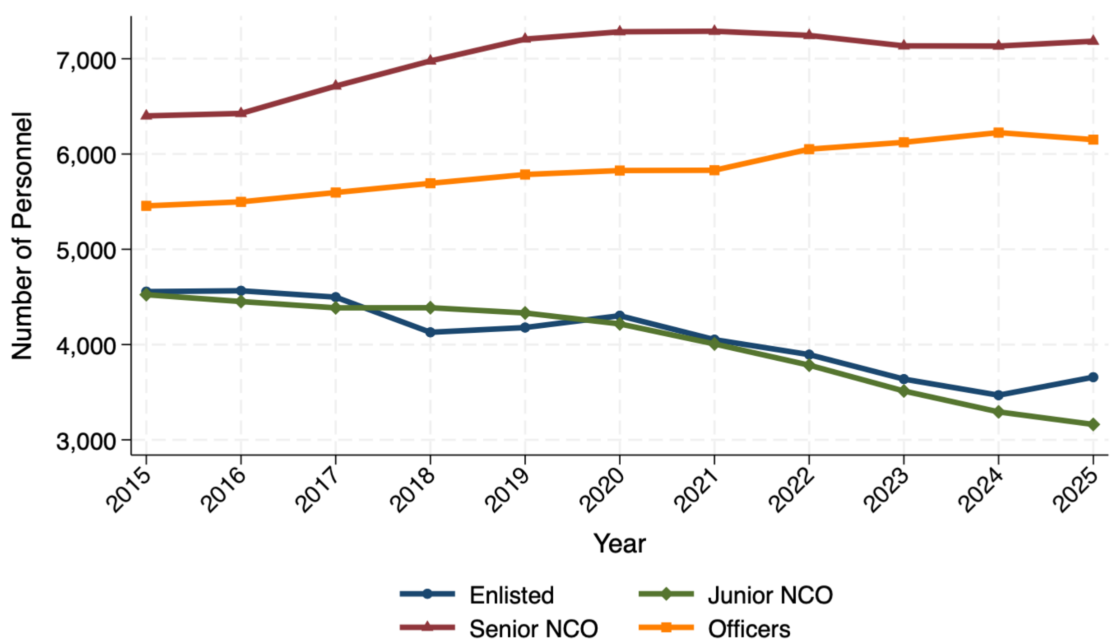

Figure 2. Overview Personnel by Career Track over Time

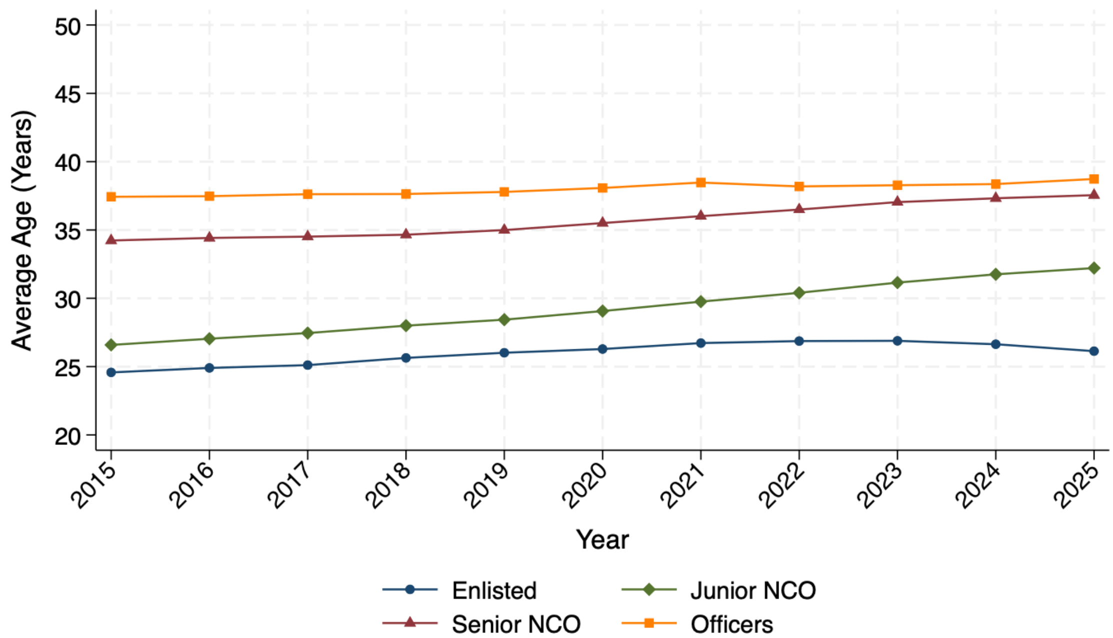

Figure 3. Mean Age by Career Track over Time

Table 1. Overview

Jahr	Total	Enlisted_N	Junior_NCO_N	Senior_NCO_N	Officers_N	Enlisted_Pct	Junior_NCO_Pct	Senior_NCO_Pct	Officers_Pct
2015	20936	4556	4524	6400	5456	21.76	21.61	30.57	26.06
2016	20941	4565	4452	6426	5498	21.80	21.26	30.69	26.25
2017	21193	4498	4386	6713	5596	21.22	20.70	31.68	26.40
2018	21186	4129	4387	6977	5693	19.49	20.71	32.93	26.87
2019	21502	4179	4332	7206	5785	19.44	20.15	33.51	26.90
2020	21630	4303	4217	7283	5827	19.89	19.50	33.67	26.94
2021	21178	4052	4007	7289	5830	19.13	18.92	34.42	27.53
2022	20975	3895	3784	7245	6051	18.57	18.04	34.54	28.85
2023	20409	3638	3513	7135	6123	17.83	17.21	34.96	30.00
2024	20121	3469	3294	7133	6225	17.24	16.37	35.45	30.94
2025	20155	3658	3162	7184	6151	18.15	15.69	35.64	30.52

C. SEA – STAFF -SCHOOL

The descriptive analysis (Figure 4) distinguishes five assignment contexts that reflect how personnel are booked in the manpower system. Besides "Sea," "Staff" and "School, two additional residual categories are used to preserve the full population: "DPäK" captures personnel temporarily carried outside a billet (in particular for training, but also for personal, medical, or disciplinary reasons), and "Other" captures Navy-uniformed personnel who are currently not employed within the "core Navy" structure represented by Sea/Staff/School.

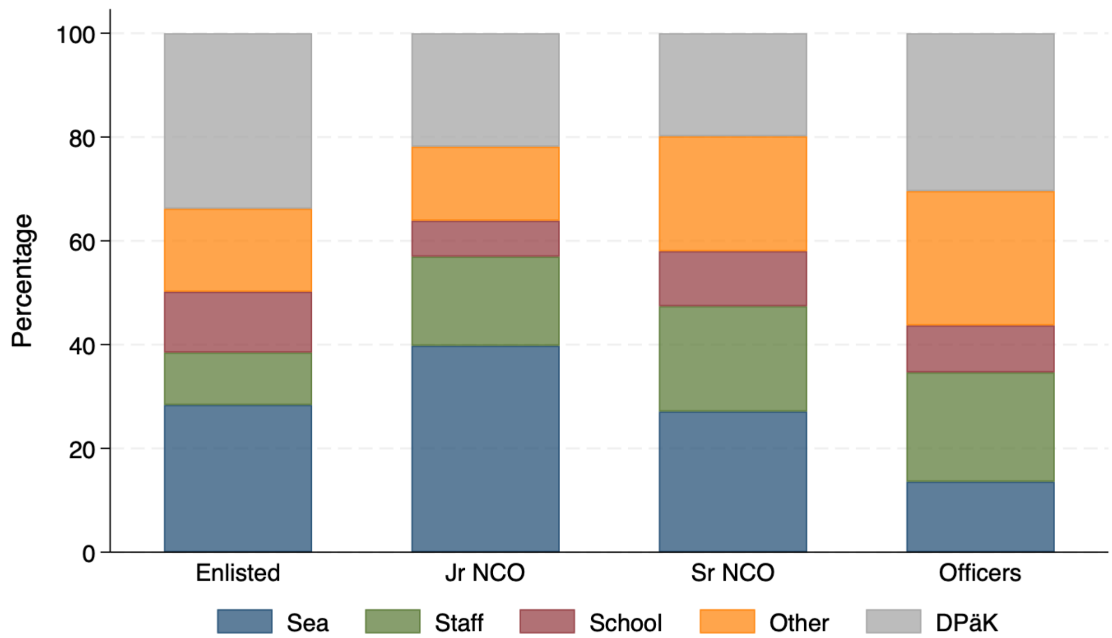

Figure 4. Assignment Distribution by Career Track (2025)

Building on this assignment structure, the next step is to examine whether age profiles differ systematically across posting contexts. Figure 5 shows that mean age rises in all three core assignment types (Sea, Staff, School) from 2015 to 2025, but at clearly different levels: Sea remains the youngest group throughout, Staff is consistently the oldest, and School lies between them. These persistent differences motivate treating assignment type as a central dimension of the descriptive analysis before moving to more detailed cuts (e.g., ship types) and to the longer-run aging dynamics analyzed later in the thesis.

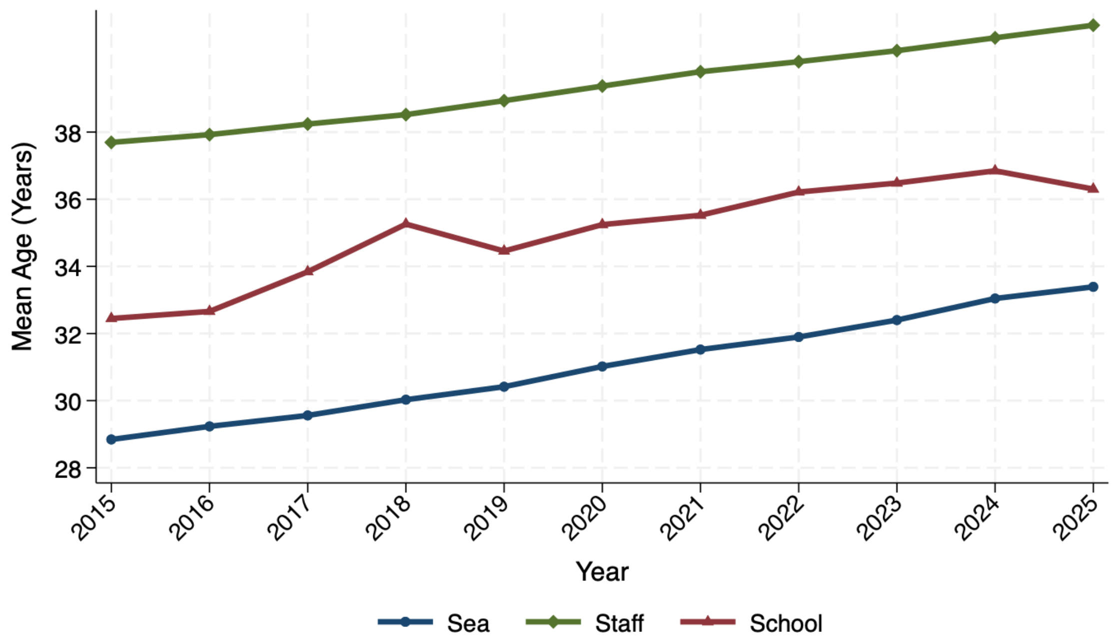

Figure 5. Mean Age by Assignment over Time

Figures 6 and 7 complement the mean-age trends by showing the full age distributions (median and spread) within Sea, Staff, and School assignments. In 2025, the Staff distribution is visibly shifted toward older ages compared with Sea, while School sits between the two, underscoring that assignment type is associated with systematically different age structures rather than only different averages. The comparison across 2017, 2020, and 2023 (Figure 7) shows an overall upward shift of the distributions over time, indicating that younger age groups are not expanding enough to keep the distribution anchored at lower ages. This distributional evidence supports interpreting the rising mean ages as a structural aging pattern rather than short-term noise.

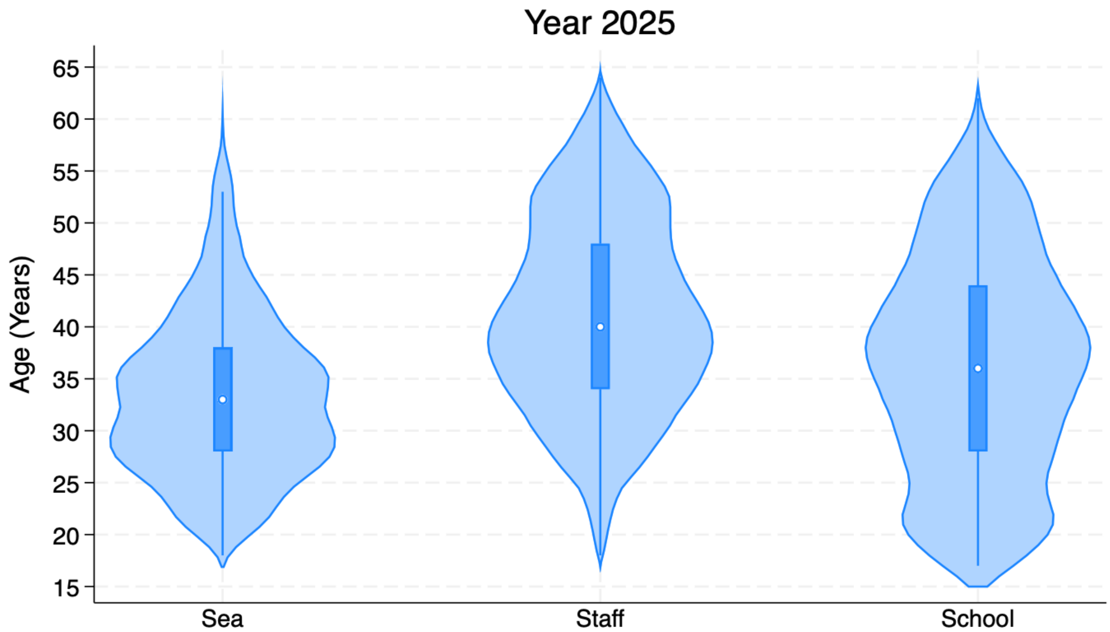

Figure 6. Graphical Age Distribution (2025)

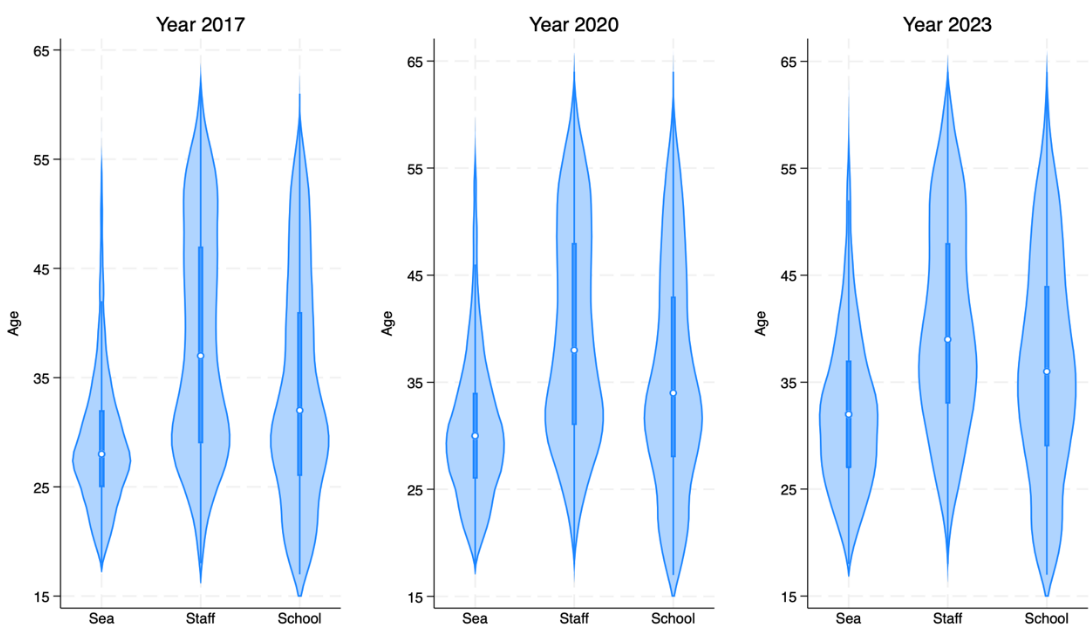

Figure 7. Graphical Age Distribution over the Years

Table 2 reports the annual mean ages and corresponding headcounts for the three core assignment contexts (Sea, Staff, School) for 2015–2025. It provides the numeric basis for Figure 4 by showing that mean age increases in all three contexts over the period, while remaining systematically lowest at Sea and highest in Staff. The table also documents the underlying group sizes (Sea_N, Staff_N, School_N) used to compute the means, which remain substantial across all years and thereby support the interpretation of the observed differences as persistent structural patterns rather than artifacts of very small samples.

From an operational perspective, Sea billets represent the part of the workforce most immediately linked to platform manning and day-to-day operational execution, while Staff and School billets primarily provide planning, governance, and training capacity. Table 2 therefore implies a double pattern for the operational core: the Sea workforce becomes older on average while also shrinking in headcount within the classified Sea group over 2015–2025.

This does not by itself measure readiness, but it provides a personnel-structure baseline that is consistent with the broader readiness literature stressing that workload, experience structure, and the distribution of personnel across operational versus non-operational roles matter for sustained output. Against that background, the persistent Sea–Staff age gap (e.g., 2015: 37.69 vs. 28.84; 2025: 41.18 vs. 33.39) underscores that "assignment type" is not a cosmetic label but a key dimension shaping the Navy's observed age structure.

Table 2. Age Overview

Jahr	Sea_Age	Staff_Age	School_Age	Sea_N	Staff_N	School_N
2015	28.84	37.69	32.45	5856	3340	1850
2016	29.23	37.92	32.66	5634	3437	1819
2017	29.56	38.24	33.84	5657	3453	1720
2018	30.03	38.52	35.26	5862	3467	1666
2019	30.42	38.94	34.46	6079	3474	1920
2020	31.02	39.37	35.24	5892	3479	1916
2021	31.52	39.80	35.52	5855	3534	1904
2022	31.90	40.10	36.22	5814	3623	1859
2023	32.40	40.43	36.48	5507	3696	1840
2024	33.04	40.81	36.85	5416	3668	1810
2025	33.39	41.18	36.30	5079	3668	1965

D. OPERATIONAL ANALYSIS

The operational Sea workforce documented in the previous section is not homogeneous; personnel are distributed across distinct platform types that differ in mission profile, technical complexity, and crewing requirements. This subsection examines how personnel-category composition and age structure vary by ship type, using data from core naval vessels: Frigates, Corvettes, Submarines, Supply Ships, Mine Warfare vessels, and Reconnaissance platforms.

1. Personnel–Category Mix by Ship Type

Figure 8 displays the career-track distribution (Enlisted, Junior NCO, Senior NCO, Officers) across six ship types for 2015–2025. The distribution reveals substantial structural differences in crewing patterns:

- Submarines exhibit the most top-heavy structure, with Officers and Senior NCOs comprising approximately 65–70% of the crew.
- Supply Ships show the highest share of Enlisted personnel (approximately 40–45%), with a more balanced distribution across all four categories.

- Frigates, Mine Warfare vessels and Corvettes display similar mid-range structures, with Junior NCOs around 30–35%, Senior NCOs around 25–30%, and Officers around 15–20%.

These differences reflect platform-specific operational requirements: Submarines demand higher technical specialization and longer training pipelines, which translates into a more senior workforce structure within the ranks, while surface combatants and support vessels rely more heavily on junior enlisted and NCO ranks for day-to-day operations.

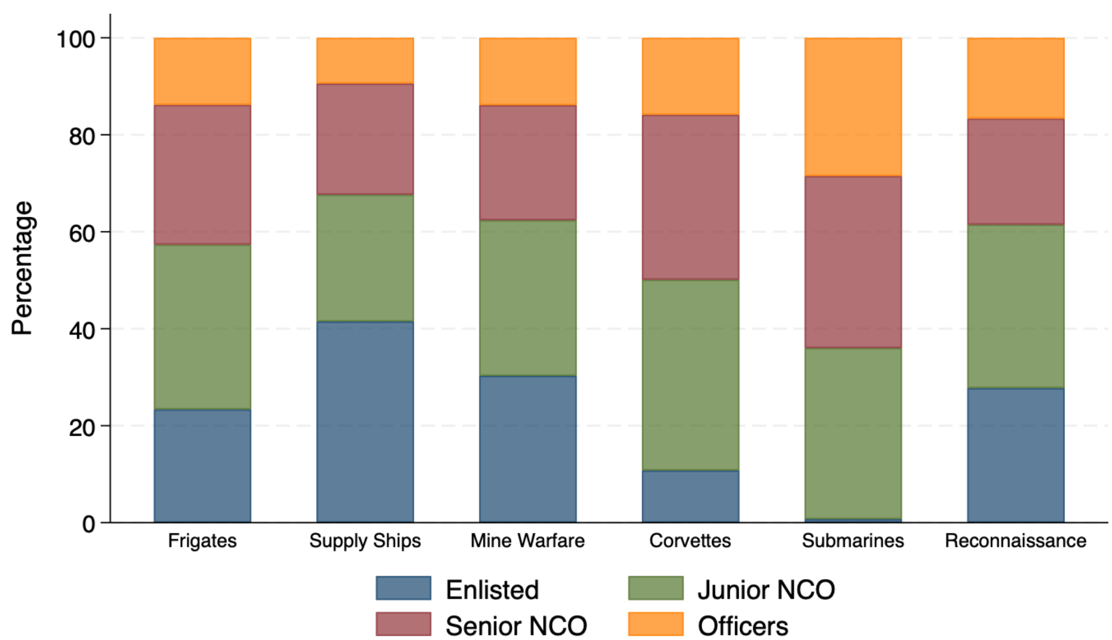

Figure 8. Personnel Distribution by Ship Type

2. Age Dynamics by Ship Type

Figure 9 plots mean age trajectories for the six core ship types from 2015 to 2025.

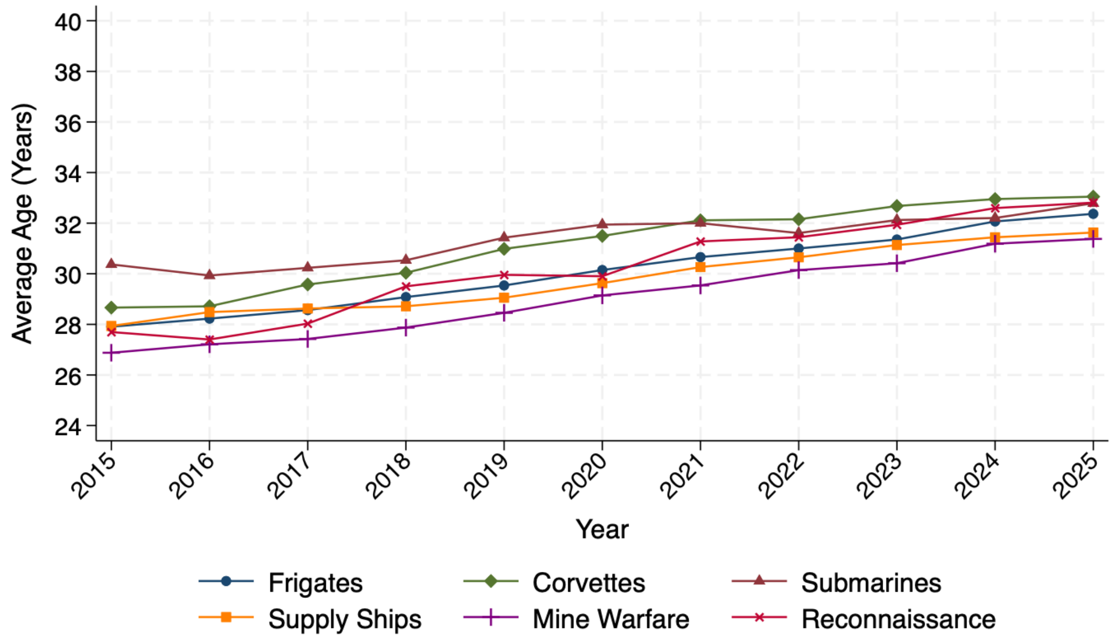

Figure 9. Aging Trend over Time

Figure 10 summarizes these trends as aging rates (years per year), calculated as the linear slope of mean age over 2015–2025.

