GI Jobs:
The macroeconomic effects of defense employment

Ethan Ilzetzki
London School of Economics*

Hugo Reichardt
CREI

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Abstract

Defense spending is the largest component of US discretionary spending and a quarter of it is spent on military personnel. The US military is the largest single employer in the US. This paper studies the general equilibrium effects of military employment on labor markets and the macro-economy. Military employment is concentrated in the 18-24 age group; military jobs have higher skill requirements than the average civilian job and resemble the more technical jobs in the goods-producing sector. This has made military employment historically a de facto training ground for a large segment of the labor force. In the early 90s, this labor market was hit by the *Cold War Demobilization* shock: the military shed 700,000 employees. Using an event study around the end of the Cold War, we find that income in occupations similar to military jobs suffered a 5% hit to income. This shock hit similar populations to those affected by trade and automation in the past three decades but we show that this is a separate and distinct shock. We explore the implications of the military as an employer in a general equilibrium model of occupational choice and human capital accumulation. The model illustrates that the military draw-down affected not only exposed populations, but also had an effect on aggregate income, through human capital externalities.

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1 Introduction

With geopolitical tensions rising and new military threats emerging, governments around the world are reconsidering the size of their defense budgets. NATO members have committed increases in defense expenditures that would double the size of the military in some European countries. President Trump announced in January of this year that military spending would increase by 50% in the 2027 fiscal year.[1]. In the US, defense spending is roughly evenly divided between equipment and military employment. In European countries the share is even larger. However, much of the literature studying the aggregate effects of defense spending either lumps these two components together (see Ramey 2011a, 2016, 2019 for reviews of the literature on the fiscal multiplier) or focuses solely on defense procurement (Cox *et al.*, 2024; Auerbach *et al.*, 2020a; Kuziemko *et al.*, 2025). Far less is known about the aggregate and general equilibrium effects of defense *employment*, which is the focus of this paper.

We study the implications of military expansions on the labor market in general equilibrium. Our focus is on medium-term implications of the size of the military rather than its business cycle implications or the use of defense spending as a counter-cyclical tool.

We begin with two motivating facts. First, military occupations have higher skill requirements than civilian jobs, on average. We show that this is true across a variety of skills ranging from mechanical to scientific to interpersonal skills. The military draws on populations of lower socio-economic background and those less inclined to attend college (Bachman *et al.*, 2000). Military recruits are typically young and the duration of military service has a median of merely 4 years, service may provide unique opportunities for early-career human capital accumulation. This is further evidenced in the skill requirements of occupations where veterans tend to work after their military service. While veterans serve in higher-skill occupations than the general population on average, these occupations have lower skill requirements than the military, suggesting that veterans arrive well-prepared for high-skilled post-military careers.

Second, a large portion of military occupations are similar in their skill requirements to those required by goods manufacturing occupations in the private sector—exactly the occupations that have hollowed out due to automation (Autor & Dorn, 2013; Graetz & Michaels, 2018; Acemoglu & Restrepo, 2018, 2019, 2020) and the shocks due to trade within NAFTA (Hakobyan & McLaren, 2016a; Choi *et al.*, 2024; Finkelstein *et al.*, 2026) and with China (Autor *et al.*, 2013a,b). As a short hand, we refer to these jobs as "hard hat" jobs and the skills required in them as "hard hat" skills. Interestingly, many of these "hard hat" military jobs also had high skill requirements on other dimensions, such as STEM skills, so that the military provided recruits with more diverse skills

[1] `https://www.reuters.com/world/us/trump-says-us-military-budget-2027-should-be-15-trillion-2026-01-07/`

than in the typical civilian job. (Think of the technological knowledge required to to repair a tank compared to repairing a car.) Indeed, military jobs and the jobs absorbing veterans are on the higher end of the skill and wage distribution among "hard hat" occupations. The decline in military employment has decreased demand for workers in these occupations, while limiting their opportunities to accumulate human capital.

Supporting this latter fact, we conduct an event study around the end of the Cold War, when the US military shed 700 thousand soldiers from its workforce. We find that occupations with skill requirements most similar to "hard hat" military jobs saw a sudden decline in earnings of around 5% following the end of the Cold War. While these occupations were also affected by automation and the China shock, our results survive controls for these confounding factors and we are considering a decade *before* China's WTO accession, when the majority of the China shock will have impacted workers. There have been many shocks and trends that harmed US manufacturing workers, workers with "hard hat" skills, and the American working class. We show, however, that the Cold War demobilization shock was distinct. Crucially, the effect cannot be attributed to the general decline in manual occupations–our results survive controls for the level of "hard hat" skills, with military-similar occupations faring worse than others *within* the same category of manual labor requirements. We also note that the jobs impacted by the demobilization shock were "good jobs" with higher skill requirements and higher wages. Nevertheless, wages grew relatively less in these occupations at the end of Cold War than in others.

We then study the general equilibrium implications of military service in an occupational choice model, following Acemoglu & Autor (2011a); Deming (2017a); Althoff & Reichardt (2026a) among others. In the model, the government provides a public good in the form of national security. The public good is produced with a (CES) aggregate of occupations. Households use their (after-tax) disposable income to consume a basket of consumption goods–produced with a separate CES aggregate of occupations. Households sort into occupations based on their existing skills while considering wages, job amenities, and the skills they will accumulate on the job–with implications for future wages. Wages in each occupation are determined by the intersection of workers' occupational choices and the demand for each occupation from consumer goods producers and from the military.

An expansion of military employment has several implications in the model. The immediate effect is the increase in demand for occupations more prominent in the military. This increases wages in these occupations with the knock-on effect of increasing the market value of skills that are used in these occupations. Given that military employment is tilted towards "hard hat" skills, it improves the fate of workers with these skill sets.

Second, the high skill requirements of military occupations imply steeper learning curves than in civilian occupations. This increases soldiers' human capital but also increases human capital in aggregate. Workers with a comparative advantage in manufacturing skills will sort in to military occupations in part because of the "training" opportunities in this sector. Because military occupations have high skill requirements in a variety of skills, soldiers develop other skills and may no longer sort into the manufacturing occupations where they had an initial comparative advantage, sorting instead into higher paid STEM occupations, for example.

We then use our model to conduct several experiments. First, at the microeconomic level, we study the "causal" effect of military service by comparing the career trajectories of military recruits to their trajectories in counterfactual simulations where they face an idiosyncratic exogenous shock to their taste for military employment. We find large, positive, and persistent effects on their wages. Their wages are nearly 20% higher even a decade after departing from the military, matching the empirical findings of Greenberg *et al.* (2022a).

We replicate the Cold War demobilization shock, evaluated empirically in the event study described above. Comparing steady states with different levels of military employment (different demand for public goods) we find that a shock of the magnitude of the end of the Cold War leads to a *permanent* decline in wages of 0.5% in civilian occupations most similar in skills to those employed in the military. Importantly, we also find a substantial decline in wages in all other occupations, illustrating the positive externalities of the military as a training program.

Our results may appear in contrast with Angrist (1990) who finds negative individual effects of the Vietnam draft. We note a separate finding, where Angrist (1998), which shows that voluntary service benefits military recruits. This latter result been subsequently reaffirmed by Greenberg *et al.* (2022a), who show positive wage effects of military service. Our model rationalizes these contrasting findings. We compare an increase in defense spending with voluntary enlistment and a draft where youths are randomly recruited to the military. When enlistment is voluntary, recruits tend to be those who would most benefit from military service and benefit they do. In contrast, the draft mis-allocates workers who would otherwise be productive in the private sector into military occupations. This leads some high human capital workers to forgo important work experience in the private sector. This is true even though we allow the military to allocate its recruits *across* military occupations based on their comparative advantage. We leave it to future research to determine whether it is more efficient (and just) to fund a military expansion through coercive service or through taxation (see Oi 1967; Friedman 1967 for Vietnam-era discussions of this question).

A note on a few things our paper cannot speak to. First, while it is possible to estimate the fiscal multiplier in our setting, this is not the best setting to investigate the question of the multiplier. We study a model where the sole labor market friction is costly movement across occupations. In our model, labor is supplied inelastically. Thus both the Keynesian and Neo-classical channels that would foster a meaningful multiplier are absent in our setting. Without the on-the-job learning externalities present in our model, the fiscal multiplier would be zero in our model, as any increase in military spending reduces private sector employment one for one.

Second, we refrain from any aggregate welfare assessments. These would require evaluating the social value of national defense, a question that is beyond the scope of this paper.

A growing empirical literature estimates the local labor-market effects of public employment and procurement, including defense-related spending. A prominent identification strategy exploits shifts in local public employment, such as the postwar creation of the West German government in Bonn, which shows that public employment can reshape the sectoral composition of private activity through local general-equilibrium channels (wages, housing costs, and amenities) (Becker *et al.*, 2021). In contrast, Faggio & Overman (2014) finds little effect of public employment on total private employment but substantial reallocation using English local authority data. They find that public employment raises non-tradable employment while crowding out tradable employment. Related work studies large public-sector relocations as place-based policy interventions and documents limited net job creation once local adjustments and displacement are accounted for (Faggio, 2015). Like us, Zou (2018) uses the end of the Cold War to investigate effects on local labor markets with high shares of military employment. He shows that congestion and price-pressure effects (e.g. higher local costs of non-tradables such as housing and services) attenuate measured employment gains. Small local labor market effects aren't inconsistent with our larger effects at the occupational level because labor mobility may spread the effects of government or military employment beyond individual labor markets.

A large literature studies the fiscal multiplier, often using total defense spending or procurement as a source of variation (see Ramey 2011b, Ramey 2016, Ramey 2019, Chodorow-Reich 2019, Ilzetzki 2025 for literature reviews). Several papers use geographically disaggregated procurement variation to estimate local multipliers (cf. Nakamura & Steinsson 2014). Early evidence from state-level procurement suggests modest employment responses (Hooker & Knetter, 1997, 2001). A recent literature has provided local labor market estimates of the employment multiplier of defense procurement spending, using rich disaggregated data (Auerbach *et al.* 2020b, 2024; Park *et al.* 2025; Briganti *et al.* 2026 among many others). As noted above, our focus is in direct defense employment and its effects across the skill distribution, rather than the fiscal or employment multiplier of defense spending. Our study speaks more to the medium term effects of shifts in defense employment rather than on its business cycle implications. "Jobs per dollars spent" is often a metric used to evaluate the effectiveness of fiscal policy in the literature on procurement. Our study highlights that this isn't a sufficient statistic to evaluate the impact of public spending because higher skill jobs may be more expensive to create, but also afford learning externalities. In this paper, we abstract from the simultaneous shock to defense procurement, which will have affected workers in defense contractors. It is likely that workers in this sector had similar high-skill and "hard high" occupations. One can therefore think of the Cold War demobilization shock we study as decreasing demand by more than the 700,000 workers directly impacted by lower military employment. In this regard, our findings complement those of Ramey & Shapiro (2001) who study the difficulties in *capital* reallocation following aircraft plant closures.

A microeconometric literature studies the individual-level effects of military service on earnings and human capital, often leveraging quasi-experimental variation. Using the Vietnam draft lottery, Angrist (1990) estimates long-run earnings effects of veteran status. Using administrative earnings records for applicants, Angrist (1998) studies voluntary service and finds impacts that vary with selection into service and measurement of counterfactual civilian experience. Recent administrative-data research in the all-volunteer era uses discontinuities in enlistment eligibility (AFQT thresholds) to estimate the causal effects of Army service on long-run earnings and related outcomes (Greenberg *et al.*, 2022b). These studies give individual-level, partial equilibrium effects of military service, while we study the effects in general equilibrium.

On the theory side, macro-labor models with search and matching frictions analyze how public-sector hiring and wage setting affect labor market tightness, unemployment, and private job creation. Michaillat (2014) defines and quantifies a public-employment multiplier in a New Keynesian framework with labor-market slack. In two-sector search models, public-sector wages can generate queues and crowd out private job creation; Gomes (2015) characterizes optimal public-sector wage policy, while Afonso & Gomes (2014) links public wage and employment policies to private wage dynamics, and Chassamboulli & Gomes (2023) studies how public-sector policies interact with education decisions. This literature studies how government employment affects slack in frictional labor markets but doesn't focus on occupations and human capital accumulated on the job.

Finally, our occupational-choice and skill-formation framework builds on the task-based literature and the empirical measurement of occupational skill demands. Canonical references include Autor *et al.* (2003) on task content and computerization, the task-based synthesis in Acemoglu & Autor (2011b), and evidence on the rising return to social skills (Deming, 2017b). Our theoretical framework is tied most closely with (Althoff & Reichardt, 2026b), who study the effects of AI on wages and employment, in contrast to our focus on public employment. These strands motivate studying military employment not only as a demand shock for particular occupations, but also as a training/skill-accumulation technology with medium-run general-equilibrium implications.

2 Motivating Facts and Data

The U.S. government spent 3.4% of GDP on national defense in 2024 and roughly a quarter of this is on military personnel. The military employs 1.25 million individuals–over 2 million including civilian employees of the department of defense. This makes the military the largest employer in the US (the remainder of the Federal government has roughly 1.3 million employees and the largest private employer is Walmart with 1.6 million US-based employees).[2] Remarkably, this reflects a *low-point* in US military employment, not seen since the beginning of World War II. The decline is even more striking as a percent of the US workforce. Roughly 5% of all new entrants into the workforce opt for military employment. Restricting attention to men, the figure is nearly double that.

This section introduces the data sources on military employment and occupations and provides some motivating facts that arise from them. We begin by comparing the skills required in military occupations to those required in civilian ones. In Figure 1, we combine skills into four broad sets that we label as "hard hat", managerial, and "soft skills", and STEM. For each set of skills, we show the skill requirements of the average occupation in three broad sectors: public, private, and military. Private sector occupations are further disaggregated into occupations in goods-producing and service sectors; and government jobs into Federal, State and local. Averages are population-weighted, with weights taken from the American Community Survey of 2023. Each broad skill set is an average of more finely-classified skills appearing in the Department of Labor's Occupational Information Network (O*NET). For example, "hard hat" skills are and average of skills in equipment maintenance, equipment selection, installation, operation and control, operations monitoring, quality control analysis, repairing, and troubleshooting; reflecting skills typically required in manufacturing, construction, mining, and related occupations. The O*NET score ranges from one to five and gives the level of skills in each category required to perform this job.[3]

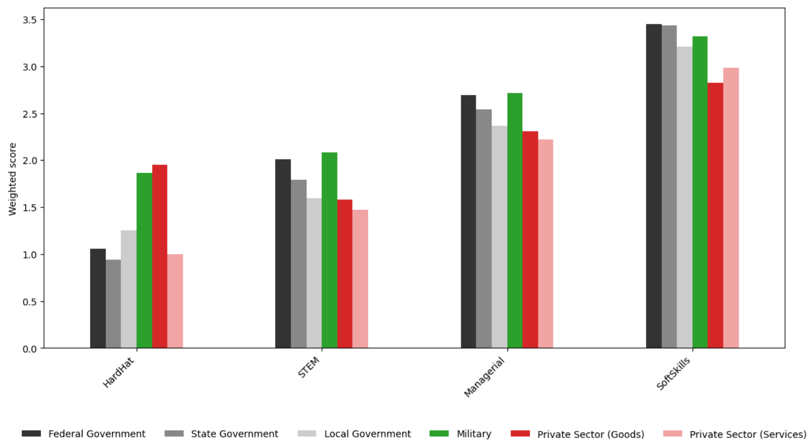
Two facts stand out from Figure 1. First, military jobs have higher skill requirements than private sector jobs in all four categories, and higher skill requirements than civilian public sector jobs in all categories except "soft skills". Military jobs are high-skill jobs.

Second, military jobs stand out as having high "hard hat" skill requirements. They are strikingly similar to private-sector goods-producing jobs. Figures A1 to A8 in the appendix show that both facts hold in each of the underlying skills used to calculate the broad skill sets in Figure 1. Table A3 delves further into this second observation, ranking private sector occupations (aggregated to the 4-digit NAICS level of aggregation) by their similarity to military occupations, along

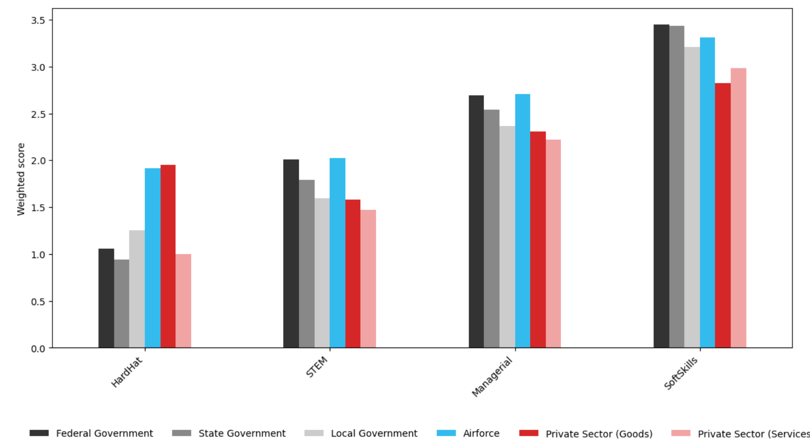
[2] Sources: Military One Source; Pew Research Walmart

[3] The O*NET is the Department's effort to keep tabs on the evolving nature of work, giving 900 occupational profiles and covering 55,000 jobs. It provides information about worker attributes and job characteristics. Occupational analysts score the importance of each of 34 skills in each occupation on a scale from one to five.

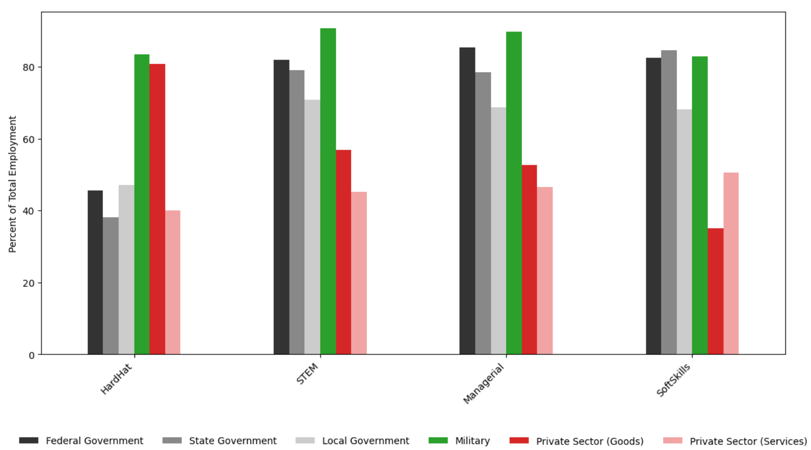
Figure 1: Skill requirements in civilian and military occupations



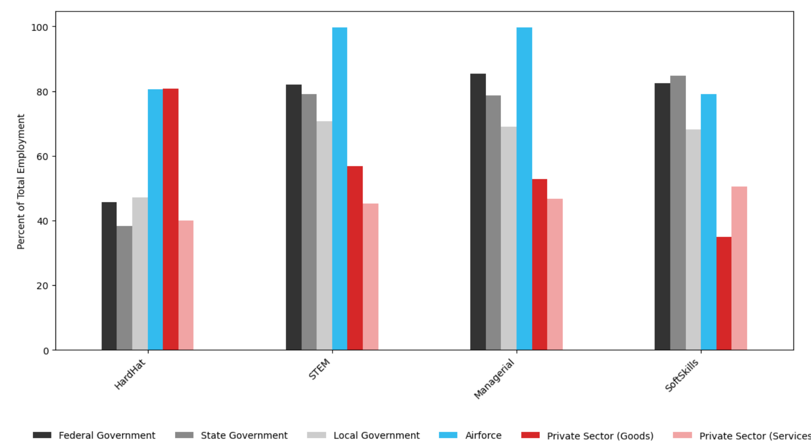
(a) Average skill requirements in military and civilian occupations



(b) Average skill requirements in the air force and civilian occupations



(c) Percent of military and civilian occupations with above median skill requirements



(d) Percent of air force and civilian occupations with above median skill requirements

Notes: This figure shows the skill requirements in occupations in several employment sectors, as evaluated by O*NET. The gray bars represent civilian government jobs, including Federal, State, and local (from darkest to lightest). The green bars represent military jobs in right hand panels and blue bar represent the airforce in the right-hand panels. Red bars give civilian jobs, with the darker bar showing the goods-manufacturing sectors and the lighter bar showing the services sector. The top panels give the average skill requirements on a scale from 1 to 7. The bottom panels give the share of jobs that have skill requirements above the median of all occupations (population-weighted).

the 4 broad skill categories. Distance between occupations is measured by the square difference between jobs, averaged across the four categories.

