Path Dependence in the Labor Market: The Long-run Effects of Early Career Occupational Experience*

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Abstract

We study the causal effect of early career occupational experiences on labor market outcomes. To do so, we pair over two decades of administrative tax data with internal personnel records from the largest employer of young adults in the United States: the US Army. Enlisted soldiers work in a diverse set of military occupations, ranging from combat roles like infantry, to non-combat roles like mechanics, legal services, financial specialists, cooks, dental hygienists, police officers, and network/computer specialists. Eligibility for different occupations is determined by test score cutoffs which we leverage for causal identification in a series of 43 regression discontinuity designs. We find that early career occupational experiences can generate a substantial amount of path dependence, with point estimates that suggest a 20% increase in the likelihood of being observed in the same occupation 11-15 years later. We also find highly heterogeneous, yet predictable, effects on long-run wages. Implied changes in occupational earnings premia account for over 60% of the causal variation in earnings, with point estimates that suggest improvements in average wage rates translate essentially dollar-for-dollar into actual causal effects on earnings. Our results suggest that average occupational wage rates can serve as a simple heuristic for their impact on economic well-being.

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1 Introduction

Early life occupational experiences are strongly related to long-run economic success. Every year, roughly three-million young American's will enter the labor market for the first time.[1] For a typical worker, the following period is critical: over 66% of lifetime wage growth will occur during the first 10 years of their career (Topel and Ward, 1992). This suggests that there is an important connection between these early career occupational experiences and sustained economic well-being, with potentially wide ranging implications for the design of the education system, the design of active labor market policy, the sources of inter-generational earnings transmission, and the role that high-quality job opportunities have in reducing economic inequality.

Policy makers have attempted to direct individuals into high-earning occupations. However, the welfare implications of such interventions remain unclear, given workers may naturally self-select into preferred occupations. The substantial wage heterogeneity across occupations may reflect either efficient self-sorting based on individual abilities and job characteristics, or market frictions that warrant policy intervention. Determining the appropriate role for policy requires understanding how a worker's initial occupation shapes their future career options and earnings, but existing evidence on this question is limited and is not causally identified. The empirical challenge lies in isolating the causal role of initial occupational experience from other worker and firm characteristics. Researchers have primarily relied on survey data and observational job transitions, potentially confounding their results with selection on unobservable worker-level characteristics (e.g. Kambourov and Manovskii, 2009a,b; Topel and Ward, 1992). An ideal experiment would randomly assign young adults to their first occupation and track their careers to observe occupational switches and long-term wages. While such an experiment is not feasible, we leverage a setting that closely mimics these conditions.

We pair over two decades of administrative tax data with internal personnel records from the largest employer of young adults in the country: the United States Army. The US military is a massive employer, with a combined labor force that is larger than the population of Chicago, IL (2.86 million workers in 2022). To manage an organization of this magnitude requires a diverse and varied set of roles. Some of these roles, like the infantry, are explicitly connected to the war-fighting mission. However, the vast majority of Army soldiers serve in non-combat occupations such as legal services, financial specialists, cooks, dental hygienists, police officers, network/computer specialists, and many others.[2] Thus studying military occupational experiences speaks directly to

[1] While exact numbers are difficult to come by, we estimate this by multiplying the number of children of minimum working age ($\approx$ 4 million aged 14 in 2022) by the age 25-54 labor force participation rate (83.3% in 2022), which will be a lower bound in steady state.

[2] See appendix table A.1 for a break-down of military occupations across several broad categories known as "Career Management Fields" among first term soldiers.

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relevant occupations in the civilian world. Further, we note that 1 in 7 adult men in the United States are military veterans, which is about half the size of the male population with a four-year college degree (U.S. Census Bureau, 2018). Thus in practice, the military plays a dominant role in the early career development of skills and credentials for a huge swathe of the labor market. Therefore, specifically studying early career occupational experiences within the military context is also a first order question.

For identification, we leverage institutional details of the way the Army determines occupational eligibility in a regression discontinuity design. In order to enlist in the Army, soldiers must take a test known as the Armed Forces Vocational Aptitude Battery (ASVAB). Sub-components of this test are then reformulated into a series of 10 test scores known as "line-scores," which determine eligibility for specific occupations. Unlike prior work on occupational training, the nature of military contracts ensures that nearly all soldiers who enlist receive both extensive occupational training and anywhere from 2-5 years of practical, on-the-job experience. Thus, by comparing soldiers that barely cleared an eligibility threshold for a given occupation to those that did not, we can isolate meaningful *within firm* variation in occupational experience that is orthogonal to other observable and unobservable individual characteristics. Uniquely to the military, pay and benefits for new soldiers are determined according to a set scale that exhibits little variation across occupations over the course of an initial enlistment term. This allows us to effectively hold these features constant, ensuring that occupational experience itself is the key mechanism.

We find that early career occupational experiences generate an enormous amount of path dependence in the labor market. For example, we observe that soldiers who enter a military occupation as a result of barely clearing an eligibility threshold are, on average, 20% more likely to *still* be in that occupation 11-15 years later. Some of this is due to re-enlistment – in other words, some military occupations cause soldiers to be more likely to make a career out of that occupation within the Army. Yet, this is a small fraction of our sample: over 70% of soldiers have left the Army within 5 years of initial enlistment, with that number increasing to nearly 90% by years 11-15.[3] Further, if we explicitly exclude retention effects by specifically looking at the impact of Army occupations on *only* civilian analogues, we still find that the average early career experience causes a 10.5% increase in the likelihood of persisting in that occupation 11-15 years later. We find similar results, both including and excluding military retention, at the 16-20 year time horizon.

Beyond persistence, we also find evidence that early career occupational experiences can create other consequential forms of path dependence. While persistence within occupation is a natural starting place, it is also the case that early career occupational experiences cause some individuals to take more complicated career paths. For example, we find that the cutoff which shifts individuals

[3]See appendix figure A.1.

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into the signal support military occupation (i.e. computer networking) has the expected effect on the long-run likelihood of working in a computer related occupation; however, it *also* has an impact on their long-run likelihood of pursuing a management related career. Similarly, we find that the cutoff which shifts individuals into combat related occupations like the infantry also causes an increase in the likelihood they are observed working as a police officer or fabricator 11-15 years later. To summarise these more complicated patterns, we generate heat-maps of causal effects and document substantial "off-diagonal" action, indicative of the complex ways that early career occupational experience can shape career outcomes beyond persistence.

Early career occupational experiences also have consequential, yet highly heterogeneous, effects on long-run wages. At the top end, we find that cutoffs that induce individuals to enter military occupations like the engineering corps and signal support (i.e. computer networking) cause large, statistically significant increases in earnings of $34,067 and $12,833 per year, respectively. On the other hand, we find that cutoffs which induce individuals to enter military careers related to logistics management actually *reduce* earnings by a statistically significant $12,422 per year. And for many of the military occupations, we find no statistically significant effect at all. What drives this heterogeneity?

Much of the heterogeneity in wage effects is likely attributed to the complicated way that early life occupational experiences shape long-run career trajectories. We find that the actual causal effects of different military occupations on earnings are well predicted by the corresponding causal effects on occupational and industry wage premia. In other words, Army occupations that, 15 years after enlistment, have shifted individuals out of occupations with low average earnings and into occupations with high average earnings, also cause large increases in wages. In fact, we find that the differences in implied earnings premia can explain *over* 60% of the variation across army occupations in their causal effect on long run wages, with a slope coefficient that implies each dollar of improvement in occupational wage premia translates essentially 1-for-1 into increases in actual earnings. This finding suggests that, in contrast to the predictions of many, more complicated models of the labor market, the simple heuristic of examining average earnings differences across occupations can serve as a good guide when making early-career decisions.

This paper contributes to the literature on occupational mobility and career dynamics by being the first to quasi-experimentally identify the causal effect of occupational experience on long run outcomes like career choice and wages. Previous research has examined the importance of job mobility in wage growth and career development (Topel and Ward, 1992; Neal, 1998, 1999; Pavan, 2011) and highlighted the role of occupation-specific human capital (e.g. Kambourov and Manovskii, 2009a,b). Yet, this research lacks a clear causal identification strategy and relies on survey data to elicit and control for worker preferences. Recent work has also explored the role

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of a worker's initial employer on intergenerational employment at that firm (Staiger, 2021; Corak and Piraino, 2011), further emphasizing the importance of early career placement, though only in how it relates to firm-specific human capital. Our context allows us to generate causal estimates of the degree of path dependence in career trajectories, and its corresponding effect on wages.

This paper also contributes to a rich literature on education and job training by being the first to examine a setting where non-college graduates experience occupational training paired with extended, mandatory on the job experience. It is clear that – among college graduates – educational quality impacts long-run earnings (Zimmerman, 2019; Mountjoy, 2022), but it remains unclear what the corollary is among non-college educated workers. While a substantial literature has documented the lasting impacts of certain macroeconomic events on career trajectories, none of these directly explore the causal effects of starting out one's career in one occupation relative to another. For example, Oreopoulos et al. (2012); Altonji et al. (2016); Kahn (2010) show the long-run effects of graduating from college and entering the labor market during economic downturns. Huckfeldt (2022) provides a theoretical model that suggests this general finding is the result of workers accepting jobs in lower-skill occupations during a recession, resulting in less valuable human capital developed in that first job. However, the existing literature leaves this hypothesis untested. Alternative explanations could be changes in skill demand during and after a recession (Hershbein and Kahn, 2018) or the effectiveness of job placement assistance (Crépon et al., 2013) and poor initial employer matches (Fadlon et al., 2020). This paper is the first to directly test how a worker's first occupation – and the associated human capital – affects her career. Our approach spans multiple occupations and worker cohorts, all within the same employer. Whereas existing literature tends to focus on college educated workers, our study sample is composed of a more diverse and representative workforce of non-college educated workers.

2 Occupations in the US Army

2.1 The range of Army occupations

The United States Military is the nation's largest single employer with roughly 2.2 million Active Duty and Reserve military and 720,000 civilian employees. To put this in context, the size of the military labor force is comparable in magnitude to the population of Chicago, Illinois, which is the third largest US city. More broadly, there are 17.9 million living veterans in the United States comprising 6.9% of the population over 18. These numbers are even larger among men, where 1 in 7 US male adults have military experience.[4] For context, this is roughly half as large as the

[4]According to Fortune Magazine, the largest private U.S. employer is Walmart, which has 2.2 million employees globally as of 2020 (Forbes list of largest US Private Companies, https://www.forbes.com/

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share of men that are 4-year college graduates. Thus veterans, and the occupational experience they accumulate while serving, play a dominant role in the labor market.

Operating an organization of this magnitude requires a diverse and varied set of roles. As a result, the US Army has over 160 distinct military occupational specialties (MOS). Each MOS is classified by a two digit number, known as a career management field (CMF), followed by a letter. Some occupations, like infantryman (11B) and cannon crew-member (13B, commonly known as field artillery) are primarily connected to the Army's war-fighting mission and have no straightforward civilian analogues. However, many other jobs do.

In fact, the majority of Army occupations correspond to a career that is common among civilians. For example, the army has career management fields dedicated to human resources (CMF 42), legal services (CMF 27), finance (CMF 36), and logistics (CMF 92). Almost 15% of soldiers (or over 24,000 soldiers) enlist in one of these CMFs in our sample. This is large compared to the size of the enlisted force concentrated in CMFs that primarily devoted to combat arms. For example, the infantry (CMF 11) and field artillery (CMF 13) career management fields contain 18% and 5.6% of our sample, respectively. The Army also maintains a large medical corps (CMF 60 and 61) that includes medics, biomedical equipment specialists, dental hygienists, and radiologists. There are military police (CMF 31); network and computer specialists (CMF 25); cooks (CMF 92); and a large number of roles devoted to transportation (CMF 88) and mechanical work (CMF 91). See Table A.1 for the distribution of entry CMFs among those who enlist in our sample.

2.2 The Army recruiting process

The Army recruiting process typically follows a standard procedure.[5] Most new recruits are young men between the ages of 17 and 21 (The median [mean] age in our applicant sample is 19.6 [20.7], see Table A.2). The enlistment process typically begins when a potential recruit first sits down for a meeting with an Army recruiter.

Recruiters are actively involved in generating such meetings through outreach at high school events, job fairs, media advertisements, and other similar activities. Those interested can also walk into recruiter offices spread throughout the country. Army recruiters are currently enlisted

largest-private-companies/). Department of Defense current employment reports are available at https://dwp.dmdc.osd.mil/dwp/app/dod-data-reports/workforce-reports. Percentages are based on author calculations. Veterans' Affairs estimates of living veterans available at https://www.va.gov/vetdata/veteran_population.asp, and estimates of the U.S. population obtained from the U.S. Census Bureau.

[5] All information here applies to enlisted soldiers only. Officers, who generally attend college prior to joining the military, follow a very different recruitment profile that often involves steps like participating in ROTC or attending one of the national military academies and are not the subject of this study.

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soldiers who have been temporarily reassigned to work as recruiters. The Army recruiter serves two primary roles. First, the recruiter is responsible for providing information to the potential recruit about the broad nature of Army service. This includes basic information about things like the military pay-scale, benefits, and qualification requirements. It also includes information about potential Army occupations. In addition to providing information, the recruiter also serves several important administrative functions. For example, the recruiter will perform an initial check to ensure a potential applicant meets some of the basic requirements for Army service (e.g. age, height and weight, etc.).

One important administrative function performed by the recruiter is to coordinate a Military Entrance and Processing (MEPS) appointment for recruits that have decided to potentially enlist. The MEPS appointment generally last for two days, during which time the recruit will verify their eligibility for service by taking a battery of cognitive and physical tests, including the Armed Forces Vocational Aptitude Battery (ASVAB). Once completed, and assuming either a qualifying Armed Forces Qualification Test (AFQT) score or a waiver, new recruits can pick their occupation and initial contract years and sign an enlistment contract from a set of options that will depend on their line scores (discussed more below) and availability/Army needs. The enlistment contract states when the new recruit will report to basic training, which can be anywhere from weeks to months after signing their contract. At this point, the new soldier officially begins their Army career.

2.3 Qualifying for an Army occupation

To qualify for a given Army occupation, recruits must meet a standard set of requirements common to every job. For example, absent waivers, new recruits must be between the ages of 17 and 35, must be a US citizen or permanent resident, must pass a background check, must have a high school diploma equivalent, and must not have any physical or mental issues that disqualify them from service.[6] All new recruits must also obtain at a minimum score on the Armed Forces Qualification Test (AFQT), or a waiver, in order to be eligible to enlist; however, we note that the AFQT does not otherwise directly influence eligibility for any individual occupation within the Army.

In addition to the general qualifications, new recruits must also meet requirements that are specific to the individual occupation they want to join. For example some occupations, like military intelligence, require that soldiers meet TOP SECRET security clearance eligibility requirements. As another example, women were not allowed to serve in combat roles such as the infantry or field Artillery over this period.

However, the most important occupation specific requirement typically comes from a series of

[6]See https://www.goarmy.com/how-to-join/requirements.