An aging rate of 0.0 would indicate a perfectly stable workforce (constant mean age via balanced inflows and exits), while 1.0 would represent pure biological aging (no turnover). All observed rates fall between these bounds, with Reconnaissance platforms aging at 58% of the biological rate and Submarines aging at only 27%. Higher rates suggest that demographic aging outpaces personnel turnover, which is operationally relevant because it implies shrinking pools of junior personnel available for physically demanding sea rotations.

The slower aging of submarines (0.27) likely reflects their selective accession pipeline and retention profile: Submarine crews are drawn from more senior, technically specialized personnel with longer training investments, which stabilizes the age structure even as absolute recruitment numbers decline.

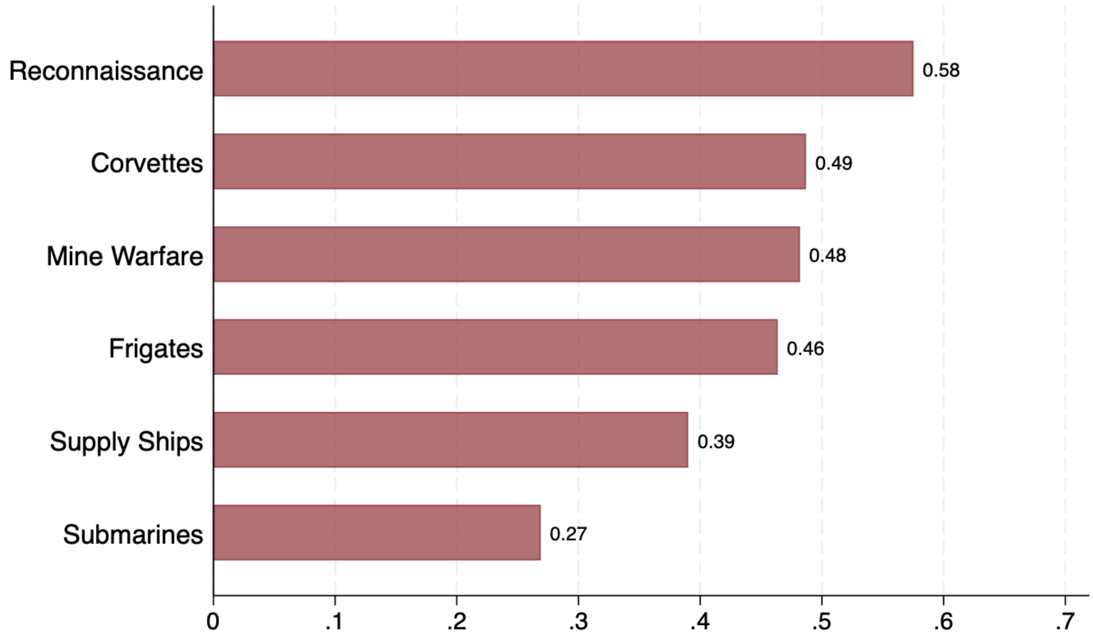

Figure 10. Aging Rates

3. Within-Type Variation: The Frigate Case

Figure 11 disaggregates frigates into the three operated generations—F123 (Brandenburg class), F124 (Sachsen class), and F125 (Baden-Württemberg class)—to examine whether platform age and modernization affect crew age structure. The three classes show distinct age profiles over 2015–2025:

F125 (Baden-Württemberg) starts oldest (approximately 30 years in 2015) and ages to roughly 33.5 years by 2025, maintaining the highest mean age throughout the period. F124 (Sachsen) and F123 (Brandenburg) begin at similar levels (around 28 years in 2015) but diverge slightly over time, both reaching approximately 31–32 years by 2025.

The elevated age profile of F125 crews is consistent with the class's later commissioning (2019 onward for full operational capability) and higher automation/technical complexity, which likely selects for more experienced personnel. In contrast, the older F123 and F124 classes, commissioned in the 1990s and early 2000s respectively, draw from more stable, less selectively aged manning pools.

This within-type variation demonstrates that “Frigates” as an aggregate category masks operationally meaningful heterogeneity: platform generation, technical sophistication, and commissioning timing interact with personnel assignment policies to produce distinct age structures even within a single ship class.

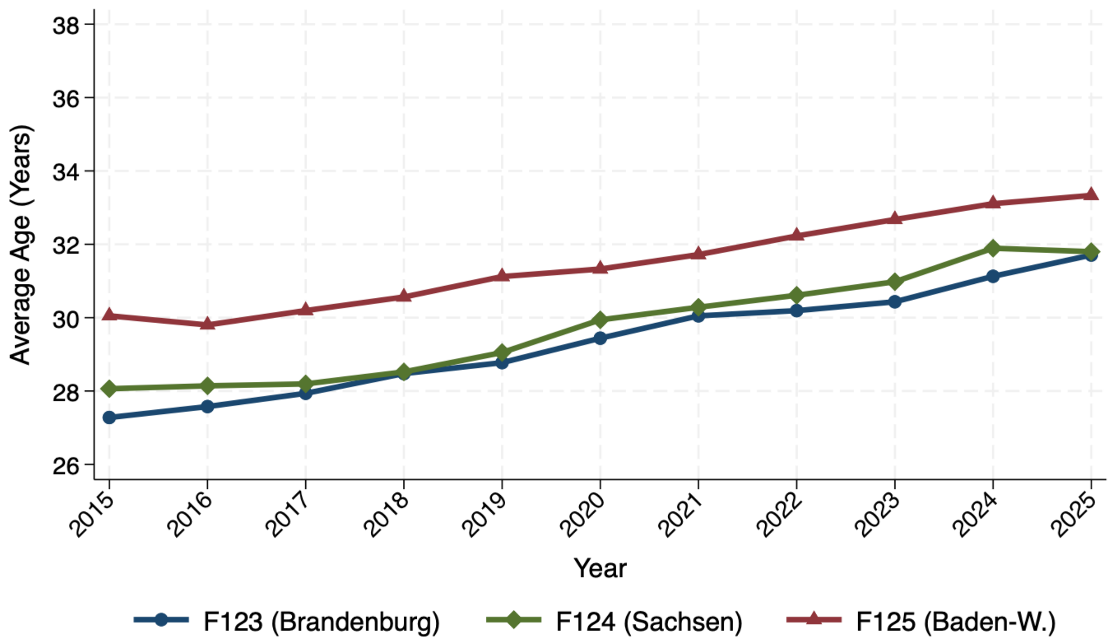

Figure 11. Aging over Time (Frigates)

4. Operational Implications

The platform-level patterns documented add operational texture to the Sea–Staff assignment trends. Aging rates above 0.4–0.5 years per year on Reconnaissance, Mine Warfare, Corvette, and Frigate platforms signal that these ship types are experiencing demographic pressure faster than personnel turnover can offset. Combined with the Sea-to-Staff headcount rebalancing (−777 Sea, +328 Staff over 2015–2025), the data suggest that the German Navy’s operational core is aging in place while support and administrative billets expand—a pattern consistent with broader literature on “hollow force” dynamics in aging militaries.

E. FEMALE REPRESENTATION

This subsection summarizes female representation trends in the German Navy over time and examines how these trends differ by personnel category, assignment type, and ship type.

1. Overall Trend

The overall female share increases gradually across the observation window, and the fitted linear trend confirms a persistent upward trajectory rather than a short-lived fluctuation (Figure 12). The year-to-year changes remain modest, which suggests that the aggregate trend likely reflects slow-moving cohort replacement and accession patterns rather than abrupt structural breaks within the period.

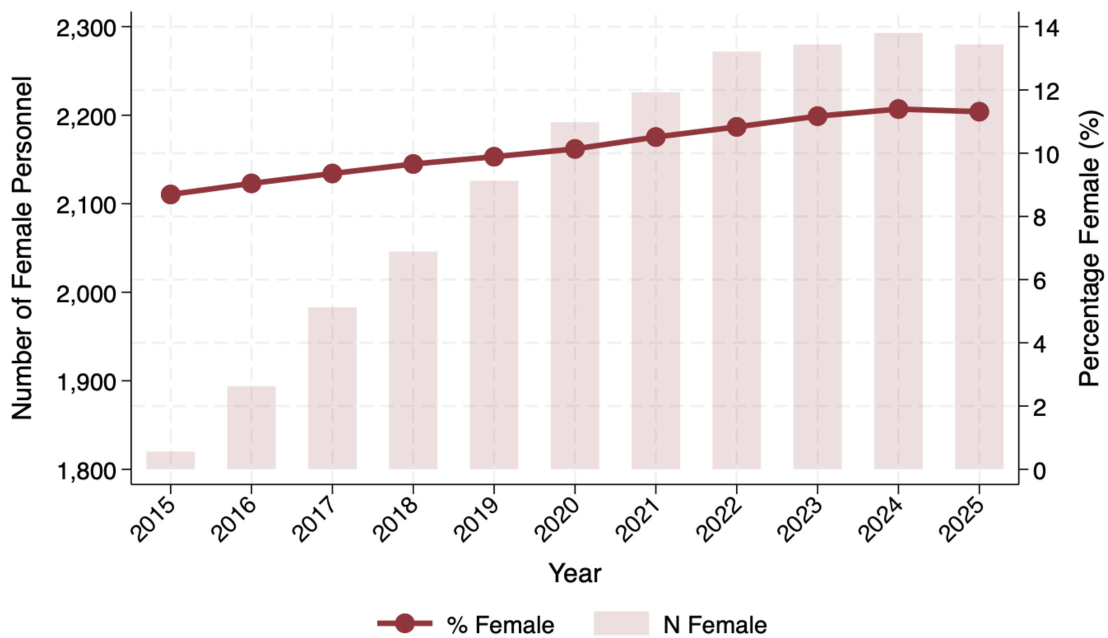

Figure 12. Female Representation over Time

2. Differences by Personnel Category

Female representation differs systematically across personnel categories, and the time paths do not move in lockstep. Figure 13 indicates that categories closer to the entry pipeline show higher and more responsive female shares, while categories that depend on longer retention and promotion pipelines change more slowly. This pattern matters for interpretation: the aggregate trend can rise even if some categories lag, because compositional shifts and pipeline timing can mask slower change in senior segments.

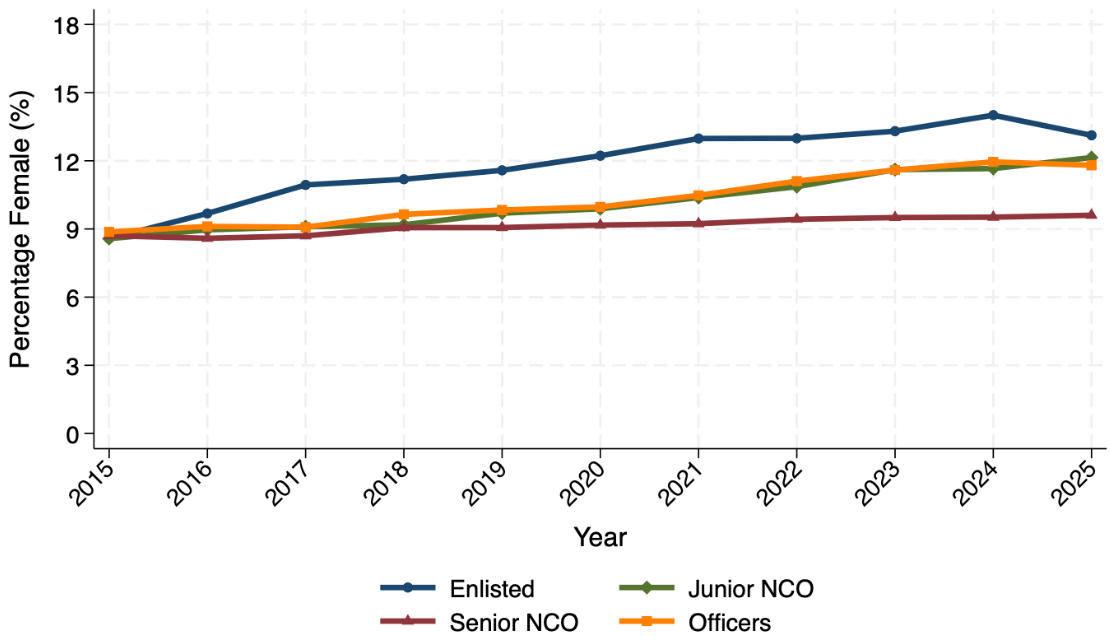

Figure 13. Female Representation by Career Track

3. Differences by Assignment Type

Female representation varies by assignment, with a persistent gap between sea assignments and non-sea assignments (Figure 14). The staff and school series remain above the sea series throughout the period, and both non-sea series trend upward, indicating that the overall increase in female representation does not translate one-for-one into sea-going billets.

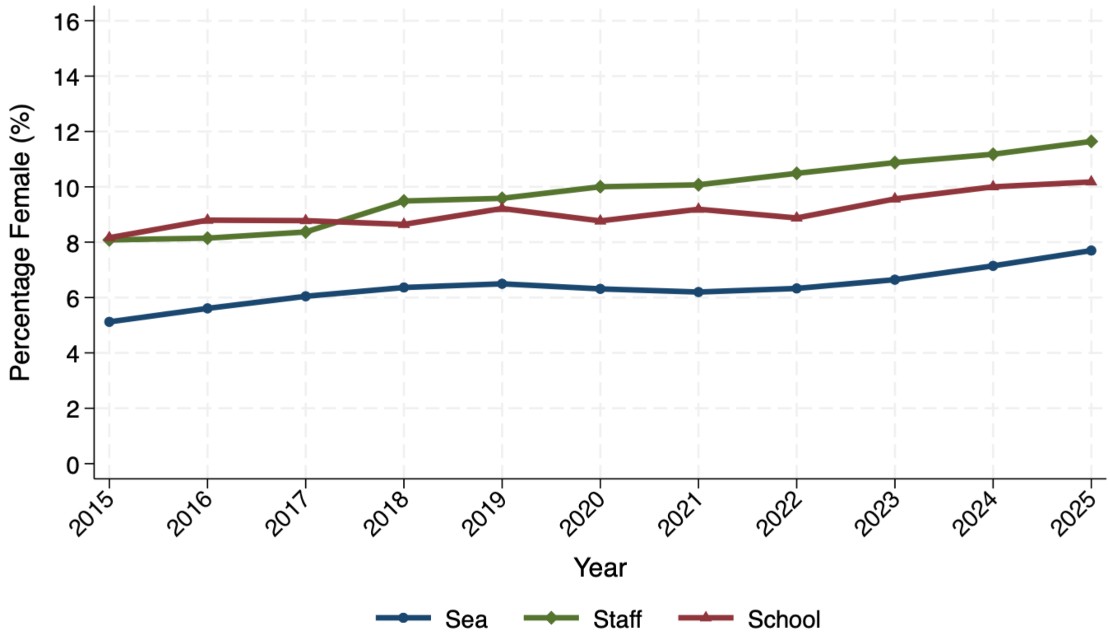

Figure 14. Female Representation by Assignment

4. Differences by Ship Type

Female representation also varies across ship types, and several series show noticeable year-to-year volatility compared to the aggregate plot (Figure 15). Some ship types track a gradual increase, while others fluctuate or exhibit short-term reversals, which is consistent with smaller ship-type denominators and the operational reality that crew composition can change with rotations and platform availability.

The next analytical step is to project this descriptive analysis forward using the Markov modeling framework which will quantify how continued aging and personnel-category imbalances affect force structure sustainability through 2040.

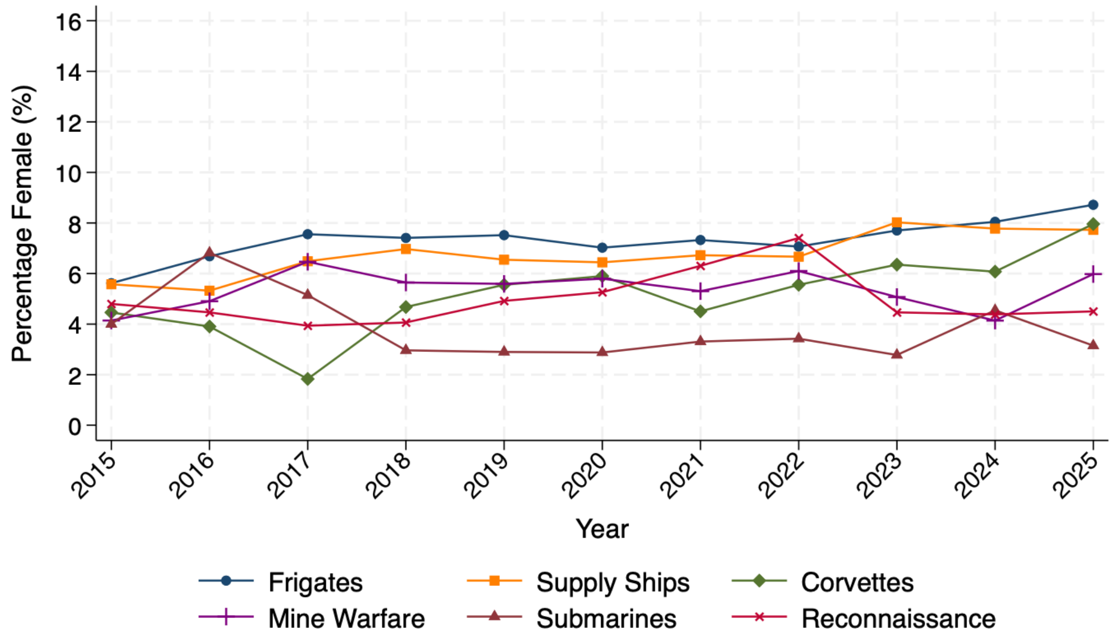

Figure 15. Female Representation by Ship Type

V. MARKOV MODEL VALIDATION

Model performance is evaluated by estimating transition parameters on one period (“training window”) and comparing resulting forecasts to observed state distributions in a different period (“holdout window”). Alternative transition matrices (e.g., 2017–2025, 2017–2021) are treated as competing parameter sets while keeping the forecasting pipeline fixed. A second axis of comparison varies the inflow specification (e.g., fixed inflows vs. observed inflows) while holding the transition matrix choice constant within each run.

A. VALIDATION TARGETS

For each holdout year, the model produces a predicted end-of-year (Q IV) stock (or normalized distribution) across states, which is compared to the observed Q IV state vector from the data. The comparison is performed at the level of the full state space (Dienstgrad × Altersklasse), consistent with the Q IV-to-Q IV time step used for estimation and forecasting.

1. Deterministic Accuracy

Two deterministic targets are reported: (i) total inventory (headcount) and (ii) average age. Deterministic accuracy is summarized via root mean square errors (RMSE) (reported as a proportion / percent error).

2. Stochastic Uncertainty Validation

In addition to point-forecast accuracy, uncertainty is assessed using Monte Carlo simulation with multiplicative noise applied to (i) transition probabilities and (ii) inflows. For each year, 80% prediction intervals are reported using the 10th and 90th percentiles (p10–p90) and evaluated via empirical coverage (whether the observed value falls inside the interval) and bias. The Monte Carlo setting used for the final comparison is ±0.3 (transitions) and ±0.3 (inflows).

B. VALIDATION RESULTS AND MODEL SELECTION

To avoid repetition, the chapter reports the full validation logic for Officers as the reference case, presents condensed model-selection summaries for Senior NCOs and Enlisted, and provides additional detail for Junior NCOs because the validation indicates structural instability that requires a separate break analysis.

1. Officers

a. Validation Results (Stage 1: deterministic screening)

Four alternative transition-matrix specifications were evaluated as competing parameter sets: pooled 2017–2025, pooled 2017–2021, 2021-only, and 2025-only. These four candidates were first compared using deterministic validation (i.e., point forecasts) on holdout years, using Q IV-to-Q IV predictions compared against observed Q IV state vectors, while keeping the forecasting pipeline fixed.

Deterministic performance was summarized using RMSE-type error metrics for total inventory and average age. Based on this deterministic screening, the 2017–2025 and 2025 matrices are retained as the two finalist specifications for further uncertainty validation.

In the deterministic backtest, 2017–2025 yields a lower age RMSE (0.27%) than 2025 (0.35%). Both models have the same RMSE (0.90%) in inventory difference (Table 3. and Table 4.).

Table 3. Stage 1: 4-Model-Ranking Officers (Inventory)

ΔInventory	2017-2025	2017-2021	2025	2021
Average	0.16%	0.13%	0.32%	0.57%
Median	0.30%	0.14%	0.48%	0.66%
Max	1.21%	2.18%	1.21%	1.31%
RMSE	0.90%	1.69%	0.90%	0.97%
Total	**2.57%**	**4.14%**	**2.9%**	**3.51%**

Table 4. Stage 1: 4-Model-Ranking Officers (Age)

ΔAge	2017-2025	2017-2021	2025	2021
Average	0.18%	0.20%	0.27%	0.84%
Median	0.22%	0.14%	0.21%	0.84%
Max	0.43%	0.41%	0.48%	1.06%
RMSE	0.27%	0.27%	0.35%	0.87%
Total	**1.10%**	**1.02%**	**1.31%**	**3.61%**

b. Validation Results (Stage 2: Monte Carlo Uncertainty Validation)

After the deterministic screening, I evaluated the two finalists under stochastic perturbations to assess whether the model produces calibrated prediction intervals (not only accurate point forecasts). Monte Carlo simulations applied multiplicative noise of ±0.3 to transition probabilities and ±0.3 to inflows, generating 80% prediction intervals using p10–p90 quantiles for both inventory and age outcomes.

Under this Monte Carlo setting, inventory coverage is 75% for both matrices across 2018–2025, while age coverage is 100% for both (Figure 16–19).