Skill requirements for military occupations aren't readily available in the ONET. To overcome this, we use a cross-walk between military occupations in the ACS and the civilian jobs listed in the ONET. (The cross-walk methodology is discussed in Appendix A2) However, military occupations in the ACS are at a high level of aggregation, with only a small number of different military occupations. To reassure the reader that this coarseness of aggregation isn't driving results, we repeat the analysis for the airforce, where we can obtain occupational data a finer level of aggregation from the Air Force Statistical Digest. This comes at the cost of looking at a single branch of the military, representing a quarter of all soldiers, and which may be less representative. The right-hand panels of Figure 1 show skill requirements in airforce jobs, giving nearly identical results to those arising from all branches of the armed forces.

The bottom panels in Figure 1 give a different cut of the data, showing the percent of jobs in each sector that have skill requirements that are above the median for the entire workforce. Military jobs stand out even more in this representation, with over 80% of military jobs being above median in each one of the skill categories.

Veterans serve in similarly high skill jobs (Figure A9 in the appendix). The skill requirements in the average job held by army veterans is higher than the average private sector job, across all four skill categories. Veterans working in the goods producing sector work in jobs with even higher "hard hat" skill requirements than even those in the military, again suggesting that the military was a useful training ground for such occupations.

The nature of military jobs–intensive in their use of "hard hat" skills, but also high skill in other categories, such as STEM, can be seen by the most common military occupations show in Tables A1 and A2 in the appendix. The most common jobs are in military operations, but these are followed by leadership positions. Nearly a fifth of Air Force personnel are in aerospace maintenance and almost 10% work in support positions related to cyberspace.

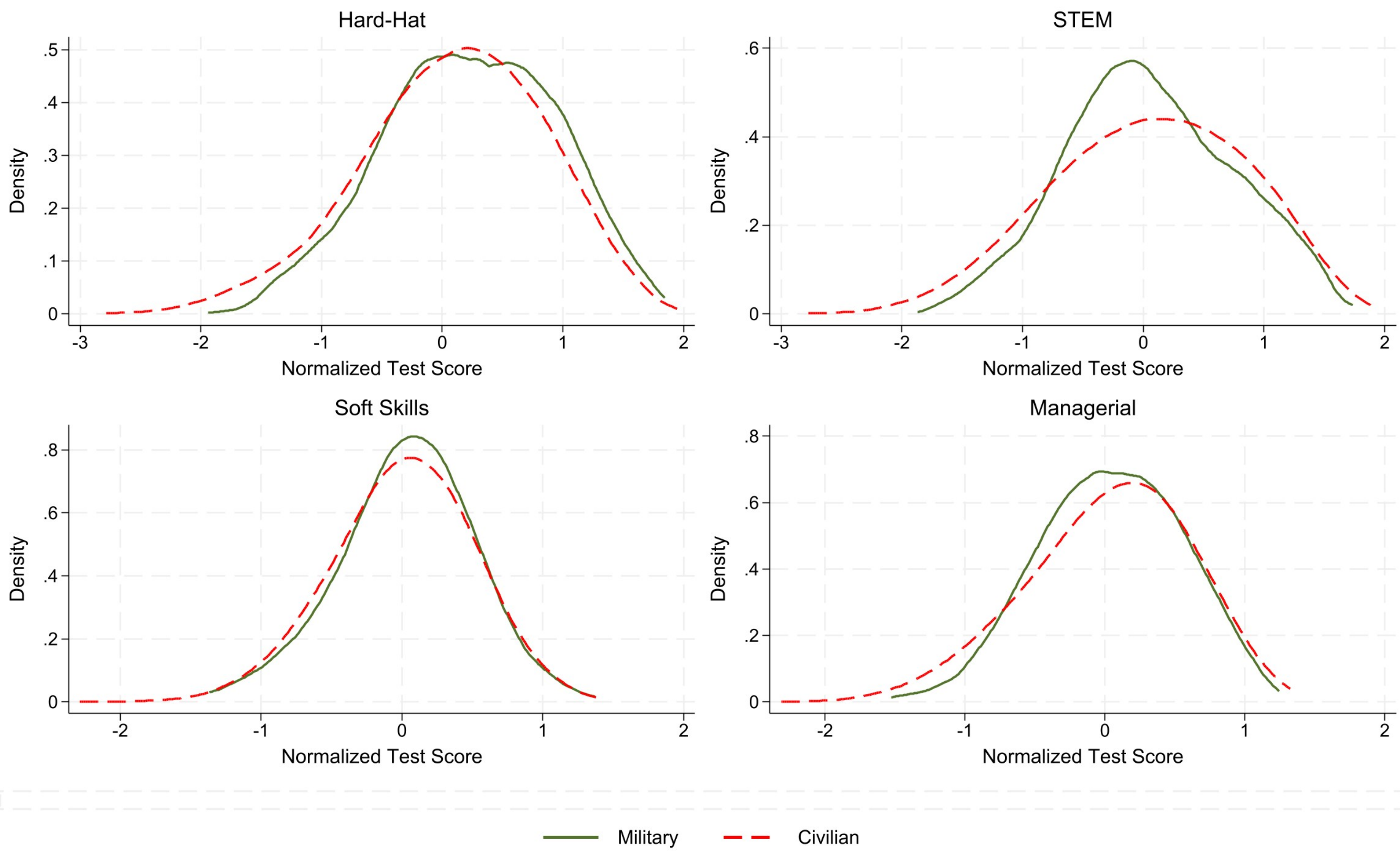
Although many military occupations have relatively high skill requirements, only a minority of soldiers have a college degree (27.8%, compared with 36% of the general population). Some complete education after military service, but veterans still have a slightly lower educational attainment (32% with a college degree) than the general population. In contrast, 85% of officers have a college degree. Roughly 7% of soldiers have post-graduate degrees, compared with 15% in the general population. However, nearly all soldiers enter with a high school diploma, compared with 7% of the US population that never completes high school. Thus entrants into the military have lower educational attainment than the general population, but the lower tail of of the educational distribution is under-represented.

The National Longitudinal Survey of Youth (NLSY) gives a further look at the human capital of soldiers and civilians. The survey gives a battery of standardized tests to early-career individuals giving a snapshot of a broad set of skill. We average individual test scores to correspond to the four skill categories reviewed above. The survey over-samples the military, giving a good comparison between civilians and enlisted soldiers. Figure 2 shows the distribution of test scores of civilians and soldiers in these four skill categories. Despite their lower educational attainment, soldiers have higher average skills in all categories compared to civilians and the differences are statistically significant. However, the stories of the four skills are different. The higher mean score in managerial, STEM, and soft skills arise from a curtailed left-tail of the distribution of test scores among soldiers. This likely arises because the military has minimal score requirements in the standardized tests it itself gives potential recruits. The top-tail of the distribution roughly overlaps in management and soft skills, and soldiers are under-represented in the top-tail of the STEM distribution. The panel showing "hard hat" scores tells a different story. Soldiers are not under-represented in the bottom-tail of "hard hat" test scores, but also greatly over-represented in the top-tail, implying that "hard hat" stars are drawn to military service. The differences are economically meaningful with the average soldier scoring eight percentage points higher in the overall test-score distribution than the average civilian. (This is one to four percentage points on the other tests.)

A few facts about military careers. The median entrant into the military is 20 years of age: The distribution of age at entry is shown in Figure A10 in the appendix. Soldiers enlist for a standard active duty of two to four years of military service, followed by a 6-8 year commitment to reserve or guard duty upon return to civilian life. Nearly a quarter of enlisted soldiers remain beyond their initial enlistment as officers or warrant officers, with an option to retire after 20 years of service. The median age of exit is 25 but the distribution of age at exit (also shown in Figure A10 in the appendix) is bimodal, with modes at 24 and just below 40, reflecting standard active duty and a military career, described above. For the majority of soldiers, army service is a short-lived job early in their career. Even those embarking on a military careers typically have a second career of roughly equal length when they are veterans. In this regard, the military serves as an early career path and a de facto training program for large swaths of the workforce. (See Topel & Ward 1992; von Wachter & Bender 2006; von Wachter 2020; Bruhn *et al.* 2025 on the importance of early career employment and Wolter & Ryan 2011 on early career training).

Over 80% of active duty members are men, with only slightly better gender parity among officers. African Americans are 50% more likely than other ethnic groups to serve in the military but are under-represented among officers. Other ethnic groups are represented in proportion to the general population, with the exception of Asians, who are under-represented. All non-white

Figure 2: Armed Forces Qualification Test (AFQT) scores for military personnel and civilians



Notes: This figure shows the distribution of Armed Forces Qualification Test (AFQT) exam scores averaged in four categories reflecting manual, mathematical and scientific, social and verbal and managerial (taken as the average of the previous two categories). The distributions are as kernel density plots, separately for civilians (red) and military personnel (green). Scores are relative to the mean score pooling all years and both sectors. Sources: NLSY and the authors.

ethnic groups are under-represented among officers.

3 Event Study: The Cold War Demobilization Shock

To further illustrate the importance of military employment on US labor markets, we begin with an event study, surrounding the end of the Cold War. At the end of the Cold War, the US military shed roughly 700 thousand jobs and this happened in a relatively short time window (Figure 3). Given the short duration of military service, this didn't require mass layoffs, but merely recruitment at a lower annual rate. Our hypothesis is that this was a sufficiently large negative labor demand shock to have an impact on labor markets, particularly in occupations with similar skill requirements to those required in the military.

We evaluate this claim using an event study regression of the following form:

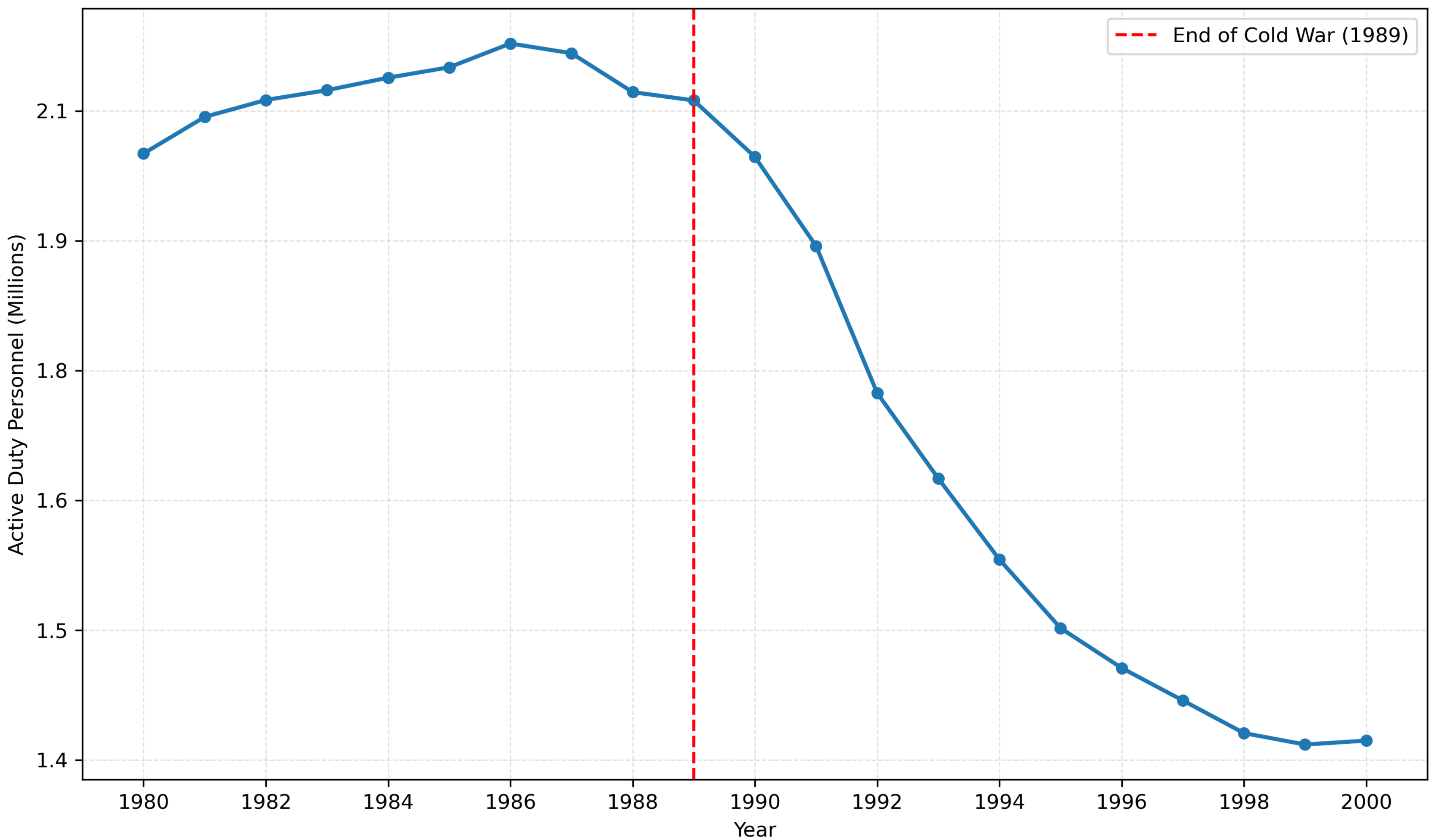
$$\ln(\text{WageIncome}_{iot}) = \sum_{\substack{k=-8 \\ k\neq -1}}^{8} \beta_k \left(\mathbf{1}\{\text{event}_t = k\} \times \text{Treated}_o\right) + \alpha_o + \lambda_t + \varepsilon_{iot}, \tag{1}$$

where i indexes individuals, o indexes occupations, t indexes calendar years, and k indexes event time, with $k \in \{-8, -7, \ldots, 8\}$ and $k = -1$ representing the year 1989, omitted as the reference period. The regression includes occupation and year fixed effects. We cannot control for individual fixed effects, as CPS is a repeated cross-section, and the regression is effectively at the occupational level. We later included individual controls.

The treatment group is civilian occupations with similar skill requirements to those employed in the military. We measure distance between occupations as the absolute value of the difference between the skill requirement in the average military occupation and each civilian occupation, averaged over the four skill sets described above. Table A3 in the appendix gives the 10 civilian occupations most similar to the military as a whole and the Air Force, where we remind the reader that the former is more comprehensive, but that we have more granularity of occupational classification for the latter. Similar occupations are very heterogeneous. Some occupations on the list reflect manual labor such as logging, stonemasons, and carpenters. Others appear to reflect high technical skills, such as "nuclear power operators" and "power distrutors and dispatchers". Yet others reflect high managerial skills (likely of the office corp) and the high overall skills of military occupations: chief executives is the most similar occupation to the military as a whole, and managerial occupations are highly represented on the list.

Given the heterogeneity in military jobs, it makes little sense to consider civilian occupations that are similar in their skill requirements to the "average" military job. Instead, we focus on "blue-collar" military occupations: those that are at the top decile of military occupations in terms of their

Figure 3: Military Employment



hard-hat skills. A list of the most similar civilian occupations to this category are listed in the last column of Appendix Table A3, with electrical engineering technicians, broadcast technicians, and medical appliance technicians topping the list. The treated civilian occupations $Treated_o$ are then those that are at the top decile of similarity to blue collar military occupations across all four skill dimensions.

Figure 4 shows the dynamics of income around the Cold War for treated occupations: the β_k values from (1). Income in occupations most similar to blue-collar military jobs followed similar trends to other occupations in the 1980, but saw a sharp and nearly immediate decline of more than 5% at the end of the Cold War relative to other occupations. This persists until at least the turn of the century. Results are similar when looking at occupations at the top quartile of similarity to blue collar military jobs, as seen in Figure A11 in the appendix. Results are also robust to controlling for individual characteristics, such as age, gender, and regional fixed effects (corresponding to the nine census divisions), and their interaction with time fixed effects (see Figure A12). Figure A13 in the appendix shows results are similar for occupations that are in the top quartile or above median in similarity to military blue-collar occupations, with the treatment effect monotonic in similarity to the military. [4]

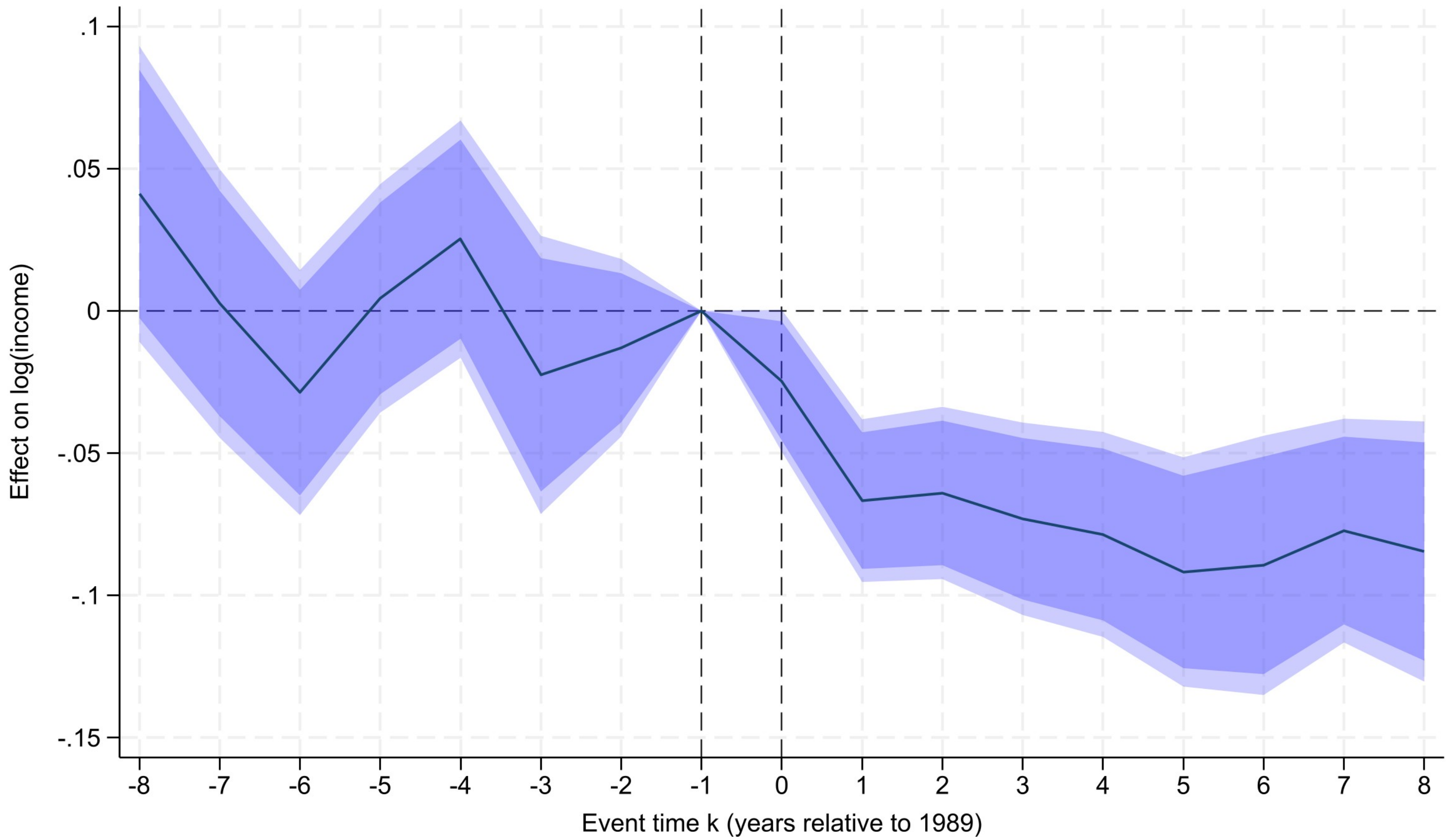
Figure A14 in the appendix shows the raw time series of income of occupations in all deciles of similarity to blue collar military jobs, each normalized to one in the year 1989. The top decile–the one we predict to be most affected by the Cold War demobilization–is in the middle of the pack before 1989. This reflects that it was roughly the median among occupations in terms of income growth in the 1980s. A clear inflection point can be seen at the end of the Cold War, with income growth flattening out for the exposed occupations, and this decile experiencing the lowest income growth in the subsequent decade.