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test scores known as "line-scores." These scores are derived from the Armed Forces Vocational Aptitude Battery (ASVAB), which soldiers take during their Military Entrance and Processing appointment. The ASVAB itself is comprised of 10 sub-tests covering different topics such as Arithmetic Reasoning, Paragraph Comprehension, General Science, and others (see table A.3). The Army uses the results of these sub-tests to create both the AFQT score and the 10 line scores that determine occupational eligibility. The line scores are Clerical (CL), Combat Operations (CO), Electronics (EL), Field Artillery (FA), General Maintenance (GM), General Technical (GT), Mechanical Maintenance (MM), Operators and Food (OF), Surveillance and Communications (SC), and Skilled Technical (ST) (see table A.4).

Every Army occupation has a set of occupation specific cutoffs that recruits must clear in order to enlist in that occupation. For example, to join as a military police officer, recruits must have a score of 91 on the ST line score. On the other hand, soldiers that enlist as a human resources specialist must have a 90 on the CL line score (and, as of 2015, a 100 on the GT line score). As with other enlistment requirements, the Army may issue exceptions to these occupation specific line score requirements.

There is substantial scope for the line scores to shape which occupations soldiers choose upon enlisting. In practice, while soldiers may enter the MEPS with an MOS in mind and, in some cases, on file, soldiers only learn their AFQT and line scores during the two-day MEPs appointment. The list of occupations actually available to them based on their line scores, training slots, and other qualifications will only then populate into the computerized interface. Furthermore, soldiers are not allowed to retake the test during their MEPs appointment. Individuals must wait at least one month after their first attempt, one month after their second attempt, and six months after a third or subsequent attempt, to make a new MEPS appointment and retake the ASVAB. Thus, if the soldier does not clear the threshold for their most preferred occupation, the choice they face is to pick a new occupation or fail to enlist during that MEPS appointment.

In practice, the primary reasons for non-enlistment at the MEPS are a disqualifying AFQT score or other disqualifying (e.g. medical) events. Our discussions with Army personnel suggest that it is extremely rare for fully qualified recruits to leave the MEPs station without enlisting at all, let alone when they do not clear the cutoff for their preferred occupation. The density and balance checks in section 4 confirm this. This makes sense for several reasons: first, soldiers often arrive at the MEPS prepared to ship out to basic training, something that can occur soon after signing an enlistment contract.[7] At this point, they also spent two days at the MEPS going through the process. Choosing

[7]Soldiers ship dates depend on training seat availability, but can occur in a matter of days or weeks after signing a contract. Soldiers who need to delay this process to finish existing commitments can enter the Delayed Entry Program.

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to leave the MEPS station and return home could therefore come with some psychological costs. Moreover, the wait time to retake the ASVAB is substantial. Second, recruiters typically have soldiers take a practice test prior to their MEPs appointment so that recruits don't arrive to the MEPs station with unrealistic expectations about the jobs they will be qualified to choose. Finally, in cases where an applicant may have high interest in a specific MOS but just missed the threshold, guidance counselors at the MEPS can request exemptions. We see some evidence that this occurs in our first stage plots (figures A.5 – A.8), where several cutoffs have a non-zero mass of soldiers to the left of the cutoff.

2.4 Army occupational training and subsequent service.

Conditional on qualifying for service and picking a job, soldiers enlist in the Army for a period of 2-6 years.[8] All soldiers begin their career by spending 10 weeks at a basic training unit where they will learn basic soldier skills like equipment maintenance, firing a weapon, and first aid. After the 10 weeks of initial basic training, soldiers will continue on to one of 17 occupation specific schools to undergo Advanced Individual Training (AIT). Infantry and Armor Soldiers stay at their basic training location and attend a training program called One Station Unit Training (OSUT). AIT varies widely in its length and intensity from 4 weeks to a year, though it most typically lasts 1-3 months.[9]

While in AIT, soldiers learn the practical skills they will need to perform an occupation. For example, as a combat medic (MOS 68W), soldiers learn to "administer emergency medical care in the field in both combat and humanitarian situations. Your training will allow you to serve as a first responder and triage illnesses and injuries to save lives, much like a paramedic in the civilian world." Similarly, as a wheeled vehicle mechanic (MOS 91B), soldiers learn to "perform maintenance, repair, and recovery operations on wheeled vehicles and select armored vehicles that serve the Army in a variety of mission-critical roles... inspect, service, maintain, repair, replace, adjust, and test wheeled vehicles, material handling equipment systems, subsystems and components, and automotive electrical systems, including wiring harnesses and starting and charging systems."[10]

Unlike many other occupational training programs, Army training is unique because of the subsequent, extensive on-the-job experience soldiers are required to accumulate. Army soldiers are

[8] The most common term lengths are 3 and 4 years (mean is 3.7, median 4). 2 and 6 year terms are uncommon: The 5th percentile of initial enlistment contract length is 3 years. The 90th percentile is 5 years.

[9] See https://www.goarmy.com/careers-and-jobs/job-training/advanced-individual-training for details.

[10] Quotes come from https://www.goarmy.com/careers-and-jobs/career-match/science-medicine/intensive-care/68w-combat-medic-specialist.html and https://www.goarmy.com/careers-and-jobs/career-match/mechanics-engineering/test-repair/91b-wheeled-vehicle-mechanic.html.

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contractually obligated to serve for the length of their enlistment contract. While there are ways to leave the Army prior to completion of the first enlistment contract, these often involve negative consequences for the soldier and a loss of benefits. For example, soldiers who fail to maintain physical standards or who engage in misconduct can be administratively discharged from service; however, they would typically not receive an honorable discharge, which can come at the cost of lost benefits. For these reasons, most soldiers spend the duration of their first contract actively employed in their occupation. Figure A.1 shows, for soldiers with different initial contract lengths, the share that remain in the military over time since enlistment.

While serving their first enlistment contract, soldiers receive a standardized pay, promotion, and benefits structure, which depends solely on rank and years of service (and not on occupation). Other benefits, such as medical care, life insurance, and retirement plans, are virtually identical for all soldiers at every rank or paygrade.[11]

At or near the conclusion of their first enlistment contract, most soldiers choose to leave the military (see figure A.1). Among soldiers with 2-4 year terms 39% remain 5 years out. Among soldiers with 5-6 year terms, 33% remain 7 years out. However, around 8-10% of soldiers will remain in the Army a full 20 years. Those who reach 20 years of service are eligible for a generous Army retirement pension – accordingly, retention rates from year to year tend to be quite high once soldiers reach around 10-12 years of service.

3 Data and Summary Statistics

3.1 Data Sources and Sample Construction

We use data from various administrative records, including U.S. Army applicant records from the Military Entrance and Processing Command (MEPCOM) spanning from February 1992 to September 2014. These records are combined with U.S. Army administrative pay and service records (1992–2024) and federal tax records (1999–2022).

Our analysis sample is composed of Active-Duty Army applicants who took their ASVAB between two sets of dates: February 1992 – December 2001 and July 2004 — September 2014 (henceforth, 1992-2001 and 2004-2014). Both the way line scores were calculated and the line score cutoffs changed in January 2002 and again in July 2004 following the ASVAB renorming, necessitating

[11] One exception is the basic allowance for housing, which is identical for soldiers in paygrades E1-E4 living in the same location and with a similar number of dependents. This benefit increases modestly with rank starting at paygrade E5. Some army non-taxable pay, such as Imminent Danger Pay and Hazardous Duty Pay, can be more common for some Army occupations than others based different deployment rates, but these tend to be small relative to other pay.

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the split sample.[12] Following Greenberg et al. (2022), we impose several additional sample restrictions: we exclude applicants with prior military service, who took the ASVAB in high school as part of the Career Exploration Program, who have invalid AFQT scores (zero or missing), and who fall outside the typical 17-35 enlistment age range. The majority of our analysis is further limited to 99% of the remaining applicants whose records could ever be matched by social security number to any tax record.

3.2 Constructing Line Scores For Army Jobs

Our analysis relies on enlistment records that allow us to observe a new enlistee's first Military Occupational Specialty (MOS). An applicant's "line scores", determine their eligibility for each MOS.[13]

We recover line scores for each applicant from their "standard scores", which measure how the applicant performed on each of the various ASVAB sub-tests. The sub-tests that comprise the ASVAB are shown in Table A.3. We observe individual-level "standard scores" (or the corresponding raw sub-test scores from which these are derived) for all applicants, though only for their most recent ASVAB test.[14]

Line scores are then constructed based on different combinations of the standard scores. Table A.4 describes the line scores. Prior to 2002, these line scores were constructed by summing select standard scores and then using a conversion table to convert this sum into the final line score. For example, the General Maintenance (GM) line score was the sum of the Mathematics Knowledge (MK), Electronic Information (EI), Auto and Shop (AS), and General Science (GS) standard scores, converted via a table to the final GM line score. The final line scores have a mean of 100 and standard deviation of 50. After 2004, the line scores are weighted averages of all standard scores. For example, the GM score is $\approx 0.24 \cdot GS + 0.46 \cdot AR + 0.45 \cdot MK + 0.29 \cdot MC + 0.30 \cdot EI + 0.50 \cdot AS + 0.22 \cdot (WK + PC) - 23.36$.

[12] Prior to February 1992 the data do not reliably contain the test score version information we need to construct line scores. We drop the 2002-June 2004 period from our analysis as during this short transitional period we are unable to reliably calculate and verify the necessary scores for our identification strategy.

[13] The Armed Forces Qualification Test (AFQT) determines whether applicants are able to enlist in the Army at all, but otherwise does not determine eligibility for any particular job in the Army. In some specifications, we also leverage two AFQT cutoffs, at the 31st and 50th percentiles of a nationally-normed distribution, that generate discontinuities in an applicant's eligibility to enlist. The Army rarely accepts applicants with AFQT scores below 31, sometimes requires GED recipients to achieve a score of 50 or higher, and often requires applicants to score 50 or higher to receive enlistment bonuses. Following Greenberg et al. (2022), whenever we use AFQT as a running variable, we use applicants' *first* AFQT on file from their initial visit to the MEPS.

[14] For the 1992-2001 period we observe raw test scores. We use time-varying and test-version specific conversion tables to translate raw scores into standard scores for each individual in our data. For the 2004-2014 period we observe standard scores directly in the data.

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One consequence of the way line scores are constructed and used is that post-2004 line scores are relatively continuous, but prior to 2002 scores are discrete and exhibit a sawtooth pattern due to the fact that several standard scores are sometimes converted to the same line score (see e.g. figures A.9–A.10).[15]

Line scores changed between our two periods. Both current and historical line scores for each 'current-year' MOS are outlined in DA-PAM 611-21 Chapter 10-3-2. Since some MOS designation codes change over time, we map MOS at each point in time to their 'current-year' MOS using a crosswalk. There are roughly 150 distinct entry MOS in both periods. Across all 10 line scores there are roughly 40 cutoffs per-period, but as explained in Section 4, we will examine a subset of these that produce sizable enough first stages.[16]

3.3 Federal Tax Records

We merge applicants to their federal tax records using the Social Security Number from their Army application. We successfully link 99% of applicants. The tax records give us third party reported earnings information (Form W-2, Form 1999-Misc, and beginning 2000, Form 1099-NEC), industry (6 digit naics), and education information (from Form 1098-Ts) for 1999-2022.

Crucially, the data also provide occupation information. Taxpayers report their occupation at the bottom of their Form 1040 each year. The IRS began storing this string variable for tax year 2005, and it is typically available for those that e-filed their returns – the high majority of filers, especially as paper filing has become increasingly rare – and for the primary filer as well as secondary filer when married. We then merge these string variables to an internally created crosswalk to 2010 three-digit Standard Occupational Classification (SOC) codes, with most string variables successfully linked to a SOC code when the individual is employed. We make two modifications to the 2010 SOC codes. First, we condense all military SOC codes to a single SOC (55-0). Second, based on the occupation strings, we create a SOC code for government, non-military jobs (60-0). We are not aware of any prior research papers linking tax data to occupations.

We are able to merge approximately 50% of Army applicants to a SOC occupation between 2005-2022, with the denominator including nonfilers and those not employed. When we analyze occupational persistence, we keep Army applicants without a linked SOC who have no earnings in our

[15] Given that the underlying standard scores prior to 2002 are also generated from conversion tables and are discrete, there is no way to construct a more continuous line score. The AFQT score percentiles in all periods and the GT score post-2004, which is based off on only the sum of VE and AR, are also discrete.

[16] In practice many cutoffs either apply to very uncommon or small, singleton jobs, or apply to jobs for which another cutoff tends to be far more binding. Cutoffs can also be adjacent (e.g. MM 87/88), which in practice cannot be separately identified, reducing the effective number of cutoffs. In such cases, we count this as one cutoff (treating all jobs affected by either MM 87 or 88) and treat it as occurring at 87 with a doughnut-hole between 87-88.

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sample (as zeros) but exclude (as missing) Army applicants who have earned income but no linked SOC.[17]

3.4 Outcomes

The main outcomes in our analysis are occupational persistence and income, though we also explore additional outcomes such as educational attainment. To account for the dynamic nature of career development, our outcomes are measured in years-since-ASVAB. That is, we consider earnings, occupation, and education outcomes for all applicants 1 year after their application, on up through 20 years post application (where possible).

3.4.1 Occupational Persistence

Our primary measure of occupational persistence is the share of years (e.g. 11-15 years after the ASVAB) for which an individual i is observed in an occupation (three digit SOC) that is linked to the corresponding Army occupations at a given cutoff.

This requires linking Army jobs to their civilian counterparts. To do so, we create a Military Occupational Specialty (MOS) to three digit SOC crosswalk. The crosswalk is constructed by manually comparing the descriptions of MOS duties to the descriptions of each SOC code provided by the Bureau of Labor Statistics. Given the fact that several civilian jobs can reasonably be linked to an MOS, we crosswalk each MOS to a "primary" SOC code and a "secondary" SOC code. We also maintained (when relevant) supervisory SOC codes for primary and secondary SOC codes for each MOS. In all, this results in each MOS having a mapping to a primary and secondary SOC code as well as any associated supervisory SOC codes. For various combat jobs like infantry or artillery for which there is no natural civilian counterpart the primary SOC is left as a military SOC (55-0).

This crosswalk allows us to explore whether an individual is still in a given set of cutoff-relevant SOCs, either because they are still in a related Army job, or because they are in a related civilian occupation. Individuals can move occupations while in the Army, so we use time-varying MOS codes where relevant. We also explore post-service (or 'civilian') persistence by not counting anyone still in the Active Duty Army in the relevant year as persisting in the same occupation.

Since each cutoff can determine eligibility for multiple MOS, we construct cutoff-specific, occupation-group outcomes. The natural way to do this is to create the outcome based on whether the individual is any of the primary, secondary, or supervisory jobs corresponding to the full set of MOS

[17] Across all our cutoffs, we test and find no evidence of selection bias in whether we are able to link Army applicants with earned income to a SOC.

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affected by that cutoff. In practice and in the interest of power, since several MOS at each cutoff are negligible in size or not substantially moved by the cutoff, we do this for the MOS with sufficiently large first stages at each cutoff.[18] If a person's final 3-digit SOC falls into any of the codes associated with these MOS at a cutoff, then the outcome variable is coded as 1, otherwise it is 0.