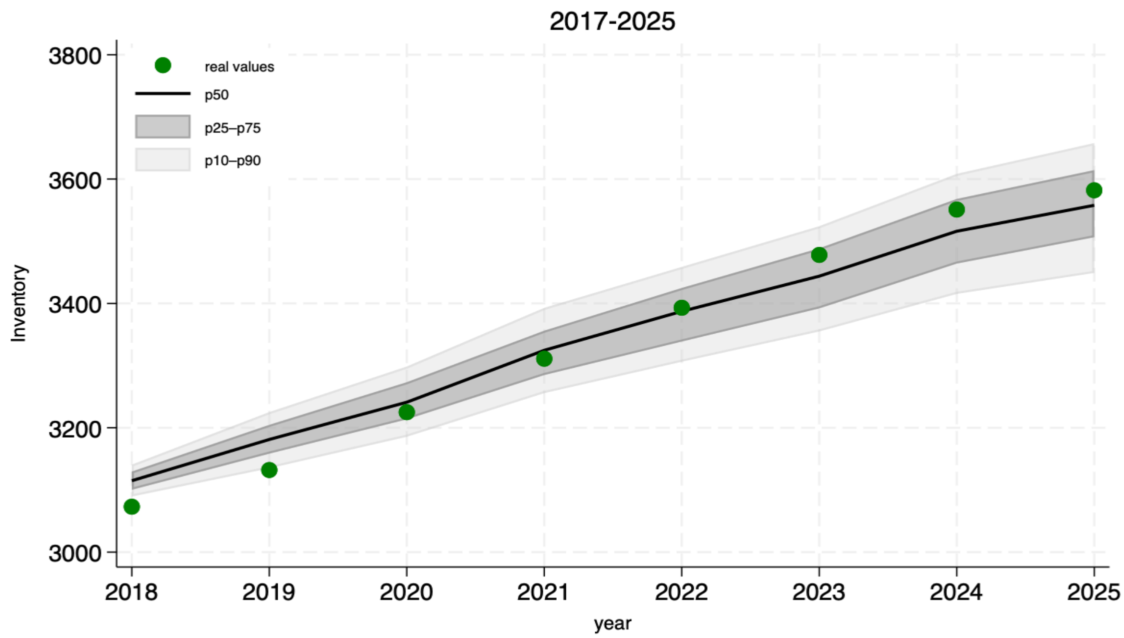

Figure 16. Officers: Monte Carlo Results 2017–2025 (Inventory)

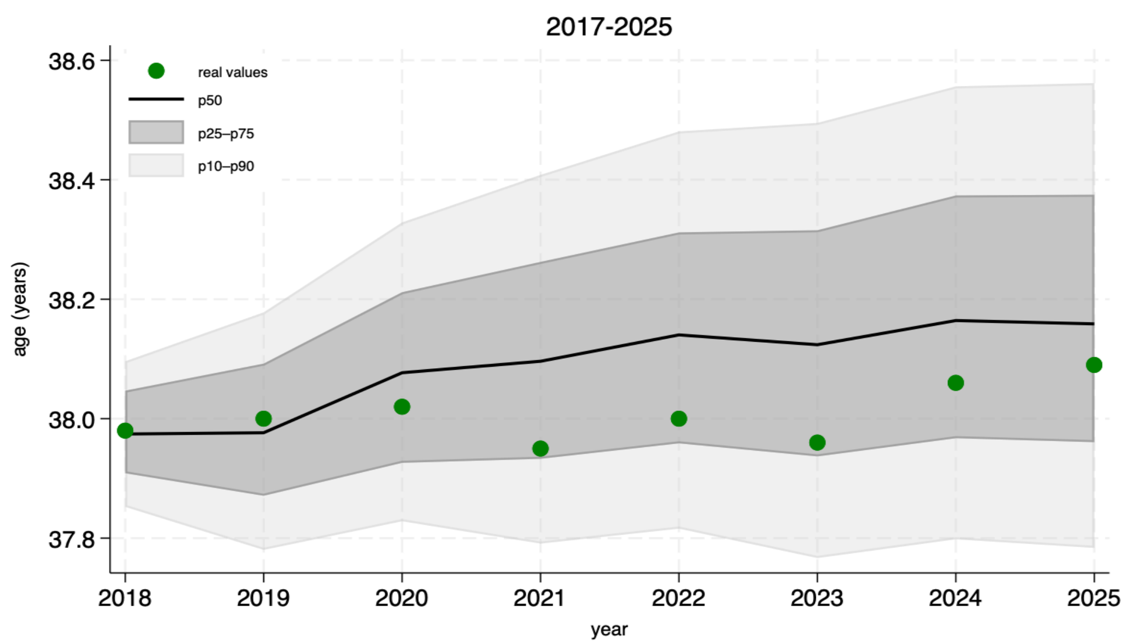

Figure 17. Officers: Monte Carlo Results 2017–2025 (Age)

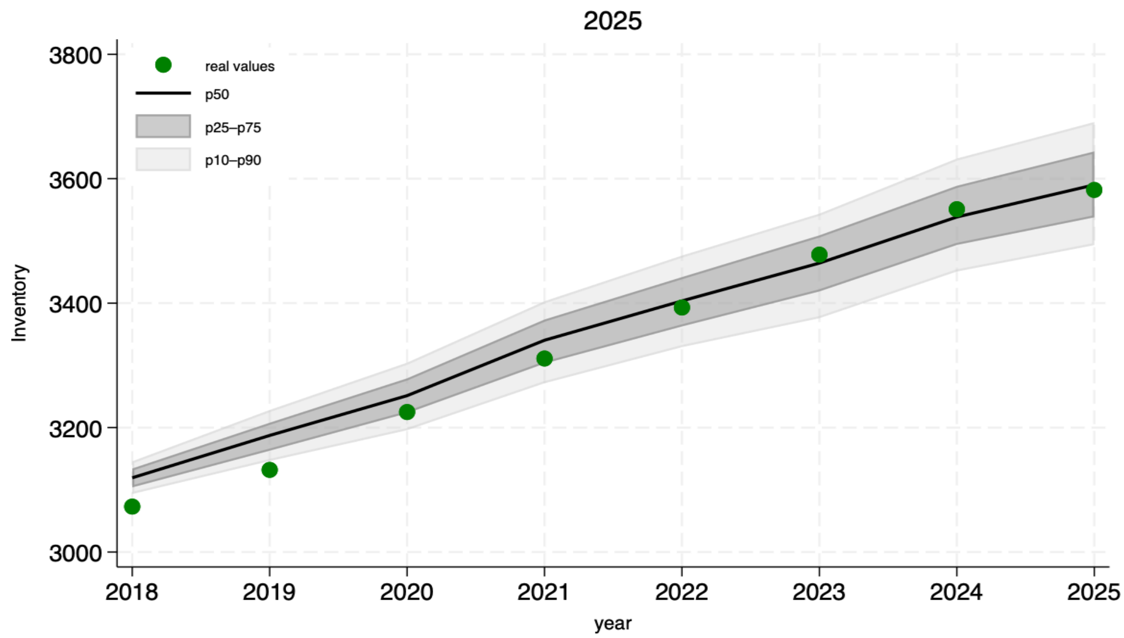

Figure 18. Officers: Monte Carlo Results 2025 (Inventory)

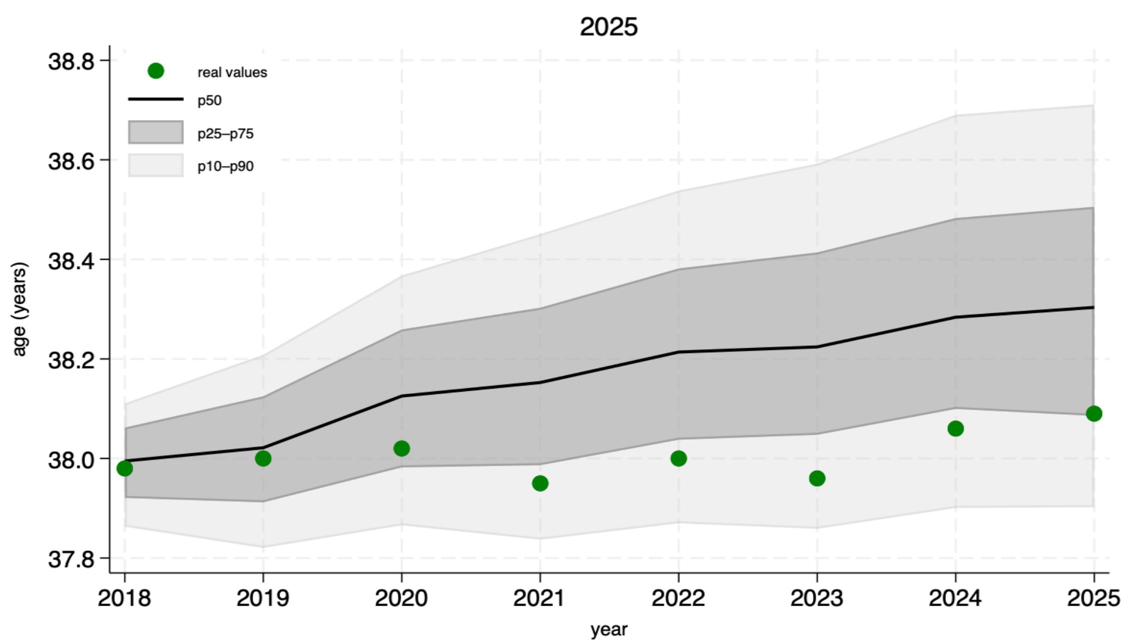

Figure 19. Officers: Monte Carlo Results 2025 (Age)

The comparative analysis of the two Markov models reveals that the pooled model (2017–2025) demonstrates marginally superior predictive accuracy across multiple metrics. While both models achieve 75% coverage for inventory and 100% for age predictions within the 80% confidence interval (p10–p90), the pooled model exhibits systematically lower forecast errors.

The mean absolute percentage error (MAPE) for inventory projections is substantially lower in the pooled model, ranging from 18% (2018) to 23% (2025), compared to 26% and 38% in the single-year model. Similarly, RMSE are consistently 30–50% smaller in the pooled specification. The single-year model (2025) systematically overestimates average age by 0.20–0.27 years in the late period (2022–2025), while the pooled model maintains age bias below 0.17 years throughout the forecast horizon.

c. *Model Selection Decision*

The given results suggest that aggregating transition probabilities across multiple years (2017–2025) better captures the underlying personnel dynamics by smoothing year-specific volatility and providing more robust parameter estimates.

The pooled model's superior performance is particularly evident in the MAPE metric, where it outperforms the single-year specification by 5–15 percentage points across all forecast years, indicating more reliable predictions for long-term workforce planning purposes.

2. Senior NCO

Following deterministic screening and Monte Carlo uncertainty validation, the 2017–2025 model is selected as the baseline specification for Senior NCO forecasting and scenario analysis. Across the 2018–2025 validation period, it achieves the best overall performance under parametric uncertainty, with the lowest RMSE (48.60) and MAPE (26.89%) among the competing specifications (Figure 20 and 21). The results for the alternative model specifications are reported in the appendix.

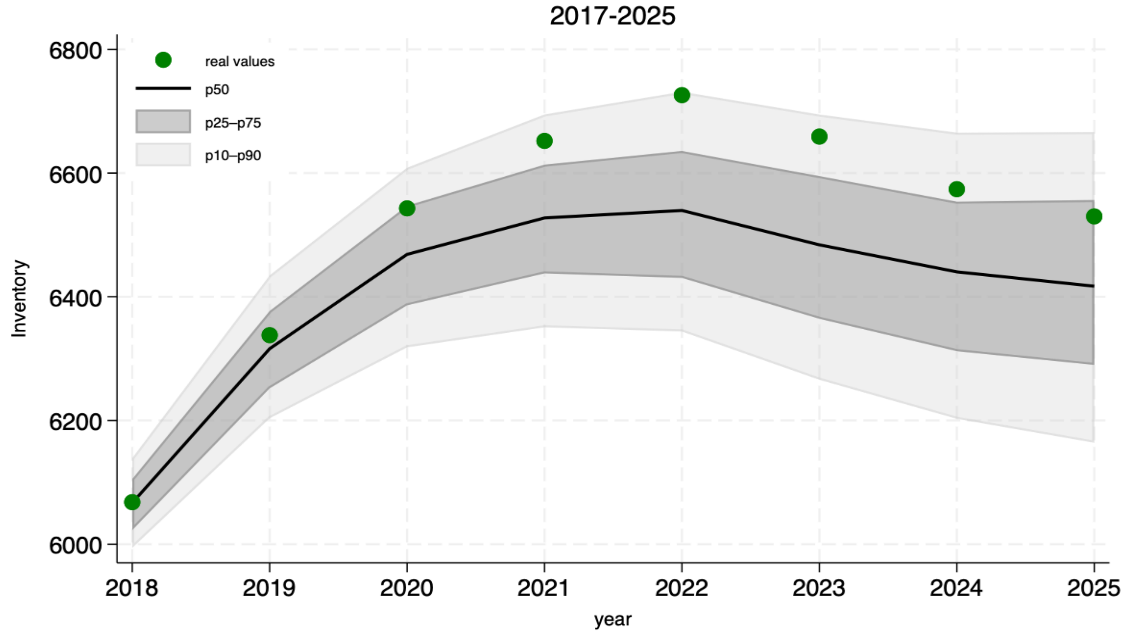

Figure 20. Senior NCOs: Monte Carlo Results 2017–2025 (Inventory)

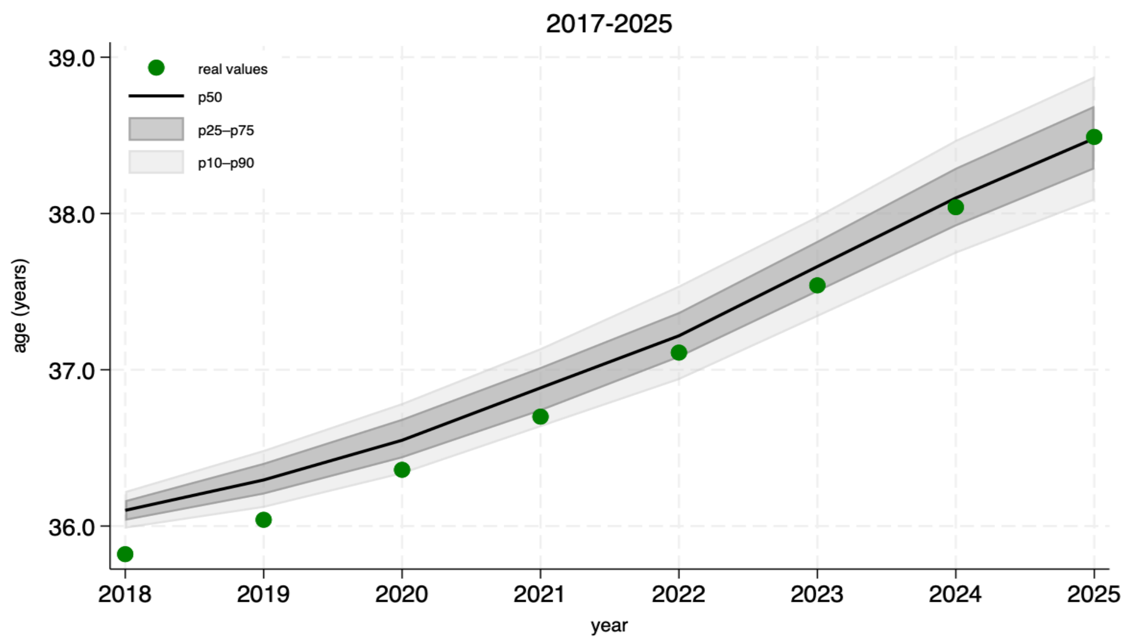

Figure 21. Senior NCOs: Monte Carlo Results 2017–2025 (Age)

3. Junior NCO

a. Validation results (Stage 1: deterministic screening)

Based on this deterministic screening, the 2017–2025 and 2017–2021 matrices are retained as the two finalist specifications for further uncertainty validation.

In the deterministic backtest, 2017–2021 yields a lower age RMSE (0.57%) than pooled 2017–2025 (0.85%). Conversely, 2017–2025 yields lower inventory RMSE (2.36%) than pooled 2017–2021 (2.56%).

Despite the 2021 single-year model achieving the lowest inventory forecast errors (RMSE 1.73%, Total Error 7.49%), it was excluded from further analysis due to its substantially weaker age prediction performance (RMSE 1.67%, Total Error 6.48%), which is nearly double the total error of the 2017–2025 model and almost triple that of the 2017–2021 model indicating that optimizing for inventory accuracy alone comes at the cost of failing to capture the critical aging dynamics of the workforce (Table 5 and 6).

Table 5. Stage 1: 4-Model-Ranking Junior NCOs (Inventory)

ΔInventory	2017-2025	2017-2021	2025	2021
Average	1.85%	2.01%	3.07%	1.18%
Median	1.61%	1.91%	2.81%	1.42%
Max	3.97%	4.24%	6.19%	3.16%
RMSE	2.36%	2.56%	3.91%	1.73%
Total	**9.79%**	**10.72%**	**15.98%**	**7.49%**

Table 6. Stage 1: 4-Model-Ranking Junior NCOs (Age)

ΔAge	(2017-2025)	(2017-2021)	(2025)	(2021)
Average	0.69%	0.47%	2.40%	1.47%
Median	0.56%	0.57%	2.58%	1.50%
Max	1.13%	0.73%	2.75%	1.84%
RMSE	0.85%	0.57%	2.73%	1.67%
Total	**3.23%**	**2.34%**	**10.46%**	**6.48%**

b. *Validation results (Stage 2: Monte Carlo uncertainty validation)*

Under the same Monte Carlo setting that is used for all career tracks, inventory coverage is 0% for both pooled matrices across 2018–2025 (Figure 22–25). Despite similar coverage, the pooled 2017–2025 matrix shows lower Monte Carlo bias than the 2017–2021 for both inventory and age across the evaluation years. Most importantly, in the late period (2022–2025), pooled 2017–2025 achieves 75% age-in-interval, while 2017–2021 achieves 0%.

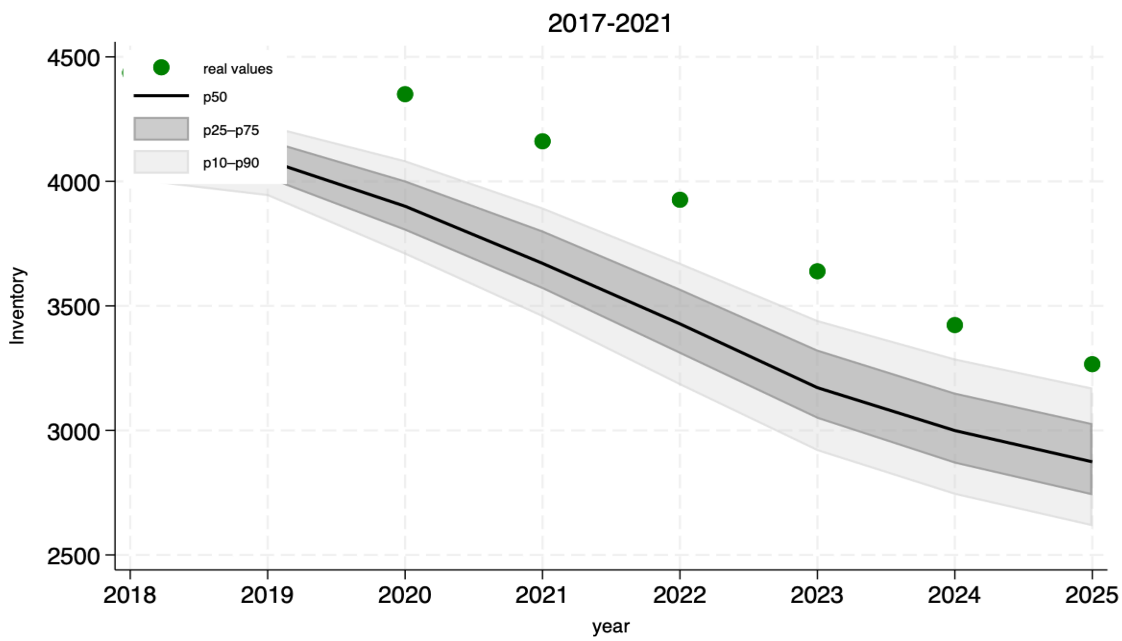

Figure 22. Junior NCOs: Monte Carlo Results 2017–2021 (Inventory)

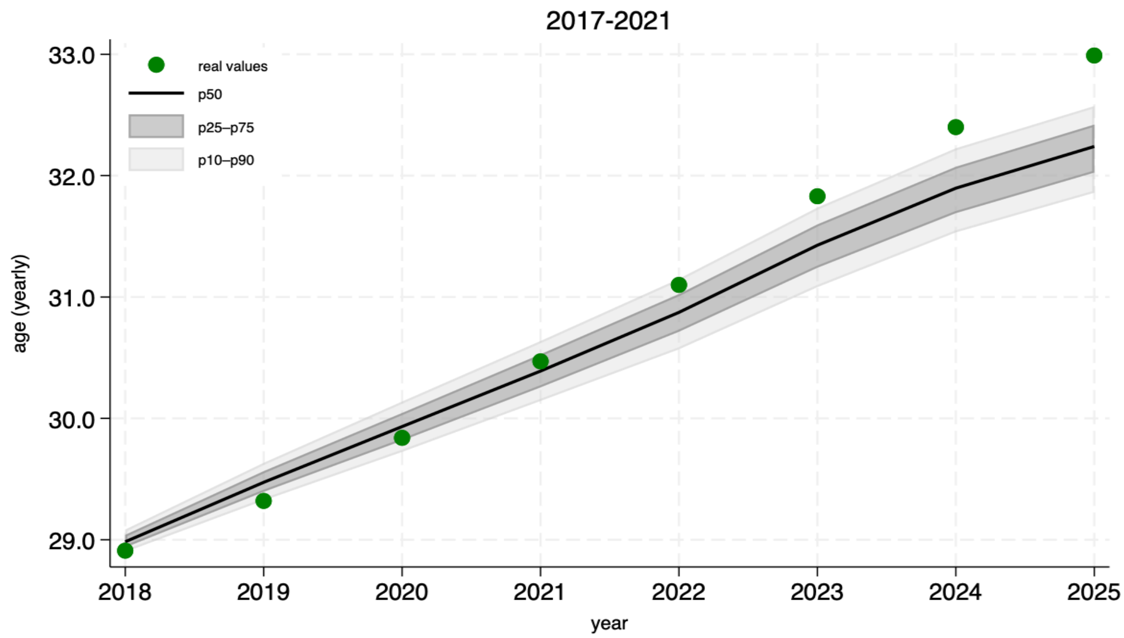

Figure 23. Junior NCOs: Monte Carlo Results 2017–2021 (Age)