There are of course other factors that may have affected the relevant occupations at the end of the 1990s other than the shock to military employment. There has been a secular decline in the fate of blue collar workers and our attention to occupations similar to blue collar military occupations may simply be picking up these trends. We note that there is no visible pre-trend before 1990 and the impact on income is sharp and persistent following the end of the Cold War. This requires confounders that saw a sharp change around this time. This likely rules out the China shock (Autor *et al.*, 2013a,b): China joined the WTO only in late 2001, outside the window of our analysis.

Nevertheless, we conduct several robustness checks. First, we control for exposure to the "China shock" and its interaction with time fixed effects. We measure exposure to the China shock

[4]We note that occupations similar to military jobs as a whole did not see a commensurate decline in wages. The economic boom of the 1990s was a particularly good time for high-skilled occupations and the *average* military job reflected these high skills. As noted earlier, the most similar occupations to the average military job were CEOs, who certainly didn't suffer in this period. Instead, the pain was concentrated among high-skilled working class populations, in occupations similar to working-class military jobs.

Figure 4: Relative income in civilian occupations similar to blue-collar military jobs around the end of the Cold War



Notes: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top decile of similarity to "blue collar" military jobs. Sources: American Community Survey and the authors.

based on individual's industry of employment, using both the upstream and downstream measures of Autor *et al.* (2013a,b); Acemoglu *et al.* (2016). We interact these cross-sectional exposure metrics with time fixed effects and include these as controls. Results are shown in Figure A15. Given the timing, the NAFTA trade shock may be a more plausible candidate, although NAFTA too was signed into law only in December 1992 and took effect only in 1994–almost half way into our event window. Figure A16 shows an event study regression that controls for exposure to NAFTA (Hakobyan & McLaren, 2016b), again interacted with time fixed effects, and corroborates that our effects aren't driven by the main 1990s trade shock.

Next we control for exposure to automation, and its interaction with time fixed effects, as shown in Figure A17 in the appendix. We measure exposure to automation as occupations that are above median in routine tasks, as evaluated by Autor *et al.* (2003). We also see that the effects hold *within* the manufacturing sector, as seen in Figure A18, where we control for manufacturing sector fixed effects, interacted with time fixed effects. In all cases, results remain nearly unchanged.

In general, there is much evidence of multiple sources of misery for the US manufacturing worker, which could be correlated with our measure of "hard hat" workers (Amior & Manning, 2018; Abraham & Kearney, 2020). We control for other such confounders through the interaction between time fixed effects and fixed effects for the *level* of hard hat skills in each occupation. This compares occupations most similar to military jobs within each skill level, absorbing non-parametrically the trend for each "hard-hat" skill group. Results are shown in Figure A19 in the appendix. The magnitude of decline following the Cold War is similar to our baseline results and results remain statistically significant. This indicates that the earnings decline reflects occupations' similarity to military jobs, not the general income decline in "hard hat" occupations.

It is informative to delve deeper into the sources of variation exploited in this last specification. Table A4 in the the appendix lists the occupation most similar and the one least similar to blue collar military jobs within each bin of "hard hat" skill score. The former are quintessential of our treatment group and the latter of our control group. The fixed effects absorb the difference between jobs that are more mechanical and technical and those with lower "hard hat' requirements (e.g. machinery maintenence workers vs. purchasing agents of farm products). Instead, it compares occupations of similar levels of "hard hat" skills that are more and less similar to military occupations (e.g. sound engineering technicians vs. cleaners of vehicles and equipment). The following columns show the STEM skills, skill requirements averaged over all four categories, and the average annual salary (in 2026, according to O*NET) of these occupations. The military-adjacent jobs are *higher* skill and *higher* pay jobs–they are "good" jobs–yet they are those that suffered most as the Cold War came to an end. This illustrates that we are not merely re-stating the general misery of the American working class, but rather documenting a different shock that affected it.

4 Theory: Military Employment in GE

The partial equilibrium empirical estimates of the previous section suggest that the decline in military employment at the end of the Cold War put downward pressure on wages in related civilian occupations. We now present a model that will help evaluate the general equilibrium implications of the decline in military employment for hard-hat workers and others.

4.1 Model

The model consists of firms, a government, and overlapping generations of workers. Workers live for A periods and all generations have measure $\frac{1}{A}$. Besides their age, workers differ in their skills in each dimension, collected in the vector $\boldsymbol{h}$, and the ability with which they can accumulate those skills, indicated by ψ. Each worker supplies a measure 1 of labor inelastically and consumes a consumption good C, using their after tax income. The government raises revenues, using a proportional labor income tax τ, which it uses to produce or procure a public good G. Both types of good are produced by combining a variety of intermediate goods. For simplicity, we assume that the two sectors use disjoint sets of intermediate goods, so that there are separate intermediate goods that serve as input to consumption goods and public goods.

Firms produce (public or private) intermediate goods using labor inputs only. Productivity and wages depend on the match between workers' skills and the skill requirements in their occupation of choice. Workers accumulate skills on the job depending on the job's skill requirements, so that their occupational choice depends on both the current wage and the learning benefits that the job offers. Prices and wages are determined in general equilibrium.

Production technology

Each occupation produces a distinct intermediate good y_j. The production function that translates labor contributions of a worker with skill set $\boldsymbol{h}$, working in occupation j, to the j^{th} good variety is given by

$$y_j(\boldsymbol{h}) = \gamma_j f(\boldsymbol{h}, \boldsymbol{r}_j) \tag{2}$$

where γ_j represents the overall productivity of the production technology of j and the function $f(\cdot)$ reflects the contribution of human capital to labor productivity and depends on the skill set $\boldsymbol{h}$ of the worker and the vector of skill requirements of the occupation, $\boldsymbol{r}$. Intuitively, this function captures how workers' productivity depends on the "match" between their skills and the skills required to complete the task (Lise & Postel-Vinay, 2020; Baley *et al.*, 2022; Althoff & Reichardt, 2026a). Workers are heterogeneous in their ages and histories, but their skill vector $\boldsymbol{h}$ is a sufficient statistic for a their human capital.

The firms' problem

Each good j is produced by a representative firm that chooses how many workers of each skill set $\boldsymbol{h}$ to hire, taking the market wage $w_j(\boldsymbol{h})$ as given. Occupations $j \in [1, J^C]$ are occupations in the consumer goods sector and $j \in [J^C+1, J^C+J^G]$ are in the government/military sector. Firms in the two sectors otherwise operate equivalently. Formally, the firm solves the following profit maximization problem:

$$\max_{n_j(\boldsymbol{h})} \int n_j(\boldsymbol{h}) \left(p_j y_j(\boldsymbol{h}, n_j(\boldsymbol{h})) - w_j(\boldsymbol{h}) \right) d\boldsymbol{h} \tag{3}$$

where the integral sums over all skills and $n_j(\boldsymbol{h})$ is the amount of labor employed with skill set $\boldsymbol{h}$.

With a perfectly competitive labor market, the worker's wage is equal to their marginal product:

$$w_j(\boldsymbol{h}) = p_j f(\boldsymbol{h}, \boldsymbol{r}_j). \tag{4}$$

Skill accumulation

Each worker draws an initial skill vector $\boldsymbol{h}_1$ and a learning ability ψ before entering the labor market at age $a = 1$. Skills at later ages evolve as they accumulate skills on the job. A worker's skill accumulation depends on their current skills, the skill requirements of their current job j, and their learning ability ψ: $\boldsymbol{h}' = g(\boldsymbol{h}, \boldsymbol{r}_j, \psi)$.

Occupational choice

In each period, workers choose from a discrete set of occupations to maximize their utility. There is no savings technology and workers consume their income each period. The expected lifetime utility of a worker aged a, with learning ability ψ, and previous occupation k is represented by the value function

$$V_a(\boldsymbol{h}, \psi, k) = \mathbb{E}\left[\max_j \log w_j(\boldsymbol{h}) + \log(1-\tau) + \log \varepsilon_j + \mu_{j,a} - \kappa(k,j) + \beta V_{a+1}\left(\lambda_j\left(\boldsymbol{h}, \psi\right), \psi, j \right) \right] \tag{5}$$

where ε_j represents a random shock to the quality of the worker's match to or productivity in occupation j and $\mathbb{E}[\cdot]$ is the expectation over this shock. A worker's observed wage equals the deterministic part $(1-\tau)w_j(\boldsymbol{h})$ times the stochastic part ε_j.

Each occupation j has an amenity value $\mu_{j,a}$ that can depend on age a. $\kappa(k,j)$ is the cost of switching from occupation k to j. In our quantitative application, we set this to $\kappa(k,j) = \kappa \mathbb{1}[j \neq k]$ for some constant κ, i.e. the cost of moving between any pair of different occupations is the same. $\lambda_j\left(\boldsymbol{h}, \cdot\right)$ is next period's human capital when choosing occupation j. The worker's life is finite and the value after the terminal age of A is zero, $V_{A+1}(\cdot) = 0$.

We assume that the productivity shocks $\log \varepsilon_j$ follow a type I generalized extreme value (Gumbel) distribution with mean 0 and scale parameter ζ.[5] This assumption implies that the conditional probability of choosing occupation j has the closed-form solution

$$\mathbb{P}_a(j \mid \boldsymbol{h}, \psi, k) = \frac{\exp\left(\frac{1}{\zeta}\left(\log w_j(\boldsymbol{h}) + \mu_{j,a} - \kappa(k,j) + \beta V_{a+1}\left(\lambda_j\left(\boldsymbol{h},\psi\right),\psi,j\right)\right)\right)}{\sum_{l=1}^{J}\exp\left(\frac{1}{\zeta}\left(\log w_l(\boldsymbol{h}) + \mu_{l,a} - \kappa(k,l) + \beta V_{a+1}\left(\lambda_j\left(\boldsymbol{h},\psi\right),\psi,l\right)\right)\right)} \tag{6}$$

so that the value function in (5) can be simplified to

$$V_a(\boldsymbol{h},\psi,k) = 1 - \tau + \zeta \log \sum_{j=1}^{J} \exp\left(\frac{1}{\zeta}\left(\log w_j(\boldsymbol{h}) + \mu_{j,a} - \kappa(k,j) + \beta V_{a+1}\left(\lambda j\left(\boldsymbol{h},\psi\right),\psi,j\right)\right)\right). \tag{7}$$

A convenient feature is that the tax rate does not affect the worker's occupational choice problem directly, only through its effect on prices captured in the $w_j(\boldsymbol{h})$. For a given sequence of prices, the occupational choice problem can be solved via backward iteration starting from age A with $V_{A+1}(\cdot) = 0$, equation, and using (7) to solve for occupational choice and continuation value by backward induction from ages A to 1.

Private and public demand

Households value individual consumption goods according to a CES function $C = \left(\sum_{j=1}^{J^C} \alpha_j^{\sigma} c_j^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, with $\sum_{j=1}^{J^C} \alpha_j = 1$, so that the optimal choice of intermediate consumption goods is

$$\frac{p_j}{P_C} \equiv \alpha_j^{\frac{1}{\sigma}}\left(\frac{c_j}{C}\right)^{-\frac{1}{\sigma},}, \qquad P^c = \left(\sum_{j=1}^{J^C} \alpha_j^c p_j^{1-\sigma}\right)^{\frac{1}{1-\sigma}} = 1 \tag{8}$$

where P_C is the consumer goods price, which we normalize to one. The government, similarly, produces a public good $G = \left(\sum_{j=J^C}^{J} \alpha_j^{\sigma} g_j^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$, which is a CES aggregate of intermediate public good varieties, with $\sum_{j=J^C+1}^{J} \alpha_j = 1$. The government attempts to provide the public good at minimal cost, giving

$$\frac{p_j}{P^G} = \alpha_j^{\frac{1}{\sigma}}\left(\frac{g_j}{G}\right)^{-\frac{1}{\sigma}}, \qquad P^g \equiv \left(\sum_{j=J^C+1}^{J} \alpha_j p_j^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{9}$$

[5]The CDF is $\Pr(\log \varepsilon < x) = \exp\left(-\exp\left(-\frac{x+\zeta\overline{\gamma}}{\zeta}\right)\right)$ where $\overline{\gamma} \approx 0.577$ is Euler's constant. This implies that ε_j follows a Fréchet distribution.

The government maximizes the procurement of the public good under the constraint that it can not spend more than the revenue it raises from labor taxes. The market clearing condition for the output of each occupation implies $c_j + g_j = y_j \; \forall j$, but note that for each j either the private or public demand for the variety is zero.

4.2 Equilibrium

The price of each occupational good p_j is determined in equilibrium through demand and supply. Occupational supply is given by the solution to the worker's problem. The workers consume their labor income and generate demand for the occupational goods. Occupational demand follows from the workers' and government's optimal choice of goods varieties. we can now define the competitive equilibrium.

Definition 1 (Competitive equilibrium) *Given an initial joint distribution of age, skills, ability, and occupation-specific labor supply, $\Lambda_{a,t}(\boldsymbol{h},\psi,k)$, a distribution of human capital at birth $\Lambda_{1,t}(\boldsymbol{h},\psi)$, and government demand for public goods of G, a competitive equilibrium is defined as a sequence of prices $\{p_{1,t},\cdots,p_{J,t}\}_{t=1}^{\infty}$ and allocations such that*

- *Workers' occupational choices maximize the present value of lifetime utility given prices. That is, their occupational choice probabilities are as in equation* (6) *given wages in equation* (4)*;*
- *Workers' and the government's choices of goods minimize costs, given prices. That is, intermediate good variety choices satisfy* (8) *and* (9)*;*
- *The distribution over states follows from occupational choices:*

$$\Lambda_{a+1,t+1}\left(\boldsymbol{h'},\psi,j\right) = \sum_{k=1}^{J}\int_{\lambda_j(\boldsymbol{h'},\psi)\leq \boldsymbol{h}} \mathbb{P}_{a,t}\left(j \mid \boldsymbol{h},\psi,k\right) d\Lambda_{a,t}\left(\boldsymbol{h},\psi,k\right); \tag{10}$$

- *The market for each intermediate good clears:*

$$c_{j,t} + g_{j,t} = \sum_{a=1}^{A}\sum_{k=1}^{J^C+J^G}\int y_j(\boldsymbol{h})\,\mathbb{P}_{a,t}(j \mid \boldsymbol{h},\psi,k)\,\mathbb{E}[\varepsilon_j \mid j,\boldsymbol{h},\psi,k]\,d\Lambda_{a,t}(\boldsymbol{h},\psi,k);^{6} \tag{11}$$

- *The government's budget constraint is satisfied:*

$$P^G G = \tau\sum_{a=1}^{A}\sum_{k=1}^{J^C+J^G}\int w_j(\boldsymbol{h})\,\mathbb{P}_{a,t}(j \mid \boldsymbol{h},\psi,k)\,\mathbb{E}[\varepsilon_j \mid j,\boldsymbol{h},\psi,k]\,d\Lambda_{a,t}(\boldsymbol{h},\psi,k). \tag{12}$$

[6] $\mathbb{E}[\varepsilon_j \mid j,\boldsymbol{h},\psi,k]$ is the expectation of the shock to occupational match quality conditional on choosing occupation j when the individual's state is $\boldsymbol{h},\psi,k$. The Gumbel distribution of $\log\varepsilon_j$ implies that this expectation has a closed-form solution: $\mathbb{E}[\varepsilon_j \mid j,\boldsymbol{h},\psi,k] = \exp(-\zeta\gamma)\Gamma(1-\zeta)\mathbb{P}_{a,t}(j \mid \boldsymbol{h},\psi,k)^{-\zeta}$.

4.3 Parametrization and Estimation

The parametrization and estimation closely follows Althoff & Reichardt (2026a). We are therefore brief in our discussion here.

Functional forms

We parameterize the production function:

$$f(\boldsymbol{h}, \boldsymbol{r}_j) = \prod_{s \in S} h_s^{\omega_s} \exp\left(-\eta \max\left\{r_{j,s} - h_s, 0\right\}^2\right).$$

where $s \in S$ indicates each of the multiple dimensions of skill. The Cobb-Douglas term in this function captures forces that make more skilled workers more productive regardless of the occupation. The exponential mismatch term captures how a worker's productivity declines when they are in an occupation that have skill requirements $\{r_{j,s}\}_{s \in S}$ above their skill level $\{h_s\}_{s \in S}$.

Given this functional form, the wage function in (4) equals

$$\log w_j(\boldsymbol{h}) = \log p_j + \sum_{s \in S} \omega_s \log h_s - \eta \sum_{s \in S} \max\left\{r_{j,s} - h_s, 0\right\}^2. \tag{13}$$

For human capital accumulation, we estimate the parameters of the following functional form:

$$g_s(\boldsymbol{h}, \psi, \boldsymbol{r}_j) = (1 - \delta) h_s + \max\left\{r_{j,s} - h_s, 0\right\} e^{-\lambda(\psi) \max\left\{r_{j,s} - h_s, 0\right\}}, \tag{14}$$

which captures how skill s accumulates when the worker does tasks that are hard, i.e., for which the skill requirements are above their current skills. The exponential term allows for learning to decay when the workers' skills are too far away from the skill requirements. It also allow this decay to differ by the learning ability of the worker, indexed by ψ.

Estimation

We estimate the parameters governing workers' comparative advantage across occupations and skill accumulation using a maximum likelihood approach with data from the NLSY79.