3.4.2 Income

Earned income is compiled form third party reported information returns available between 1999 and 2022. The measure is primarily derived from the wage income subject to medicare tax reported by employers on Form W-2. We also add in contractor income reported by contractor businesses on Form 1099-MISC (and beginning in 2020, Form 1099-NEC). Our earned income measure is in 2010 real dollars, winsorized at the 99% level. To account for the fact that those in service also receive compensation that would typically be included as taxable wages in the civilian sector but is exempt from taxation for servicemembers, as noted by Loughran et al. (2011), we inflate taxable wages while in the military by a factor of 1.25.[19]

3.4.3 Other Outcomes

We measure college attendance from Form 1098-T, a third party reported information return filed by colleges and universities on behalf of their students. This data is available between 1999 and 2022 and indicates whether the student is enrolled as an undergraduate for at least half time, undergraduate less than half time, or a graduate student. We create a measure of the share of years enrolled between 1 and 19 years after application (for years between 1999-2022) and whether the applicant ever attended college in this period. We also supplement our data with associate and bachelor's degree completion information from the National Student Clearinghouse (NSC) linked to the Army administrative data and matched by social security number.

[18] Specifically, we base our outcomes on the MOS at each cutoff that either have a first stage coefficient greater than or equal to 0.003 or that make up 10% or more of the jobs at the cutoff.

[19] Military pay that is not reported on the W-2 as subject to medicare tax encompasses various allowances and payments, such as the Basic Allowance for Housing (BAH), Basic Allowance for Subsistence (BAS), and additional compensation for deployment or foreign assignments, including Hardship Duty Pay, Imminent Danger Pay, Hazardous Duty Pay, and Family Separation Allowances. We do not account for other benefits, such as health coverage, retirement contributions, or G.I. Bill tuition and related housing allowances, some of which may have more natural civilian counterparts. Appendix B of Greenberg et al. (2022) states that military pay not subject to taxation accounts for 17-25% of servicemembers' *total* compensation.

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3.5 Summary Statistics

Summary statistics for all U.S. Army applicants in our two key samples (1992-2001 and 2004-2014) are presented in Table A.2. The data shows that applicants are typically young (20-21 years old), predominantly male (76-81%), and most have not attended college (91-94%). Compared to a nationally representative sample of 17–23 year-olds from the 2000 Current Population Survey (CPS), the applicants in the study are more likely to be Black (18-25% versus 15%) and less likely to be Hispanic (10-13% versus 15%).

We next present some summary statistics on how eventual *civilian* occupations (three digit SOC 15 years after the ASVAB date) vary by entry MOS for enlistees with a valid 15 year-out SOC. These serve both to provide context for understanding the different type of Army jobs and common three digit SOC codes, as well as to help validate our crosswalk from MOS to SOC. Figure A.2 shows a heatmap with each row representing an entry MOS and each column representing the "heat" (or proportion) of soldiers with that entry MOS that end up in that column's SOC 15 years post-ASVAB.[20] Cells outlined in blue correspond to either the primary or secondary SOC codes we have crosswalked to the corresponding MOS. It is clear that many of the signal jobs (CMF 25) end up in computer occupations (SOC 15-1), many of the health jobs (CMF 68) end up in health related occupations (29-1 and 29-2), many of the intelligence and military police (as well as to some extent the standard infantry, armor and field artillery jobs) end up in law enforcement (33-3), Human Resource soldiers (42A) ends up in Human Resources (13-1), many of the mechanics (CMF 91) end up in maintenance, mechanic, and repair jobs (SOC 49-3 and 49-9), and so forth.

Figures A.3 and A.4 zoom in on select entry MOS. Figure A.3 shows the relative proportion of soldiers in various 15-year out occupations relative to the proportion of all enlisted soldiers in that occupation. It shows the 10 highest and lowest relative proportion SOCs. For example, Infantry soldiers are more likely to be construction and law enforcement jobs 15 years out, and less likely to be in health, administrative, or teaching jobs than the average enlistee. Meanwhile, signal support specialists are more likely to be in computer and electronic-related occupations, and less likely to be mechanics or law enforcement workers. Figure A.4 conveys the same information in Sankey Plots which provide a clearer sense of magnitudes. For example, about 15% of infantry soldiers end up as civilian construction trades workers, material moving workers, law enforcement workers, or other protective service workers. About 8% of signal support specialists end up in civilian computer occupations. 16% of combat medics end up in civilian healthcare occupations, and about 16% of military police end up in non-military law enforcement or other protective services.

[20] To reduce the dimensionality of this figure, we restrict to MOS with large first stages at our analysis cutoffs and restrict to the universe of SOCs in our MOS-SOC crosswalk.

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The observed occupational persistence could certainly be driven by selection: those with a specific interest computer jobs presumably are more likely to be in such occupations in the long-run. In the remaining sections of this paper, we will explore how much of this persistence can be explained causally (i.e. by shifting people into and out of different occupations).

4 Empirical Strategy

4.1 Research design

Our empirical strategy for identifying the causal effect of different military occupations is a fuzzy regression discontinuity design. As discussed in section 2.3, the army determines eligibility for different occupations using thresholds in a series of 10 test scores known as line scores. Intuitively, our identification strategy will compare the outcomes of soldiers who barely cleared one of these cutoffs to soldiers who fell just short. If this variation is as good as random, then we can sharply identify the reduced form causal effect that eligibility for certain army occupations has on long run outcomes. If the only way that eligibility affects the outcome is by changing the likelihood a soldier enlists in a relevant job, then we can use this variation as an instrument for enlisting in that occupation in a fuzzy RD framework.

Formally, we estimate reduced form effects specific to each cutoff using the following sharp regression discontinuity model:

$$Y_i = \gamma Z_i + f(X_i) + \epsilon_i \tag{1}$$

Where Y_i is the long run outcome of soldier i measured at some specific point in time (e.g. average wages or share of years in an occupation 11-15 years after taking the ASVAB);[21] X_i is soldier i's line score from the relevant subtest; $Z_i = \mathbb{1}(X_i > c)$ is binary variable indicating whether soldier i's line score cleared the cutoff (c);[22] and ϵ_i is a residual. The parameter of interest from equation 1 is γ. It represents the predicted difference in mean outcomes for soldiers with a line score at the RD threshold.

[21] Because tax data is only available 1999-2022 (or 2005-2022 for occupation-related outcomes), when we examine outcomes at different time horizons (e.g. 11-15 years out) we weight each individual by the number of years she could potentially be observed in tax records.

[22] In practice, there are multiple line scores and sometimes also multiple cutoffs per line-score; however, because our preferred empirical approach involves estimating one regression discontinuity model per cutoff, we suppress the implied indices on the line score and cutoff variables for notational simplicity.

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The key assumption we rely on for causal identification is that the conditional expectation function mapping the running variable into the outcome would have otherwise been continuous provided clearing the threshold did not change Army occupational eligibility. If this assumption holds, then γ represents the reduced form causal effect of occupational eligibility on the outcome of interest (Lee and Lemieux, 2010). This assumption has a number of testable implications which we explore in section 4.2.

Our baseline model specifies $f(\cdot)$ as a piece-wise quadratic polynomial within a bandwidth of 10 test score points around the threshold. In all cases, the 10 point bandwidth is close to the optimal bandwidth selected using the method of Calonico et al. (2014). However, we fix it to be common across cutoffs because as discussed in section 3, prior to 2002 the running variable is discrete and has a saw-tooth pattern and hence it is not possible to select an optimal bandwidth for cutoffs over that time period. In several cases the 10 point bandwidth overlaps another cutoff in our data. In order to avoid mis-specification, in these cases we constrain the bandwidth to be smaller than 10 such that it never crosses another cutoff. When it is not possible to have a bandwidth larger than 5, we switch to a linear polynomial for power purposes.[23] However, our key findings are robust to varying the bandwidth and the order of the polynomial, including to using all quadratic polynomials. Standard errors are robust to heteroskedasticity.

In practice, we examine 43 (39 non-AFQT cutoffs). In all but two cases, the remaining cutoffs had no or extremely small (< 0.005) first stage effects, typically because they were the second cutoff for a job where the first cutoff dominated. In other words, these are cases where soldiers that clear the first cutoffs almost always clear the second cutoff, which renders it non-binding. We dropped these cutoffs from the analysis.[24]

Moving beyond the reduced form effect of job eligibility, we also explore the impact of joining the individual Army occupations associated with each cutoff using the following fuzzy regression discontinuity model:

[23] With a linear polynomial, the bandwidth selection procedure of Calonico et al. (2014) tends to select small bandwidths close to 5, suggesting that at these bandwidths a linear is appropriate. In a few cases where a linear appears potentially misspecified based on the first stage plots we retain the quadratic out of caution.

[24] We also drop two additional cutoffs: FA96 in the 2004-2014 period and FA100 in the 1992-2001 period, which apply to a single MOS (13F - joint fire support specialist). Both cutoffs exhibit imbalance on race, with Black applicants more 0.6-1pp more likely above the threshold. This could simply be due to chance given the large number of cutoffs explored, but out of caution to avoid introducing potentially biased results, we chose to drop these cutoffs from the analysis. Ultimately, our results are insensitive to their inclusion. Note that the more common field artillery jobs are covered by lower FA cutoffs that are retained in our analysis.

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$$Y_i = \beta D_i + g(X_i) + \eta_i \tag{2}$$

$$D_i = \pi Z_i + h(X_i) + u_i \tag{3}$$

Where D_i is an indicator that takes a value of 1 if the soldier enlists in the army in a job they became eligible for as a result of clearing cutoff c; the functions h and g are specified identically to f from the reduced form model; u_i and η_i are residuals; and the remaining variables are as described previously. The parameter of interest from 2 is β, which we estimate using two-stage least-squares.

Causal identification in equation 2 requires that two more key assumptions hold in addition to the assumptions necessary for causal identification of the reduced form. The first additional assumption is that there is a non-zero first-stage. In other words, job eligibility does, in fact, change the likelihood a soldier enlists in the Army in the relevant occupation. We provide evidence that this assumption holds in section 4.2. The second additional assumption is an exclusion restriction. This requires that the only reason occupational eligibility affects the outcome is by changing the likelihood of enlisting in that occupation. We believe this assumption is reasonable in our setting given the institutional details of the enlistment process. The line scores themselves affect no other aspect of military service and are not used in the civilian world in any capacity. Nevertheless, in the next subsection, we present results from over-identification tests that are consistent with exclusion.

4.2 Evidence in support of identifying assumptions

First Stages. We first present evidence that the first stage effect of crossing an eligibility threshold on occupation takeup is strong. Empirically verifying a strong first stage is important for interpreting the reduced form estimates and for ensuring that our fuzzy regression discontinuity design doesn't suffer from weak instrument bias. Figures A.5 through A.8 provide graphical evidence of strong first-stage effects. In addition to the graphical evidence, Table A.5 provides the estimated first-stage coefficients and their significance at each of the cutoffs. As the table shows, all first stages exceed 0.005, or half of a percentage point, and are statistically significant at the 1% level or higher. Note that this also implies that all of the cutoffs have implied first stage F-statistics above 10, which is a commonly used threshold for diagnosing potential problems with weak-IVs (see Andrews et al., 2019, for a recent review).[25] The largest first stages are observed at the fol-

[25] We acknowledge that recent work has suggested that the F-stat threshold of 10 may be insufficient to address problems related to weak instruments (Lee and et al., 2022); however, in all of our preferred specifications, we use

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lowing cutoffs: in the pre-2002 period, CO90 (0.078), CL95 (0.063), and ST95 (0.06); and in the post-2004 period, OF85 (0.068), ST91 (0.058), and CO87 (0.05). To illustrate the practical implications, consider the CO87 cutoff, which applies to MOS 11B (Infantry), 11C (Indirect Fire Infantry), 12B (Combat Engineer), 12C (Bridge Crewmember), 19D (Cavalry Scout), 19K (Armor Crewmember), and 92R (Parachute Rigger). Applicants who wish to work in these roles need their Combat line score (CO) to be above 87. Just below the cutoff, only 5% of applicants enter one of these seven jobs. In contrast, just above the cutoff, over 10% do, demonstrating the substantial impact of the cutoff on job assignment.

No Manipulation. Having established a set of first stages, we next present evidence consistent with no manipulation. As pointed out by McCrary (2008), if individuals manipulate the running variable in order to obtain the treatment, then that would invalidate the continuity assumption that underlies causal inference in a regression discontinuity design. To examine this potential confound, we begin by presenting standard density or "bunching" checks. The histograms of all the running variables in both periods are presented in Figures A.9 through A.10. For each line score, we illustrate all relevant score cutoffs. Note that in the 1992-2001 period, line scores are discrete because they are constructed from formal tables rather than a functional transformation. Due to how the underlying standard scores combine to create line scores, some of the underlying scores are converted to the same percentile points, leading to the "sawtooth" appearance of the density charts. Despite this, it is visually clear that there is no obvious score manipulation at the cutoffs in both the 1992-2001 and 2004-2014 periods. While the discrete scores for pre-2002 years also make formal density checks unavailable, we can collapse the densities to the integer level and run our baseline specification on the "counts". When doing so, we fail to reject nulls at all pre-period cutoffs. For the 2004-2014 period, where most of the running variables are more continuous and non-lumpy, the charts also report the bias-adjusted p-values from Cattaneo et al. (2018)'s density test using their optimal bandwidth and a local linear, triangular kernel specification. All these p-values are above standard statistical significance levels. Given the institutional context and these density checks, we find no evidence suggesting any meaningful manipulation around the job cutoffs.

Balance. We check for balance across the available set of pre-service covariates in the applicant data, as in Greenberg et al. (2022). These covariates are available for applicants who enlisted as well as those who did not. The covariates include age, gender, race (white, Black, and Hispanic), and education (in High School, no high school diploma, high school diploma, and some higher education). For each of these variables, we employ our baseline specification (see Section 4). Since

just-identified IV which is median unbiased even in finite sample and hence less subject to these concerns (Angrist and Kolesár, 2024).

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there are 43 cutoffs checked across nine covariates, the resulting table is excessively large and is included in table A.6 in the Appendix. As an additional visual check, we plot the distribution of p-values across all 43 cutoffs $\times$ 9 covariates in figure A.11. Consistent with a balanced treatment, the distribution of p-values appears relatively uniform. We condense these results in table 1, which shows a joint p-value for each covariate across all cutoffs. These are calculated by stacking all 43 cutoff regressions together. Only one of the p-values is below 0.1, consistent with the number of tests being run. The joint p-value across all covariates and cutoffs is 0.16. In all, our treatment appears balanced across observable covariates.

Exclusion. We now present evidence in support of our exclusion restriction. As described further in section 5, our preferred method for summarizing the variation contained across all our regression discontinuity designs is a visual-IV. One benefit of the visual-IV approach is that it offers a number of simple, transparent tests of instrument validity. For example, our model passes (p = 0.80) an overidentification test that jointly examines instrument validity and LATE homogeneity (Angrist and Hull, 2023). This is consistent with exclusion being satisfied.