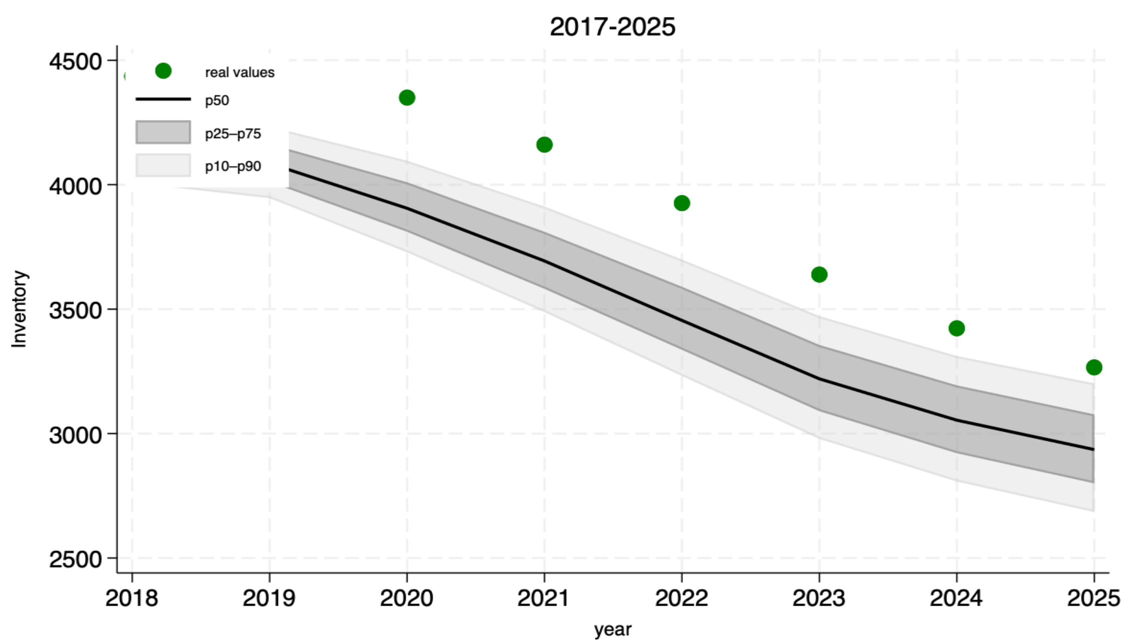

Figure 24. Junior NCOs: Monte Carlo Results 2017–2025 (Inventory)

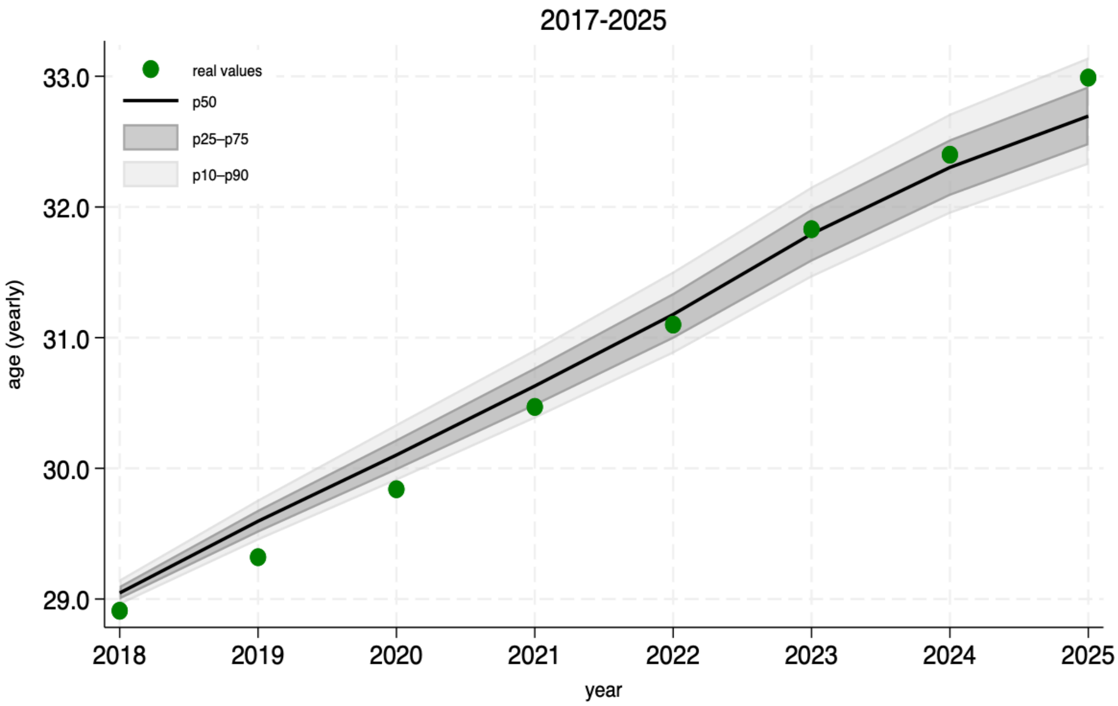

Figure 25. Junior NCOs: Monte Carlo Results 2017–2025 (Age)

c. *Validation results (Stage 3: Structural Break Check)*

The Stage 3 validation shows that the quarterly Junior NCO stock series is characterized by two structural breaks (Figure 26), so treating the full observation window as one stable personnel-development process is not supported. Using the aggregated quarterly stock series, we apply an unknown break-date structural break test that evaluates parameter stability over all admissible candidate breakpoints (with trimming) and reports the supremum Wald statistic as the maximum evidence against stability across those candidates (Andrews, 1993). The first test identifies a break at 2021 QI (Supremum Wald = 493.08, $p < 0.001$). Repeating the test within the post-2021 period reveals a second break at 2023 QIV (Supremum Wald = 16.70, $p = 0.0053$), which is corroborated when excluding 2021 and re-testing 2022–2025 (Supremum Wald = 22.91, $p = 0.0003$).

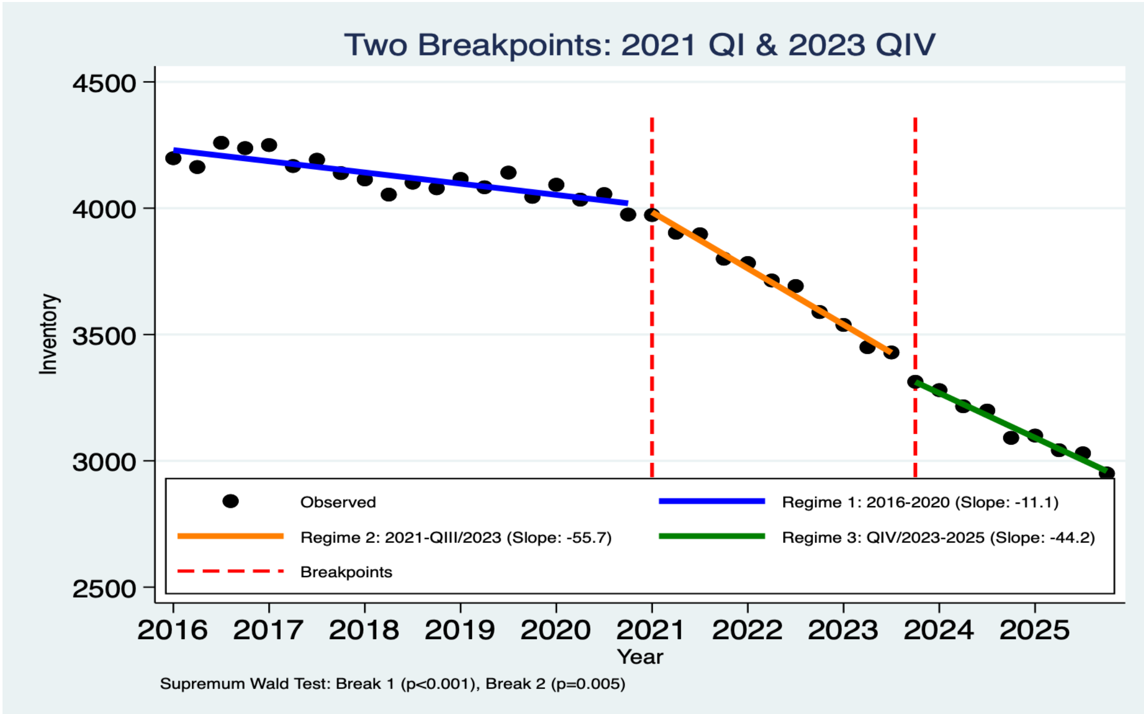

Figure 26. Junior NCO Break Check Visualization

d. *Model selection decision*

Given the Stage 3 structural break results, we do not pool all years into one transition model because the assumption of a single stable personnel-development process over the full observation window is rejected. Specifically, the quarterly Junior NCO stock series exhibits two statistically significant breaks (2021 QI and 2023 QIV), implying that model parameters differ across regimes.

Based on the comparative analysis, Model B (2023-2025) is selected as the baseline model for forecasting Junior NCO personnel dynamics for the following reasons:

- The 2023–2025 model captures the complete post-break period, incorporating three years of data under the new structural regime, compared to only two years for the 2024–2025 model.

- The Model demonstrates consistently lower error metrics across all evaluation criteria, suggesting greater statistical stability and predictive validity.
- A three-year estimation window provides better balance between capturing recent dynamics and maintaining sufficient sample size for reliable parameter estimation.
- For projections beyond 2025, a model trained on 2023–2025 data is more representative of the post-break equilibrium than one trained on only 2024–2025.

4. Enlisted

Following deterministic screening and Monte Carlo uncertainty validation, the 2024–2025 model is selected as the baseline specification for Enlisted forecasting and scenario analysis. Among the competing specifications, it shows the strongest overall predictive performance, with the lowest inventory RMSE (1.14%), the lowest age RMSE (0.17%), and the best combined error score (0.85%) in Stage 1 screening. The selected model also performs best under stochastic validation, achieving the lowest average RMSE and the smallest average absolute inventory bias across the 2022–2025 test period (Figure 27 and 28). Results for the alternative model specifications are reported in the appendix.

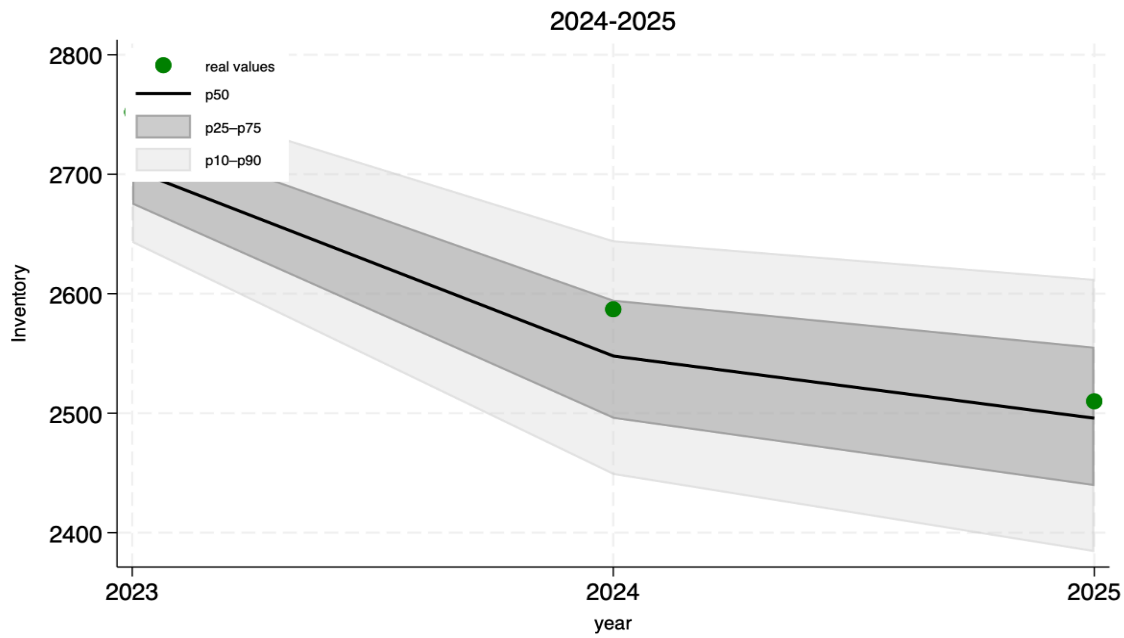

Figure 27. Enlisted: Monte Carlo Results 2024–2025 (Inventory)

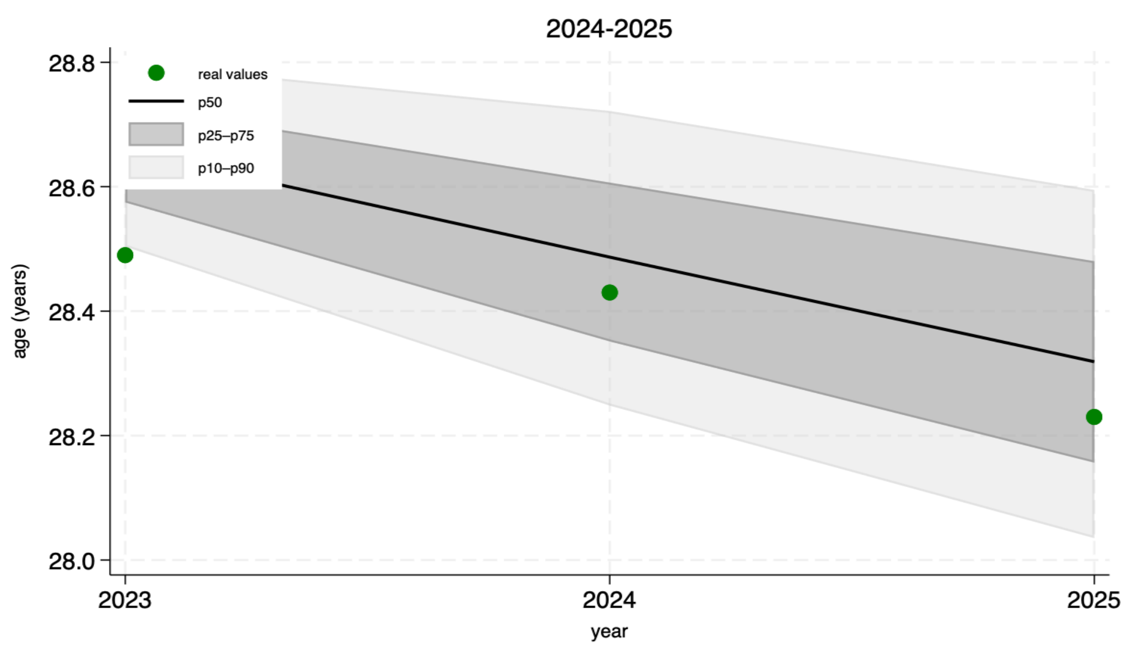

Figure 28. Enlisted: Monte Carlo Results 2024–2025 (Age)

VI. RESULTS

A. OVERVIEW

This chapter presents the results for the selected career tracks using the best Markov models selected in the previous chapter. For each career track, the analysis forecasts both inventory (headcount) and average age under two model setups: a historical setup calibrated on 2017 data and projected through 2035, and a current setup calibrated on 2025 data to reflect the most recent personnel dynamics till 2040.

Both setups use the observed inflows through 2025 as the baseline input and then apply a constant steady-inflow assumption from 2025 onward. Building on this baseline, the chapter evaluates three policy scenarios for each career track to quantify how alternative recruiting assumptions change future inventory and average age.

B. SCENARIO DEFINITIONS

The following scenarios are fictional, stylized inflow assumptions used to test how sensitive the Markov projections are to different accession paths; they are not forecasts of what will happen and not proposals that such targets can be operationally achieved. In particular, the model treats scenario inflows as externally imposed inputs (via the inflow vectors) and does not endogenously enforce recruiting and training capacity limits, qualification bottlenecks, or cohort-size constraints; therefore, feasibility can differ substantially by career track.

The scenarios are also not intended to be equally realistic. The Boost and Increase cases serve primarily as upper-bound sensitivity tests that illustrate how strongly projected inventory and mean age would respond if recruiting conditions improved abruptly or persistently. By contrast, the Degressive Increase case is the most policy-relevant intervention scenario because it assumes that recruiting improves, but that these gains taper over time rather than continuing to accelerate indefinitely. This framing is more consistent with the broader demographic constraints discussed in this thesis and with the recent inflow patterns observed in the data, where recovery appears possible but not unconstrained.

- Scenario 1 (Boost): The model applies a one-time recruiting boost in 2029 by adding 1,000 additional entrants to the respective career track.
- Scenario 2 (Increase): The model increases annual inflows by 10% per year starting in 2029 to represent sustained recruiting improvements.
- Scenario 3 (Degressive increase): Where feasible, the model applies a degressive (tapering) inflow increase, motivated by patterns observed in the 2023–2025 data.

C. OFFICERS

1. Baseline Model Fit (2017–2025)

Figure 29 compares observed ("Real") outcomes with the baseline Markov specification over 2017–2025 for inventory and Figure 30 for mean age. Over this period, the baseline inventory series stays close to observed values, with a mean absolute deviation of about 29.89 personnel and a maximum absolute deviation of 72 personnel. In relative terms, the average inventory percentage error is about 0.185%, and the maximum absolute percentage error is about 2.345%.

For mean age, the baseline series also aligns closely with observations, with a mean absolute deviation of about 0.136 years and a maximum absolute deviation of 0.22 years. These results indicate that the baseline specification reproduces the historical joint behavior of headcount and age with small errors at the annual resolution used in this thesis.

2. Baseline Projection (2026–2035)

Using the 2017 state as the projection start, the baseline model projects inventory to increase gradually from 3596 in 2026 to 3862 by 2035. Over the same horizon, the baseline mean age rises slowly from about 38.26 in 2026 to about 38.57 by 2035.

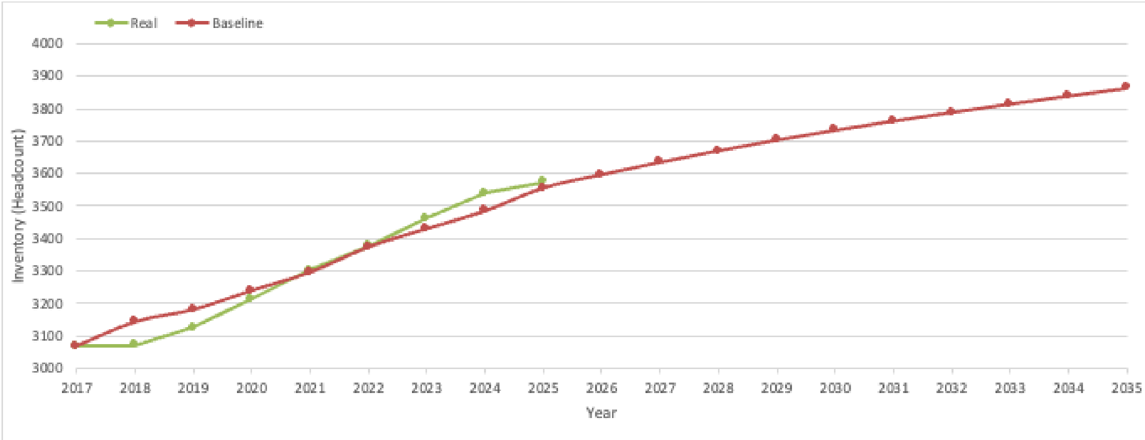

Figure 29. Officers Inventory: Baseline vs. Real (Data 2017)

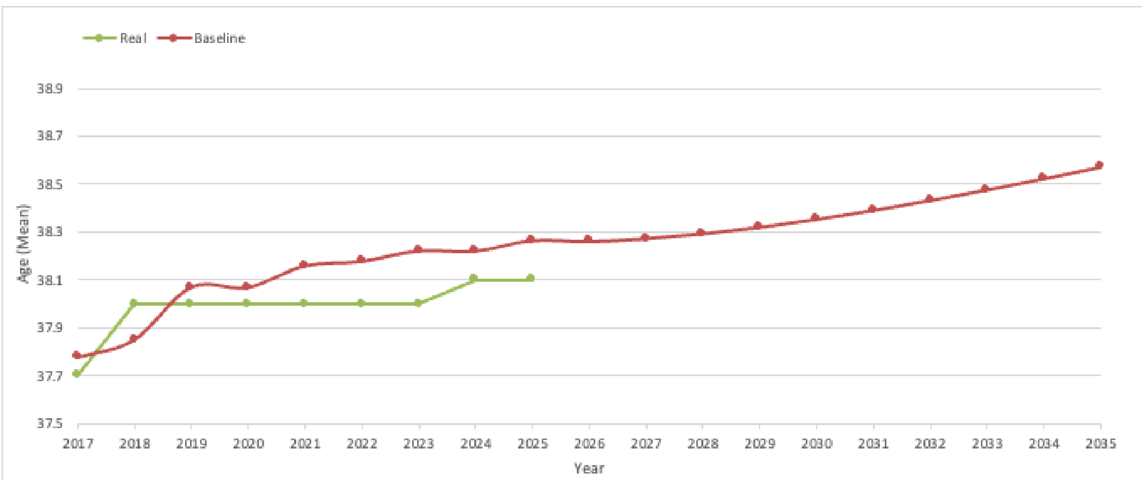

Figure 30. Officers Age: Baseline vs. Real (Data 2017)

3. Scenario Results (2025 Start, through 2040)

Figures 31 and 32 report the baseline projection and three recruiting scenarios, all initialized in 2025 and projected forward with the same Markov transition structure. The degressive recruiting scenario applies a tapered growth rule to inflows: the model updates next-period inflows using a combination of a 10% increase with a 5% degression factor.

a. Inventory Effects

Relative to baseline, all three scenarios increase projected inventory by 2040. The "Increase" scenario produces the largest 2035 inventory, reaching 5770 compared with

3983 in the baseline (+44.87%), while the Degressive scenario reaches 5292 (+32.87%). and the Boost scenario reaches 4580 (+15%).

b. *Mean-Age Effects*

All three scenarios reduce mean age relative to the baseline by 2040, where baseline mean age reaches 38.84 years. The highest reduction delivers the increase policies by 9,18% and degressively by 5.31%. The Boost scenario produces an immediate drop in mean age beginning in 2029 (35.58 vs. 38.19 baseline), reflecting the influx of younger accessions and ends in 2040 with a 1.2% decrease.

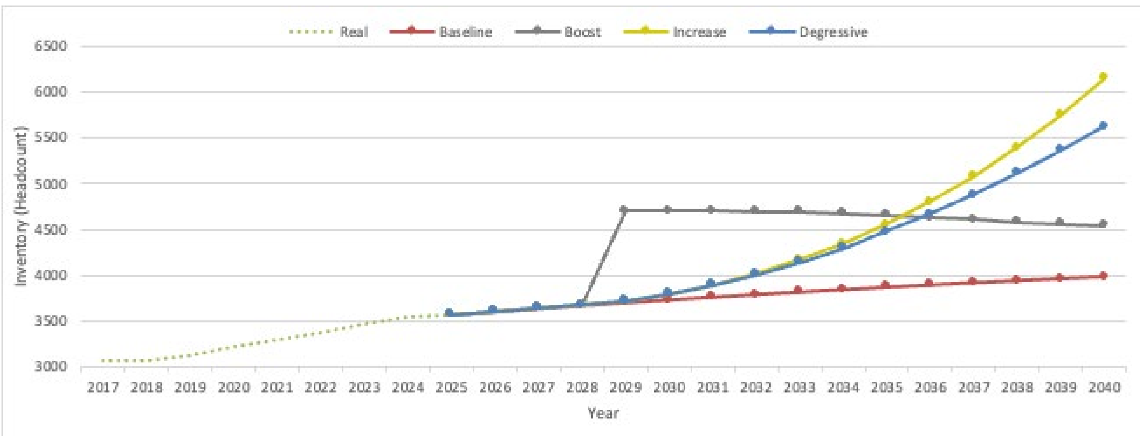

Figure 31. Officers Inventory 2025–2040 (Data 2025)

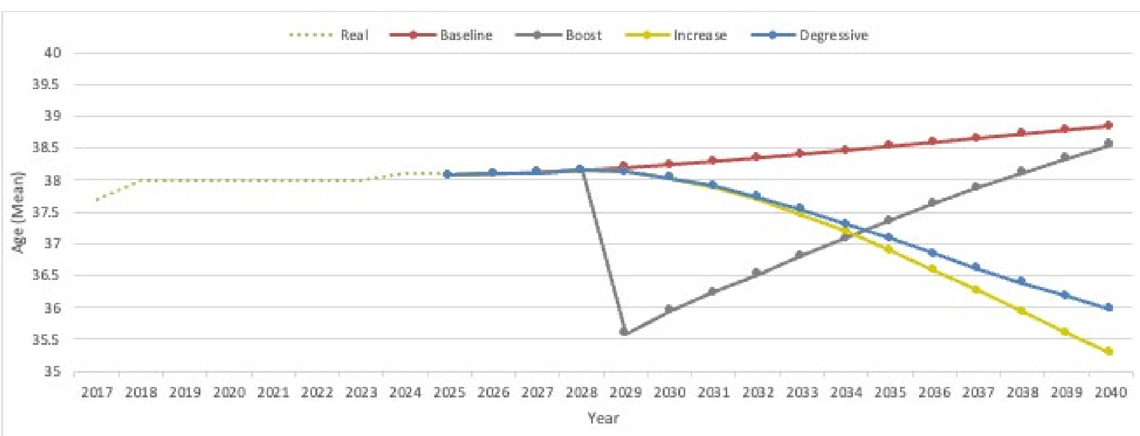

Figure 32. Officers Age 2025–2040 (Data 2025)

4. Forecast Uncertainty

The Officer inventory model delivers remarkably precise projections in the near term. Starting from a baseline of 3,620 personnel in 2026, the forecast exhibits exceptional confidence, with a coefficient of variation of merely 0.24% and an absolute spread between the 10th and 90th percentiles of just 23 personnel (Figure 33 and Table 7). This narrow band reflects the model's strength in capturing structured career progression patterns typical of officer cohorts, where promotion timelines and retention rates follow established institutional pathways.