The first step of the estimation follows (Althoff & Reichardt, 2026a), except that we include military occupations in the analysis.[7] That is, we use NLSY79 data on workers' assessed skills at age $a = 1$ and their occupational and wage histories to estimate the parameters of equations (13) and (14), those governing sensitivity of occupational choice to wage difference and the initial skill distribution. To make this computationally feasible, we use the logic that the equilibrium

[7] Besides that, we do not consider tasks or, equivalently, each occupation is one task.

prices can be directly estimated from the wage data, so that it is not necessary to solve the model's equilibrium as part of the estimation strategy. Specifically, we estimate $\log p_j$ from occupational fixed effects in a regression where we control for the workers' skills, their skill mismatch, and a term that controls for selection. Because the skills are themselves to be estimated (as it depends on skill accumulation), this linear regression is part of a larger optimization routine that maximizes the likelihood over the remaining parameters.

The second step consists of estimating the occupational amenities $\mu_{j,a}$. In this paper, we allow for amenities that are age-specific to capture that the military tends to employ young workers. Specifically, we parameterize amenities as $\mu_{j,a} = \mu_a^g \mathbb{1}[j \in \{J^C + 1, \ldots, J]] + \mu_j$ where the first term captures that the amenity values of any military occupation (relative to non-military occupations) changes with age. This allows us to match that military employment is dominated by younger workers, which is important in shaping its effect on human capital accumulation. The second term captures that some occupations may be more or less attractive regardless of age. For parsimony, we do not allow age-specific amenity differences for occupations within the military or private employment. We estimate these amenities from employment shares by age using an iteration procedure à la (Berry *et al.*, 1995).

4.4 Quantitative Results

We begin with a microeconomic question: what is the model prediction of the causal effect of military service on lifetime wage income? To do so, we set the tax rate τ to a value that matches the share of military personnel costs in the model to equate its current value in US data, both as a share of GDP. Namely, we set $\tau = 0.7\%$. Counterfactual analysis and therefore causal inference is straightforward in the model. While workers' probability of choosing the military depends on their skills and age, it also depends on their draw of the occupation-specific productivity ε_j. We can therefore compare individuals who did versus did not choose to join the military solely as a result of a high ε_j draw. Importantly, we compare individuals only within groups that had the same age and ex-ante probability of choosing the military. Since ε_j is independent over time, the difference in outcomes is due solely to entering the military at that time relative to the relevant outside options for these individuals.

Simulation results are shown in Figure 5. The figure shows the difference between the wages of the individual who randomly choose in simulation rounds where they have served in the military at any age, with their wages in other simulation rounds. Time zero represents the time at entry and the absence of pre-trends reflects that assignment to military service is random within the comparison groups. Wages increase by 20 percent on entry to the military and decay over time. The red horizontal bar in the figure shows Greenberg *et al.*'s 2022a estimates of the causal effect of military service on earnings 11 to 19 years later. The model fits the empirical evidence remarkably well given that this result was not used at all in estimation.

Turning from micro to macro, we now alter the value of military spending and investigate its effects on wages. That is, we increase τ, so that more and more resources are spent on military employment. Each dot in Figure 6 gives steady state wages in the model for different groups of workers and for different shares of GDP devoted to military employment. All wages are normalized to one in the baseline scenario where total spending on military wages is at current rate of 0.7% of GDP. The red dots and lines then give wages for occupations most similar to blue collar military occupations–the treatment group in our empirical analysis–under other levels of defense spending. The model predicts that wages increase for similar occupations as defense spending increases. The second dot from the right represents the level of defense employment spending at the end of the Cold War (1989), of 1.4 of GDP. Wages increase, by roughly 0.5%, a meager amount relative to the empirical evidence, but qualitatively in the correct direction. However, recall that these are comparisons between steady states–wages after new generations of workers have had the chance to adapt to the reality of lower defense spending. With long-run elasticities larger that short-run ones, a smaller long-run effect is expected. However, subsequent observations in the figure show that wages of the affect occupations would increase far more dramatically, even in the long-run, if military employment increased to higher levels, like those observed in the Korean War or World War II. In the latter case, military wages were 20% of GDP and the model predicts a 6% wage increase in professions similar to those in the military

The blue dots and line represent an effect that cannot be estimated in the micro data–the effect of the control group, in occupations that are less similar to blue color military occupations–the missing intercept. The model predicts that wages increase overall, not only for the most affected populations. This general equilibrium effect is large: spillovers are nearly half as large as the direct effect on the most affected population. Recall that the consumer good is the numeraire, so that this reflects a real increase in households' purchasing power. Increased public spending is financed with higher taxes, so that higher public consumption crowds out private consumption. But the sum total of public and private goods, measured in units of the private good, increases in tandem with wages.

A positive fiscal multiplier shouldn't be taken for granted in this model. After all, workers supply labor inelastically–the wealth effect of government spending is shut off, as is any Keynesian employment channel. Instead, the entire wage increase is due to higher worker *productivity*. This arises because of the human capital effects of military employment, which is in turn a result of the relatively high skill requirements of military jobs.

Figure 5: Causal effects of military service in the model

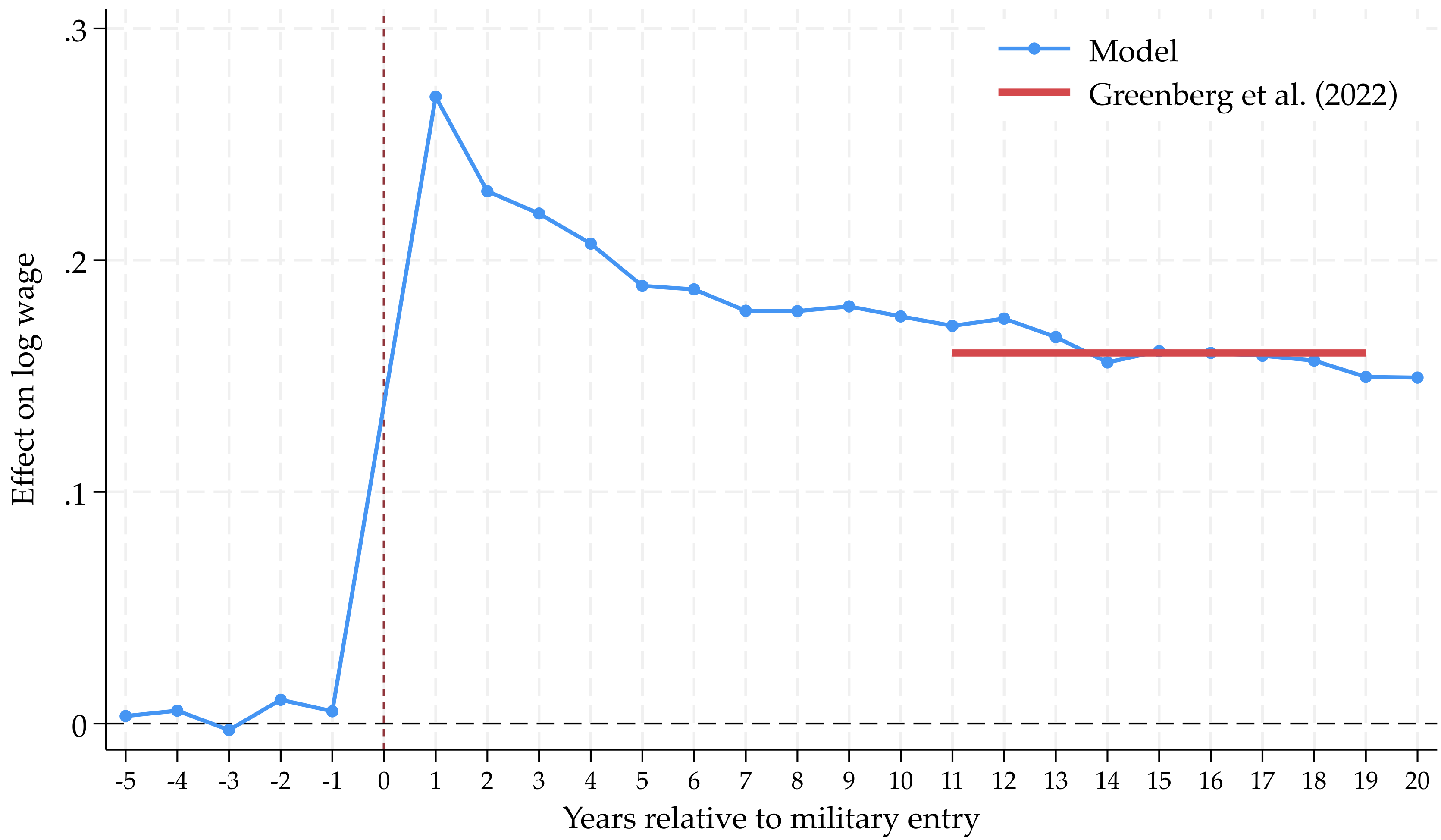
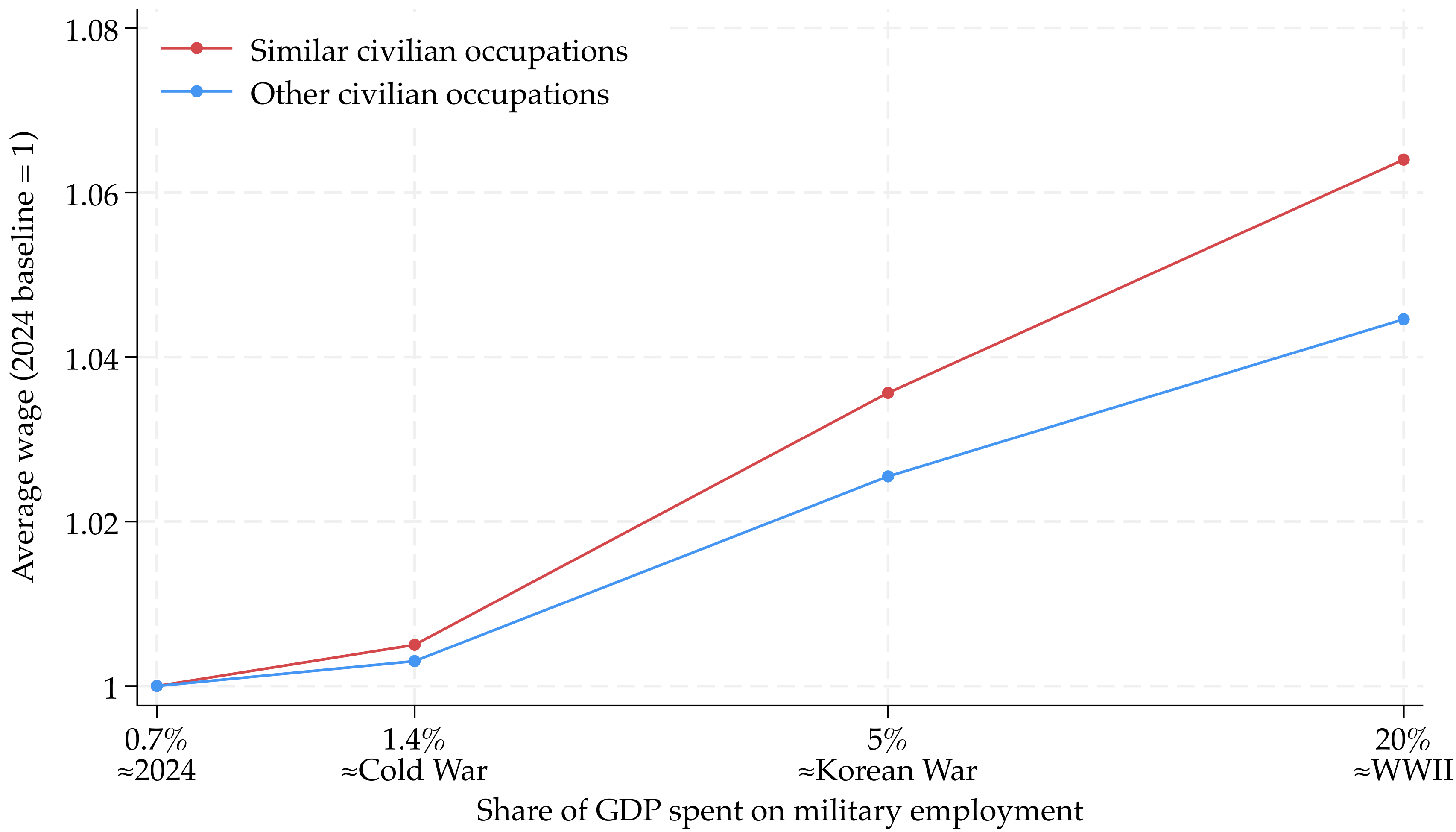


Figure 6: General equilibrium effects of mobilization in the model



5 Concluding Remarks

This paper has examined the general equilibrium effects of military employment on labor markets and the macroeconomy. We have documented two central facts: military occupations demand substantially higher skills than civilian jobs across all dimensions, and a large share of these military jobs closely resemble the "hard hat" occupations in goods-producing industries that have borne the brunt of automation and trade shocks over the past three decades. These are not coincidental features of military employment but rather reflect the military's role as a large-scale trainer of workers with high abilities in manual skills.

Our event study around the end of the Cold War provides empirical support for the labor market importance of military employment. The demobilization of roughly 700,000 military personnel translated into a persistent, 5% decline in earnings for civilian occupations most similar to blue-collar military jobs–a result robust to controlling for the China shock, NAFTA, automation exposure, and the general secular decline in hard-hat occupations. This shock was an additional blow to communities battered by trade and automation, but preceded and was distinct from those forces, underscoring that defense employment policy is itself a meaningful determinant of the fate of working-class Americans.

Our general equilibrium model of occupational choice and on-the-job human capital accumulation rationalizes these findings and extends them in important directions. The military functions not merely as a source of demand for particular occupations but as a human capital institution: one that draws workers with a comparative advantage in hard-hat tasks, trains them intensively across multiple skill dimensions, and returns them to the civilian labor market better prepared than when they left. The model predicts that military expansions raise wages both in directly exposed occupations and, through human capital externalities, in the broader economy. Voluntary military service tends to attract those who benefit most from it, yielding individual wage gains consistent with the empirical literature, while a draft may misallocate workers to occupations less suitable to their skills and less beneficial to their career paths.

Several important questions remain open. The optimal mix between defense procurement and defense employment has received little formal attention, yet our results suggest the two have meaningfully different macroeconomic implications. The distributional consequences of military expansion–for racial minorities, for women, and for workers across the skill distribution–deserve further investigation, particularly as policymakers consider large-scale rearmament. We leave these to future work, while hoping that the framework developed here provides a useful foundation for thinking rigorously about the macroeconomic consequences of military service.

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Appendices

A1 Additional Figures

This appendix presents additional figures referenced in the main text.

Figure A1: Skill requirements in private sector, government, and military jobs: Hard hat skills

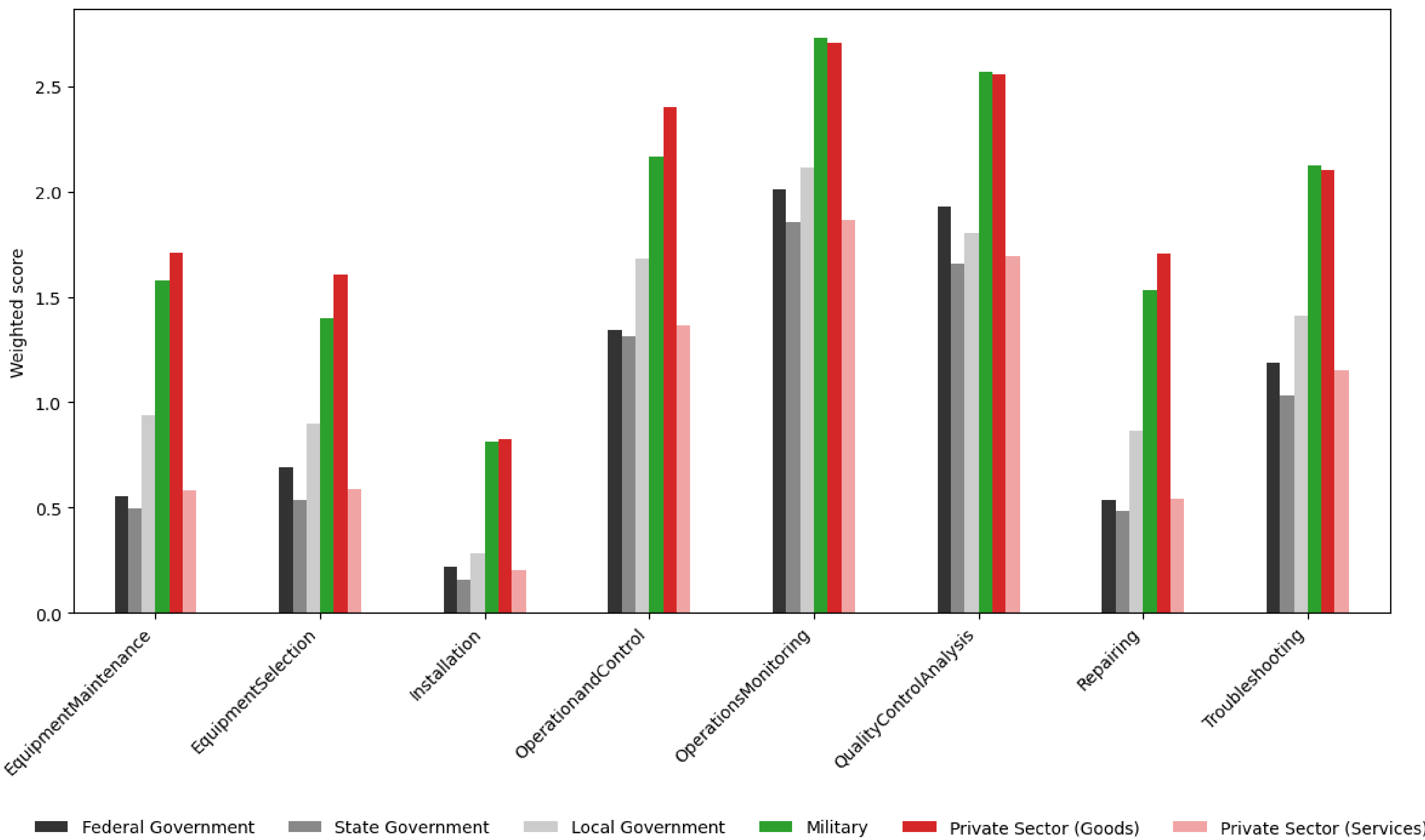


Figure A2: Skill requirements in private sector, government, and military jobs: STEM skills