We also present results from a placebo test that is based on extrapolating the reduced form variation across the support of the first stages from all our regression discontinuities. As described in Section 4.1, the exclusion restriction implied by model 2 requires that the only reason occupational eligibility affects long run career trajectories is by changing the likelihood the individual enlists in a relevant occupation. Intuitively, this exclusion restriction implies that there should be no reduced form effect of job eligibility in instances where the first stage is known to be zero. Mathematically, this implies that the intercept of the visual-IV best fit line should be zero. Thus, we report a simple F-test of the linear restriction that the best fit line of the visual-IV plot passes through the origin. For both our preferred measure of occupational persistence, and a secondary measure that restricts to civilian occupations only, we fail to reject an intercept of zero (p = 0.427 and 0.476, respectively). This is consistent with our exclusion restriction. See figure 1 for a visual depiction of the unrestricted best fit lines.

5 The Long Run Effects of Early Life Occupational Experience

This section presents our key finding: that early life occupational experiences have important long-run effects on career outcomes. We begin by showing that early career occupational experiences cause important changes in long-run career choice. In particular, we find a substantial degree of path dependence across all cutoffs. We then turn to wages, where we find a substantial amount of

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heterogeneity that is well predicted by differences in occupational wage premium.

5.1 Path dependence in the labor market

Occupational persistence. We begin by quantifying the long-run effect of early career occupational experiences on long-run career choice. While early career occupational experience may influence later life career choice in a variety of complicated ways, a natural starting point to explore path dependence is the extent to which these experiences create occupational persistence. In other words, does eligibility for an occupation increase the likelihood that individuals will be in the same occupation 15 years later?

To quantify persistence, we estimate our reduced form model (equation 1) for each cutoff separately. The outcome variable for each of these separate regressions is the share of years individual i is observed in an occupation that is linked by our cross-walk to the corresponding Army occupations at the cutoff. For example, obtaining a score of 85 on line score OF is necessary for soldiers to be eligible for Army occupations 92G (Culinary Specialist) and 88M (Motor Transport Operator).[26] These occupations are naturally linked to the civilian occupations of Cooks and Food Preparation Workers (SOC 35-2), Food Service Managers (a subset of SOC 11-9), Motor Vehicle Operators (SOC 53-3) and Material Moving Workers (SOC 53-7). In this case, the outcome variable would be equal to the share of years an individual is observed in those occupations (SOC codes 35-2, 11-9, 53-3 and 53-7), or their supervisory counterparts (in this case, 35-1, 53-1), 11-15 years after they date that they took the ASVAB test.

One important question concerns how to handle military careers. Take the example of Matt the military mechanic. On the one hand, if early career occupational experience as a military mechanic causes Matt to be more likely to spend the rest of his life as a military mechanic, that is a real causal effect of the treatment on his later career outcomes. On the other hand, if the *only* treatment effects on subsequent career paths are the result of inducing individuals to persist in the same occupation within the military, then the path dependence could be at least partly explained by unique features of military contracts which would potentially undermine the broader generalizability of the findings to the analogous civilian careers. To address this, we will show both results that count spending time in the relevant military occupation as part of the treatment effect, and results that do not.[27]

[26] In practice, the cutoff is also attached to several additional Army MOS's; however, we ignore them here for clarity of exposition.

[27] More precisely, when incorporating retention effects, we define the outcome variable as "years spent in the relevant set of occupations, after crosswalking Army jobs to SOCs", so that it covers both years spent in the focal occupations in the Army or as a civilian. Note that we do use time-varying MOS in the Army, so people who switch MOS to a material different job, which does occur, will not be counted as in the same occupation. When excluding retention

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Panels (a) and (b) of figure 1 displays a "visual-IV" (V-IV) plot of our occupational persistence results (Angrist and Pischke, 2009). Each point in this figure corresponds to a distinct line-score cutoff. The y-axis corresponds to the reduced form estimate from our regression discontuity model (equation 1) where the outcome variable was the share of years observed in an occupation relevant to that cutoff 11-15 years after the date of the ASVAB. The x-axis corresponds to the first-stage estimates from model 2. Panel (a) shows our baseline results that include causal effects on retention in the same military career. Panel (b) restricts to civilian career only. See table A.7 for the point estimates used to generate figure 1.

The V-IV slope from panels (a) and (b) of figure 2 is our preferred way to summarize the persistence we find across different cutoffs. Up to a weighting, the V-IV slope in panels (a) and (b) of figure 1 is equivalent to the slope of the corresponding 2SLS regression on the underlying micro-data. Thus, our estimate is naturally interpreted as the causal effect that joining an army occupation has on the likelihood of remaining in that occupation later in life.[28] Another natural way to summarize the persistence is by directly examining the individual IV estimates. Panels (c) and (d) of figure 1 are identical to (a) and (b), except that we replace the reduce form estimates on the Y-axis withe the corresponding IV estimate. This allows us to see visually how the the treatment effects vary with average compliance rates (i.e. the size of the first stage). It also allows us to visualize "average" persistence across occupations by reporting the mean of the individual fuzzy RD estimates as a horizontal line.

By either measure, we find that early career occupational experiences create an enormous amount of persistence. The V-IV slope on the estimates that include persistence within the military suggest that early life occupational experiences cause a 20.4% increase the likelihood of being found in the same occupation 11-15 years later. Retention within the military accounts for approximately half of this effect; however, even excluding retention we find a 10.5% increase in the likelihood of being found in an identical civilian occupation over the 11-15 year time horizon. Turning to panels (c) and (d), we find that the mean-IV summary measure estimates causal persistence at 23.3% with

effects, we define the variable as, "years spent in the focal occupations as a civilian." We operationalize this by assigning everyone still in the Active Duty in the relevant year to an unused SOC.

[28] We prefer the V-IV slope to the slope of the corresponding 2SLS regression on the underlying micro data for reasons of computational tractability. We estimate the V-IV slope using OLS with the reduced form estimates as the dependent variable and the first stage estimates as the independent variable, and we construct standard errors using the delta method and the full variance-covariance matrix of the estimated parameters. Importantly, the variance-covariance matrix is calculated using a person-id level cluster, and hence our approach to inference is also robust to typical forms of error dependence. In practice, we have also estimated the slope of the corresponding 2SLS model on the micro-data for several of our key outcomes, and both the point estimate and standard errors (accounting for cluster dependence) are nearly identical to what we obtain from our preferred approach. For example, the 2SLS model applied to the underlying micro data with the same occupation as an outcome yields a point estimate of 0.205 with a standard error of 0.022. The analogous V-IV regression yields a point estimate of 0.219, and the delta method produces a standard error of 0.021.

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retention, and 10.5% without. Panel (a) of table 2 summarises the key point estimates and provides corresponding standard errors.[29]

Another intriguing feature of these estimates is that they suggest relatively limited heterogeneity (given our sampling variance) in persistence across cutoffs. There are two ways to note this. First, in the V-IVs, following Angrist and Hull (2023), we can conduct an over-identification test for proportionality (i.e. the reduced form and first stage parameters are roughly proportional across cutoffs). When doing so for our main occupational persistence measures we obtain a $\chi^2(37) = 29.5$ [pval$= 0.80$] for civilian or military persistence and $\chi^2(37) = 22.6$ [pval$= 0.91$] for civilian persistence only. Second, we can directly test for whether the IV effects are jointly equal to each other in a stacked regression across cutoffs and obtain p-values around 0.8 (table 2).

Our main occupational persistence findings (as well as our key findings pertaining to wages, discussed in Section 5.2), are robust to varying bandwidth and polynomial order. Table A.8 shows how our key results change when using all quadratic polynomials, using a tighter, maximum bandwidth of 5 everywhere, and using only linear polynomials for a bandwidth of 5.

Dynamics. Figure 2 plots our preferred summary measure of persistence over time. The Y-axis corresponds to the V-IV slope coefficient. The x-axis corresponds to different time horizon's relative to date of the ASVAB. Circles correspond to estimates that include persistence into the same occupation. Triangles correspond to estimates that exclude military occupations and therefore represent the causal effect of having an identical occupation as a civilian. Whiskers denote 95% confidence intervals.

The dynamic pattern reveals large increases in army occupational experiences in the short run that give-way to causal effects on the relevant civilian occupations over time. In years 1-5, we see an 71% increase in the share of years spent in the same occupation; however, virtually all of this is due to the causal effect on military service in the relevant occupation. But by years 6-10, after all enlisted soldiers have had the opportunity to leave the Army, we see a large decline in the estimates of persistence that include military occupations coupled with a 9% increase in the causal effect on having an identical civilian occupation. And by years 16-20, at which point nearly all soldiers in our sample have exited the military, we find that the two series have nearly converged, showing that persistence into analogous civilian jobs dominates over long time horizons.

[29] We also report results on our preferred V-IV measure of occupational persistence for Black and white subsamples in table A.10. Results, as expected, are substantially noisier, but overall 11-15 occupational persistence is generally not statistically distinguishable across race and close to the full sample findings. However, consistent with Black soldiers staying longer in the military, occupational persistence results for Black applicants are large driven by persistence in the military as opposed to civilian persistence (Greenberg et al., 2022). While much of the observed white persistence occurs post-service (at least based on point estimates).

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Other forms of path dependence. While persistence within the same occupation is a natural starting place, it is also possible that early career experiences shape your long-run career trajectory in other, more complicated ways. For example, the skills developed as a military aviation mechanic may be well suited to other occupations, such as construction or motor vehicle repair. Thus, we also explore the impact that early career experiences could have on other long run occupational outcomes.

We find that early life occupational experience does, indeed, shape career outcomes in ways other than persistence. To see this, observe figure 3 which presents a heat map of causal effects. Each row in the heatmap corresponds to a cutoff. Columns represent the corresponding group of occupations that clearing a cutoff renders a soldier eligible to join. Each box denotes the IV estimate from model 2 of the cutoff in that row on the share of years observed in the occupations in that column as measured 11-15 years after the date of the ASVAB. Thus, the "diagonal" entries simply restate the IV estimates from panel (c) of figure 1; however, the off-diagonal estimates highlight causal impacts on other career paths. Blue denotes positive effects. Red denotes negative effects. For visual clarity, we show the ten jobs with the largest first stages.

Figure 3 shows that early career experiences can have complicated effects on long run career trajectories. As expected given the evidence in figure 1, we see a strong diagonal in the heatmap, which simply confirms that there is a powerful persistence effect. However, we also see evidence of action on the off diagonals. For example, crossing the FA93 cutoff for Field Artillery jobs makes soldiers more likely to be motor vehicle operators (part of the OF85 job group) and in computer occupations (part of the EL93 job group). These jobs are not crosswalked to Field Artillery jobs as they do not correspond to the same occupation (and hence are 'off-diagonal'), but are nevertheless plausibly linked. Fire control specialists (MOS 13J), for example, employ automated computer-based systems.

For another example, consider, the CL90 cutoff for human resource specialists. Crossing this threshold has a large positive effect on the ST101 job group (intelligence and healthcare jobs) and a large negative effect on the OF85 job group (food service workers, truck drivers). Indeed, figure 5 panel (b) shows that crossing the threshold necessary to become an HR specialists causes individuals to more likely to be in management occupations or office and administrative support workers (the diagonal), but also more likely to be health technologists (off-diagonal), and less likely to be motor vehicle operators or material moving workers (off-diagonal). These off-diagonal results make sense: figure A.22 panel (e) shows that the threshold pulls people away from transportation-related jobs, which helps explain the reduction in motor vehicle operators. This threshold also affects some small medical-related MOS (medical logistics specialist and patient administration specialist) which could help explain the off-diagonal effect on medical-related occupations. Finally,

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this cutoff also shifts people into teaching positions, which would not show up on the heatmap (as they are not directly linked to any of our MOSs), but reinforces the idea that our cutoffs — and the changes in early life occupational experiences that they generate — can shape career outcomes in ways other than direct occupational persistence.

Case Studies. To make the findings across this section more concrete, we discuss how a few specific cutoffs, affecting different types of Army jobs, alter individuals' careers. Figure 5 plots reduced form effects on specific post-service, occupations (3-digit SOCS) at select cutoffs, 11-15 years after the ASVAB. Since there are almost 100 SOC codes (and hence estimates), we restrict our attention to the largest 8 (and smallest 5) estimates at each cutoff.[30] To get a sense of which initial military occupations people are pulled away from, these figures also depict the smallest and largest reduced form effects on initial military CMFs at each cutoff.

At the EL93_post cutoff (panel (a)), which shifts people into signal support specialists (and away from mechanical maintenance, military police, and quartermaster), we see large positive, post-service effects on computer occupations. Yet we also see reductions in operations managers, law enforcement workers, and health care support occupations, which make sense given the military jobs people are fulled away from. At the CL95_pre cutoff (panel (b)), which shifts people into logistics and HR jobs (away from transportation, maintenance, and non-active duty), we see clear increases in eventual business operations specialists and office and administrative support workers (as well as reductions in vehicle mechanics and material moving workers). At the ST95_pre cutoff (panel (c)), which shifts people into health care and military police jobs (away from quartermaster, infantry, and mechanical maintenance), we see long run effects on health related occupations and law enforcement jobs (with reductions in vehicle and mobile equipment mechanics, material moving workers, and information and record clerks). At the OF85_post cutoff (panel (d)), which shifts people into truck drivers and food service jobs (away from maintenance and HR), we see increases in motor vehicle operators, dispatch and distributing workers, and food preparation workers (and reductions in maintenance and repair, among others). These, as well as many other such examples, paint a clear and coherent picture of how the line score cutoffs shift people into and out of different initial military occupations, in turn, shaping long-run, post-service occupational patterns.

Altogether, our findings highlight the different ways that the cutoff-induced changes in early career occupational experiences influence long run career outcomes. The net effect of the career changes

[30]Figures A.20-A.25 show similar exhibits for the top 24 cutoffs, sorted by first stages.

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caused by these early life occupational experiences on other outcomes, such as wages, will likely depend both on what occupation cutoff induced an individual to enter, and also the nature of the long-run counterfactual occupation the cutoff caused them to leave. This makes raw patterns on other outcomes like wages trickier to interpret, a problem we tackle in more detail next.

5.2 Effects on wages

We now quantify the impact that these early career experiences have on long run wages. However, unlike the results on path dependence explored in the previous section, there is reason to believe wages are potentially quite sensitive to the heterogeneous nature of the long-run counterfactual career across cutoffs. For example, we would expect an early career experience that induced an individual to move from a low paying occupation (like a food service worker) into a high paying occupation (like an electrician) will have a larger impact on wages than an early career experience that simply moves an individual from a low paying occupation and into yet another low paying occupation. Thus, to interpret the causal effect of these early career occupational experiences on wages, we will benchmark them to the corresponding causal effect on occupation specific average wages. Comparing effects on wages to effects on occupation-wages at the same cutoff yields an apples-to-apples comparison that accounts for the heterogeneous nature of the counterfactual across cutoffs. Intuitively, we expect to find that military occupational experiences which, 11-15 years later, have caused soldiers to move out of low-paying occupations and into-high paying occupations will also have large effects on wages.