However, uncertainty accumulates significantly as the projection horizon extends. By 2040, when mean inventory reaches 4,129 personnel, the p10-p90 spread widens to 251 personnel—nearly an elevenfold increase from the initial period. The coefficient of variation rises to 2.29%, while relative spread expands from 0.64% to 6.08%. This growing dispersion signals a key limitation: the model's ability to capture long-term behavioral shifts diminishes with time, as compounding uncertainties in promotion decisions, career exits, and policy changes propagate through the forecast.

The model performs particularly well in maintaining low relative uncertainty despite inventory growth. The central 80% interval by 2040 spans from 4,002 to 4,253 personnel around the mean projection of 4,129. This suggests the model effectively tracks aggregate trends even when individual-level variability increases. The monotonic growth in both inventory and uncertainty bands indicates stable underlying assumptions, though the accelerating relative spread reveals that forecast precision deteriorates faster than the population expands—a characteristic weakness when projecting beyond a decade.

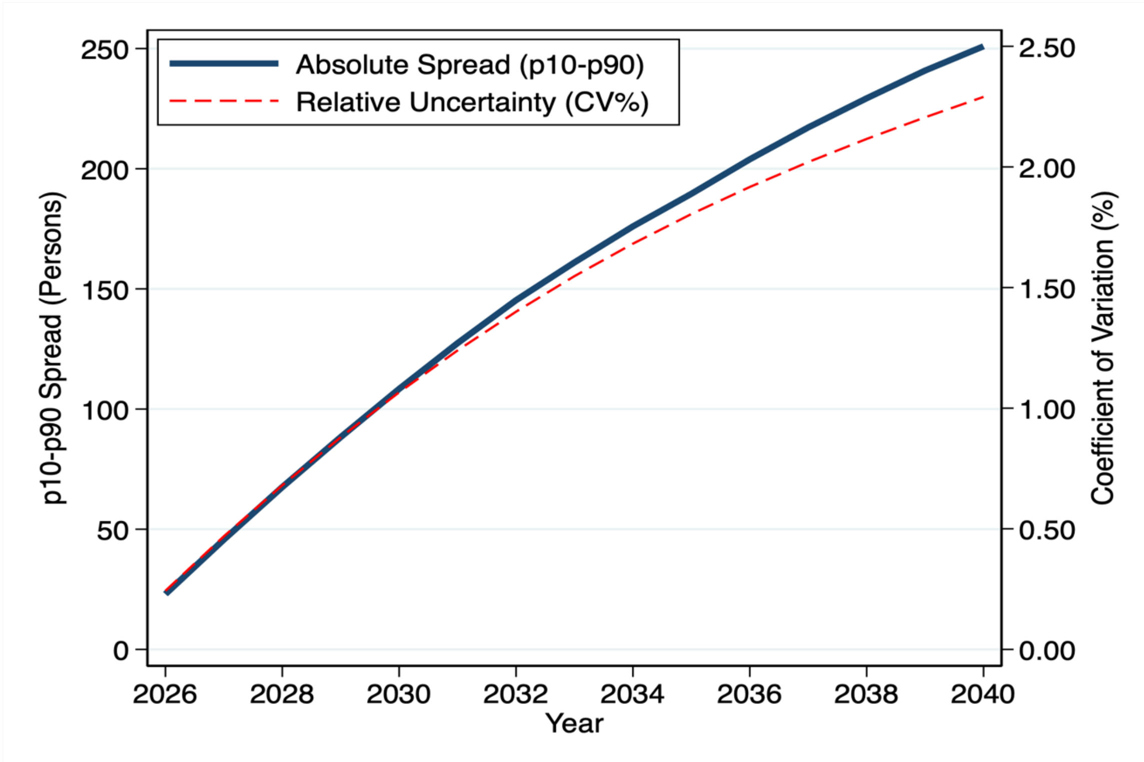

Figure 33. Officers: Uncertainty Growth over Forecast Horizon

Table 7. Officers: Inventory Uncertainty Table

Year	Mean Inventory	Standard Deviation	10th Percentile	25th Percentile	Median (50th)	75th Percentile	90th Percentile	p10-p90 Spread	CV(%)	Relative Spread (%)
2026	3620	8.79	3608	3613	3620	3627	3631	23.01	0.24	0.64
2027	3667	17.19	3643	3653	3667	3681	3689	45.69	0.47	1.25
2028	3712	25.26	3677	3691	3712	3732	3744	67.56	0.68	1.82
2029	3755	33.02	3710	3728	3755	3781	3798	88.34	0.88	2.35
2030	3796	40.46	3741	3763	3796	3829	3849	108.41	1.07	2.86
2031	3836	47.55	3770	3797	3836	3874	3898	127.44	1.24	3.32
2032	3874	54.24	3800	3829	3874	3917	3945	145.30	1.40	3.75
2033	3911	60.51	3829	3860	3911	3959	3990	161.03	1.55	4.12
2034	3946	66.36	3856	3890	3946	3999	4032	176.01	1.68	4.46
2035	3980	71.81	3883	3919	3980	4036	4073	189.58	1.80	4.76
2036	4012	76.91	3909	3947	4013	4073	4113	203.93	1.92	5.08
2037	4043	81.68	3934	3974	4044	4108	4151	217.18	2.02	5.37
2038	4073	86.19	3957	4000	4073	4141	4187	229.33	2.12	5.63
2039	4102	90.46	3980	4025	4101	4174	4221	240.86	2.21	5.87
2040	4129	94.56	4002	4049	4128	4205	4253	250.95	2.29	6.08

D. SENIOR NCOS

1. Baseline Model Fit (2017–2025)

For inventory, the baseline series tracks observed values closely but shows a mild negative bias in the later years. Across 2017–2025, the mean absolute inventory deviation is about 88 personnel, with a maximum absolute deviation of 184 personnel. The average inventory percentage error is about −1.30%, with a maximum absolute percentage error of about 2.74%.

For mean age, the baseline model aligns closely with observed outcomes across the full 2017–2025 window. The mean absolute age deviation is about 0.15 years, and the maximum deviation is 0.25 years. In 2025 specifically, the baseline underestimates inventory by 101 personnel and underestimates mean age by 0.04 years relative to the observed values.

2. Baseline Projection (2026–2035)

Starting from the 2025 level, the baseline inventory projection remains approximately stable in the low-6400 range through 2035. Over the same horizon, baseline mean age increases steadily from 38.91 (2026) to 40.83 (2035) (Figure 34 and 35).

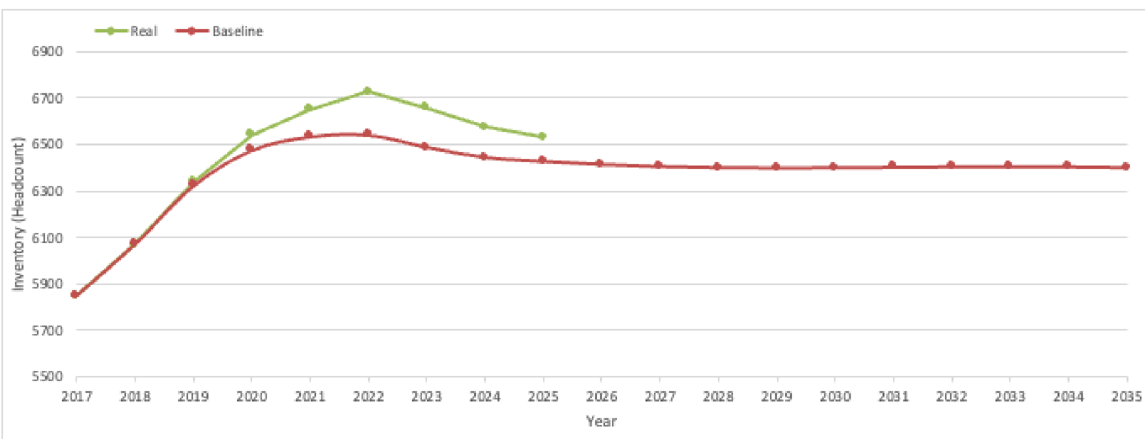

Figure 34. Senior NCO Inventory: Baseline vs. Real (Data 2017)

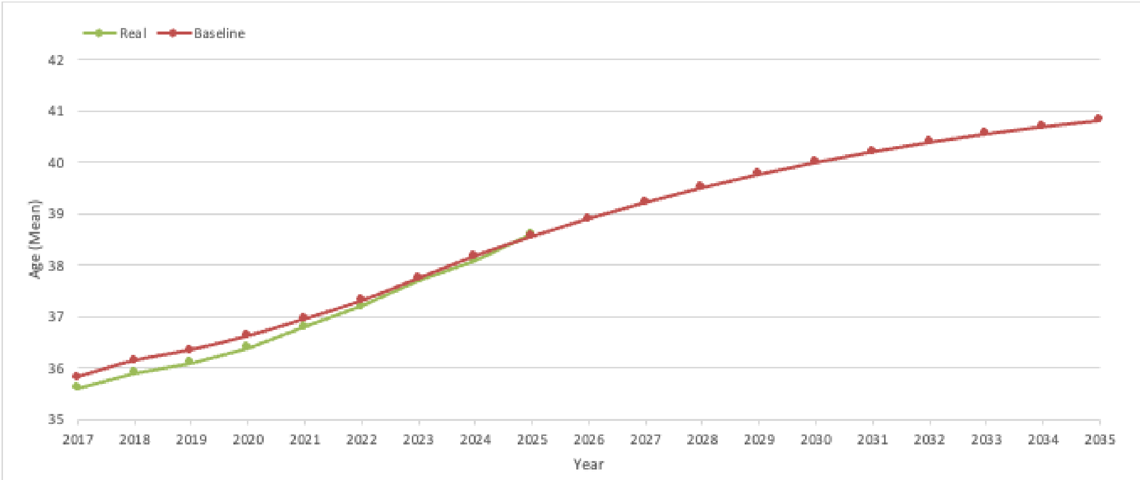

Figure 35. Senior NCO Age: Baseline vs. Real (Data 2017)

3. Scenario Results (2025 Start, through 2040)

Figures 36 and 37 report the baseline projection and three recruiting scenarios, all initialized in 2025 and projected forward with the same Markov transition structure. The degressive recruiting scenario applies a tapered growth rule to inflows: the model updates next-period inflows using a combination of a 10% increase with a 5% degression factor.

a. Inventory Effects (headcount)

All scenarios are initialized at 6,530 in 2025 and remain identical through 2029 (inventory 6,471). From 2030 onward, inventories diverge, with the Boost case producing the largest headcount (e.g., 7,472 in 2030 versus 6,472 baseline). By 2040, baseline inventory reaches 6,975, while Boost reaches 9,621 and Degressive reaches 8,468; relative to baseline in 2040, Boost is +2,646 (+37.93%) and Degressive is +1,493 (+21.41%).

b. Mean-Age Effects

Mean age is aligned across scenarios through 2029 (mean age 39.75 in 2029). Starting in 2030, Boost reduces mean age immediately (38.88 in 2030 versus 39.99 baseline), consistent with an influx of younger accessions. By 2040, baseline mean age reaches 41.28 years, while Boost reduces mean age to 38.94 (−2.34 years; −5.67%) and Degressive reduces mean age to 39.63 (−1.65 years; −3.99%) relative to baseline.

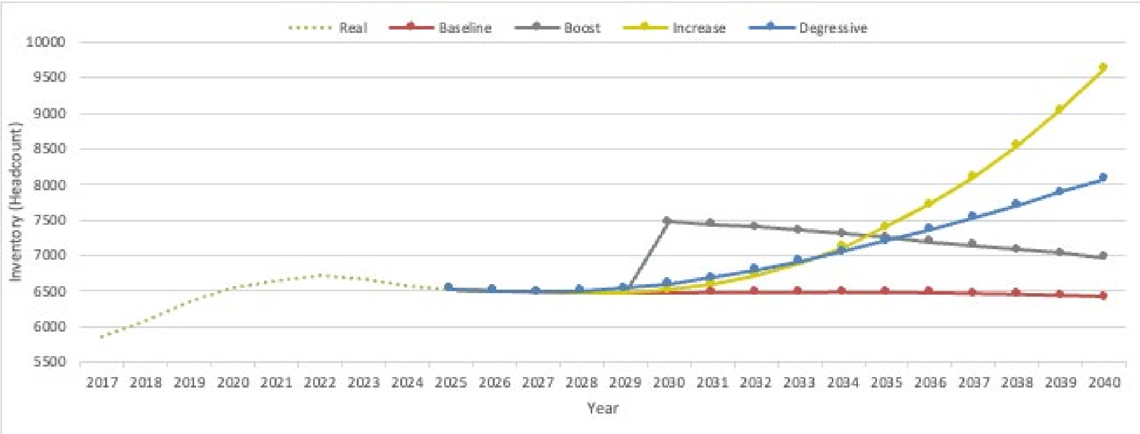

Figure 36. Senior NCO Inventory 2025–2040 (Data 2025)

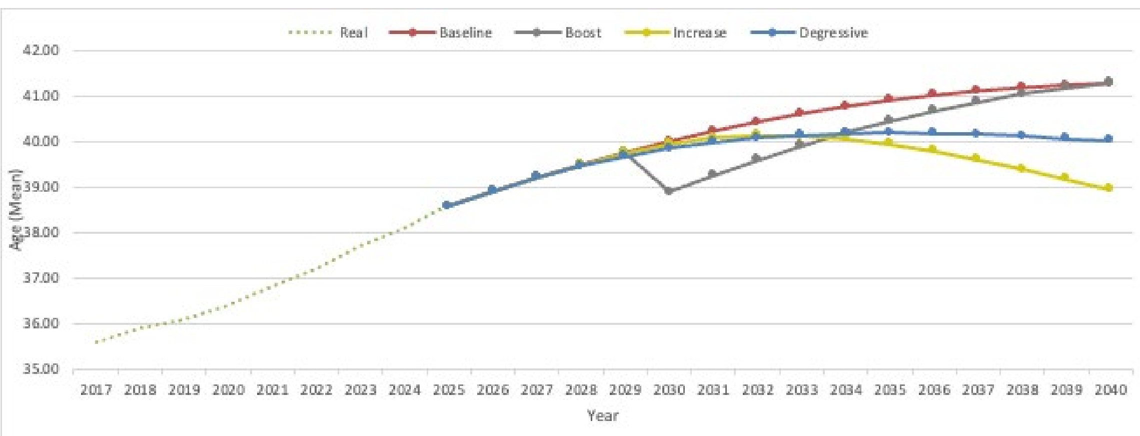

Figure 37. Senior NCO Age 2025–2040 (Data 2025)

4. Forecast Uncertainty

Across the 2026–2040 projection window, forecast uncertainty for Senior NCOs inventory rises monotonically, visible in both the table and the uncertainty-growth figure through a steadily widening 10th–90th percentile band. The absolute p10–p90 spread increases from 86 personnel in 2026 to 748 personnel in 2040, while the mean inventory remains relatively stable, declining slightly from 6508 to 6485 over the same period.

This decoupling of growing uncertainty from stable inventory levels fundamentally shapes model behavior: In relative terms, the "Relative Spread (%)" grows from 1.33% (2026) to 11.54% (2040), indicating that dispersion grows substantially as the horizon extends despite the stable inventory level. Consistently, the reported coefficient of variation increases from 0.51% in 2026 to 4.45% in 2040. By 2040, the central 80% interval spans from 6114 (p10) to 6862 (p90), i.e., a width of about 748 personnel around a mean of 6485, underscoring materially larger uncertainty in the late-horizon forecasts.

a. Strengths of the Senior NCO Model

The Senior NCO forecast exhibits several robust characteristics (Figure 38 and Table 8). In the near term, the model demonstrates excellent precision: with a coefficient of variation of 0.51% in 2026, initial uncertainty falls within the optimal range for operational personnel planning. The structurally stable inventory trajectory additionally provides planning certainty for core functions within this personnel segment—unlike growing or declining cohorts, the nearly constant size enables robust resource allocation across the entire time horizon.

For medium-term planning horizons (through 2032), the model remains highly reliable: the coefficient of variation of 2.58% and relative spread of 6.72% position well within established standards for military personnel models. This quality enables well-founded strategic decisions for career management and succession planning over a 6–8-year horizon.

b. Limitations and Challenges

The central weakness lies in disproportionate uncertainty growth at long horizons. While inventory itself remains stable, the confidence interval expands nearly linearly: from 2035 onward, relative spread exceeds 8.80%, surpassing 10% after 2038. This pattern signals that underlying transition probabilities exhibit higher intrinsic volatility than other personnel segments—likely driven by complex interactions of aging effects, retention dynamics, and heterogeneous career paths within the Senior NCO cohort.

The absolute uncertainty width of 748 personnel in 2040 corresponds to approximately 11.5% of mean inventory and marks the boundary of methodological reliability for long-range strategic planning. Planning decisions with horizons exceeding 12 years should explicitly account for this limitation and be supplemented by scenario-based approaches.

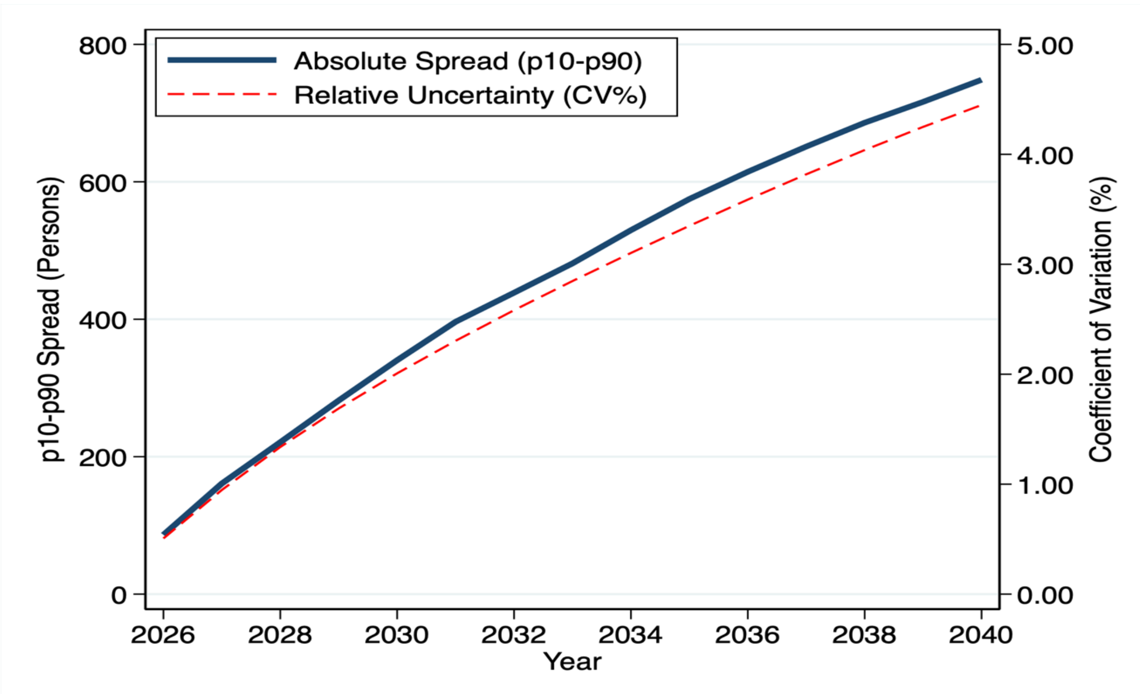

Figure 38. Senior NCO: Uncertainty Growth over Time

Table 8. Senior NCO: Inventory Uncertainty Table

Year	Mean Inventory	Standard Deviation	10th Percentile	25th Percentile	Median (50th)	75th Percentile	90th Percentile	p10-p90 Spread	CV (%)	Relative Spread (%)
2026	6508	32.98	6465	6486	6507	6531	6552	86	0.51	1.33
2027	6496	61.56	6415	6455	6496	6539	6576	161	0.95	2.48
2028	6492	86.89	6383	6434	6492	6554	6604	221	1.34	3.40
2029	6496	109.72	6354	6426	6495	6571	6636	282	1.69	4.34
2030	6504	130.63	6334	6418	6507	6591	6674	340	2.01	5.23
2031	6514	150.09	6315	6416	6517	6613	6711	396	2.30	6.08
2032	6524	168.46	6306	6414	6527	6637	6744	439	2.58	6.72
2033	6531	185.98	6290	6409	6532	6654	6771	481	2.85	7.37
2034	6536	202.79	6268	6401	6537	6669	6798	530	3.10	8.10
2035	6537	218.94	6246	6385	6538	6682	6821	575	3.35	8.80
2036	6533	234.42	6224	6371	6535	6688	6839	615	3.59	9.41
2037	6526	249.18	6200	6355	6528	6688	6852	651	3.82	9.98
2038	6515	263.15	6175	6337	6516	6689	6861	686	4.04	10.53
2039	6501	276.27	6146	6313	6500	6685	6862	716	4.25	11.02
2040	6485	288.48	6114	6286	6484	6679	6862	748	4.45	11.54

E. JUNIOR NCOS

1. Baseline Model Fit (2017–2025)

For inventory, the baseline series follows the observed downward trend from 2017 to 2025, but it is consistently lower than the observed headcount after 2017 (e.g., 2018: 4,052 baseline vs. 4,079 observed; 2025: 2,889 baseline vs. 2,950 observed) (Figure 39).

For mean age, the baseline series is consistently higher than the observed mean age across 2018–2025 (e.g., 2018: 28.44 baseline vs. 28.2 observed; 2025: 33.00 baseline vs. 32.7 observed) (Figure 40).