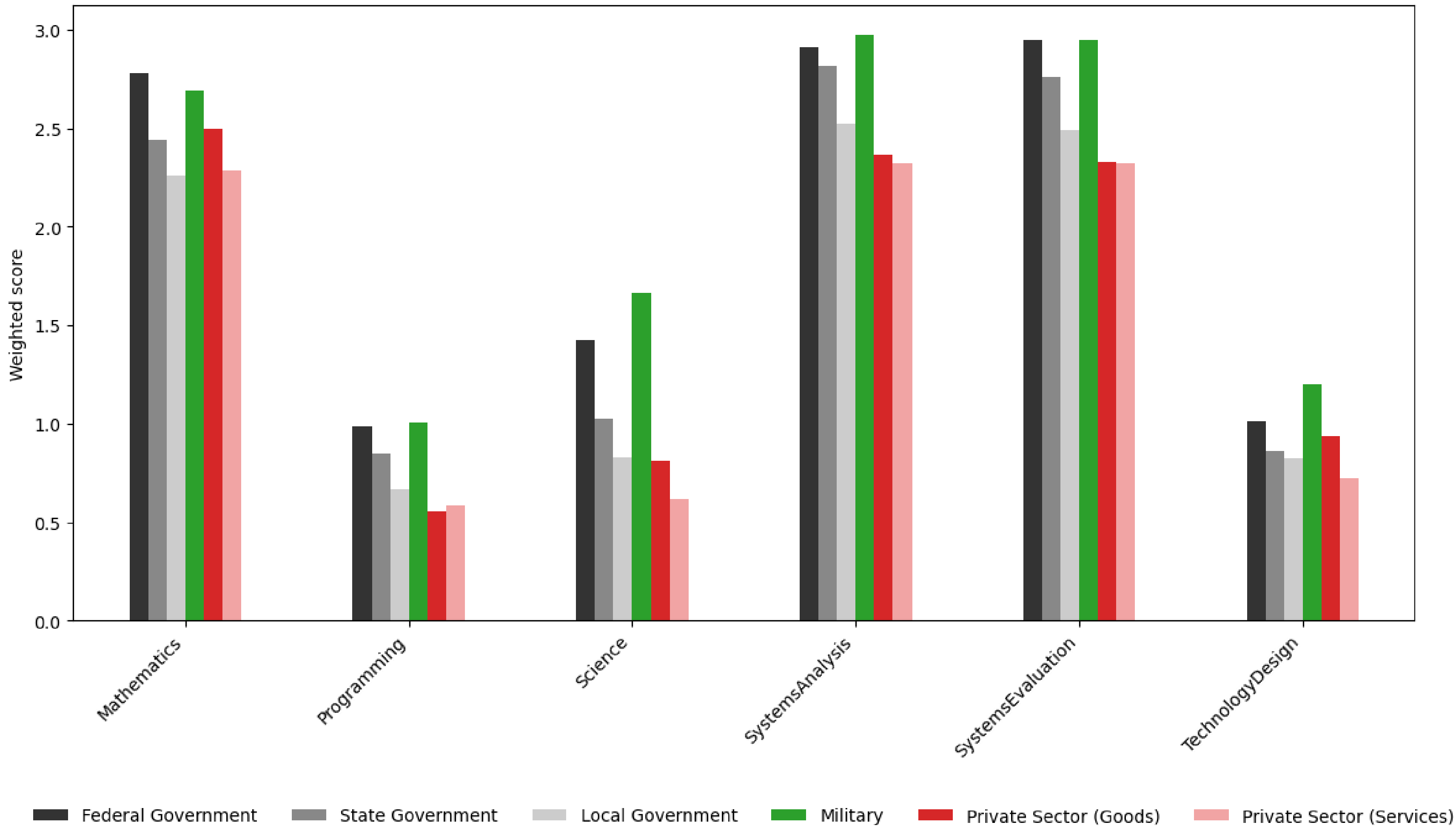


Figure A3: Skill requirements in private sector, government, and military jobs: Management skills

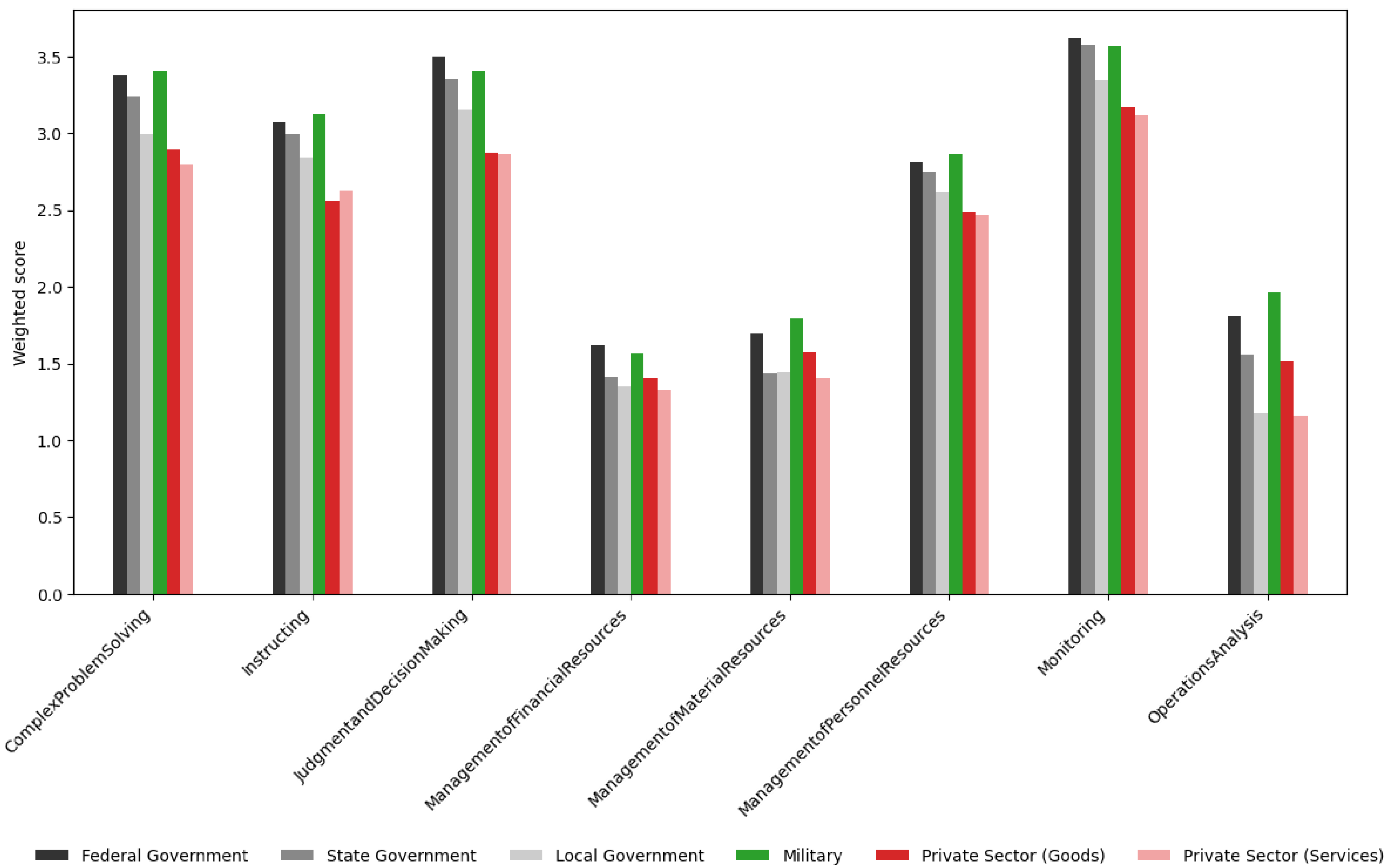


Figure A4: Skill requirements in private sector, government, and military jobs: Soft/social skills

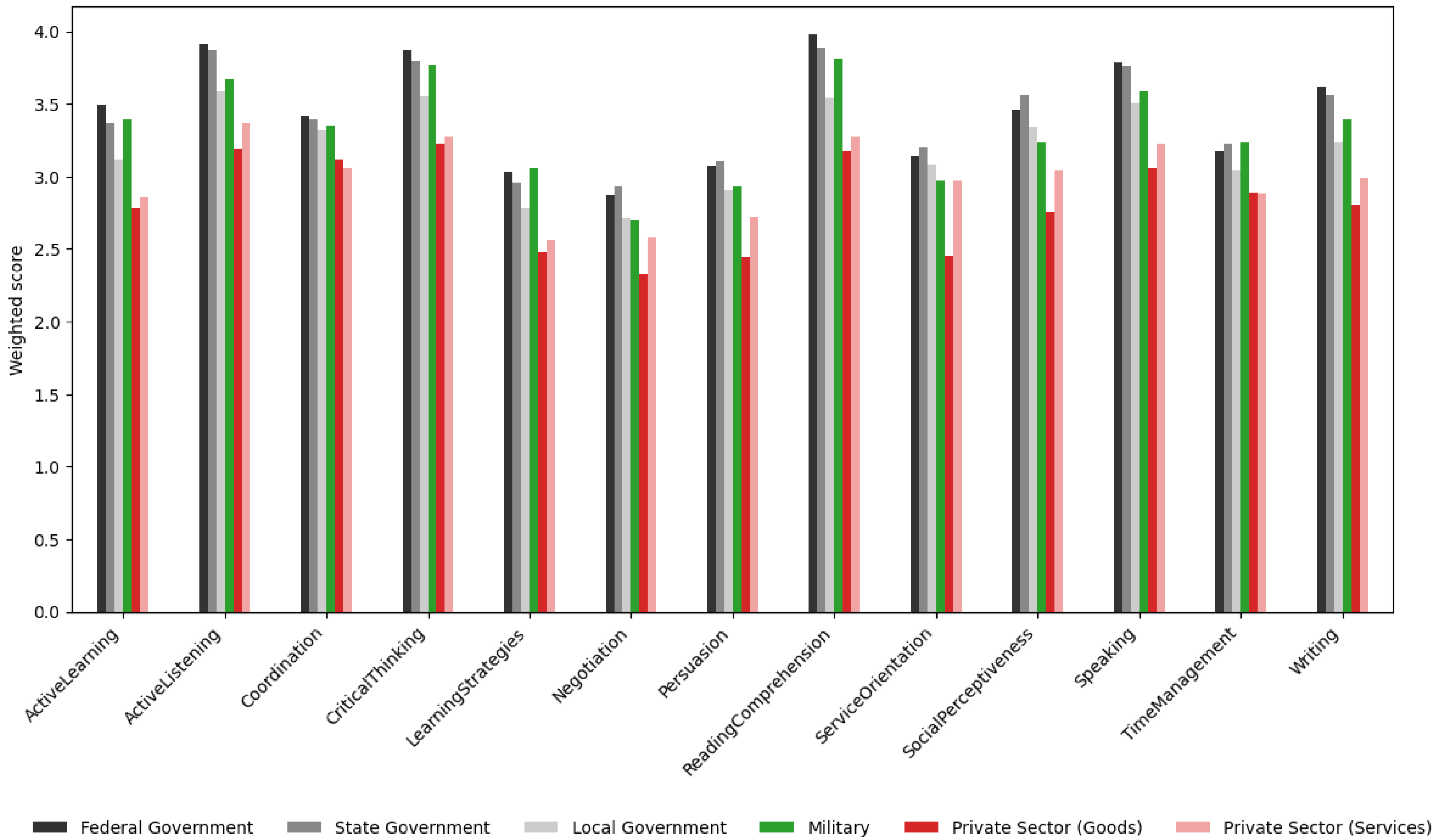


Figure A5: Skill requirements in private sector, government, and airforce jobs: Hard hat skills

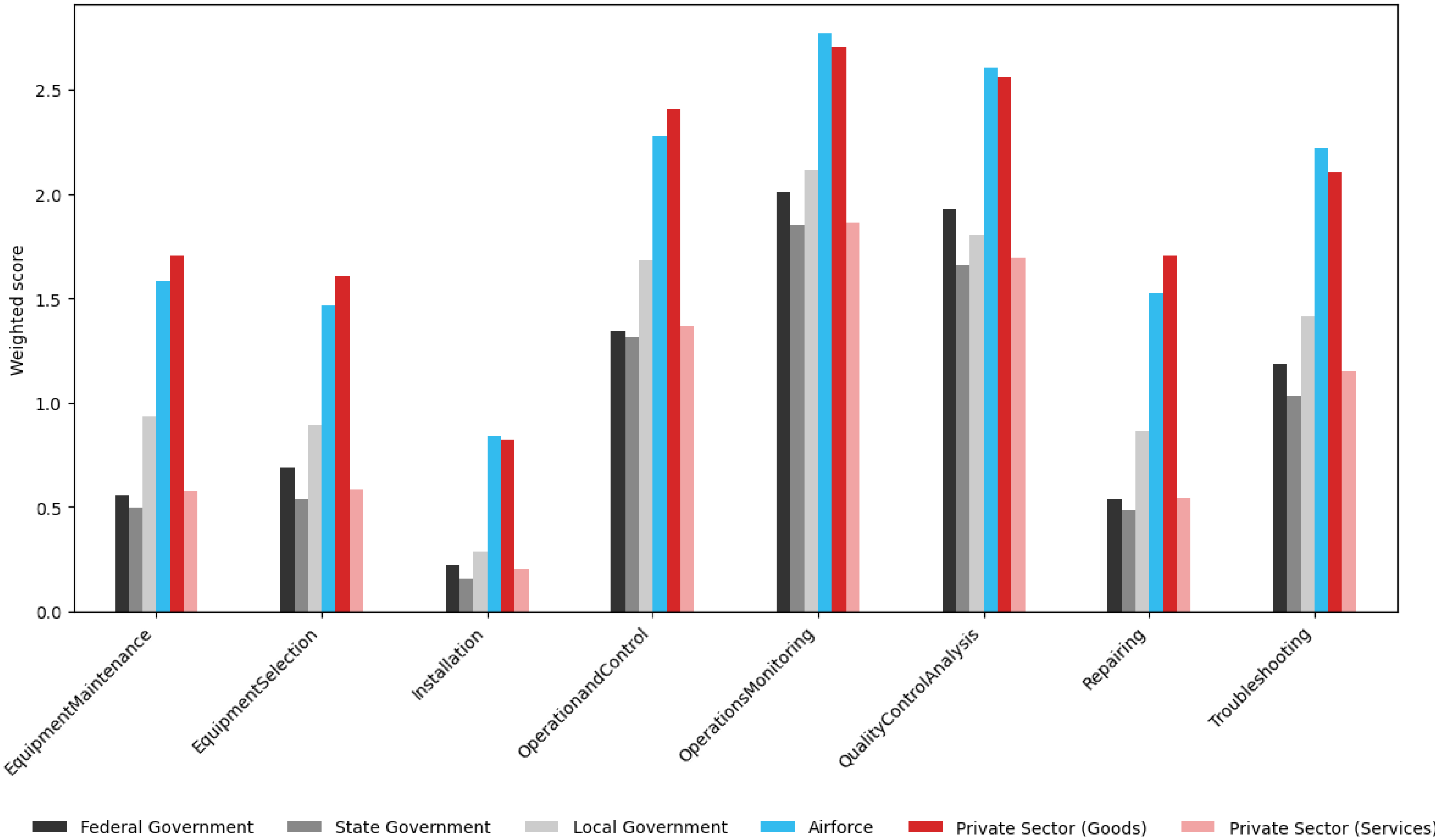


Figure A6: Skill requirements in private sector, government, and airforce jobs: STEM skills

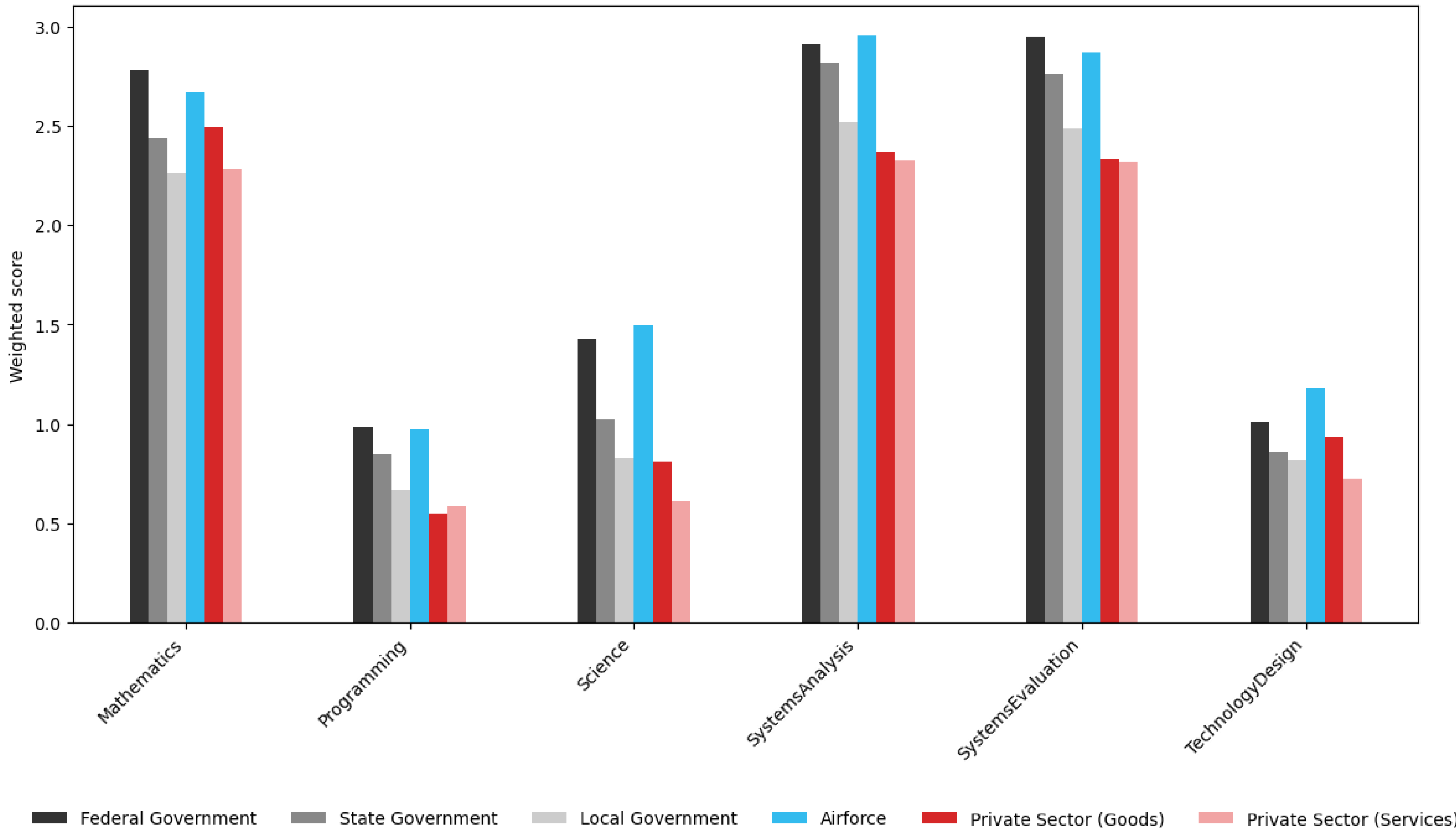


Figure A7: Skill requirements in private sector, government, and airforce jobs: Management skills