Figure 4 presents our key results. In both figures, each point is a cutoff. The y-axis denotes fuzzy RD estimates from model 2 of the causal effect that the corresponding military occupational experience had on wages. In panel (a), the x-axis denotes to the corresponding causal effect on occupational-wage premia.[31] Panel (b) is identical to panel (a) except that the x-axis corresponds to causal effects on (6-digit naics) industry specific average wages, rather than occupation.[32] In both panels, the dashed line is the 45 degree line. The solid line is the line of best fit.

These figures reveal clear and heterogeneous effects of these early career occupational experiences

[31] More precisely, we calculate occupational specific wages as the in-sample, leave-one-out average, 11-15, three-digit SOC wages of all other individuals in our data. Since observing occupation already requires the filing of a tax return, we also include self employment income reported on Form 1040 for a more comprehensive measure of earned income (though the results are very similar with their exclusion, due in part to the small share of self employed). To measure the causal effect of the early career occupational experience on this outcome, we simply replace "wages" with this "average occupation wage" variable in model 2. Thus, the causal effect on this variable gives exactly the causal effect that the early career experience had on the occupation specific wage premia for ones' occupations 11-15 years post-ASVAB.

[32] We construct 11-15 industry wages as the wages paid to everyone in our sample in a given 6 digit industry by years since ASVAB, leaving out one's own wages. We use separate 6 digit codes for military and for government (non-military).

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on wages. Cutoffs that shift people away from low-wage occupations to high-wage occupations cause large increases in wages, and vice-versa. For example, at the top end we find that cutoffs that induce individuals to enter military occupations like infantry/engineering corps and signal support result in statistically significant increases in actual wages of $34,067 (P=0.003) and $12,833 (P=0.095), respectively.[33] These causal effects are mirrored in the corresponding changes in wage premia ($15,719 and $8,996) and in industry wage premia ($27,068 and $5,124). At the bottom end, we find that cutoffs which induce entry into military careers like logistics/HR actually *reduce* earnings by a statistically significant $12,422, with causal effects that are also mirrored in the corresponding changes in occupational wage premia (-$6,317).[34] And for many military occupational experiences, like those related to food service / truck driving, we find no statistically detectable impact on either earnings or occupational specific wage premia. Note that these null effects occur despite the fact that these same cutoffs generate occupational changes. This is consistent with the cutoff generating changes across occupations with otherwise similar average wage premia.

The point estimates and standard errors for individual cutoffs underlying these figures are contained in appendix table A.9. Table 2 presents results from an F-test that the causal effect on wages are identically zero for all cutoffs. We reject the null of no wage effects. Moreover, and consistent with the heterogeneity on display in figure 4, we also reject the null that all of the IV wage effects are equal to each other (table 2). This is true for both the actual causal effect on wages as well as the corresponding impact on the occupation and industry specific wage premia.

The tight correspondence between changes in occupational/industry earnings premia and the actual average effect on earnings in figure 4 suggests that much of the heterogeneity in wage effects is well explained by the heterogeneous way that different early life occupational experiences change career paths. Indeed, the implied changes in occupation and industry wage premia can explain an enormous amount of the heterogeneity in the actual causal effect on earnings. For example, a simple regression of the causal effect on earnings on the causal effect on occupational wage premium yields an R^2 of 0.633, showing that over 60% of the causal variation in earnings is explained by simply examining the average change in earnings implied by the underlying causal effect on career path. Perhaps more strikingly, the slope coefficient from this regression is indistinguishable from 1 (0.985 with a standard error of 0.109), which shows that changes in occupational wage premia

[33] For CO87_post, enlistees enter the combat occupations from both quartermaster jobs and non-active duty about equally. For EL93_post applicants enter signal support from a range of other military occupations, but mainly from mechanical maintenance, military police, and quartermaster (see figure 5). If later logistical and administrative jobs pay less than computer and law enforcement jobs, you would expect to see wage increases at these cutoffs given the nature of the counter-factual.

[34] For CL95_pre, enlistees enter the quartermaster and HR from outside of active duty, transport, maintenance, and field artillery. The reduction in wages at this cutoff is consistent with mechanic and law enforcement jobs paying more than admin and business operations jobs (figure 5).

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are also forecast unbiased for the actual causal effect on earnings. In other words, each dollar of wage premia translates essentially 1-1 into an additional dollar of actual earnings. Taken together, these two facts suggest that simply examining differences in average earnings across occupations provides an *extremely* accurate guide to the how the causal effect of an early career occupational experience will shape income in the long run. We also find similar patterns (both in terms of variance explained and forecast unbiasedness) for industry specific earnings premia, suggesting that these also serve as a useful guide to the long run consequences of early life occupational experience.[35]

5.3 Which types of early career experiences are most consequential for long-run outcomes?

So far we have seen i) that regardless of the jobs that people are shifted away from, there tends to be strong occupational persistence in the long-run. And ii) that, in practice, through occupational persistence and other more complicated occupational changes, our cutoffs generate changes in applicants' post-service occupations in a way that alters wages (and is tightly linked to average occupational wages). One remaining question is what characteristics of initial jobs are most consequential for long-run wages?

One way to explore this question is to compare the effect on wages to the effect of crossing the threshold on initial MOS-level characteristics (treating non-Army as a single MOS).[36] Figures A.27 and A.28 plot the causal effects on wages (or occupational persistence), 11-15 years out, at each cutoff against the causal effects on various entry MOS-specific characteristics, like average AFQT in that MOS, average initial terms, average months deployed, and average eventual years served and post-secondary educational attainment. Across the board, for both figures, there is no statistically significant link between how the cutoff shifts these MOS-level characteristics and how it shifts eventual (11-15) occupational persistence or wages. This suggests that – across *all types of jobs* (as proxied for by the initial job characteristics in this exercise) – a large share of people persist in their initial occupation. However, since these jobs are connected to civilian occupations with different average wages, these occupational persistence patterns eventually generate wage differentials, which turn out to also be uncorrelated with initial job characteristics.

[35] Table A.11 shows effects on years of service in the Army and education at each of the cutoffs. While around 4 cutoffs significantly alter years of service, Figure A.26 shows that ultimate IV wage gains are not tightly linked to causal IV effects on years of service or army service.

[36] An alternative approach leverages the fact that in our unique setting we actual observe the occupations (SOCs) and education patters of those who do not join. Hence, we can compare eventual IV effects on wages or occupational persistence to IV effects on average SOC-based characteristics 1-5 years after the ASVAB, after crosswalking military jobs to SOCs. Relative to the MOS-based approach, this helps refine the counter-factual for those who do not serve. However, since we only observe occupations starting in 2005, this also limits our sample.

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Put differently, starting out one's career in MOS linked to civilian occupations with high wage premia relative to MOS linked to occupations with lower wage premia appears most consequential for eventual wage gains. Yet, the MOS that are most closely related to high wage occupations are not easily summarized by other observable characteristics, at least among the set considered here.

6 Conclusion

In this paper, we estimated the causal effect of early career occupational experiences on labor market outcomes using data on applicants to the U.S. Army. The 150+ Army jobs use different line score cutoffs to determine an enlistee's eligibility for a given Army job. Leveraging these thresholds in various regression discontinuity designs, we found that just crossing (or just missing) the threshold on a test taken at approximately age 20 has long-run career impacts on future occupational and wage trajectories (at ages 30-35 and 36-40). Across almost all thresholds, occupations are path dependent. On average, approximately 20% of drivers remain drivers, 20% of mechanics remain mechanics, 20% of human resources and logistics employees remain so, 20% of computer-related employees remain in similar jobs, and so forth. This high and relatively homogeneous persistence has implications for eventual wages: those shifted by the cutoffs from low to high average wage occupations benefited the most. Our results suggest that nudging people into higher eventual wage occupations or focusing apprenticeships and training programs on such occupations at the early career stage could help increase lifetime earnings.

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References

Altonji, Joseph G, Lisa B Kahn, and Jamin D Speer, "Cashier or consultant? Entry labor market conditions, field of study, and career success," *Journal of Labor Economics*, 2016, *34* (S1), S361–S401.

Andrews, Isaiah, James H Stock, and Liyang Sun, "Weak instruments in instrumental variables regression: Theory and practice," *Annual Review of Economics*, 2019, *11*, 727–753.

Angrist, Joshua and Michal Kolesár, "One instrument to rule them all: The bias and coverage of just-ID IV," *Journal of Econometrics*, 2024, *240* (2), 105398.

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly harmless econometrics: An empiricist's companion*, Princeton university press, 2009.

_ **and Peter Hull**, "Instrumental variables methods reconcile intention-to-screen effects across pragmatic cancer screening trials," *Proceedings of the National Academy of Sciences*, 2023, *120* (51), e2311556120.

Calonico, Sebastian, Matias D Cattaneo, and Rocio Titiunik, "Robust nonparametric confidence intervals for regression-discontinuity designs," *Econometrica*, 2014, *82* (6), 2295–2326.

Cattaneo, Matias D, Michael Jansson, and Xinwei Ma, "Manipulation testing based on density discontinuity," *The Stata Journal*, 2018, *18* (1), 234–261.

Corak, Miles and Patrizio Piraino, "The Intergenerational Transmission of Employers," *Journal of Labor Economics*, January 2011, *29* (1), 37–68.

Crépon, Bruno, Esther Duflo, Marc Gurgand, Roland Rathelot, and Philippe Zamora, "Do labor market policies have displacement effects? Evidence from a clustered randomized experiment," *The quarterly journal of economics*, 2013, *128* (2), 531–580.

Fadlon, Itzik, Frederik Plesner Lyngse, and Torben Heien Nielsen, "Causal effects of early career sorting on labor and marriage market choices: A foundation for gender disparities and norms," Technical Report, National Bureau of Economic Research 2020.

Greenberg, Kyle, Matthew Gudgeon, Adam Isen, Corbin Miller, and Richard Patterson, "Army Service in the All-Volunteer Era," *The Quarterly Journal of Economics*, November 2022, *137* (4), 2363–2418.

Hershbein, Brad and Lisa B Kahn, "Do recessions accelerate routine-biased technological change? Evidence from vacancy postings," *American Economic Review*, 2018, *108* (7), 1737–1772.

Huckfeldt, Christopher, "Understanding the Scarring Effect of Recessions," *American Economic Review*, 2022, *112* (4), 1273–1301.

Kahn, Lisa B, "The long-term labor market consequences of graduating from college in a bad economy," *Labour economics*, 2010, *17* (2), 303–316.

Kambourov, Gueorgui and Iourii Manovskii, "Occupational mobility and wage inequality," *The Review of Economic Studies*, 2009, *76* (2), 731–759.

_ **and** _ , "Occupational specificity of human capital," *International Economic Review*, 2009, *50* (1), 63–115.

Lee, David S. and et al., "Valid t-ratio Inference for IV," *American Economic Review*, 2022, *112*

Approved for limited disclosure. Not for public distribution.

(10), 3260–3290.

Lee, David S and Thomas Lemieux, "Regression discontinuity designs in economics," *Journal of economic literature*, 2010, *48* (2), 281–355.

Loughran, David S., Paco Martorell, Trey Miller, and Jacob Alex Klerman, *The Effect of Military Enlistment on Earnings and Education*, Santa Monica, CA: RAND Corporation, 2011.

McCrary, Justin, "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of econometrics*, 2008, *142* (2), 698–714.

Mountjoy, Jack, "Community colleges and upward mobility," *American Economic Review*, 2022, *112* (8), 2580–2630.

Neal, Derek, "The Link between Ability and Specialization: An Explanation for Observed Correlations between Wages and Mobility Rates," *The Journal of Human Resources*, 1998, *33* (1), 173–200.

_ , "The Complexity of Job Mobility among Young Men," *Journal of Labor Economics*, April 1999, *17* (2), 237–261.

Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz, "The short-and long-term career effects of graduating in a recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

Pavan, Ronni, "Career Choice and Wage Growth," *Journal of Labor Economics*, July 2011, *29* (3), 549–587.

Staiger, Matthew, "The intergenerational transmission of employers and the earnings of young workers," *Washington Center for Equitable Growth Working Paper. https://equitablegrowth. org/working-papers/the-intergenerational-transmission-of-employers-and-the-earnings-of-young-workers/[Accessed 22 June 2022]*, 2021.

Topel, Robert H and Michael P Ward, "Job mobility and the careers of young men," *The Quarterly Journal of Economics*, 1992, *107* (2), 439–479.

U.S. Census Bureau, "2018 American Community Survey 1-Year Public Use Microdata Samples," 2018. U.S. Census Bureau.

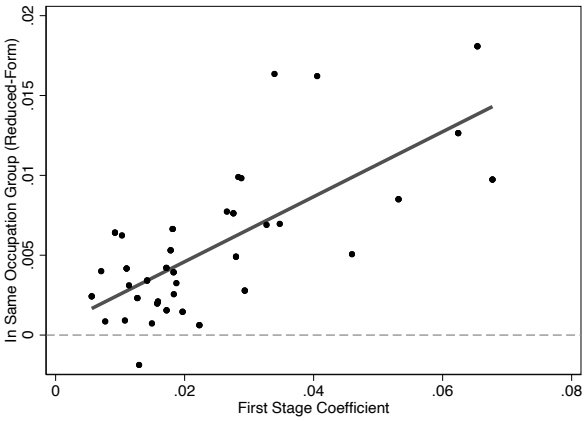
Zimmerman, Seth D, "Elite colleges and upward mobility to top jobs and top incomes," *American Economic Review*, 2019, *109* (1), 1–47.

Approved for limited disclosure. Not for public distribution.