2. Baseline Projection (2026–2035)

Starting from the 2025 baseline level (inventory 2,889; mean age 33.00), the baseline projection shows a continued decline in inventory through 2035, reaching 2,590. Over the same horizon, baseline mean age increases from 33.38 (2026) to 35.14 (2035).

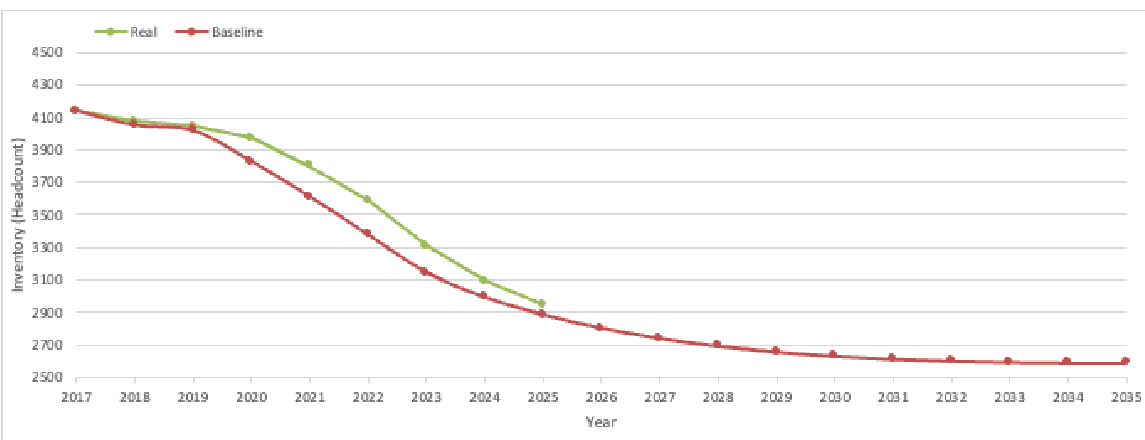

Figure 39. Junior NCO Inventory: Baseline vs. Real (Data 2017)

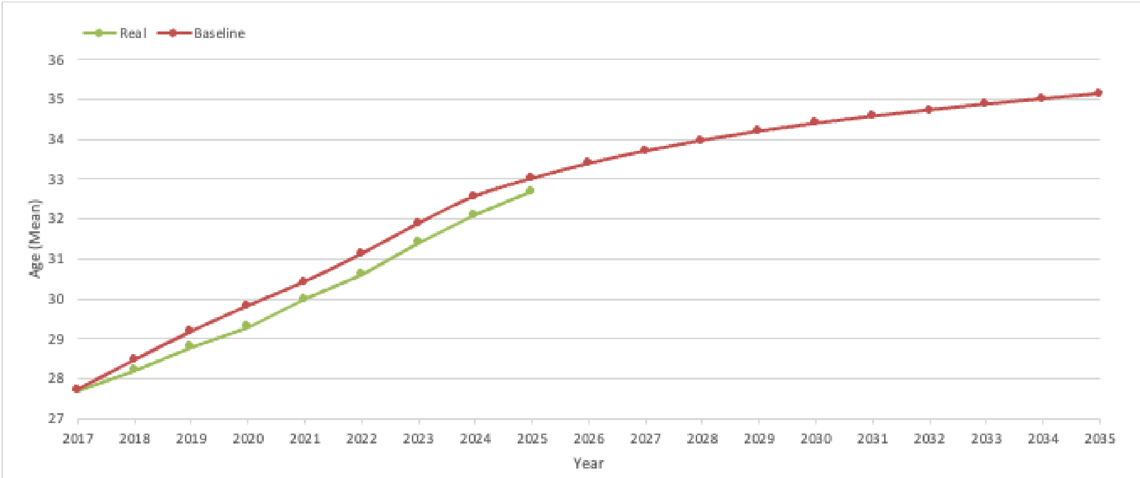

Figure 40. Junior NCO Age: Baseline vs. Real (Data 2017)

3. Scenario Results (2025 Start, through 2040)

The results for the Junior NCOs are presented as a five-policy comparison (Baseline, Boost, Increase, Degressive, and Natural), all initialized in 2025 and projected to 2040 under an identical Markov transition structure.

In 2025, all policies begin from the same state—inventory 2,950 and mean age 32.73—so differences in outcomes can be attributed to the policy-specific inflow assumptions rather than different starting conditions To complement the four-policy comparison, we include a Natural Recovery benchmark so that "no-intervention" is not implicitly defined as either flat inflows or an arbitrary growth rule. This benchmark is motivated by the observed post-break rebound in Junior NCO inflows after the 2023 trough (280 inflows), which increases to 321 in 2024 and 338 in 2025, with the year-over-year rebound clearly slowing between 2023→2024 and 2024→2025. We therefore derive Natural Recovery inflows by anchoring the projection to the observed 2025 level and extrapolating forward with a degressive recovery profile that preserves the empirical "rebound-then-deceleration" pattern seen from 2023–2025, providing a data-driven counterfactual against which the four recruiting policies can be interpreted as incremental effects.

a. *Inventory Effects*

Inventory effects in 2040 vary substantially across the five policy cases. By 2040, the baseline inventory is 2,605, while Boost reaches 2,798, Degressive reaches 4,534, and Increase reaches 5,259. The data driven Natural scenario reaches 3010. Relative to the 2040 baseline, these correspond to +193 (+7.41%) for Boost, +1,929 (+74.05%) for Degressive, and +2,654 (+101.88%) for Increase while the Natural scenario goes up by +405 (+15.54%) (Figure 41).

b. *Mean-Age Effects*

Mean-age effects mirror the inventory response but differ by policy mechanism. Baseline mean age reaches 35.63 years in 2040; Increase reduces mean age to 33.47 (−2.16 years; −6.06%) and Degressive reduces mean age to 34.23 (−1.40 years; −3.93%), whereas Boost increases mean age to 35.96 (+0.33 years; +0.93%). The Boost case shows an immediate mean-age reduction in 2029 (32.68 vs. 34.04 baseline), coinciding with the one-time inventory increase in 2029 (3,667 vs. 2,667 baseline), after which the mean-age path converges back toward the baseline aging trend. In comparison the Natural scenario will lead to a mean age of 35.31 in 2040 (-0.32 years; -0.9%) (Figure 42).

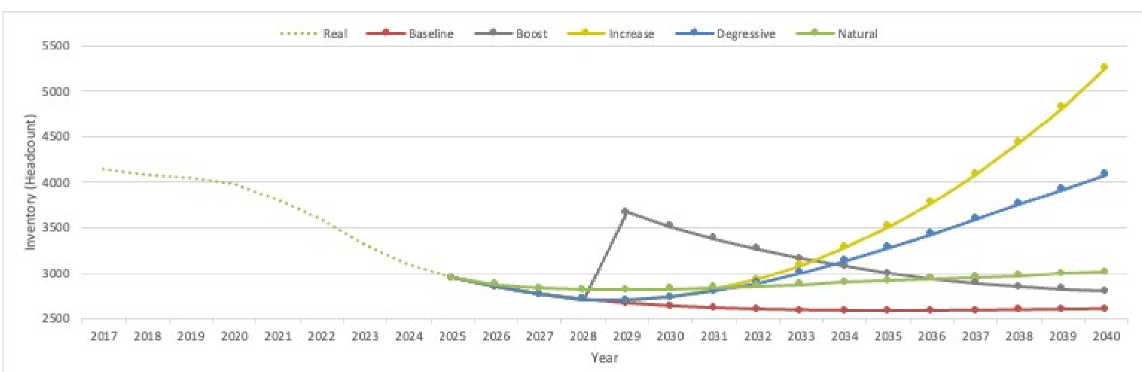

Figure 41. Junior NCO Inventory 2025–2040 (Data 2025)

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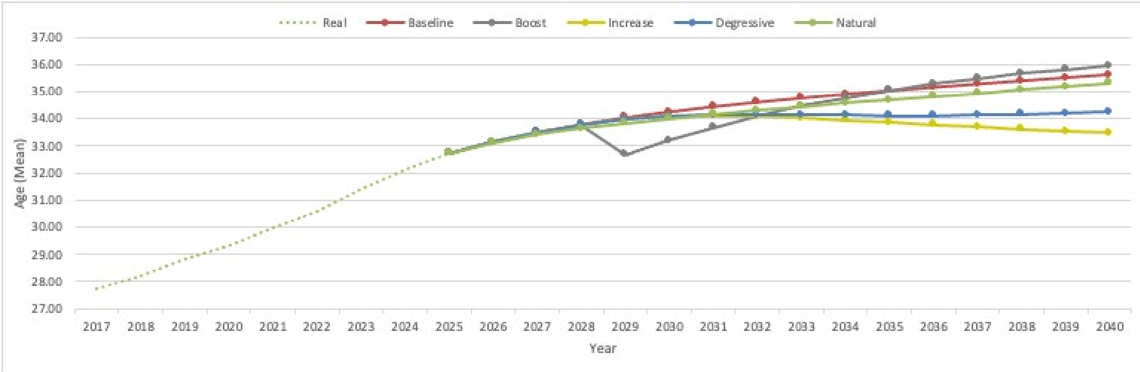

Figure 42. Junior NCO Age 2025–2040 (Data 2025)

4. Forecast Uncertainty

The Junior NCO inventory forecast indicates a planning challenge: uncertainty rises while expected personnel levels decline. Over the 2026–2040 horizon, the 10th–90th percentile prediction interval widens from 90 to 369 personnel, while mean inventory declines from 2,827 to 2,496 (a reduction of 331 personnel, approximately 11.7%) (Figure 43 and Table 9).

The relative spread increases from 3.19% in 2026 to 14.77% in 2040, indicating that dispersion grows faster than the change in expected inventory. By 2040, the central 80% interval spans 2,310 to 2,679 around a mean of 2,496, implying a 369-person uncertainty range (14.77% of expected strength). The coefficient of variation increases from 1.24% to 5.90% over the same horizon, consistent with widening uncertainty as the forecast extends further from the calibration period.

a. Model Strengths and Strategic Value

Despite rising forecast uncertainty over the horizon, the Junior NCO model provides planning value because it makes volatility explicit rather than masking it through smoothing assumptions. Over 2026–2040, mean inventory declines from 2,827 to 2,496 (−331 personnel; approximately −11.7%), while the p10–p90 spread widens from 90 to 369 personnel and the coefficient of variation rises from 1.24% to 5.90%.

In the near term, uncertainty remains relatively contained (e.g., p10–p90 spread of about 90 in 2026 and about 210 in 2028), supporting practical pipeline and billet planning, but dispersion becomes materially larger by the late 2030s and should be treated as a planning constraint rather than noise.

b. Critical Limitations

The Junior NCO forecast exhibits a compounding uncertainty challenge that limits long-horizon precision. While mean inventory declines from 2,827 (2026) to 2,496 (2040), the p10–p90 spread widens from 90 to 369 personnel and the coefficient of variation increases from 1.24% to 5.90%.

In relative terms, dispersion grows faster than the expected inventory change, as relative spread rises from 3.19% (2026) to 14.77% (2040); by 2040 the central 80% interval spans 2,310 to 2,679 around a mean of 2,496. This widening envelope indicates that late-horizon Junior NCO projections should be used primarily for risk bounding (i.e., plausible ranges) rather than for precise target-setting, especially when decisions depend on small headcount differences. In addition, the Junior NCO transition dynamics show evidence of instability over time (structural breaks at 2021q1 and 2023q4 in the quarterly stock series), which motivates caution when extrapolating beyond the post-break calibration regime.

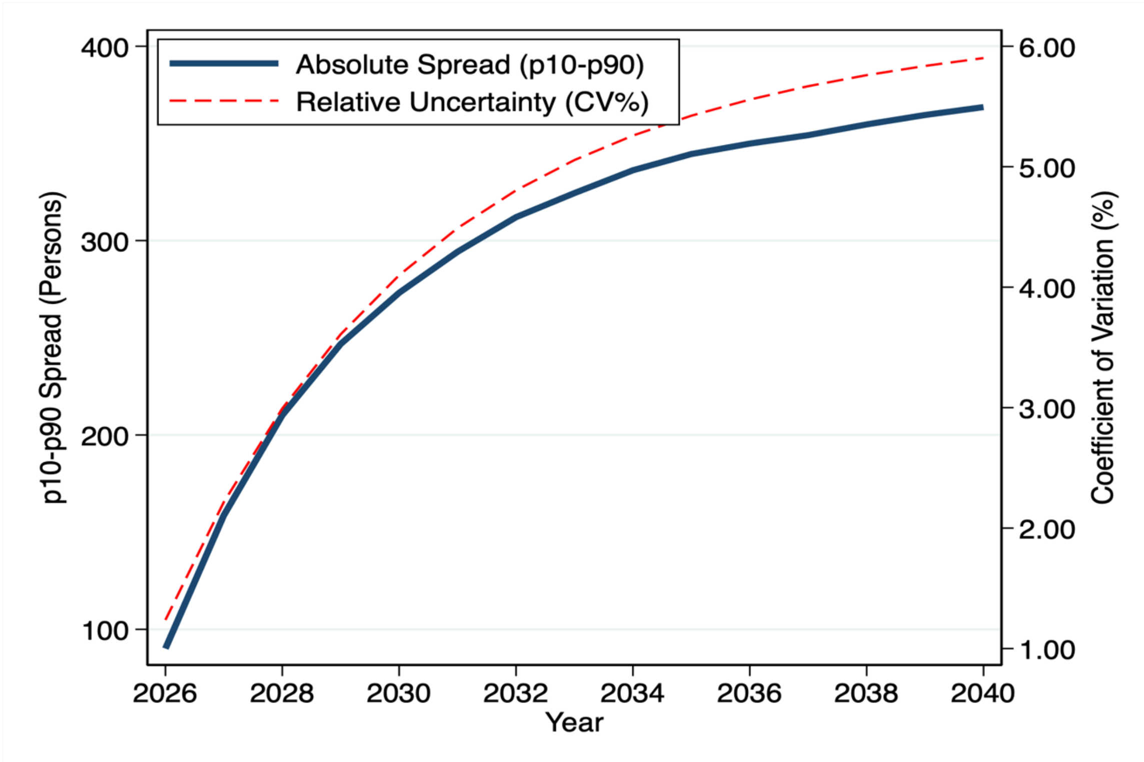

Figure 43. Junior NCO: Uncertainty Growth over Time

Table 9. Junior NCO: Inventory Uncertainty Table

Year	Mean Inventory	Standard Deviation	10th Percentile	25th Percentile	Median (50th)	75th Percentile	90th Percentile	p10-p90 Spread	CV (%)	Relative Spread (%)
2026	2827	34.98	2780	2805	2828	2851	2871	90	1.24	3.19
2027	2734	60.60	2652	2696	2736	2777	2811	159	2.22	5.80
2028	2665	79.74	2556	2613	2667	2721	2766	210	2.99	7.89
2029	2612	94.28	2484	2550	2614	2677	2731	247	3.61	9.45
2030	2574	105.50	2431	2505	2576	2646	2704	273	4.10	10.61
2031	2545	114.28	2392	2472	2545	2621	2686	294	4.49	11.56
2032	2524	121.25	2362	2446	2524	2606	2674	312	4.80	12.36
2033	2509	126.85	2342	2427	2507	2593	2666	324	5.06	12.93
2034	2499	131.41	2325	2412	2497	2585	2661	336	5.26	13.45
2035	2493	135.19	2317	2400	2490	2580	2661	345	5.42	13.82
2036	2489	138.35	2312	2394	2487	2578	2662	350	5.56	14.06
2037	2488	141.04	2310	2394	2485	2577	2664	354	5.67	14.24
2038	2489	143.38	2308	2394	2487	2580	2668	360	5.76	14.45
2039	2492	145.44	2308	2393	2488	2583	2672	365	5.84	14.63
2040	2496	147.29	2310	2395	2493	2588	2679	369	5.90	14.77

F. ENLISTED

1. Baseline Model Fit (2023–2025)

For enlisted personnel, we re-base the baseline model to 2023 because the rank structure changed at that point, which makes pre-2023 series not directly comparable within the same state definition. The baseline projection therefore starts from the 2023 observed state distribution (inventory) and uses the post-2023 baseline parameterization for inflows and transitions (Figure 44 and 45).

Model fit is assessed only for the post-reform period (2023 onward) by comparing baseline projections to the observed inventory and mean age paths. In the enlisted dataset, 2023 provides the anchor point (Real inventory 2752 vs. Baseline 2708; inflows 220), followed by 2024 (Real 2587 vs. Baseline 2548; inflows 239) and 2025 (Real 2510 vs. Baseline 2493; inflows 212).

2. Baseline Projection (2026–2035)

Starting from the 2025 baseline (inventory 2,889; mean age 33.00), the baseline forecast shows continued attrition, with inventory falling to 2,590 by 2035. In parallel, the force ages gradually, with the mean age increasing from 33.38 in 2026 to 35.14 in 2035.

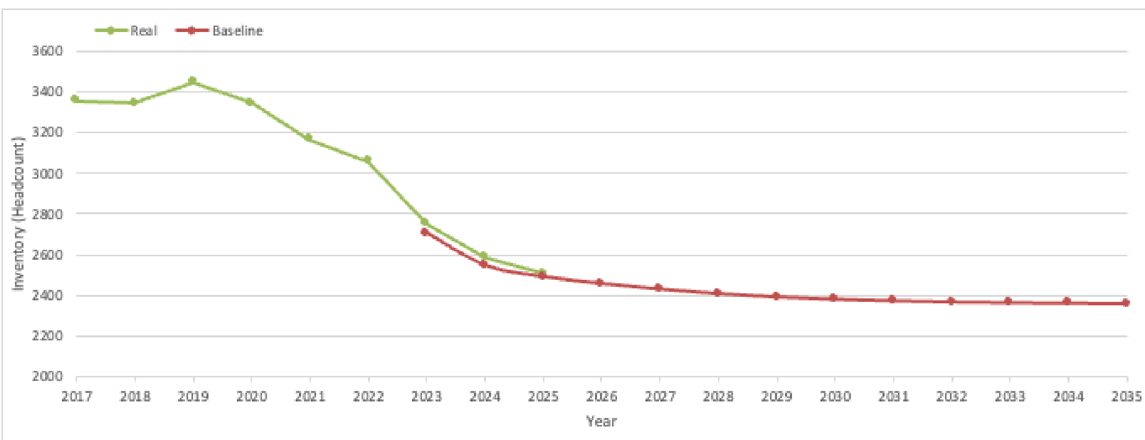

Figure 44. Enlisted Inventory: Baseline vs. Real (Data 2023)

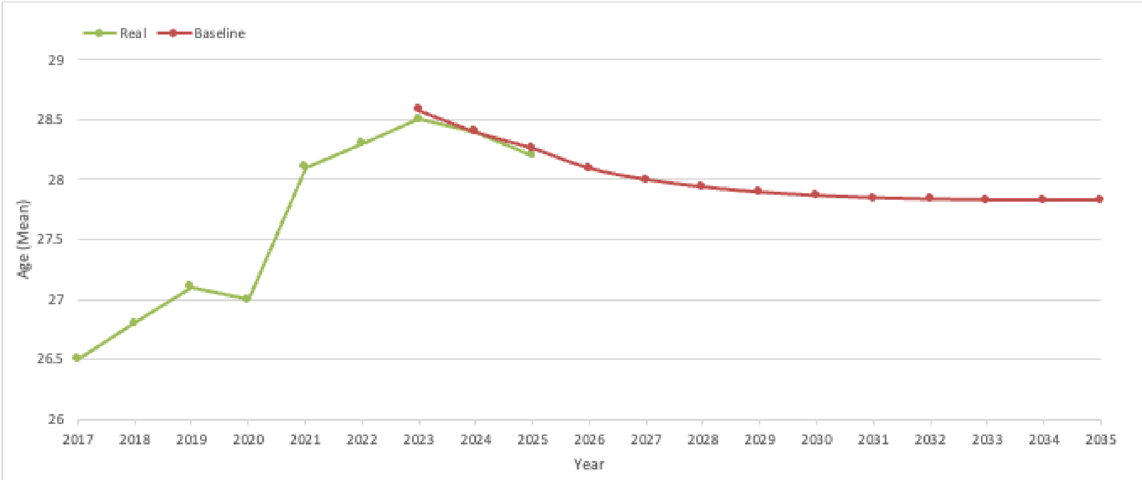

Figure 45. Enlisted Age: Baseline vs. Real (Data 2023)

3. Scenario Results (2025 Start, through 2040)

All scenarios are initialized in 2025 at the same modeled starting point (inventory 2,510; mean age 28.23) and remain identical through 2028. The first clear divergence occurs in 2029, when the Boost case jumps to an inventory of 3,396 (mean age 26.90), while the baseline is 2,396 (mean age 27.90). By 2040, baseline inventory is 2,358 with a mean age of 27.85, compared with 2,393 and 27.99 (Boost), 5,916 and 26.88 (Increase), and 4,896 and 27.10 (Degressive) (Figure 46 and 47).

a. Inventory Effects

Relative to the 2040 baseline (2,358), Boost adds 35 personnel (+1.48%), Increase adds 3,558 (+150.89%), and Degressive adds 2,538 (+107.63%). The main near-term inventory impact occurs in 2029: Boost is +1,000 (+41.74%) above baseline, while Increase and Degressive are each +64 (+2.67%). From 2025 to 2040, baseline inventory declines by 152 (-6.06%), whereas Increase and Degressive rise by 3,406 (+135.70%) and 2,386 (+95.06%), respectively.

b. Mean-Age Effects

At the 2040 horizon, mean age is slightly higher under Boost (+0.14 years vs. baseline) but lower under Increase (-0.97 years) and Degressive (-0.75 years). In 2029, Boost produces an immediate age reduction of 1.00 year relative to baseline (26.90 vs. 27.90), while Increase and Degressive are 0.08 years lower than baseline (27.82 vs. 27.90). Across 2025–2040, the modeled mean age decreases by 0.38 years in the baseline and by 1.35 and 1.13 years in the Increase and Degressive cases, respectively.