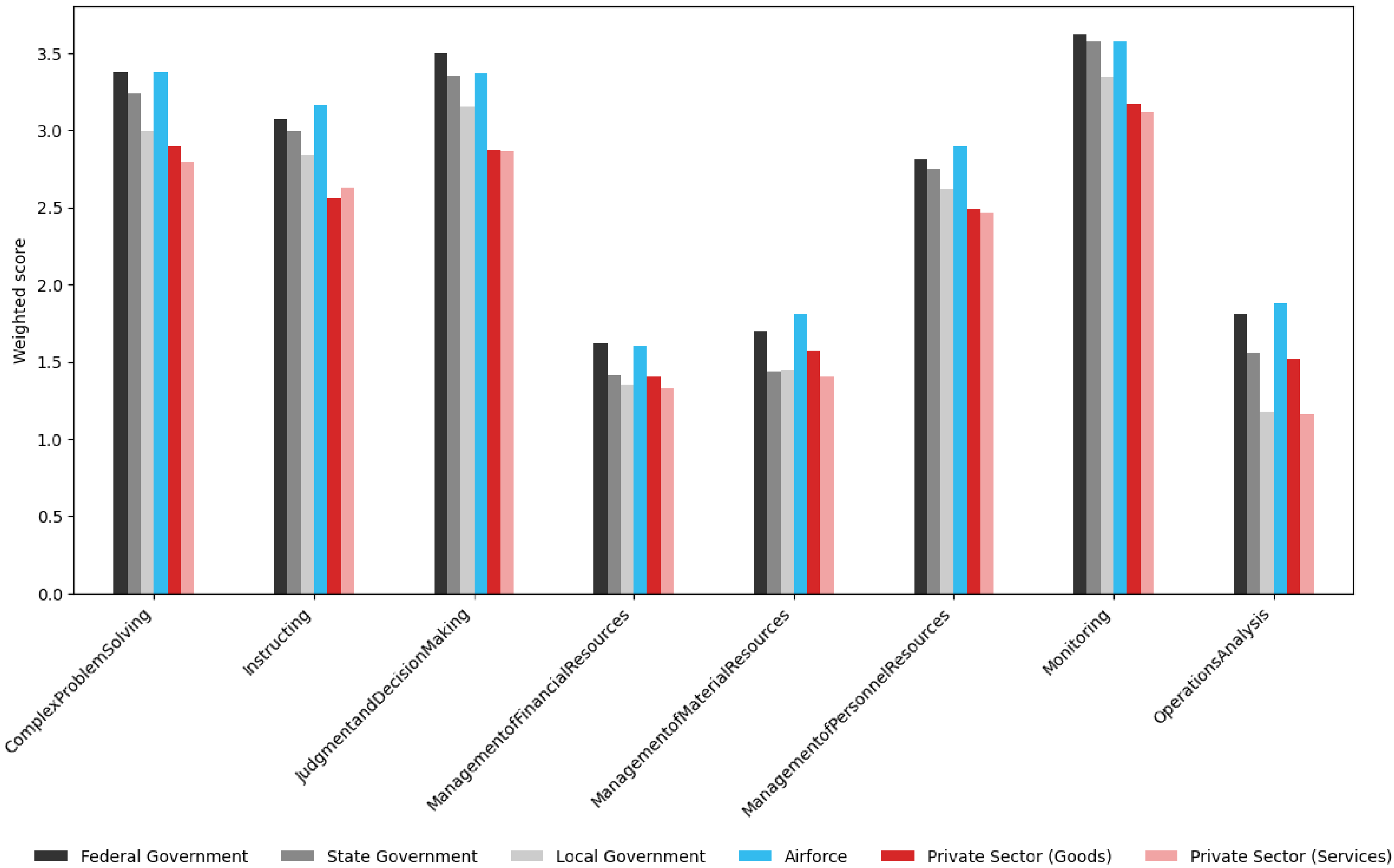


Figure A8: Skill requirements in private sector, government, and airforce jobs: Soft/social skills

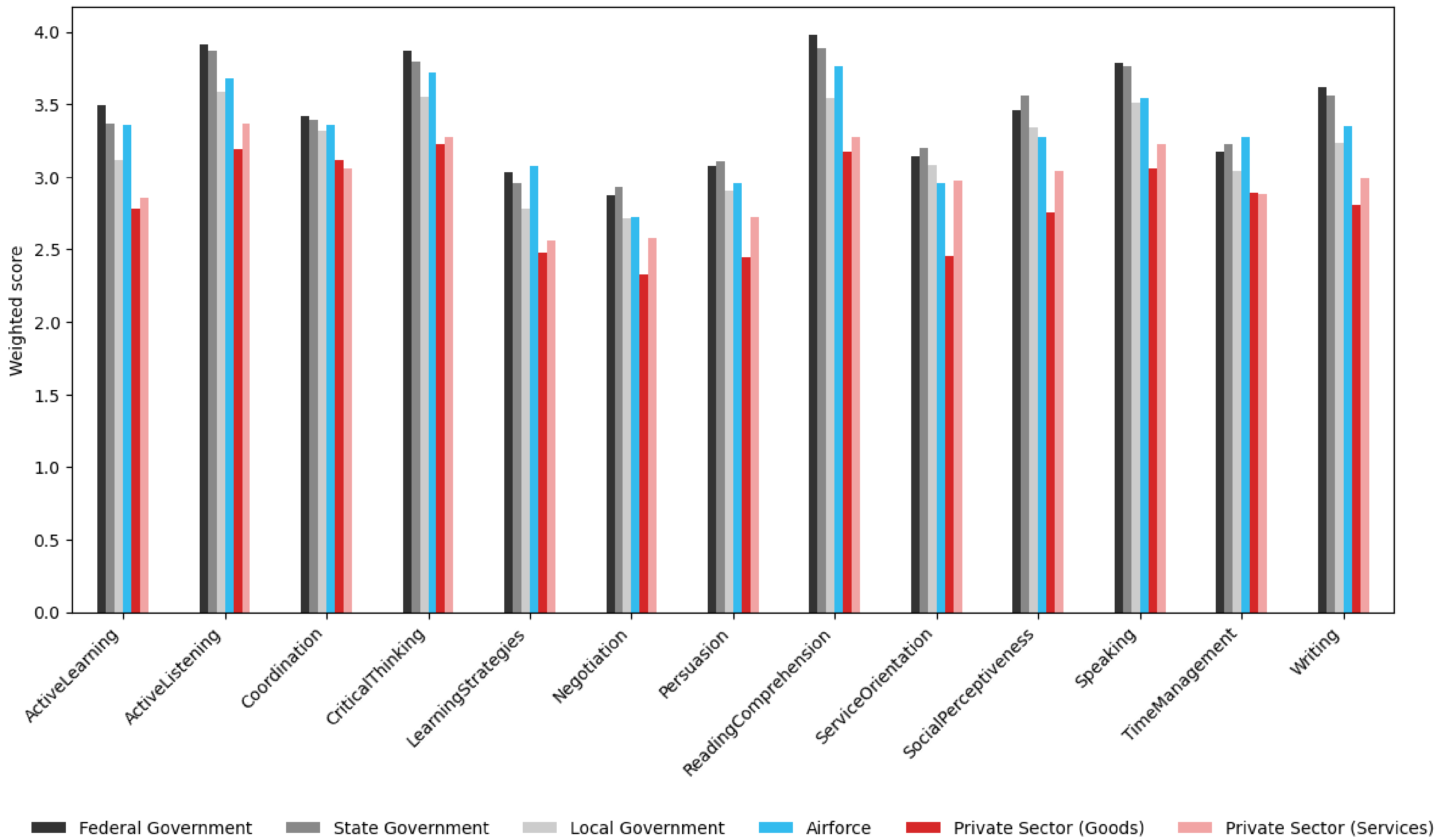


Figure A9: Skill requirements in military jobs, private sector jobs, and jobs held by military veterans

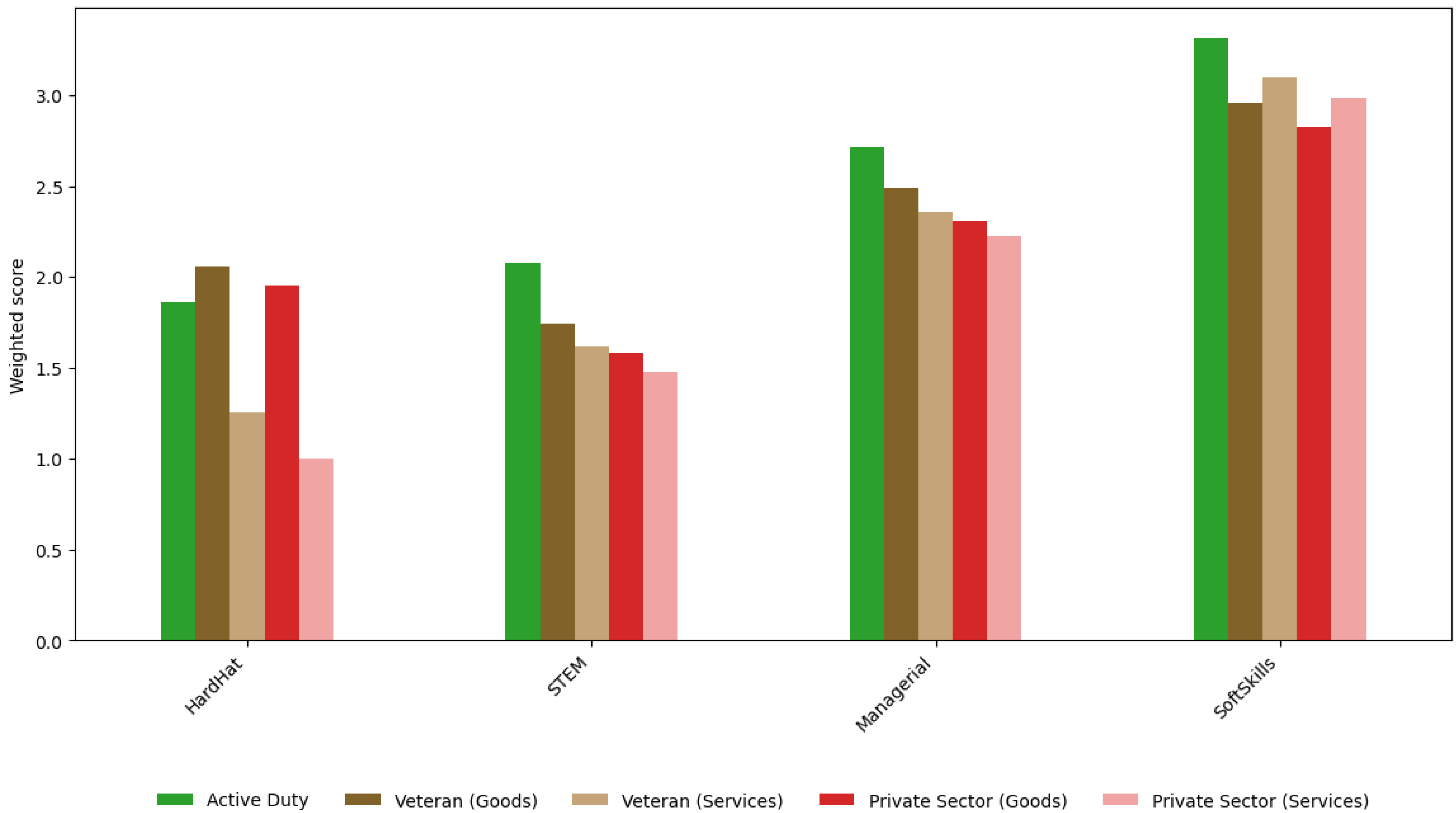
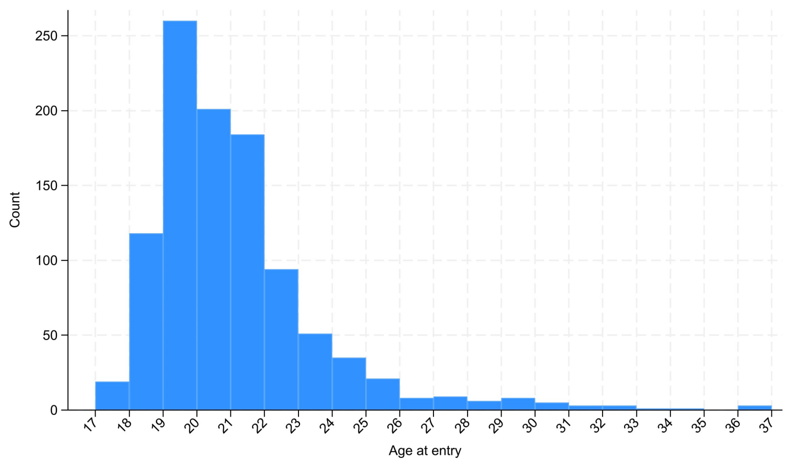
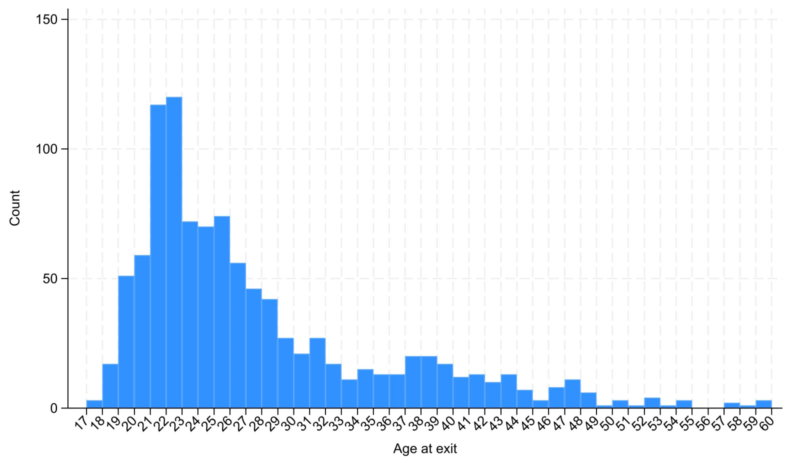


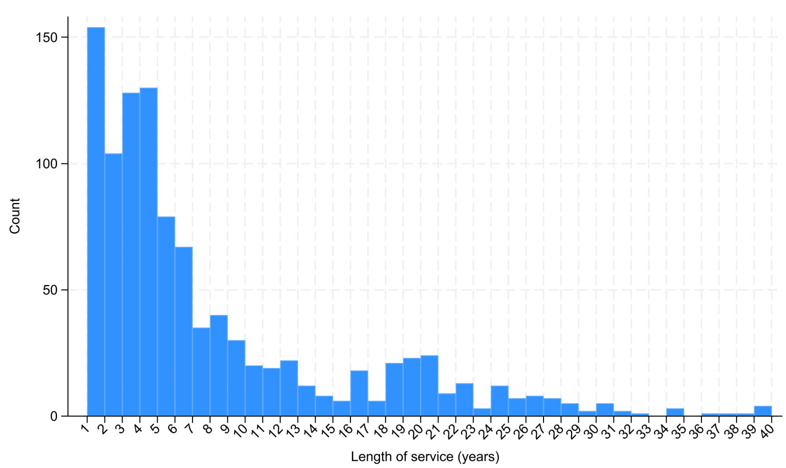
Figure A10: Distributions of military entry age, exit age, and length of service.



(a) Distribution of age at entry



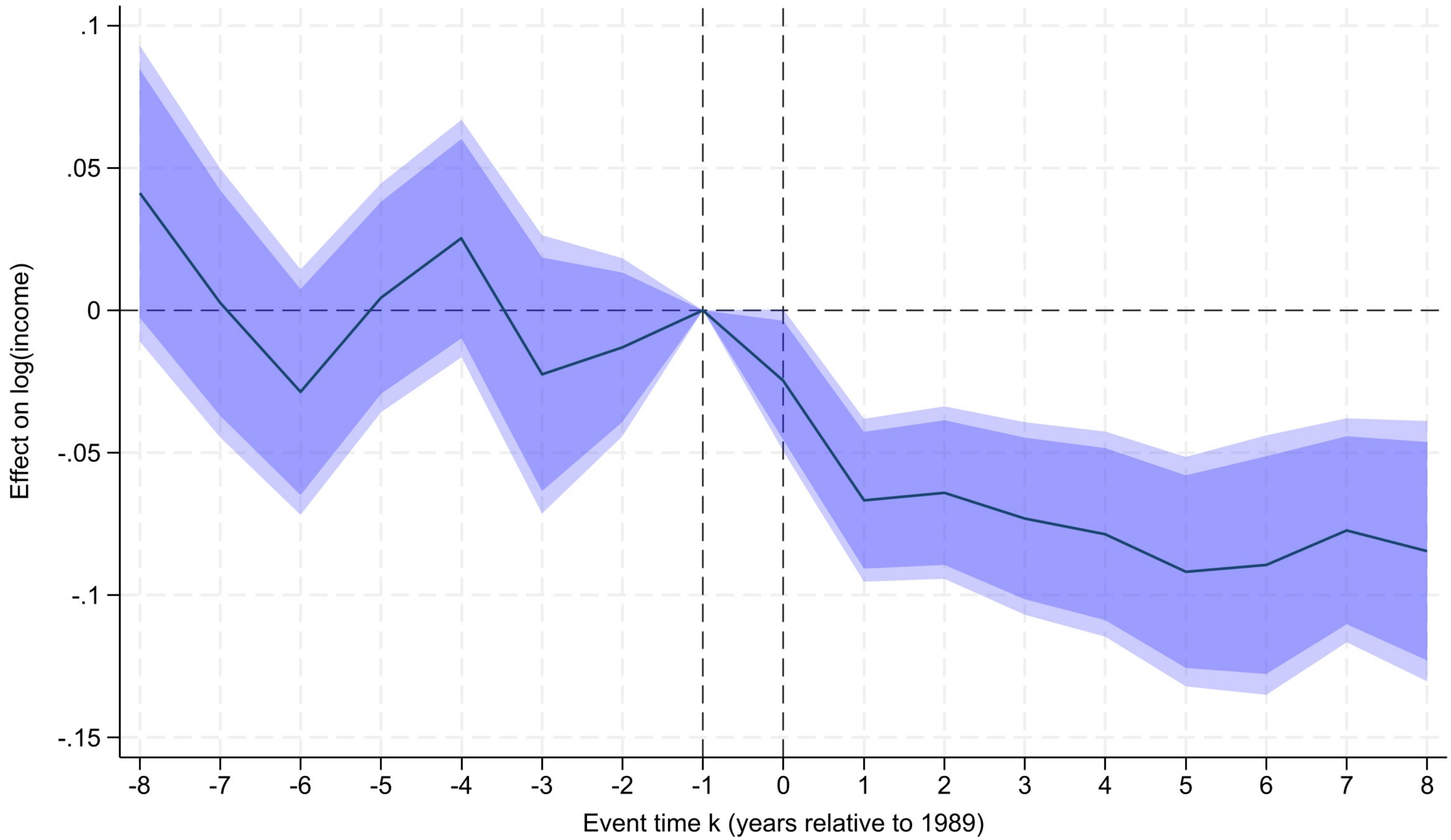
(b) Distribution of age at exit.



(c) Distribution of length of service.