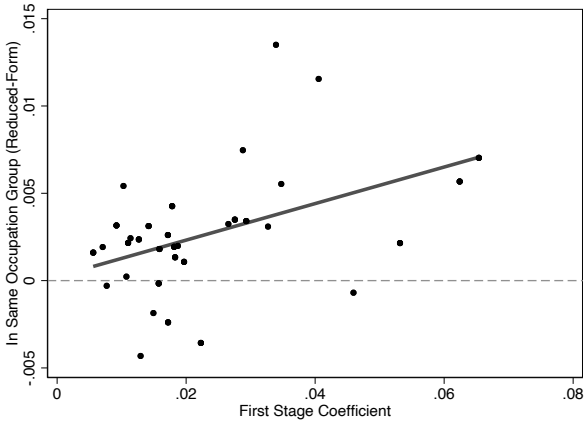
Figures

Figure 1: Causal Effects on Having the Same Occupation 11-15 Years Later

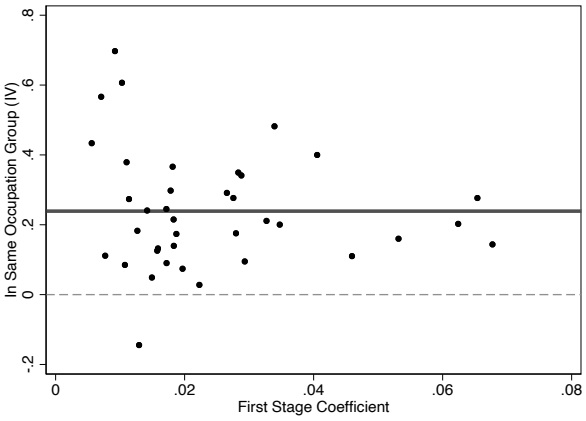
(a) Military + civilian occupations (V-IV)



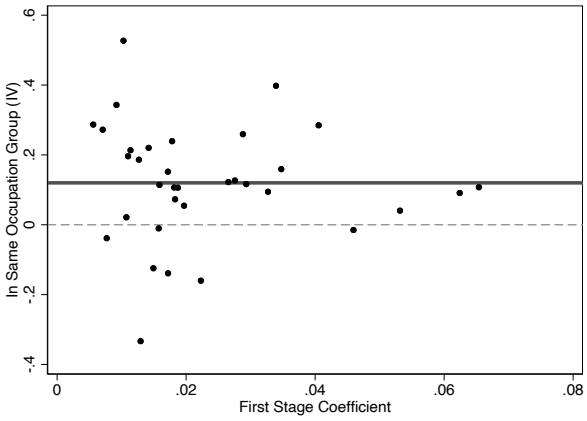
(b) Civilian occupations only (V-IV)



(c) Military + civilian occupations (mean-IV)



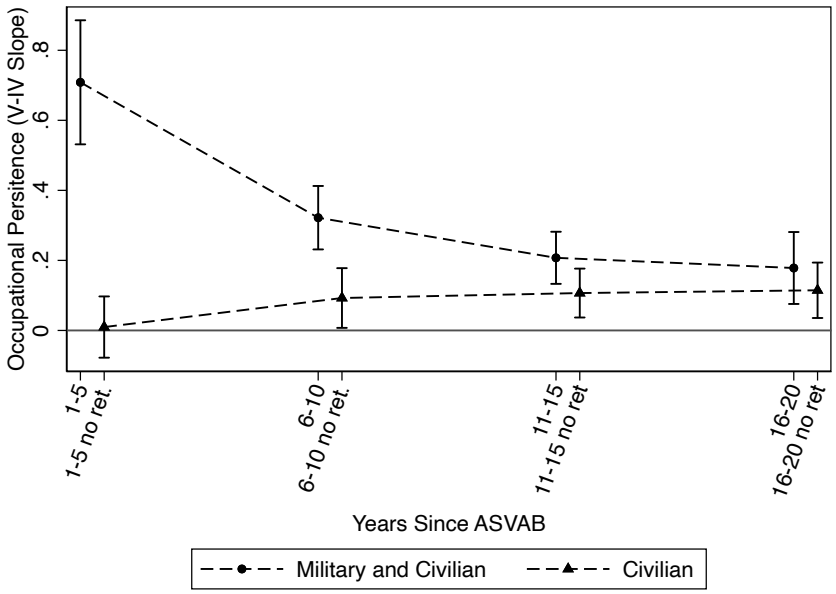
(d) Civilian occupations only (mean-IV)



Notes: Panels (a) and (b) plot the cutoff-specific, estimated reduced form effects on our preferred measure of occupational persistence against the first stage effects at that same cutoff. Occupational persistence is measured as the share of years 11-15 post-AFQT that an individual is observed in occupation that is linked by our crosswalk to the corresponding Army occupations affected by each relevant cutoff. The persistence effects in panel (a) encompass persistence across military and civilian careers, while those in panel (b) correspond to exclusively post-Active Duty Army persistence. The line of best fit is shown on the graph. Panels (c) and (d) are analogous to (a) and (b) but plot the IV effect on persistence on the y-axis instead of the RF effect. The average of these IV effects is depicted using a horizontal line. The effects in panels (a) and (c) are plotted for the 38 non-afqt cutoffs (and dropping st106_post which has the lowest first stage < 0.005), while the plots in panel (b) and (d) additionally drop the Field Artillery and Combat thresholds which do not have as natural civilian counterparts as the other thresholds.

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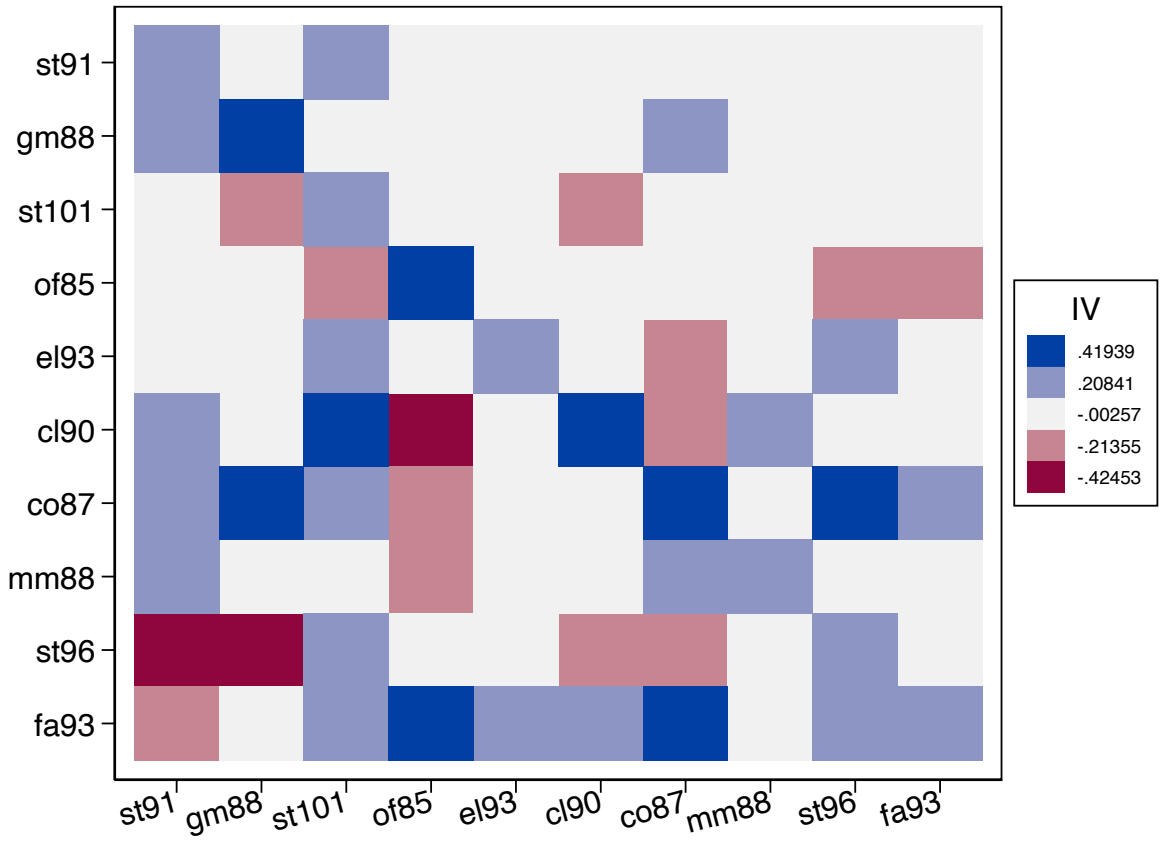
Figure 2: The Dynamics of Occupational Persistence



Notes: This figure plots our preferred measure of occupational persistence (V-IV slope) for different time horizons: 1-5 years, 6-10 years, 11-15 years (these correspond to the slopes in Figure 1 panels (a) and (b)), and 16-20 years post-ASVAB. The circles represent the persistence effect across either civilian or military jobs. The triangles represent the persistence effect on civilian jobs. For consistency across periods, we present estimates for 37 cutoffs (dropping st106_post and el107_post which have < 0.005 first stage for the 16-20 sample), though results are insensitive to the inclusion of these cutoffs. For post-service persistence, we additionally drop the Field Artillery and Combat thresholds as they do not have as natural civilian counterparts as the other thresholds. 95% confidence intervals, based on heteroskedasticity robust standard errors on the line of best fit, are depicted.

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Figure 3: Heatmap of IV effects on Occupation Groups

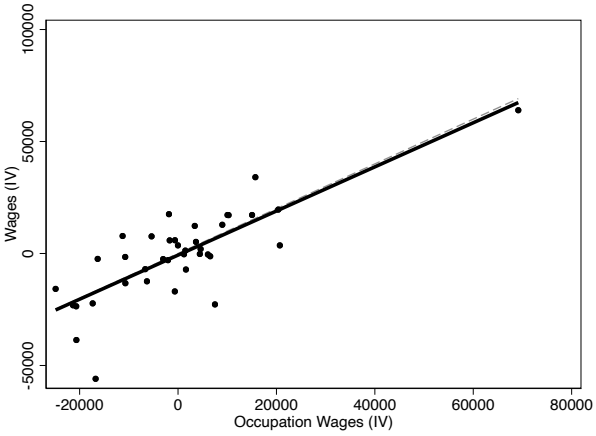


Notes: This heatmap depicts IV effects on being in a given occupation group 11-15 years post-AFQT for the ten 2004-2014 cutoffs with the largest first stages. The diagonal shows persistence in the focal occupations (i.e. the estiamtes plotted in Figure 1 panel (c)). The off-diagonals represent persistence in the focal occupations of other cutoffs (which are not necessarily mutually exclusive). The legend value corresponds to the midpoint of the bin (with the exception of the top and bottom bin, bins are 0.211 units wide). Figure A.16 shows the analogous set of results for the top ten 1992-2011 cutoffs.

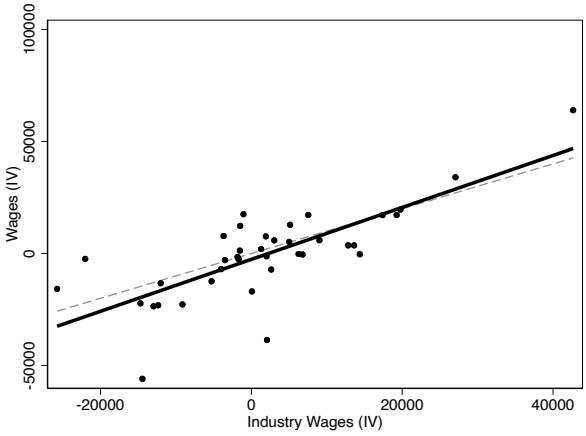
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Figure 4: Occupations, Industries, and Wages

(a) Wage vs. Occupation Wage Effects (IVs)



(b) Wage vs. Industry Wage Effects (IVs)

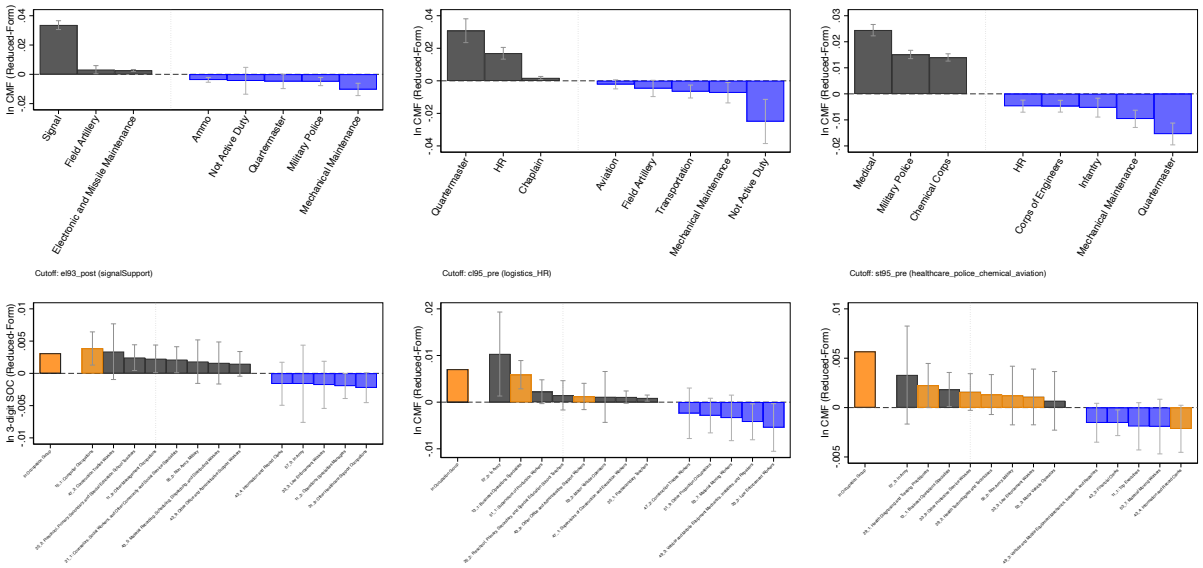


Notes: This figure plots the correlation between the cutoff-specific IV effect on 11-15 average own wages and, in panel (a), the 11-15 IV effect on average (leave-out) occupation wages. Panel (b) plots the IV effects on own wages against the IV effect on average (leave-out) industry wages. Occupation and industry wages reflect full sample, leave-out average wages based on three digit SOCs (treating all military as its own SOC) and in 5 digit industry, respectively. Both panels show 38 points, or cutoffs. As in Figure 1, all panels drop the cutoff with the lowest FS (st106_post, first stage < 0.005 for the 11-15 sample). The line of best fit is shown on each graph in solid black. The dashed gray line corresponds to the 45-degree line.

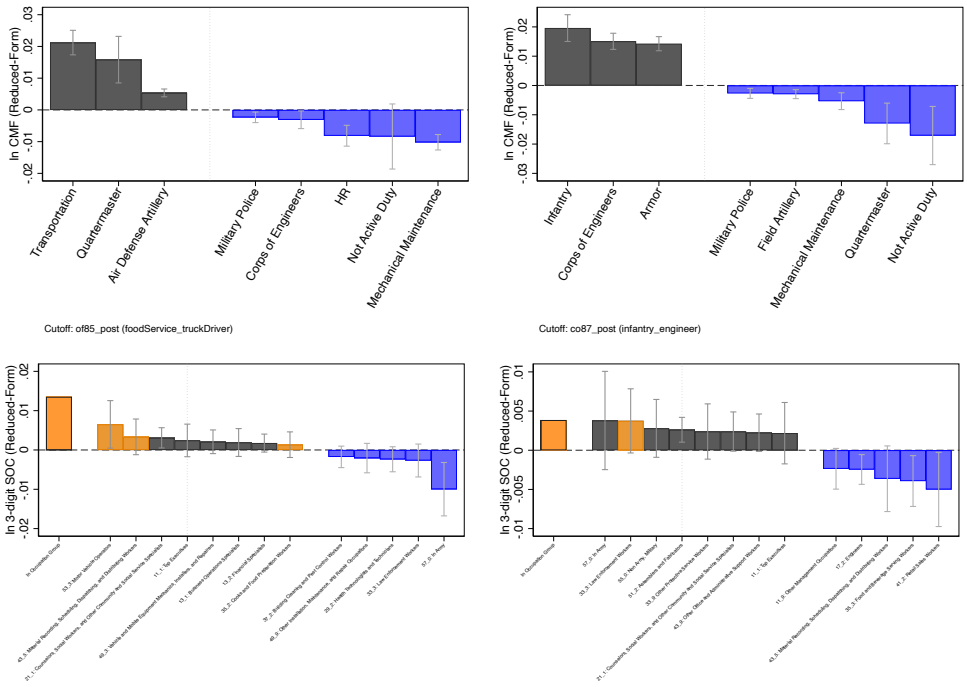
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Figure 5: Case Studies

(a) Signal Support (EL93_post) (b) HR/Logistics (CL95_pre) (c) Medical/Police (ST95_pre)



(d) Transport, Food (OF85_post) (e) Infantry/Eng./Armor (CO87_post)



Notes: Each panel of this figure focuses on a different cutoff and shows two subfigures. The first plots top 3 and bottom 5 reduced-form effects of crossing the threshold on various military CMFs, to show which job groups enlistees are pulled from. The bottom subfigure in each panel plots reduced-form effects on the share of years, 11-15, that the person is one of 97 three-digit, post-service SOCs (all still in active duty are set to 57-0). The first orange bar shows the reduced form effect on our main measure of persistence - being in any of the relevant post-service SOCs for that cutoff. Then we show the top 8 largest reduced effects on individual SOCs (black) and the bottom 5 (blue). The bars are in orange if they are in the list of jobs we identified as being relevant at that cutoff. The El93 cutoff affects primarily mos 25U, signal support specialist; CL95 affects primarily mos 42A, 92A, and 92Y (HR, unit supply specialist, and logistical specialist); ST95 affects primarily mos 68W, 31B, and 74D (combat medic, military police, and CBRN specialists); CO87 affects primarily mos 11B, 12B, 19D/K, 12C (infantry, combat engineers, and armor jobs); and OF85 affects primarily 92G, 88M, 92F (culinary specialist, motor transport operators, petroleum supply specialist).