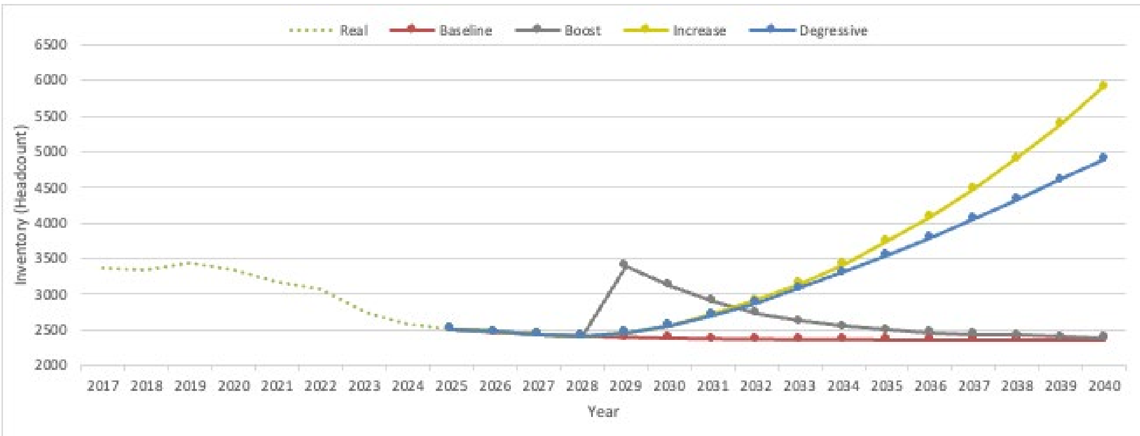

Figure 46. Enlisted Inventory 2025–2040 (Data 2025)

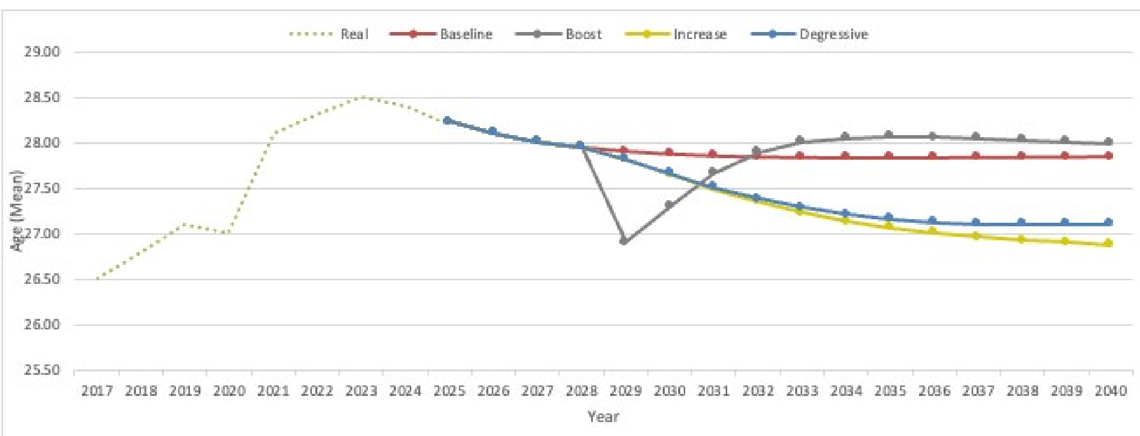

Figure 47. Enlisted Age 2025–2040 (Data 2025)

4. Forecast Uncertainty

The Enlisted ranks exhibit the most severe forecast uncertainty profile across all personnel segments. From 2026 through 2040, the confidence interval expands relentlessly: the p10–p90 bandwidth grows from 90 to 369 personnel, while underlying inventory simultaneously erodes from 2827 to 2496—an 11.7% contraction that amplifies proportional dispersion (Figure 48 and Table 10).

What sets this cohort apart is the terminal relative spread of 14.77% in 2040, representing the widest proportional confidence band system wide. This exceeds Senior NCOs (11.54%) by 28% and nearly triples Officers' 6.08% spread, signaling extraordinary volatility in entry-level career dynamics. The coefficient of variation climbs from 1.24% to 5.90%, with the 2040 central 80% interval stretching from 2310 to 2679 personnel around a mean of just 2496—a 369-person range representing nearly 15% of expected strength.

a. Data Quality Constraints and Interpretive Caution

A fundamental methodological caveat requires emphasis: The 2022 introduction of Korporal and Stabskorporal ranks created a structural discontinuity in the enlisted career architecture, severing historical data continuity precisely when transition patterns matter most.

This organizational redesign constrains forecast reliability through multiple channels. First, transition matrices estimated from 2017–2021 data necessarily reflect pre-reform promotion flows, retention incentives, and career paths that may no longer govern contemporary personnel dynamics. Second, insufficient post-reform observations (2022–2025)—merely four data years—prevent robust statistical calibration of new rank-specific transition probabilities, forcing dependence on legacy patterns of questionable relevance. Third, the reform itself introduces policy-driven uncertainty beyond normal stochastic variation: altered career incentives, changed promotion timelines, and redistributed rank distributions that historical data cannot anticipate.

The reported coefficient of variation (CV) and relative spread values thus reflect both genuine transition volatility and structural model uncertainty stemming from inadequate post-reform data coverage. Point estimates should be interpreted as illustrative trajectories rather than high-confidence projections, particularly beyond 2030 when compounding effects of parameter uncertainty accumulate substantially. As Korporal/ Stabskorporal cohorts mature and generate sufficient observation histories through 2030, model recalibration using contemporary transition patterns will materially improve reliability.

b. Compounding Weaknesses

The Enlisted segment confronts cascading uncertainty challenges. Initiating with a baseline CV of 1.24%—higher than Officers (0.24%) or Senior NCOs (0.51%)—the cohort exhibits elevated volatility even before projection uncertainty compounds. This reflects structural realities: as the military's primary entry gateway, enlisted ranks experience maximum transition turbulence from fluctuating recruitment cycles, early-career attrition peaks, and promotion flows to NCO grades.

Most critically, the 14.77% terminal relative spread marks the highest dispersion across all personnel categories. This extreme bandwidth traces to reinforcing dynamics:

- Statistical erosion: As cohort size contracts 11.7%, individual transitions gain disproportionate weight, degrading averaging effects that stabilize larger populations
- Entry-cohort volatility: Variable accession flows introduce high-variance initial conditions that propagate through the system
- Rank reform uncertainty: Post-2022 Korporal/Stabskorporal integration generates unmeasured transition dynamics absent from historical matrices
- Coupled flow dependencies: Enlisted inventory depends on both external recruitment inflows and internal promotion outflows to NCO ranks, compounding upstream and downstream uncertainties

The steep uncertainty gradient—CV multiplying 4.8× from 2026 to 2040—demonstrates how limited post-reform data amplifies long-horizon forecast degradation. By 2035, CV surpasses 5%, approaching methodological boundaries for reliable personnel forecasting in military contexts absent scenario-based risk frameworks.

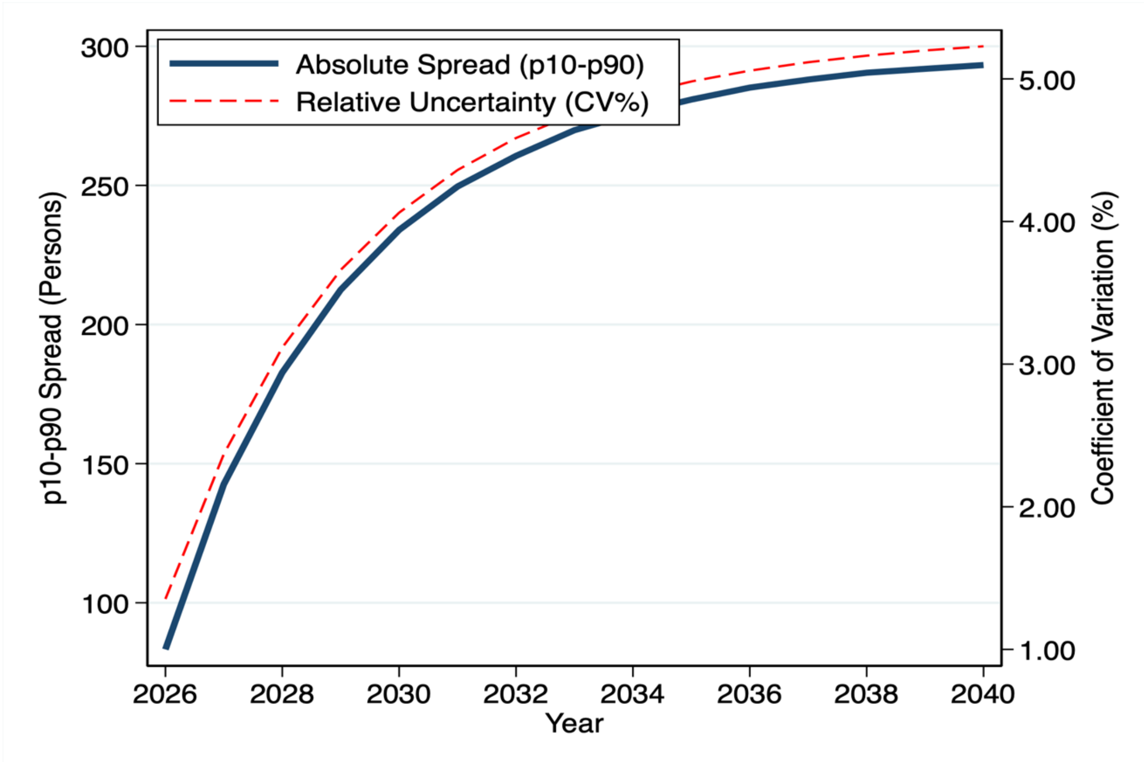

Figure 48. Enlisted: Uncertainty Growth over Time

Table 10. Enlisted: Inventory Uncertainty Table

Year	Mean Inventory	Standard Deviation	10th Percentile	25th Percentile	Median (50th)	75th Percentile	90th Percentile	p10-p90 Spread	CV (%)	Relative Spread (%)
2026	2452	33.19	2409	2429	2451	2474	2492	83	1.35	3.40
2027	2402	56.92	2329	2362	2401	2440	2472	143	2.37	5.94
2028	2363	73.65	2270	2311	2363	2411	2453	183	3.12	7.73
2029	2338	85.58	2229	2276	2338	2392	2442	213	3.66	9.09
2030	2319	94.22	2201	2251	2321	2380	2435	234	4.06	10.09
2031	2306	100.59	2180	2234	2306	2371	2430	250	4.36	10.82
2032	2297	105.32	2166	2221	2296	2364	2426	261	4.59	11.35
2033	2290	108.86	2155	2211	2288	2359	2425	270	4.75	11.79
2034	2284	111.55	2147	2203	2282	2356	2423	276	4.88	12.08
2035	2280	113.59	2141	2196	2278	2354	2422	281	4.98	12.32
2036	2277	115.17	2136	2192	2275	2351	2421	285	5.06	12.52
2037	2275	116.39	2132	2189	2272	2350	2420	288	5.12	12.66
2038	2273	117.35	2129	2187	2270	2349	2420	291	5.16	12.78
2039	2272	118.11	2127	2186	2269	2348	2419	292	5.20	12.85
2040	2271	118.71	2125	2184	2267	2347	2419	293	5.23	12.92

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VII. CONCLUSION

Between 2015 and 2025, the German Navy's total strength declines only 3.7%, but the internal rank pyramid shifts markedly: Enlisted (−19.7%) and Junior NCOs (−30.1%) shrink while Senior NCOs (+12.3%) and Officers (+12.7%) grow, producing a top-heavier force even before any forecasting is applied. Under the baseline assumptions, projections extend this direction of travel through 2040—Officers increase to 4,129 (+14.1%), Senior NCOs remain near equilibrium, while Junior NCOs fall to 2,496 (−11.7%) and Enlisted to 2,271 (−7.4%).

At Bundeswehr level, the parliamentary commissioner similarly characterizes the rank distribution as "top-heavy" and reports that officers account for 21.6% while enlisted personnel account for 29.3%, implying nearly one officer per enlisted soldier and raising doubts about whether such a structure can sustainably support national and alliance defense tasks (German Bundestag, 2026). Building on this readiness-relevant benchmark, this thesis computes the same officer-to-enlisted ratio for the German Navy over 2015–2025 and under the 2040 baseline projection to assess whether the Navy is converging toward, or diverging from, the Bundeswehr-wide pattern—and what that implies for personnel policy levers.

For the "war-capable by 2029" time frame, the results imply a practical constraint: scenario levers are modeled as changes to inflows starting in 2029 (Boost) or from 2029 onward (Increase/Degressive), so near-term structure through the late 2020s is largely path-dependent on the already-observed pipeline rather than rapidly adjustable. In addition, forecast uncertainty is not uniform across career stages; the thesis' planning implications therefore support differentiated horizons—longer-range decisions can lean more on Officer/Senior NCO projections, while Junior NCO and Enlisted planning should remain more conservative and scenario-based beyond the early-to-mid 2030s, especially given post-reform discontinuities in the junior segments.

A. INVENTORY TRAJECTORIES AND WORKFORCE COMPOSITION

The baseline projection indicates a divergent development across career segments, producing a progressively different workforce composition over the projection horizon. Officer strength increases from 3,620 to 4,129 personnel (+14.1%), while the Senior NCO cohort remains essentially stable (6,508 to 6,485; −0.4%). In contrast, the junior cohorts contract, with Junior NCOs declining from 2,827 to 2,496 (−11.7%) and enlisted personnel decreasing from 2,452 to 2,271 (−7.4%).

Consequently, the force structure becomes increasingly top-heavy: the officer-to–Junior NCO ratio is projected to reach 1.65:1 by 2040, and the enlisted-to-officer ratio declines to 0.55:1, implying fewer junior personnel available per leader and increased supervisory density.

B. AGING DYNAMICS ACROSS CAREER STAGES

Across the projection period, all segments exhibit aging, albeit at different intensity levels. The officer cohort ages modestly from 38.1 years in 2025 to 38.8 years in 2040 (+0.7 years), and Senior NCOs are described as following the same general aging pattern. Aging is expected to be more pronounced in the Junior NCO and enlisted segments, because their inventories decrease through reduced new recruitment while experienced mid-career personnel remain in service, increasing the average age of the remaining cohort. Notably, the excerpt reports that the aging trend follows comparable patterns across all four tested scenarios (baseline, boost, continuous increase, degressive increase), suggesting that the underlying force structure and its demographic dynamics are the dominant drivers of the aging outcome in the model.

C. FORECAST UNCERTAINTY AND METHODOLOGICAL RELIABILITY

The model validation shows excellent short-term accuracy, yet it shows that uncertainty increases when looking at longer time periods. The backtesting accuracy results show:

1. Officers

The officer predictions produce the most accurate forecasts which indicate CV will maintain levels below 2.5% until 2040 while the RMSE values from inventory and age predictions stay under 1% throughout the validation period. The superior performance results from three main factors which include stable career patterns and selective accession pipelines and low transition volatility.

2. Senior NCOs

Senior NCOs show average reliability throughout their 8–10-year military service but their ability to predict accurately becomes worse as time passes since their last prediction. The coefficient of variation will achieve 4.45% by 2040 while relative spread will reach 11.54% because aging affects people differently and their skill retention abilities and career choices within this defined population.

3. Junior NCOs

The Junior NCOs show the highest terminal uncertainty because their CV reaches 5.90% while their relative spread in 2040 amounts to 14.77%. The available data from 2022 to 2025 does not provide enough information to establish reliable new rank-specific transition probabilities because there are only four post-break observation years. The research method creates a major limitation because it produces high levels of parameter uncertainty which exceeds typical random fluctuations when making predictions for periods after 2030.

4. Enlisted

The uncertainty levels of enlisted personnel reach higher values (CV 5.23%, spread 12.92%) because of a fundamental data problem which emerged when Korporal and Stabskorporal ranks became active in 2022. The segment functions as the main entry point for new employees which creates additional stability risks because of changing hiring patterns and staff members who leave their jobs shortly after starting work.

D. PLANNING IMPLICATIONS

The systematic decoupling of uncertainty from inventory levels carries crucial workforce planning lessons. Senior NCOs demonstrate stable inventory (-23 personnel) yet generate the second-highest absolute uncertainty (748-person p10-p90 spread by 2040). Conversely, Officers maintain lowest relative uncertainty (6.08% spread) despite substantial growth (+509 personnel). This pattern indicates that organizational position within career hierarchy-not cohort size-primarily determines forecast reliability. The finding validates differentiated planning horizons by segment:

- Officers support confident 12–15-year strategic planning
- Senior NCOs enable reliable 10–12-year forecasts
- Junior NCOs and Enlisted require conservative 6–8-year horizons, with scenario-based approaches essential beyond 2035

For German Navy personnel management, this means long-range force structure decisions (e.g., shipbuilding programs, technology investments) should anchor on Officer forecasts, while near-term operational planning must account for elevated uncertainty in junior enlisted segments.

E. RECOMMENDATIONS FOR FUTURE RESEARCH

1. Post-Reform Data Collection and Model Recalibration

The 2022 Korporal/Stabskorporal rank introduction serves as the primary methodological challenge which impacts the precision of total Enlisted personnel projections. The system needs shorter (quarterly) performance assessments to monitor personnel growth which determines their career advancement and their eligibility for Korporal/Stabskorporal roles and their ability to stay with the Bundeswehr. The project requires about 60 months of data observation beginning in 2027 to achieve suitable statistical model calibration.

2. Incorporate Retention and Promotion Policy Instruments

The current models use transition probabilities as static parameters which derive from past average values. The policy evaluation process according to the specification must focus on new personnel onboarding but it does not evaluate how different retention methods and career advancement programs affect specific career tracks.

3. Integrate Demographic Recruitment Constraints

Current inflow assumptions hold constant or apply simple growth multipliers without anchoring to external demographic realities. Given Germany's documented fertility decline and aging civilian population, sustainable military recruitment faces structural headwinds.

4. Validate Operational Readiness Implications

While this study quantifies aging and inventory trends, the operational consequences remain implicit. Critical questions for follow-on research:

a. Age-Performance Relationships:

Empirically assess how aging affects mission-critical capabilities (technical proficiency, physical fitness, decision speed, innovation adoption) across different Naval occupational specialties. Some roles may benefit from experience accumulation while others face age-related performance degradation.

b. Span-of-Control Optimization:

Model implications of changing Officer-to-NCO ratios for leadership effectiveness, training quality, and unit cohesion. Identify threshold ratios beyond which organizational performance degrades.

c. Deployment Tempo Sustainability:

Assess whether declining junior enlisted cohorts create unsustainable rotation tempos for remaining personnel, risking burnout and retention crises.

d. Technology Adoption Capacity:

Evaluate whether aging workforce demographics constrain ability to integrate emerging technologies (AI-enabled systems, autonomous platforms, cyber operations) requiring digital-native skill profiles.

APPENDIX A. VALIDATION RESULTS AND MODEL SELECTION SENIOR NCO

The models demonstrated consistent performance with minimal deviation in their RMSE values for age predictions. Specifically, across the validation period from 2018 to 2023, all models maintained RMSE values within a narrow range, except for the 2021 model variant, which exhibited a marginally lower RMSE of 0.64% for inventory projections.

Furthermore, when evaluating age predictions across all model variants, the deviations from observed values remained within a ±0.3% corridor, indicating high accuracy and model reliability across the entire validation dataset.

Table 11. Stage 1: 4-Model-Ranking Senior NCOs (Inventory)

Δinventory	**2017-2025**	**2017-2021**	**2025**	**2021**
Average	0.83%	0.92%	1.21%	0.45%
Median	0.86%	0.96%	1.26%	0.39%
Max	1.89%	2.02%	2.47%	1.12%
RMSE	1.11%	1.21%	1.55%	0.64%
Total	**4.69%**	**5.11%**	**6.49%**	**2.60%**

Table 12. Stage 1: 4-Model-Ranking Senior NCOs (Age)

Δage	**2017-2025**	**2017-2021**	**2025**	**2021**
Average	1.21%	1.10%	1.37%	1.14%
Median	1.23%	1.09%	1.36%	1.12%
Max	1.49%	1.40%	1.56%	1.46%
RMSE	1.36%	1.24%	1.53%	1.28%
Grand Total	**5.29%**	**4.83%**	**5.83%**	**5.00%**

Model 2017–2021 has a strong historical early-period performance (RMSE 36.80) but drops substantially in the accuracy in recent years (late–period RMSE 71.34), with errors escalating from 60.65 (2022) to 85.62 (2025). This 47% deterioration suggests temporal instability and inadequate capture of post-2021 structural changes in Senior NCO personnel dynamics.

The 2021 model has a moderate performance with higher. It achieves moderate overall RMSE (54.89), 13% worse than Model 2017–2025. While demonstrating strength in the transitional year 2022 (RMSE 47.23), a substantially higher MAPE (36.16%) indicates larger relative errors, suggesting single-year estimation may introduce variance despite acceptable absolute accuracy.

The model from 2025 systematically underperforms. It demonstrates consistent poor performance across all periods with an overall RMSE of 72.79 (50% worse than the 2017–2025 model), with no compensating strengths in any evaluation year. The systematic failure across 2018–2025 suggests unrepresentative transition estimates or high sampling variance.