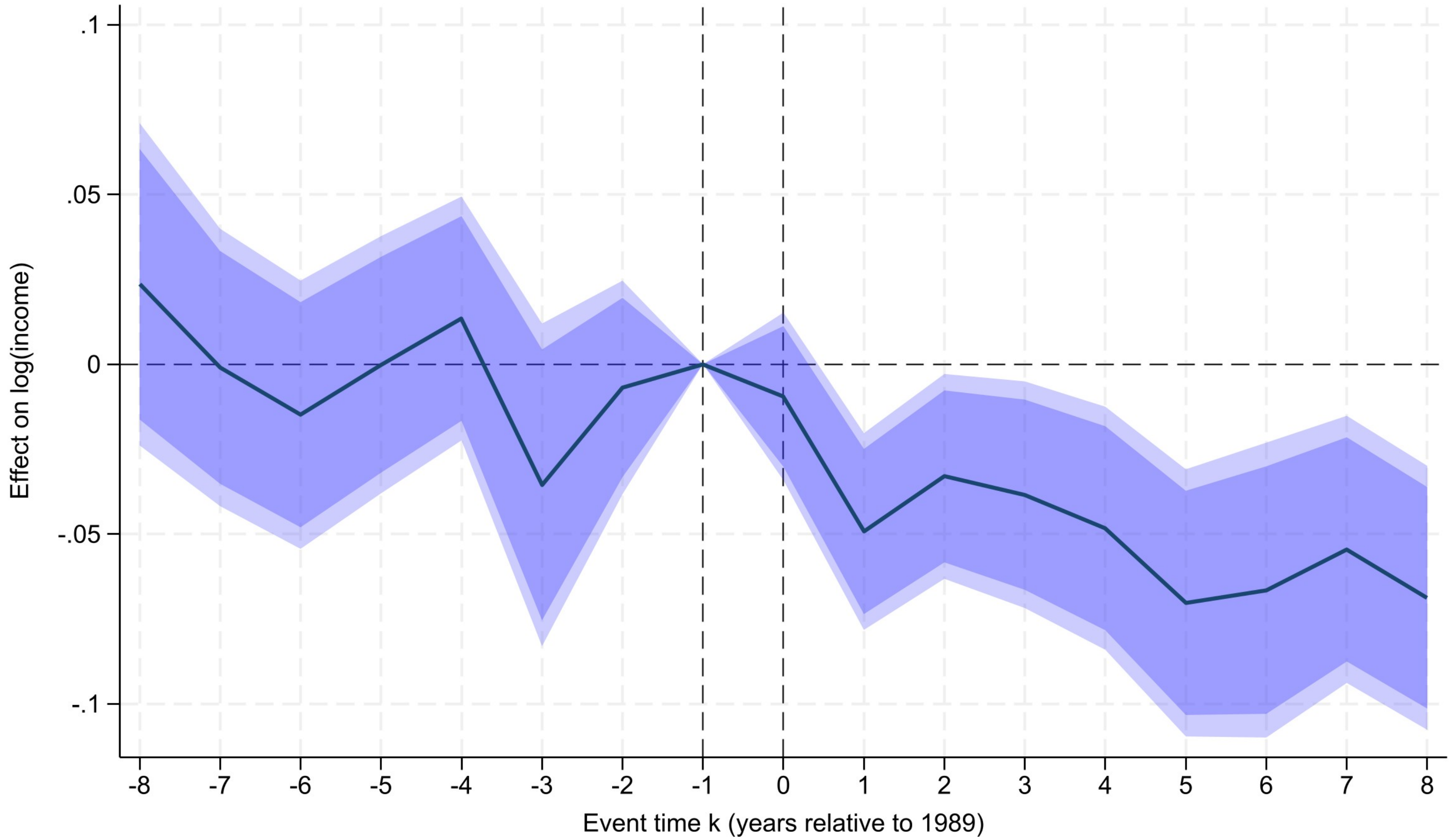
Notes: Share of military population in the National Longitudinal Survey 1979, by age of entry to (panel a) and exit from (panel b) the military, and duration of military service (panel c). Sources: NLSY and the authors.

Figure A11: Relative income in civilian occupations similar (top quartile of similarity) to blue-collar military jobs around the end of the Cold War



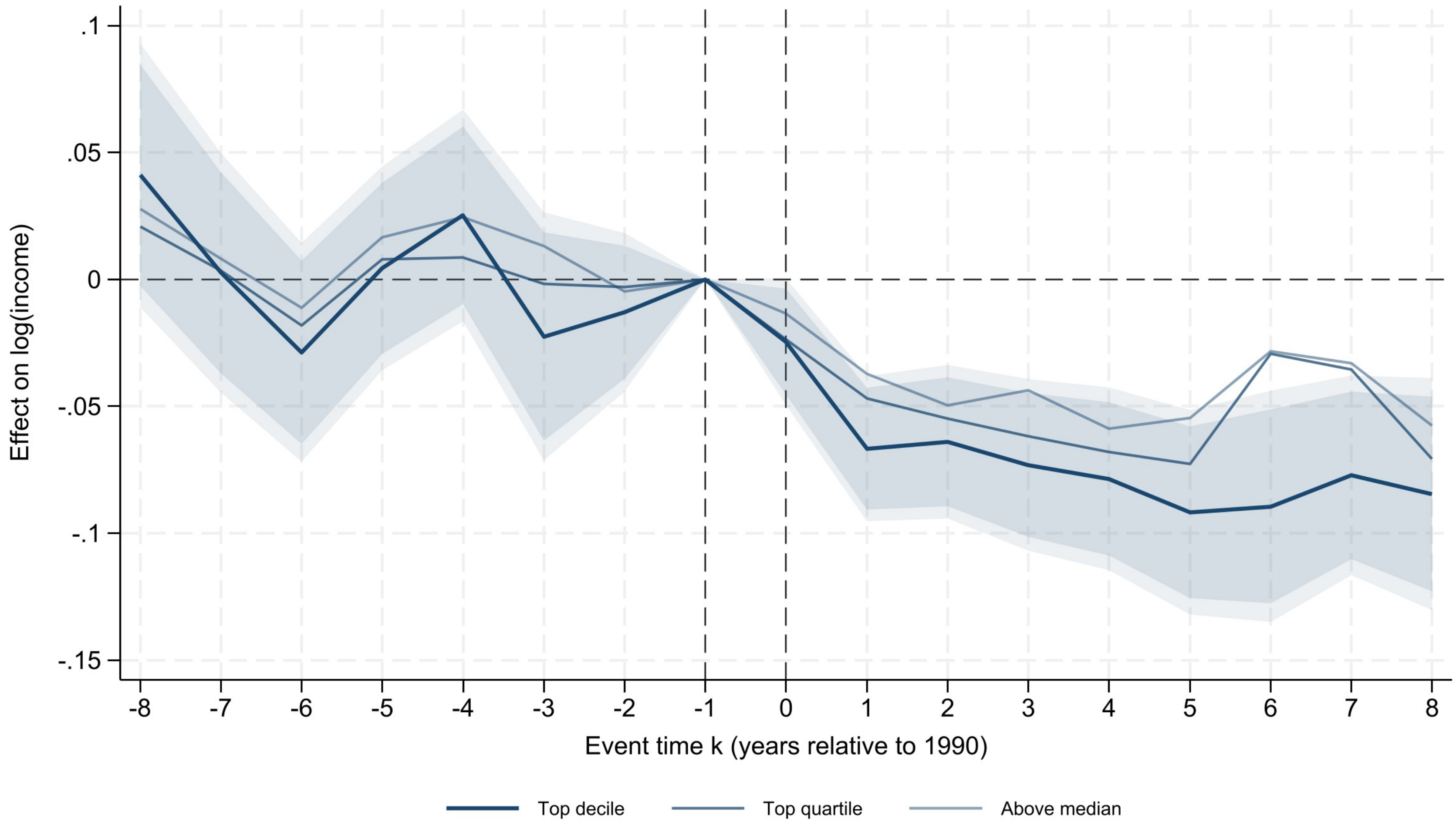
Notes: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top decile of similarity to "blue collar" military jobs. Sources: American Community Survey and the authors.

Figure A12: Relative income in civilian occupations similar to blue-collar military jobs around the end of the Cold War, including controls for individual characteristics



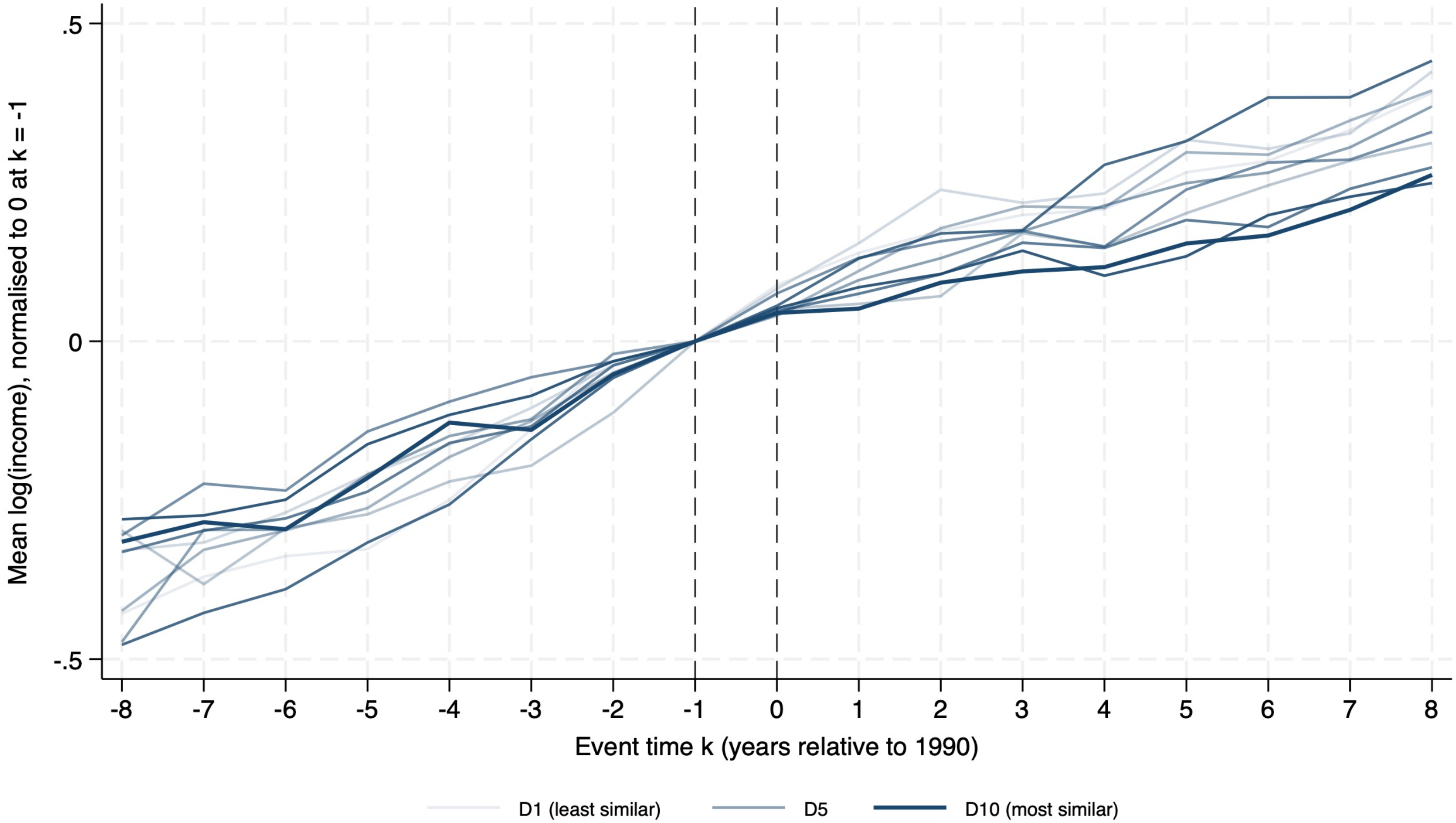
Notes: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top decile of similarity to "blue collar" military jobs. Includes controls for age, gender, region (cesnsus division) fixed effects, and their interactions with time fixed effects. Sources: American Community Survey and the authors.

Figure A13: **Event study regressions with treatment groups differing in their degree of similarity to blue collar military jobs**



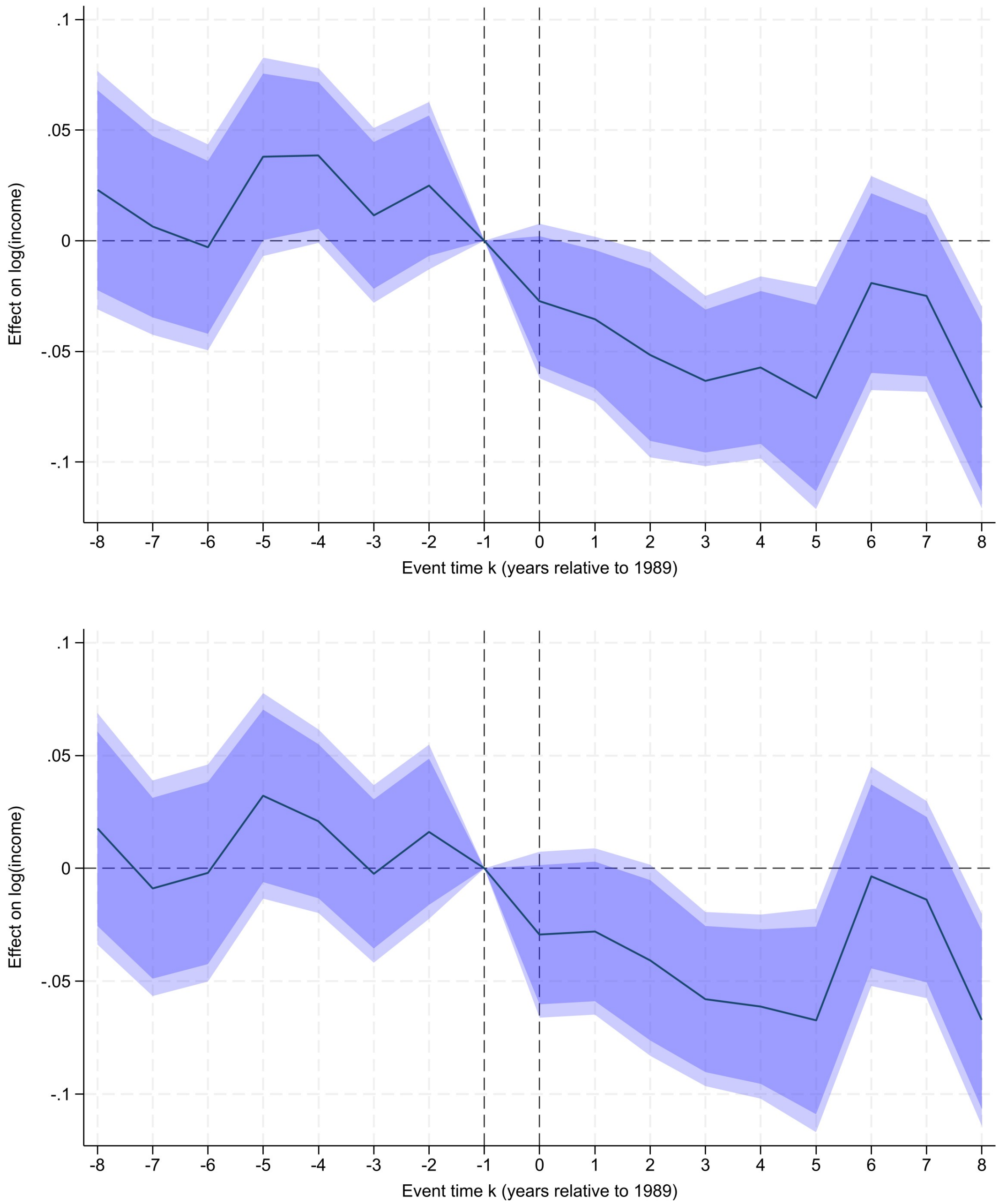
Notes: Each line in the figure shows an event study regression as in (1), each with a differing definition of the treatment group. The treatment groups are the top decile, quartile, and above and below median in similarity to blue-collar military jobs. Each of workers in a single decile, ranked by similarity of their occupation to blue collar military jobs. The first of these is the baseline regression as in Figure **??**. The first three reflect different quantiles of treatment. Treamtent effects are monotonic in how narrowly defined is the treatment group defined. The last line shows the relative performance of the control group of the last regression. Sources: American Community Survey, ONET, and the authors.

Figure A14: **Income in civilian occupations by decile of similarity to blue-collar military jobs**



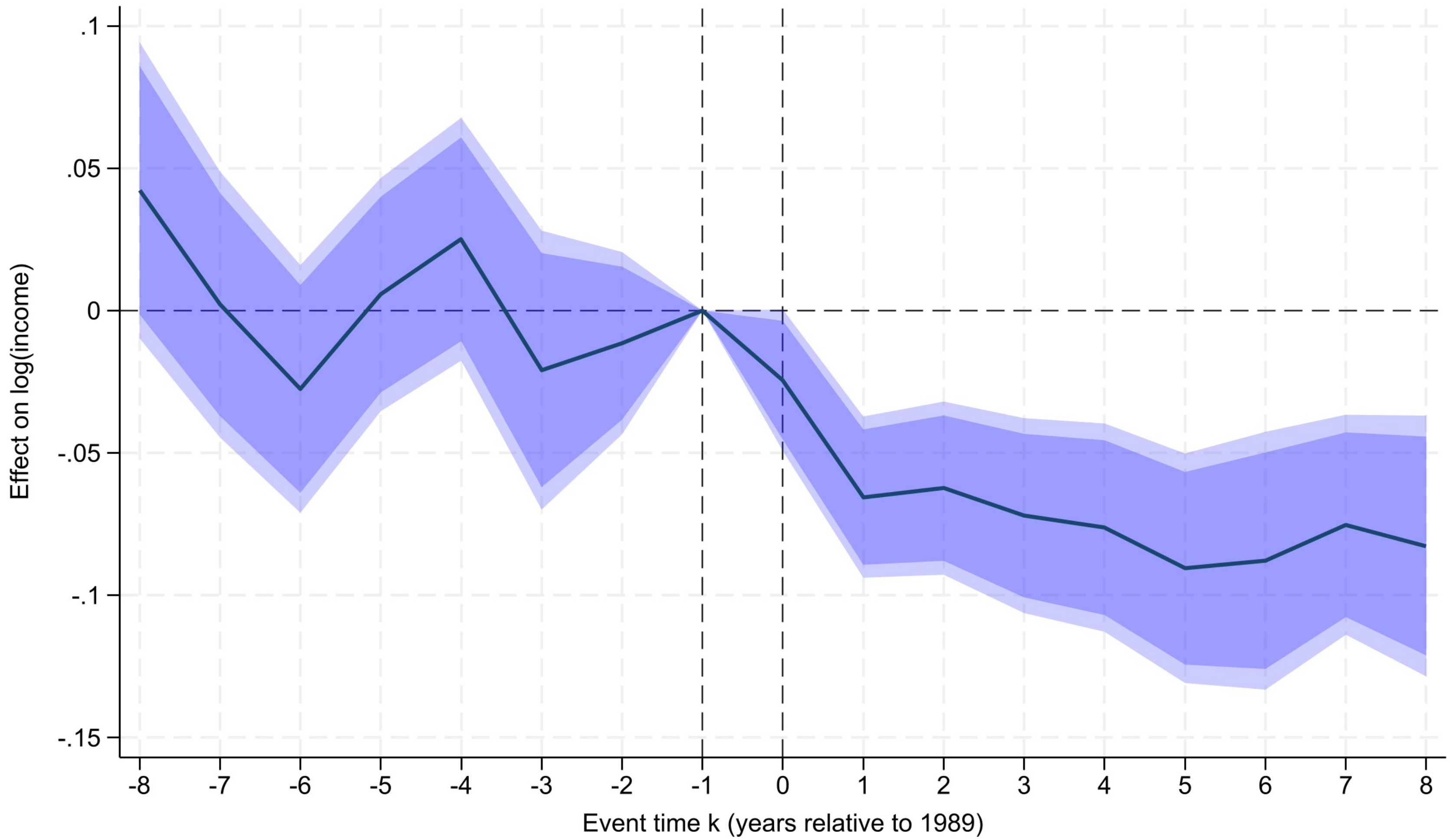
Notes: Each line in the figure shows (the logarithm) income of workers in a single decile, ranked by similarity of their occupation to blue collar military jobs. All lines are normalized to one in 1989. Higher deciles show a decline in income growth starting in 1989. Sources: American Community Survey, ONET, and the authors.