Tables

Table 1: Covariate Balance Across All 43 Cutoffs

	Mean	Joint P-value (43 cutoffs)
Age	20.47	0.111
Male	0.74	0.233
White	0.52	0.042
Black	0.27	0.254
Hispanic	0.13	0.799
In High School	0.26	0.323
No HS Diploma	0.16	0.976
HS Diploma	0.53	0.202
Some college+	0.05	0.330
All covariates and cutoffs:		0.156

Notes: This Table reports p-values for various covariate balance tests across all the cutoffs studied in this paper. The first row reports the p-value for a test that the effects of crossing the threshold on age are jointly 0 across all 43 cutoffs, and so on for the other rows. Below the table, we report the joint p-value from a joint test across all 9 covariates and 43 cutoffs. Every underlying coefficient is reported in Table A.6, with p-values from all these regressions depicted in Figure A.11. See Table A.2 for a description of the mutually exclusive education categories.

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Table 2: Summary of Key Results

	Panel (a): Occupational Persistence	
	Military & Civ.	Civilian Only
V-IV:		
Slope Coef.	0.204	0.105
	(0.034)	(0.038)
Slope Coef. (no constant)	0.219	0.111
	(0.021)	(0.023)
IV Persistence Effects:		
Average IV Effect	0.233	0.105
	(0.032)	(0.029)
$P(H_0 : \beta_c = 0 \, \forall c)$	< 0.0001	0.009
$P(H_0 : \beta_c = \beta \, \forall c)$	0.792	0.797

	Panel (b): IV Wage Effects				
	Wages	ln(wages)	Work	Occ. Wages	Ind. Wages
$P(H_0 : \beta_c = 0 \, \forall c)$	0.003	0.013	0.018	0.006	0.0005
$P(H_0 : \beta_c = \beta \, \forall c)$	0.002	0.011	0.014	0.005	0.0004

	Wages v. Occ Wages	Wages v. Ind. Wages
Slope Coef.	0.985	1.160
	(0.109)	(0.196)
R^2	0.633	0.583

Notes: This Table summarizes the key results and relationships described in Section 5. Panel (a) summarizes our occupational persistence results. It first reports the V-IV slopes and heteroskedasticity robust standard errors (constructed using the delta method and using the full covariance-variance matrix of reduced form and first stage estimates) from Figure 1 panels (a) and (b). Below this, it reports the same objects but for a regression without a constant, which yields efficiency gains. It then reports the average of the IV effects and associated standard error (generated from a stack of all 38 IV regressions) from panels (c) and (d) of Figure 1, as well as joint tests that these are jointly equal to zero and jointly equal to each other. In panel (b), this Table reports joint tests for whether or not the 38 IV estimates for wages, ln(wages), any wages, occupation-wages (leave-out), and industry-wages (leave-out) are jointly zero or jointly equal. It also reports the post-estimation OLS slope, heteroskedasticity-robust standard error, and R^2 between the IV estimates on wages and occupation wages and between the IV estimates on wages and industry wages, depicted in Figure 4.

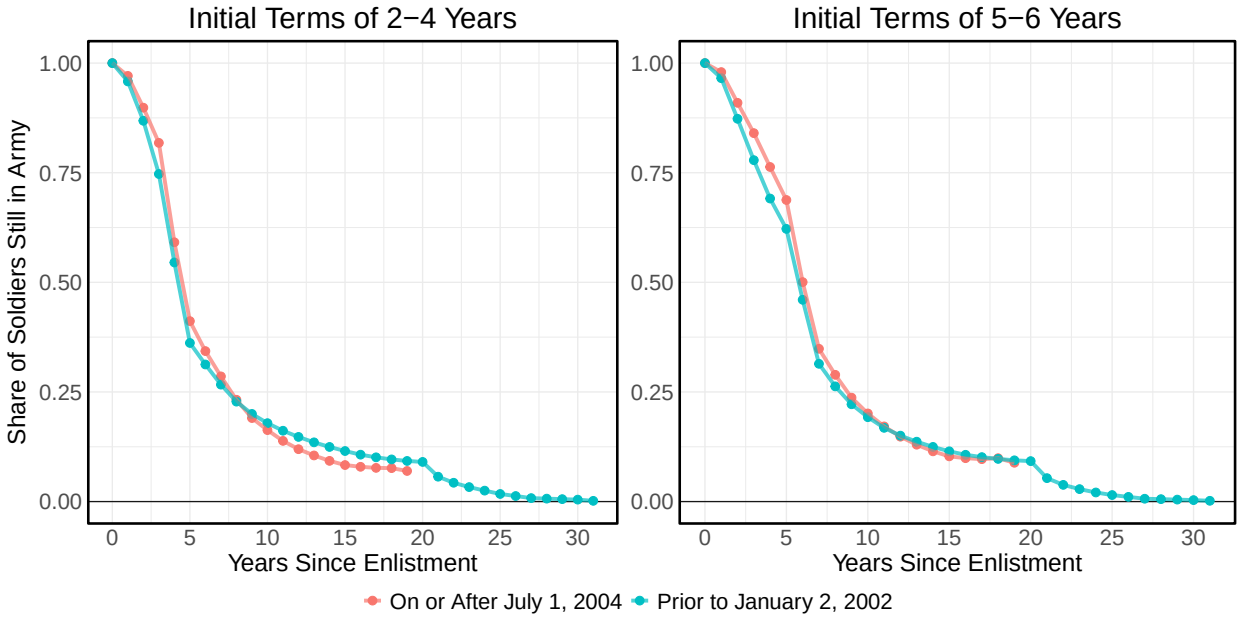
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Online Appendix

A Appendix Figures and Tables

Appendix Figures

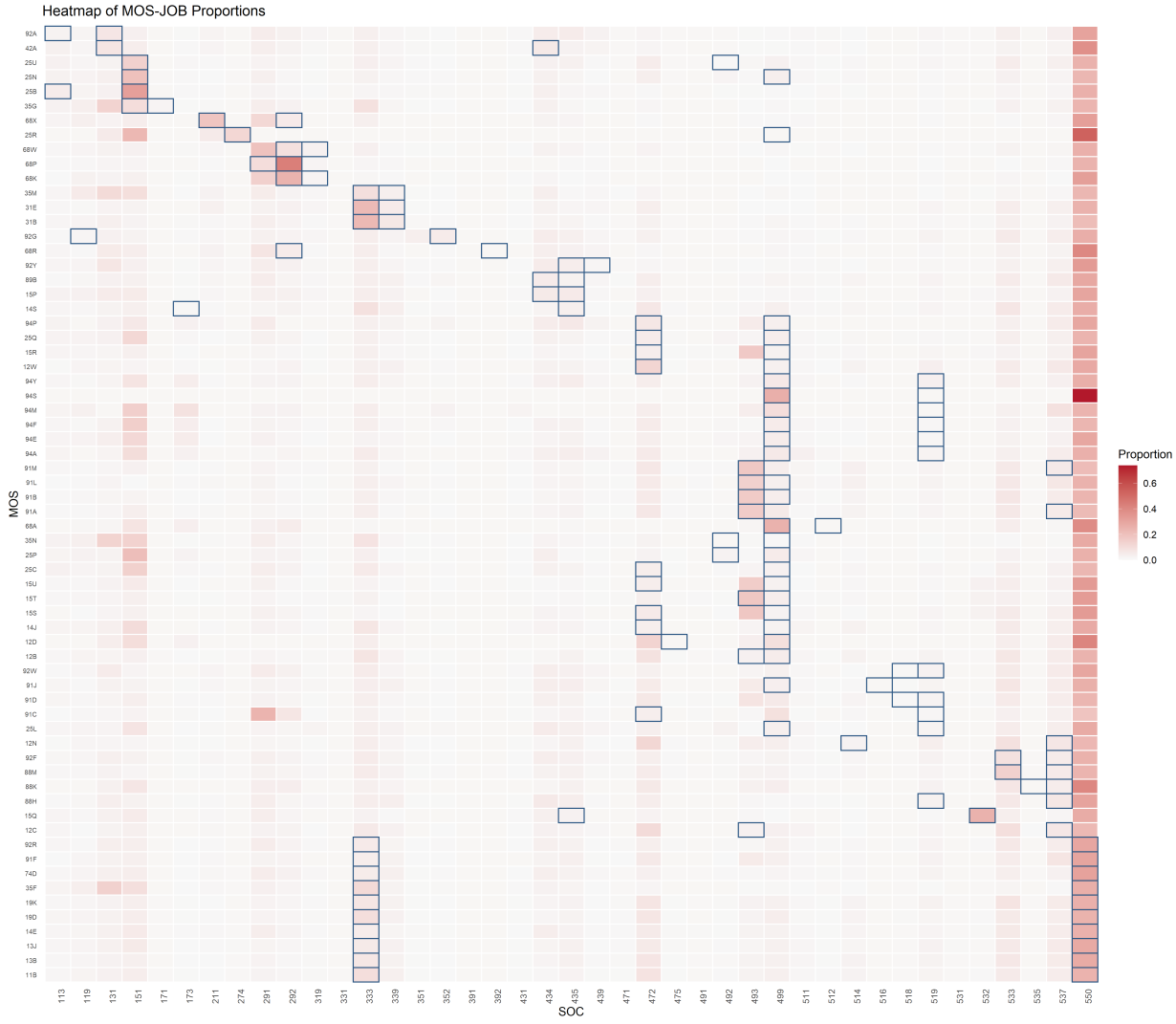
Figure A.1: Years in Army



Notes: This figure plots the share of soldiers still in the Army by years since entry to the Army. It conditions on those that enlist with a valid entry date and partitions the data into soldiers with initial entry terms of 2-4 years in the left panel and 5-6 years in the right panel. Within each panel, the share of soldiers still in the Army is calculated separately for the 1992-2001 sample (cyan) and 2004-2014 sample (orange). All means are shown for the unbalanced set of soldiers for whom the relevant years since enlistment is prior to the end of our data in February 2024.

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Figure A.2: Distribution of Occupations 15 Years Post-ASVAB by Entry MOS

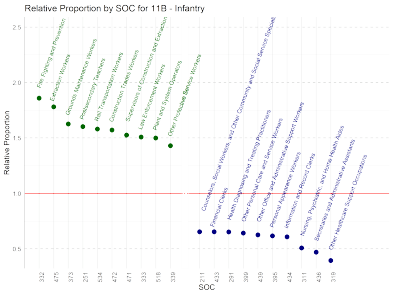


Notes: Each cell represents the proportion of Soldiers within that row's MOS who are in the corresponding SOC by 15 years after the ASVAB. The sample includes all enlisted soldiers in both the 1992-2001 and 2004-2014 samples. Cells outlined in blue indicate the primary and secondary SOC codes we have crosswalked to the corresponding MOS. We have included only SOC codes that are considered primary, secondary, primary supervisor, and secondary supervisor codes for at least one of the MOS in the sample. We only include MOS that have at least a 0.003 first stage at one of the cutoffs in the analysis (or that make up at least 10% of the total first stage at a cutoff, if < 0.003). The MOS and SOC codes are ordered such that the primary SOC code falls roughly along the diagonal. This is done by sorting SOC codes to group shared primary SOC codes and put in ascending order, then sorting MOS by these groups.

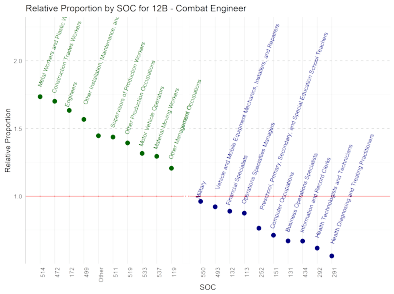
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Figure A.3: Over- and Under- Represented Occupations for Select MOS

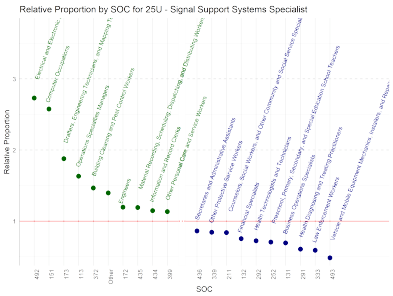
(a) 11B - Infantry



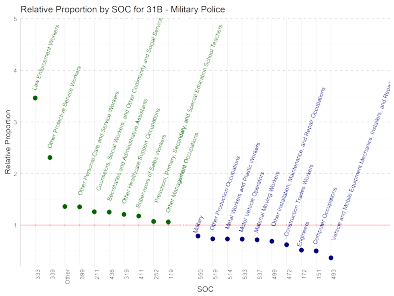
(b) 12B - Combat Engineer



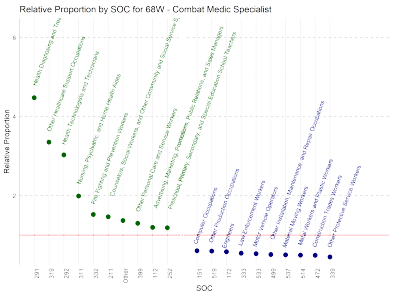
(c) 25U - Signal Support Specialist



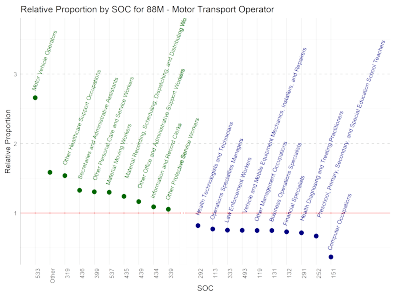
(d) 31B - Military Police



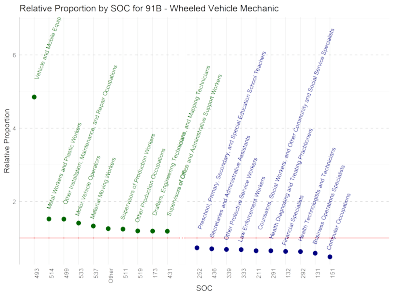
(e) 68W - Combat Medic Specialist



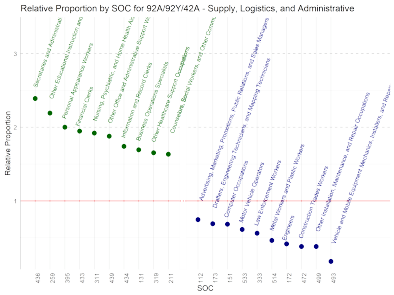
(f) 88M - Motor Transport Operator



(g) 91B - Wheeled Vehicle Mechanic



(h) 92A/92Y/42A - Logistics and HR

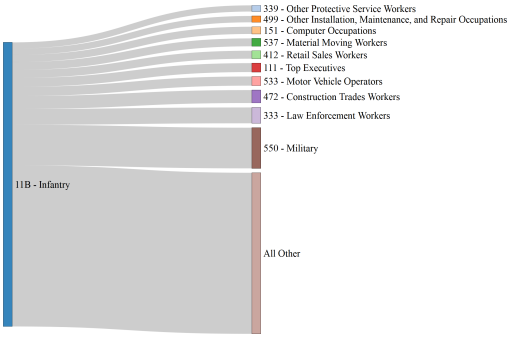


Notes: The relative proportions are calculated as (Fraction of MOS in SOC)/(Fraction of Sample in SOC), where the sample is all enlisted within our dataset, both from the 1992-2001 and 2004-2014 samples, and the SOC codes are measured as of 15 years after the ASVAB. This measure provides an easy view of where members of an MOS are over- or under-represented within a SOC code. A relative proportion of greater than one indicates the MOS is over-represented in that SOC, whereas under one indicates under-representation. The highest and lowest 10 relative proportions are kept for each MOS. We have selected eight examples with well-populated MOS with distinctive skillsets.