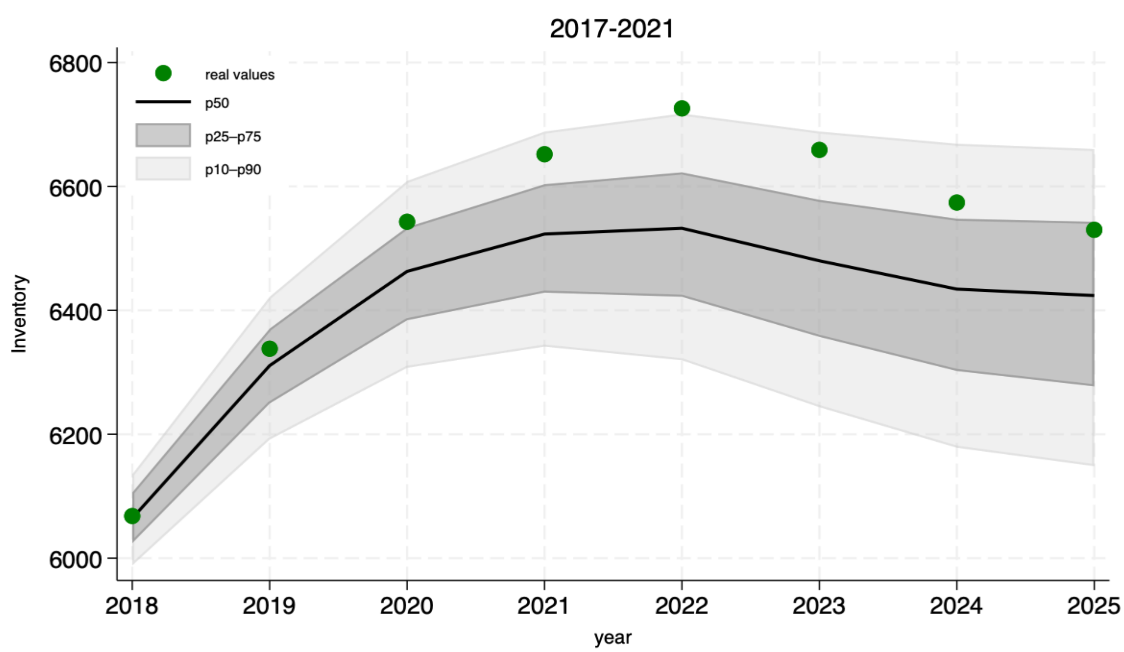

Figure 49. Senior NCOs: Monte Carlo Results 2017–2021 (Inventory)

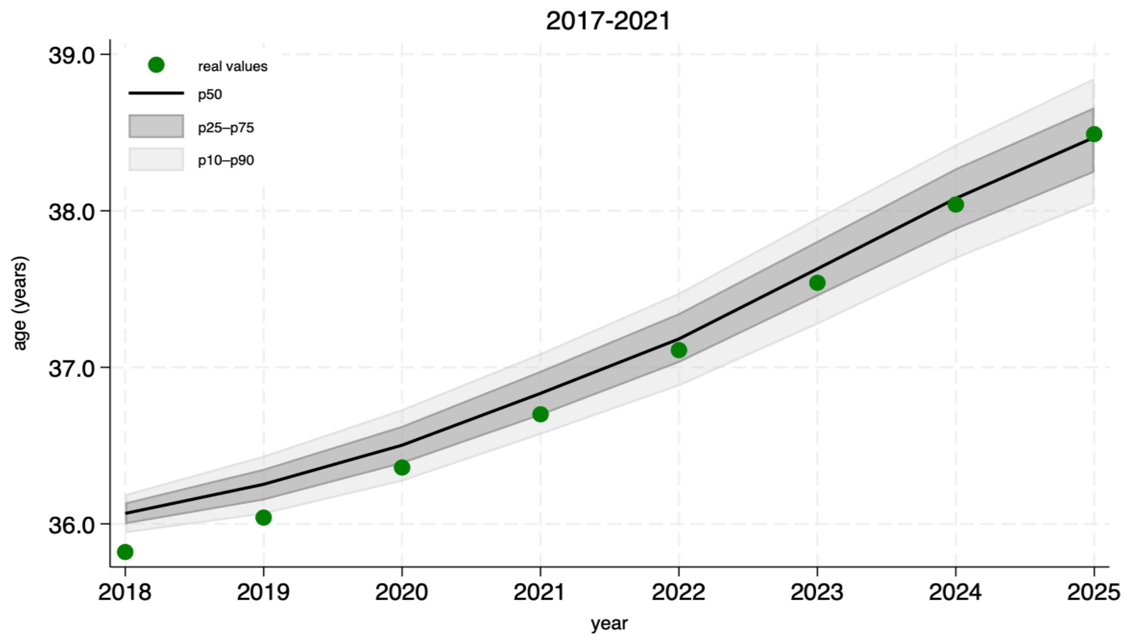

Figure 50. Senior NCOs: Monte Carlo Results 2017–2021 (Age)

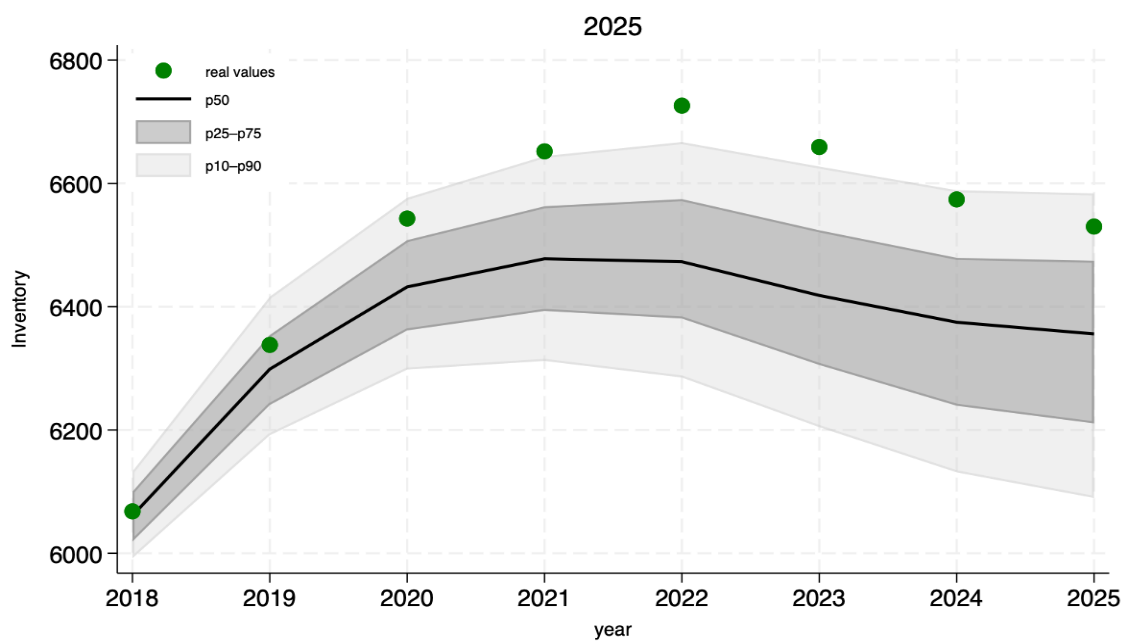

Figure 51. Senior NCOs: Monte Carlo Results 2025 (Inventory)

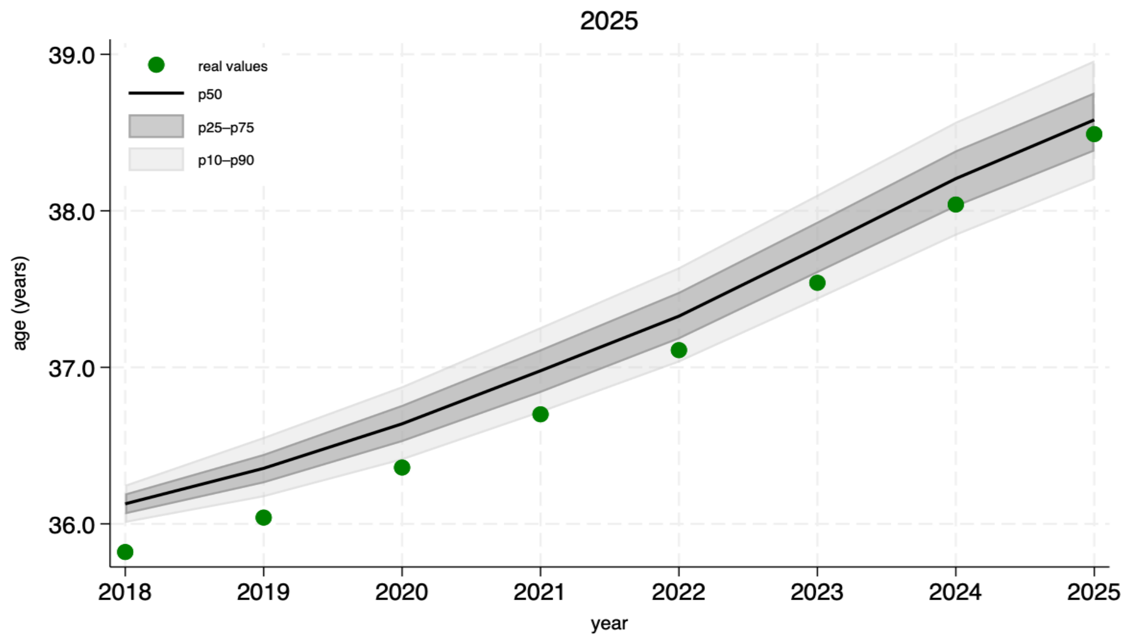

Figure 52. Senior NCOs: Monte Carlo Results 2025 (Age)

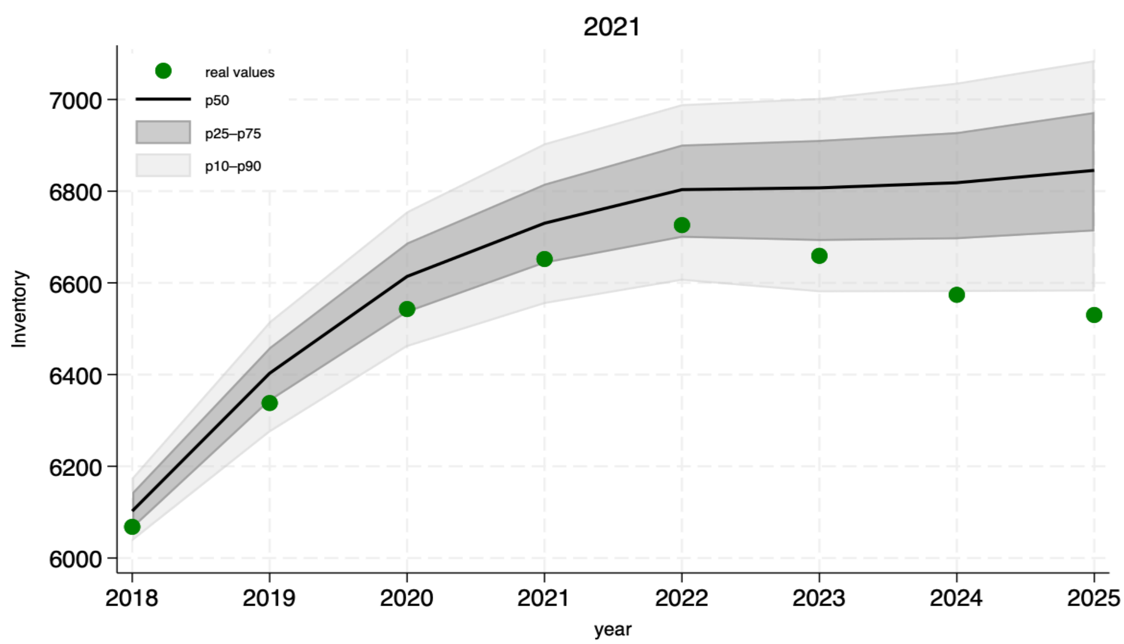

Figure 53. Senior NCOs: Monte Carlo Results 2021 (Inventory)

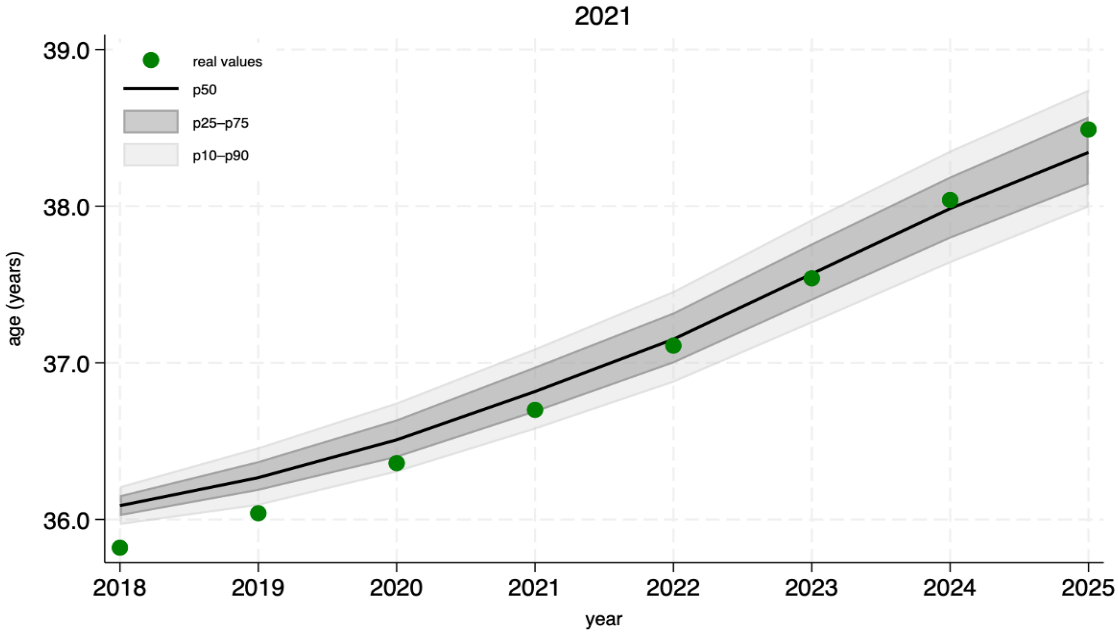

Figure 54. Senior NCOs: Monte Carlo Results 2021 (Age)

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APPENDIX B. VALIDATION RESULTS AND MODEL SELECTION ENLISTED

For the Enlisted Validation, three models demonstrate acceptable forecasting performance:

- Model 2024–2025 exhibits excellent predictive accuracy with inventory RMSE of 1.14% and age RMSE of 0.17%. This model achieves the lowest combined error score (0.85%), demonstrating strong capability for both inventory and age predictions.
- Model Year 2025 shows good performance with a combined score of 1.58%. While inventory prediction (RMSE 1.90%) remains acceptable, age prediction accuracy (RMSE 0.82%) is notably lower than the top-ranked model.
- Model 2022–2025 demonstrates good but moderate performance with a combined score of 1.78%. This model shows higher inventory error (RMSE 2.43%) but maintains reasonable age prediction accuracy (RMSE 0.25%).

Model 2022 is excluded from further analysis due to almost triple RMSE (6.49%) in the inventory compared to the three finalists.

Table 13. Stage 1: 4-Model-Ranking Enlisted (inventory)

ΔInventory	**2024-2025**	**2022-2025**	**2025**	**2022**
Average	0.92%	2.17%	1.77%	6.15%
Max	1.63%	3.76%	2.58%	8.68%
Median	1.01%	2.08%	1.75%	6.08%
RMSE	1.14%	2.43%	1.90%	6.49%
Grand Total	**4.70%**	**10.44%**	**8.00%**	**27.40%**

Table 14. Stage 1: 4-Model-Ranking Enlisted (age)

ΔAge	2024-2025	2022-2025	2025	2022
Average	0.14%	0.24%	0.67%	0.38%
Max	0.28%	0.36%	1.22%	0.47%
Median	0.13%	0.23%	0.71%	0.38%
RMSE	0.17%	0.25%	0.82%	0.39%
Grand Total	**0.71%**	**1.08%**	**3.42%**	**1.62%**

The 2024–2025 model achieves the lowest average RMSE (10.35) and the smallest average absolute inventory bias (33.6 personnel) across the 2022–2025 test period. Notably, Model 2024–2025 maintains consistent performance across all three years, demonstrating stable predictive validity.

All models achieve perfect inventory coverage (100%), indicating that observed personnel stocks consistently fall within the Monte Carlo-derived 80% confidence intervals.

While Model 2022–2025 demonstrates superior performance in 2023 (RMSE 7.68), its degrading accuracy in subsequent years (RMSE increases to 12.76 by 2025) and higher systematic bias (62.4 vs. 33.6) suggest overfitting to the longer historical period. Model Year 2025, despite excellent age prediction, exhibits 5% higher RMSE and may suffer from higher variance in single-year transition estimates.

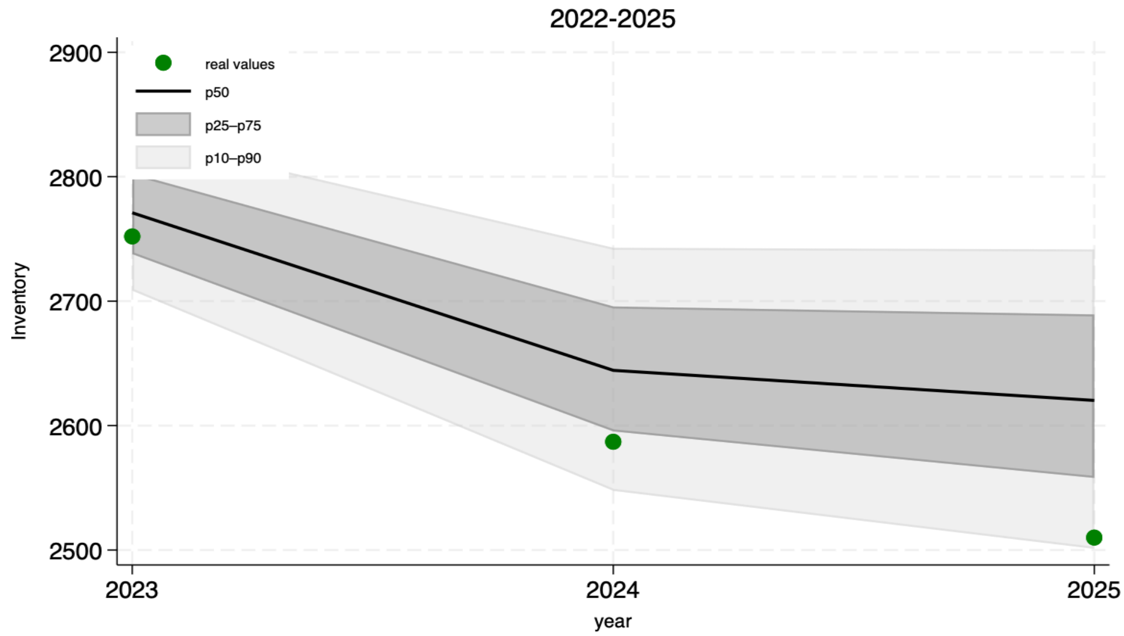

Figure 55. Enlisted: Monte Carlo Results 2022–2025 (Inventory)

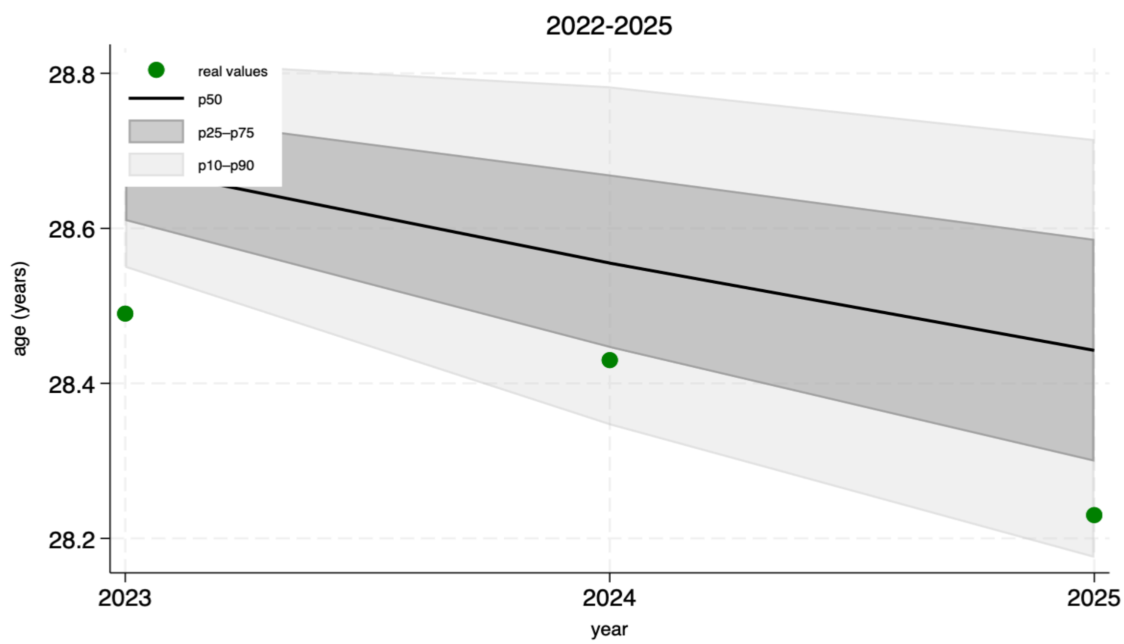

Figure 56. Enlisted: Monte Carlo Results 2022–2025 (Age)

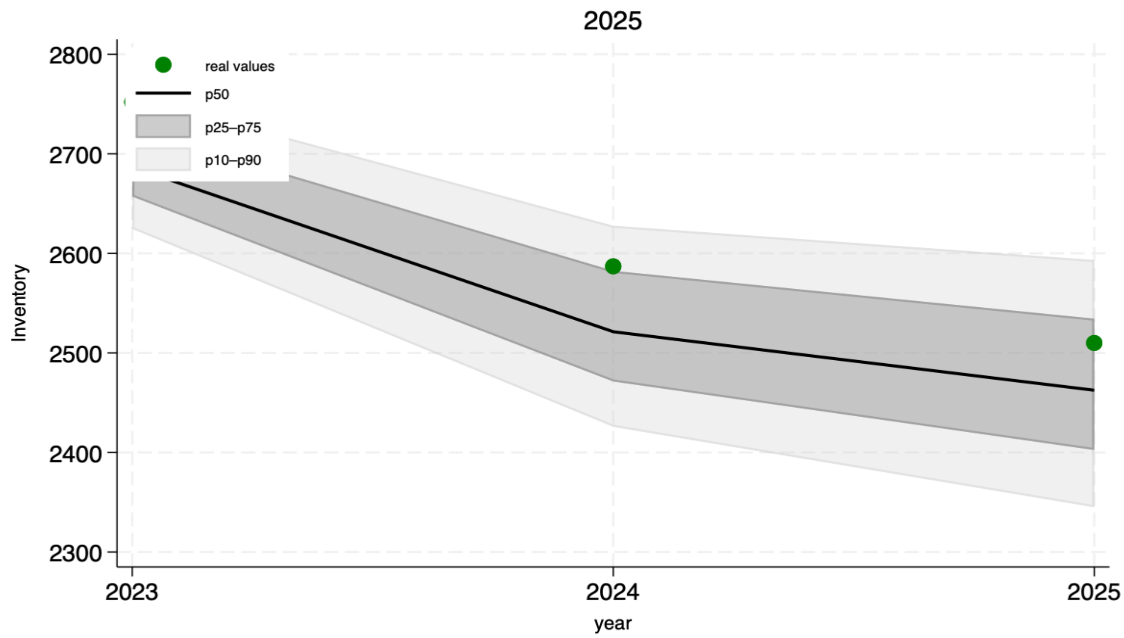

Figure 57. Enlisted: Monte Carlo Results 2025 (Inventory)

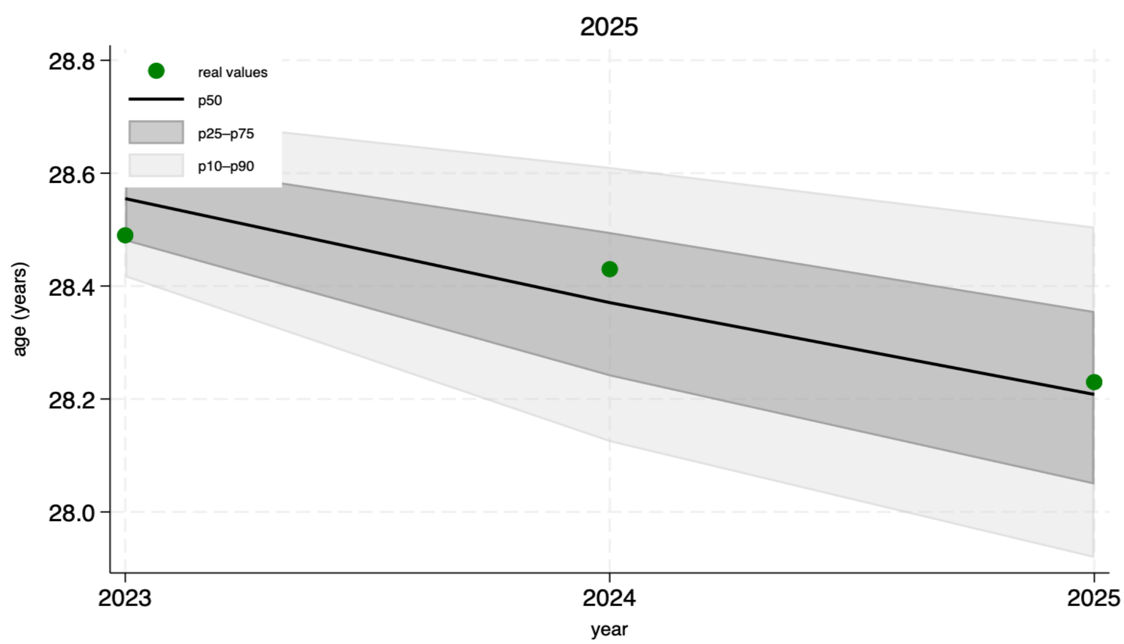

Figure 58. Enlisted: Monte Carlo Results 2025 (Age)

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