Figure A15: Relative income in civilian occupations similar to blue-collar military jobs around the end of the Cold War, controlling for the "China Shock"



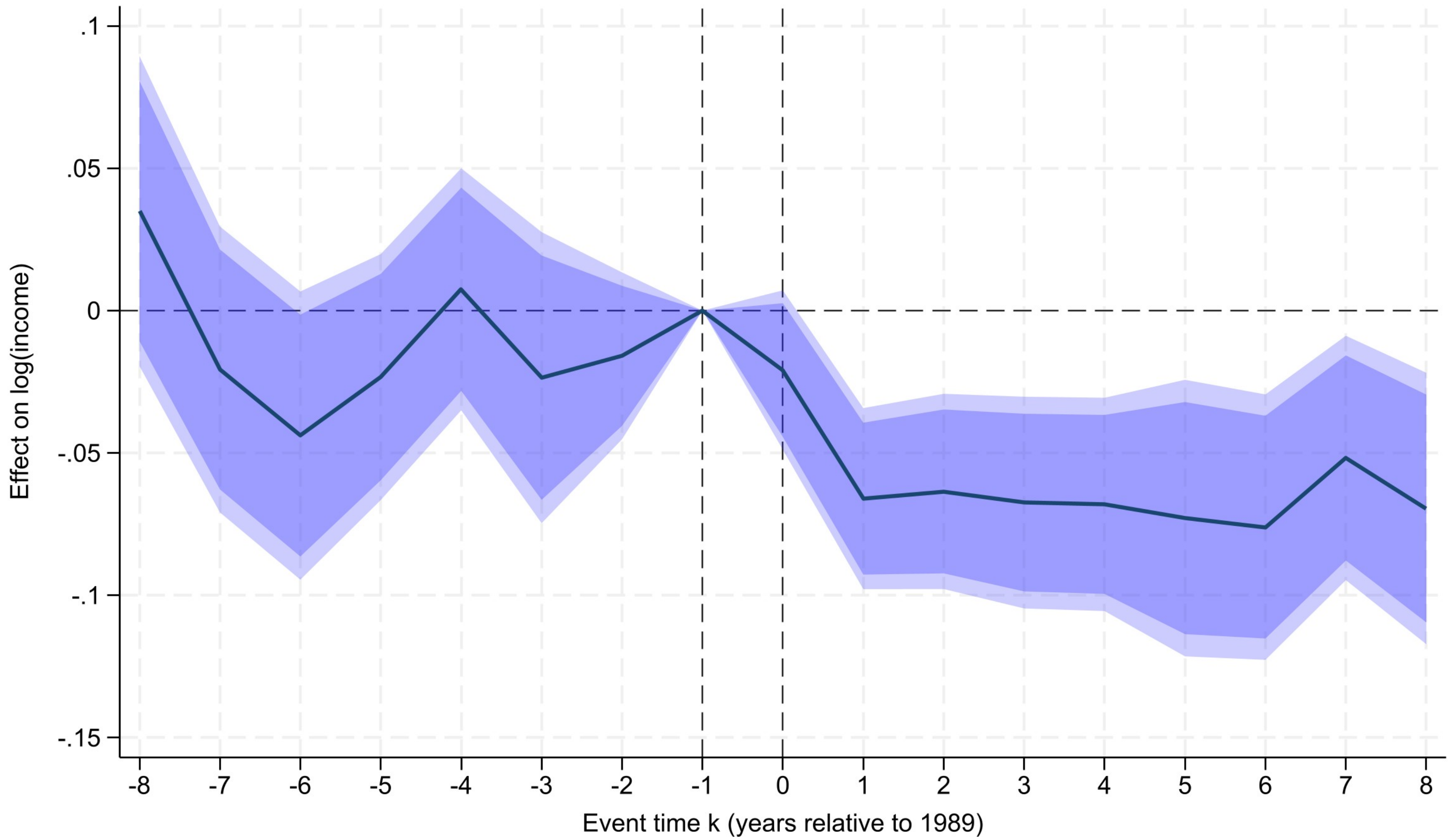
Note: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top quartile of similarity to "blue collar" military jobs. Includes controls for the interaction between time fixed effects and a fixed effect equaling one if the worker is in an industry that had above median exposure to upstream (top panel) or downstream (bottom panel) imports from China. Sources: American Community Survey, Acemoglu *et al.* (2016); Autor *et al.* (2013b); **?**, and the authors

Figure A16: Relative income in civilian occupations similar to blue-collar military jobs: controlling for exposure to NAFTA



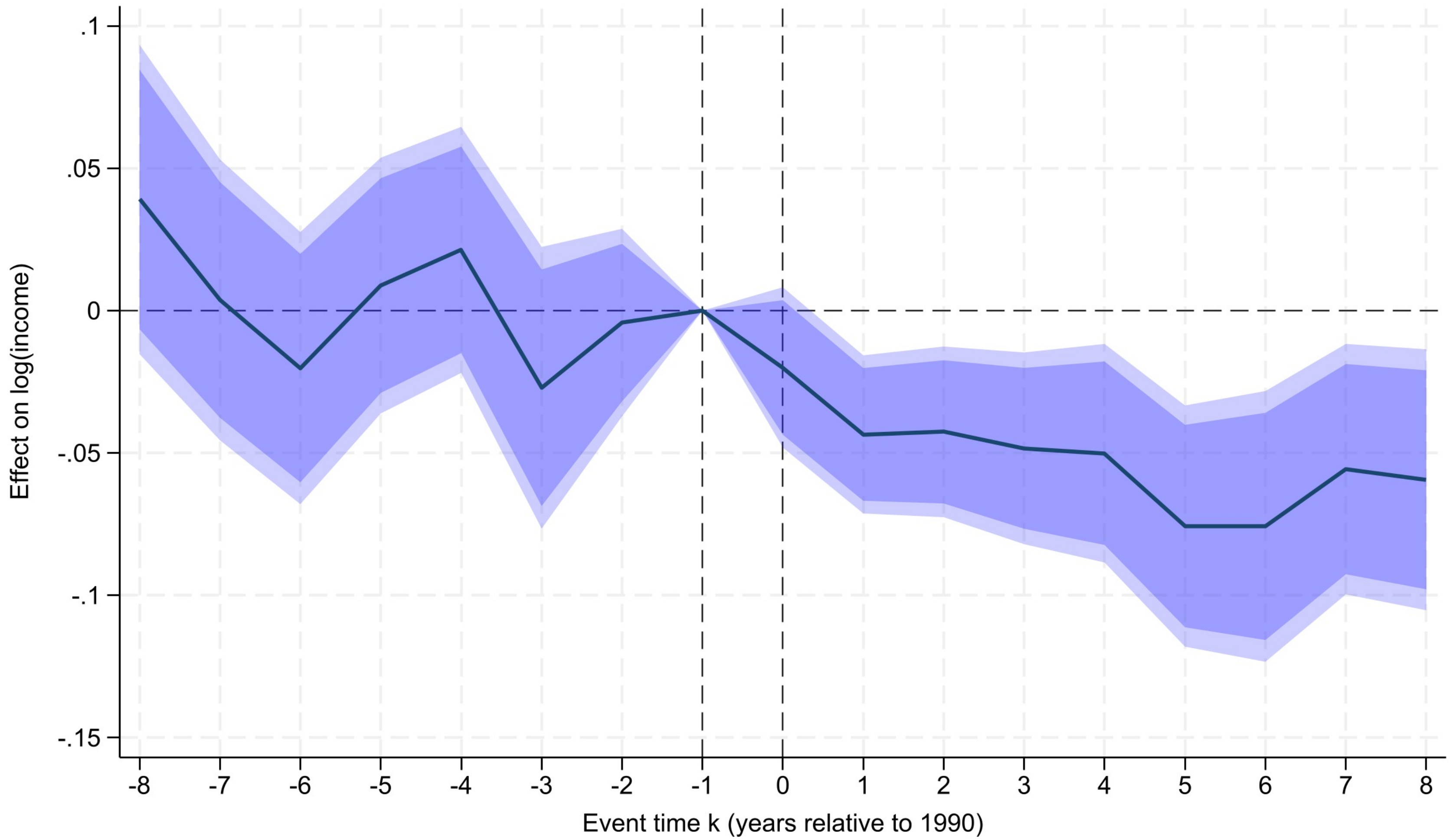
Notes: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top decile of similarity to "blue collar" military jobs. Includes controls for fixed effects for bins of "hard hat" skills and and their interactions with time fixed effects. Sources: American Community Survey, ONET, Hakobyan & McLaren (2016b) and the authors.

Figure A17: Relative income in civilian occupations similar to blue-collar military jobs: controlling for exposure to automation



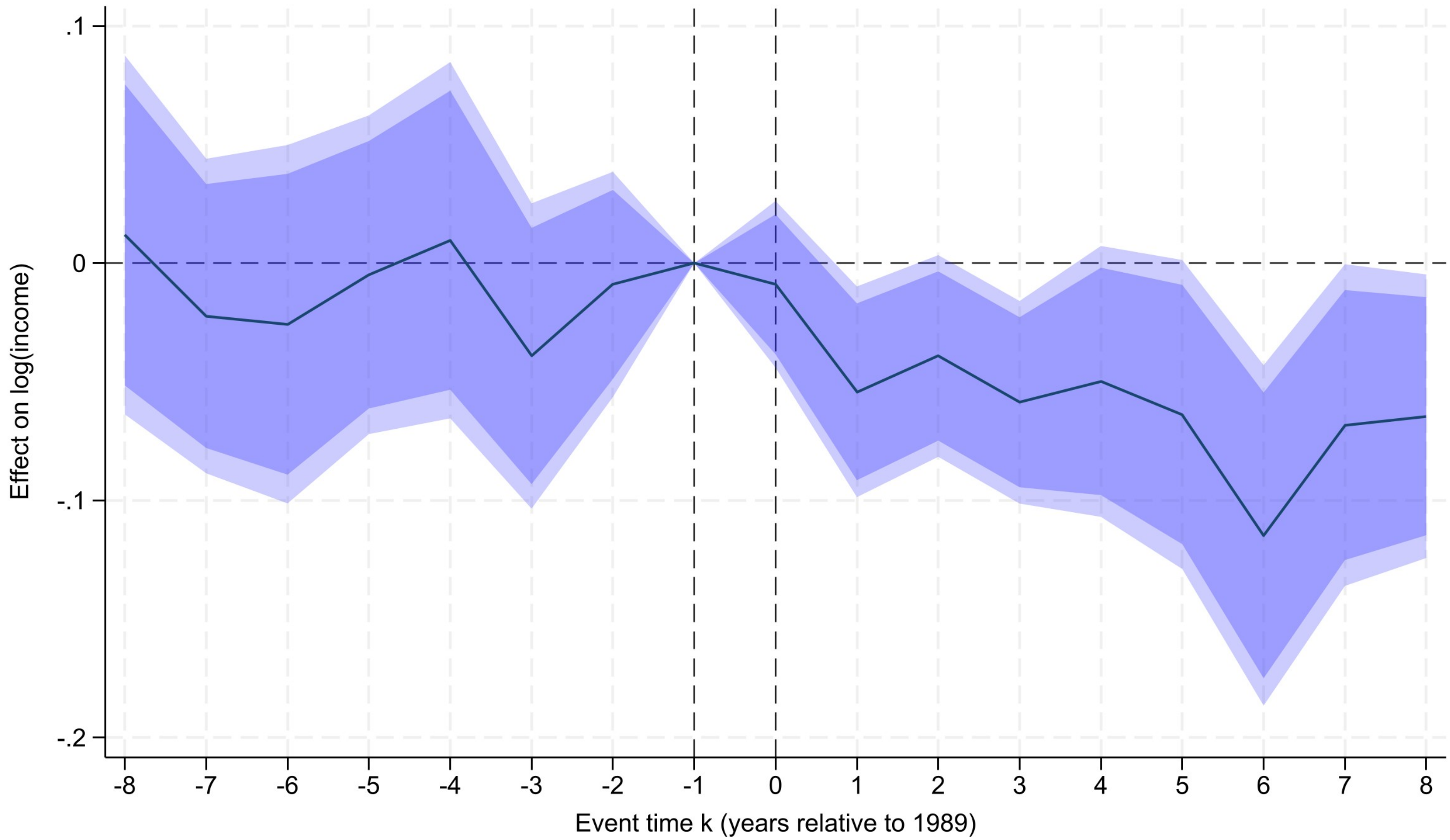
Notes: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top decile of similarity to "blue collar" military jobs. Includes controls for fixed effects for bins of "hard hat" skills and and their interactions with time fixed effects. Sources: American Community Survey, ONET, Autor & Dorn (2013) and the authors.

Figure A18: Relative income in civilian occupations similar to blue-collar military jobs: controlling for manufacturing sector fixed effects



Notes: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top decile of similarity to "blue collar" military jobs. Includes controls for fixed effects for a fixed effect indicating whether the job is in the manufacturing sector, interacted with time fixed effects. Sources: American Community Survey and the authors.

Figure A19: Relative income in civilian occupations similar to blue-collar military jobs: controlling for "hard hat" skill fixed effects



Notes: The figure shows an event study, with two way fixed effects, estimating income relative to 1989 in civilian occupations in top decile of similarity to "blue collar" military jobs. Includes controls for fixed effects for bins of "hard hat" skills and and their interactions with time fixed effects. Sources: American Community Survey and the authors.

Table A1: Top 10 military occupations by employment share

Rank	Occupation	Emp%
1	Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members	23.38%
2	Military Officer Special and Tactical Operations Leaders	8.18%
3	First-Line Enlisted Military Supervisors	6.70%
4	Aircraft Mechanics and Service Technicians	5.49%
5	Aircraft Pilots and Flight Engineers	4.21%
6	Human Resources Workers	3.22%
7	Police Officers	2.76%
8	Logisticians	2.11%
9	Maintenance and Repair Workers, General	2.11%
10	Avionics Technicians	1.38%

Table A2: Top 10 Air Force occupations by employment share

Rank	Occupation	Emp%
1	Aerospace Maintenance - Enlisted	17.28%
2	Security Forces - Enlisted	8.42%
3	Cyberspace Support - Enlisted	8.40%
4	Civil Engineering - Enlisted	5.34%
5	Munitions & Weapons - Enlisted	4.37%
6	Pilot - Officer	4.30%
7	Intelligence - Enlisted	4.19%
8	Transportation And Vehicle Management - Enlisted	3.84%
9	Command Control Systems Operations - Enlisted	3.77%
10	Aircrew Operations - Enlisted	2.85%

Table A3: Occupations with Most Similar Skill Requirements: Military and Airforce

Rank	Military	Airforce	Military (High HardHat)	Airforce (Hard hat)
1	Chief Executives	Veterinary Technologists and Technicians	Electrical and Electronic Engineering Technologists and Technicians	Electrical and Electronic Engineering Technologists and Technicians
2	Fallers	First-Line Supervisors of Firefighting and Prevention Workers	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	Broadcast Technicians
3	Logging Equipment Operators	Forest Fire Inspectors and Prevention Specialists	Broadcast Technicians	Medical Appliance Technicians
4	Log Graders and Scalers	Fish and Game Wardens	Medical Appliance Technicians	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
5	First-Line Supervisors of Construction Trades and Extraction Workers	Nuclear Power Reactor Operators	Commercial Divers	Computer Network Support Specialists
6	Boilermakers	Forest and Conservation Technicians	Chemical Plant and System Operators	Chemical Plant and System Operators
7	Brickmasons and Blockmasons	Surveyors	Computer Network Support Specialists	Captains, Mates, and Pilots of Water Vessels

Continued on next page

Table A3: Occupations with Most Similar Skill Requirements: Military and Airforce (with High Hard Hat Scores)

Rank	Military	Airforce	Military (High HardHat)	Airforce (hard hat)
8	Stonemasons	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	Nuclear Technicians
9	Carpenters	Power Distributors and Dispatchers	Audiovisual Equipment Installers and Repairers	Petroleum Pump System Operators, Refinery Operators, and Gaugers
10	Carpet Installers	Aircraft Cargo Handling Supervisors	Gas Plant Operators	Manufactured Building and Mobile Home Installers

Table A4: **Occupations with Most and Least Similar Skill Requirement to Military Within Each bin of "Hard Hat" Skills**

	Most similar occupation				
Bin	Title	HH	STEM	Avg	Salary
$[0,1]$	Buyers & Purchasing Agents, Farm Products	0.97	1.94	2.28	$75,650
$(1,2]$	Diagnostic Related Technologists & Technicians	1.93	2.10	2.42	$77,660
$(2,3]$	Broadcast & Sound Engineering Technicians	2.70	1.99	2.55	$53,920
$(3,4]$	Radio & Telecom Equipment Installers & Repairers	3.31	2.12	2.64	$64,190

	Least similar occupation				
Bin	Title	HH	STEM	Avg	Salary
$[0,1]$	Crossing Guards	0.16	0.38	0.97	$37,700
$(1,2]$	Pressers, Textile, Garment & Related Materials	1.47	0.56	1.19	$33,880
$(2,3]$	Cleaners of Vehicles and Equipment	2.10	0.58	1.39	$35,270
$(3,4]$	Maintenance Workers, Machinery	3.25	1.40	2.25	$60,500

A2 Cross-walks from military to civilian occupations

The O-NET doesn't provide skill scores for military occupations, which requires a cross-walk between military and civilian occupations. We follow the cross-walk provided by O-NET (found here). It is designed to crosswalk from Military Occupation Codes (MOCs) or DoD codes to the most similar civilian Standard Occupational Classificiation (SOC) codes (which are *very* near to O-NET). We can then use the O-NET skill requirements for the corresponding civilian occupations to estimate the skill requirements for military occupations.

A2.1 Military O-NET to Civilian O-NET

Military occupations in the O-NET (occupations starting with "55-", e.g., 55-1012) do not have skill requirements. We fill in this gap in two steps. Firstly, we use a mapping from military O-NET to MOCs provided by O-NET (see an example for Armored Assault Vehicle Officers). This gives multiple MOCs per O-NET military code. From this, we directly apply the O-NET crosswalk to find exact matches of MOCs to ONET-suggested most similar civilian occupations.[8] MOCs are matched with up to four similar O-NET civilian occupations. We give equal weighting to the matched codes.

The ACS data gives civilian occupational codes for some military personnel, in which case we use the skill requirements of this civilian code for the skill requirements of this military occupation. Where no civilian code is present we use the miliary code. This, however, is less granular O-NET military codes than used in the crosswalk (e.g., 55-1010 - Military officer special & tactical operations leaders instead of 55-1012 - Aircraft Launch and Recovery Officers). In this case, we use the average of our estimated skill requirements for all sub-level O-NET military codes with equal weight.

A2.2 Air Force Statistical Digest to Civilian O-NET

For enlisted personnel and officiers, the Air Force Statistical Digest (AFSD) gives a 2-digit alpha-numeric occupation code (e.g., "1A" is "Aircrew Operations" for enlisted personnel"). We use the O-NET crosswalk to map from MOC to civilian O-NET.

As these are the aggregated codes, we also use an aggregated version of the crosswalk. I.e., when searching for "1A", we search for all MOCs that start with "1A", even though the actual length may be longer. To improve the matching, we filter for rows by service branch (i.e., Air Force in this case) and by rank (i.e., Enlisted, Officer, or Warrant Officer). We then take all matched civilian codes (excluding any military O-NET 55- codes, given that we have a sufficient number

[8]We filter out the cases where the crosswalk would match MOCs back to O-NET military codes (i.e, the 55- codes).

of matches to civilian O-NET codes). Again, each matched civilian occupation is given an equal weight in computing scores when we compute average skills in the AFSD “1A" occupation.