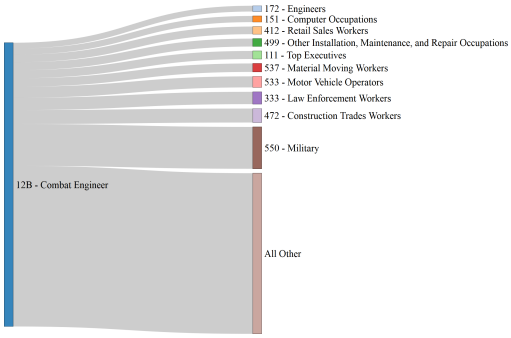
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Figure A.4: Sankey Plots

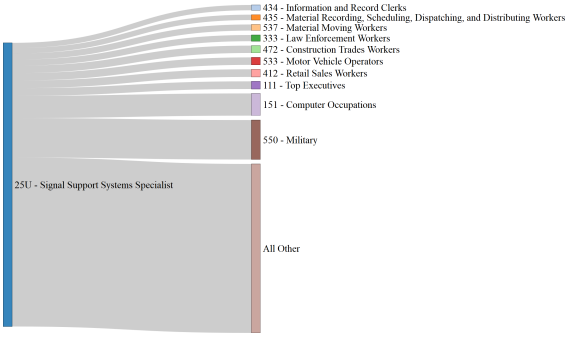
(a) 11B - Infantry



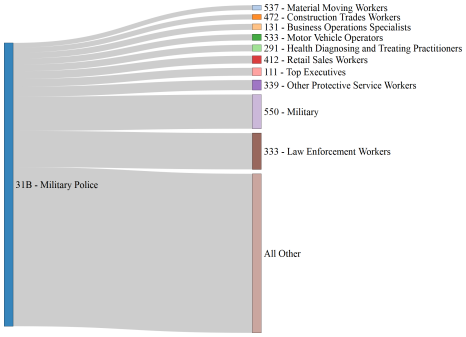
(b) 12B - Combat Engineer



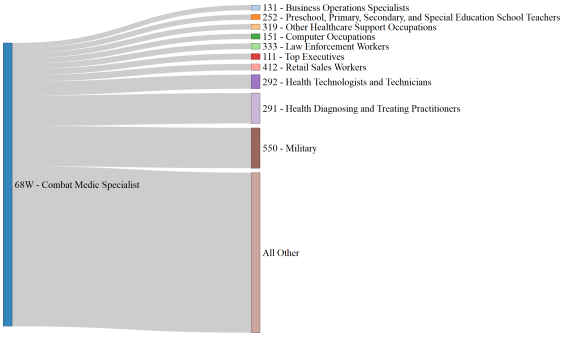
(c) 25U - Signal Support Specialist



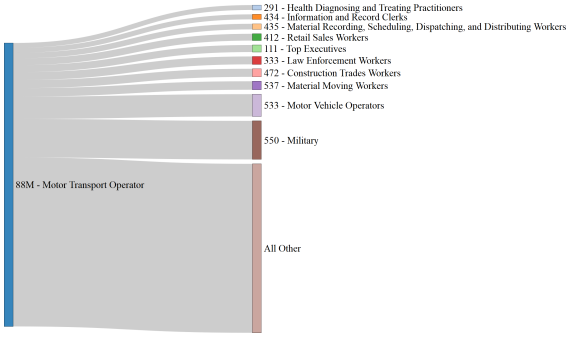
(d) 31B - Military Police



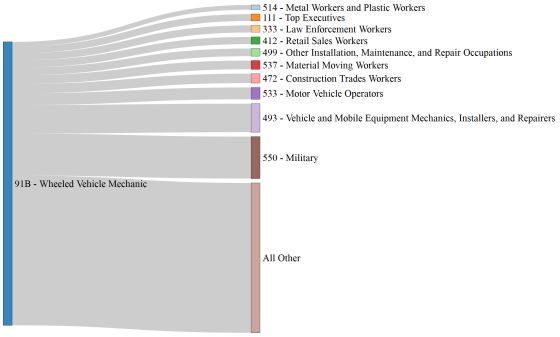
(e) 68W - Combat Medic Specialist



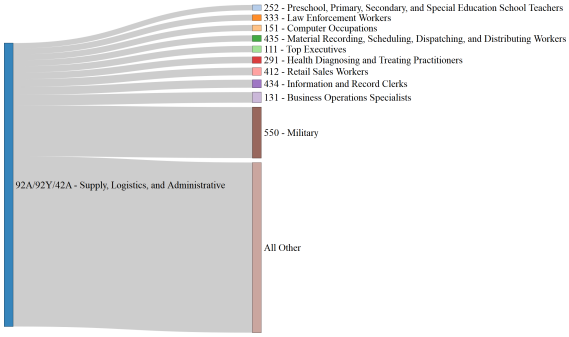
(f) 88M - Motor Transport Operator



(g) 91B - Wheeled Vehicle Mechanic



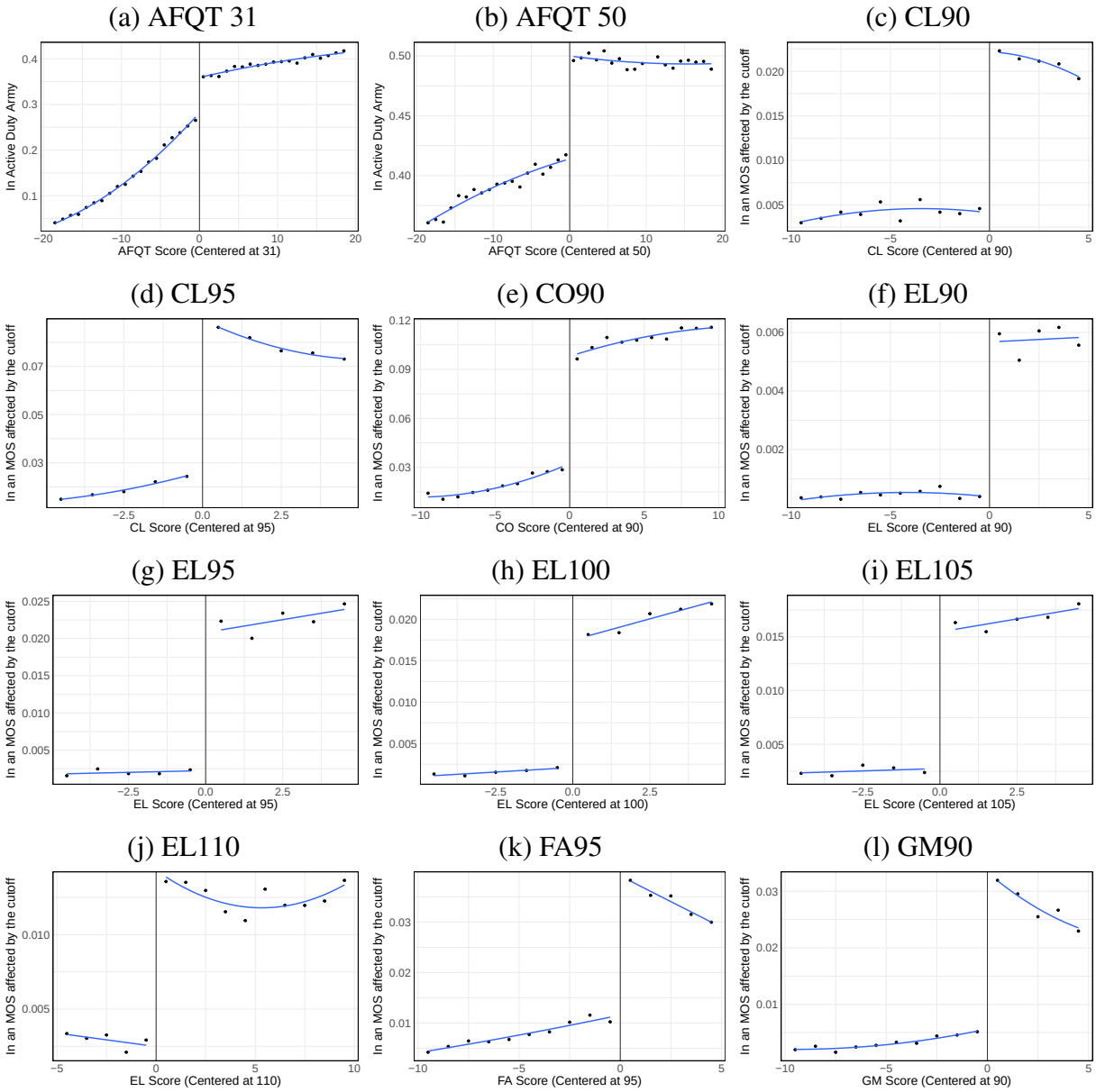
(h) 92A/92Y/42A - Logistics and HR



Notes: These plots demonstrate the distribution of jobs 11 years after enlistment for each MOS. The top 10 jobs for each MOS are shown, while all other jobs are grouped together. The sample combines both the 1992-2001 and 2004-2014 samples. Eventual occupations (three digit SOC) are measured as of 15 years after the ASVAB. We have selected eight examples with well-populated MOS with distinctive skillsets.

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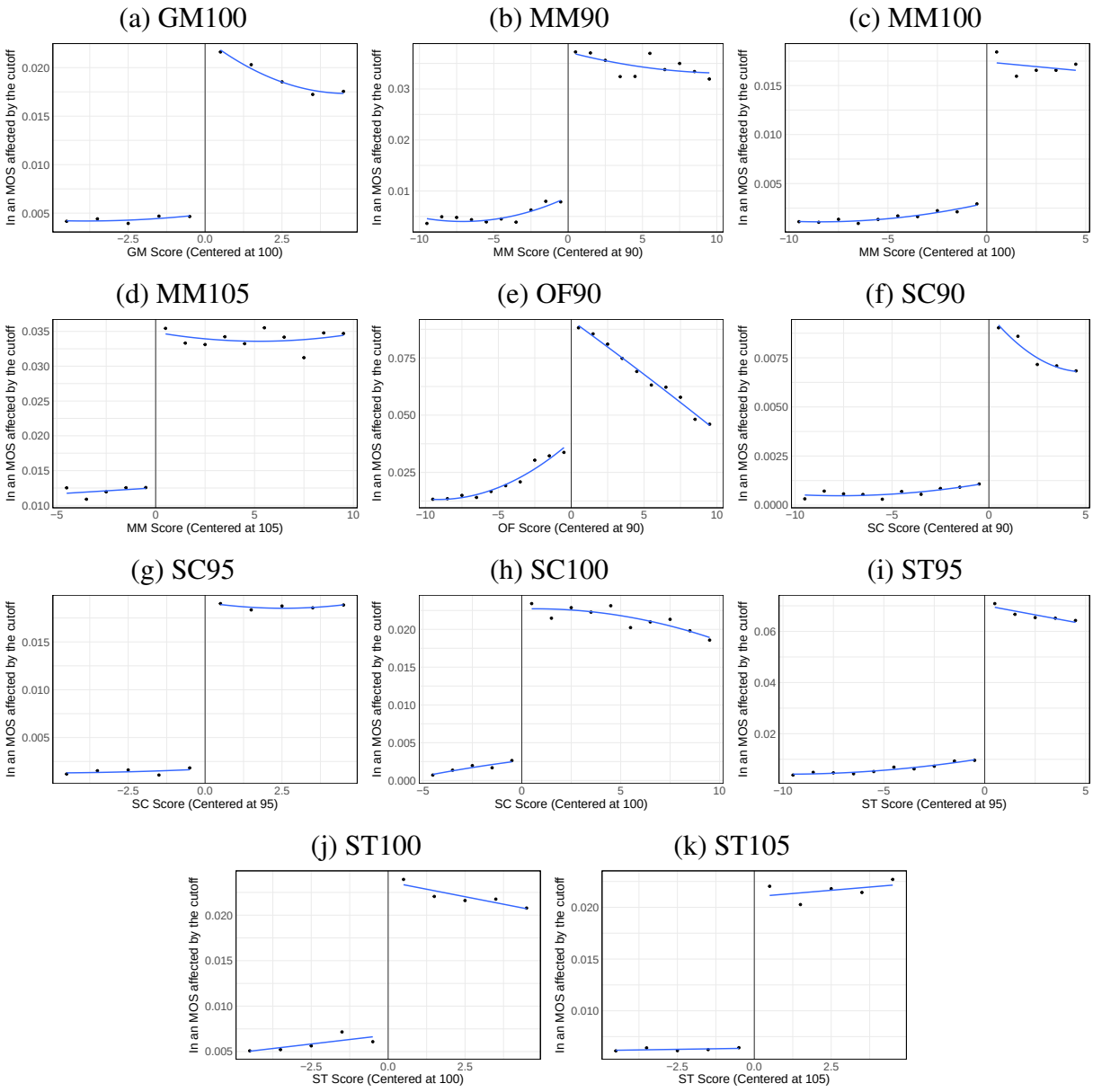
Figure A.5: 1992-2001 First Stage Plots



Notes: These figures depict the first stages around each 1992-2001 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table A.5.

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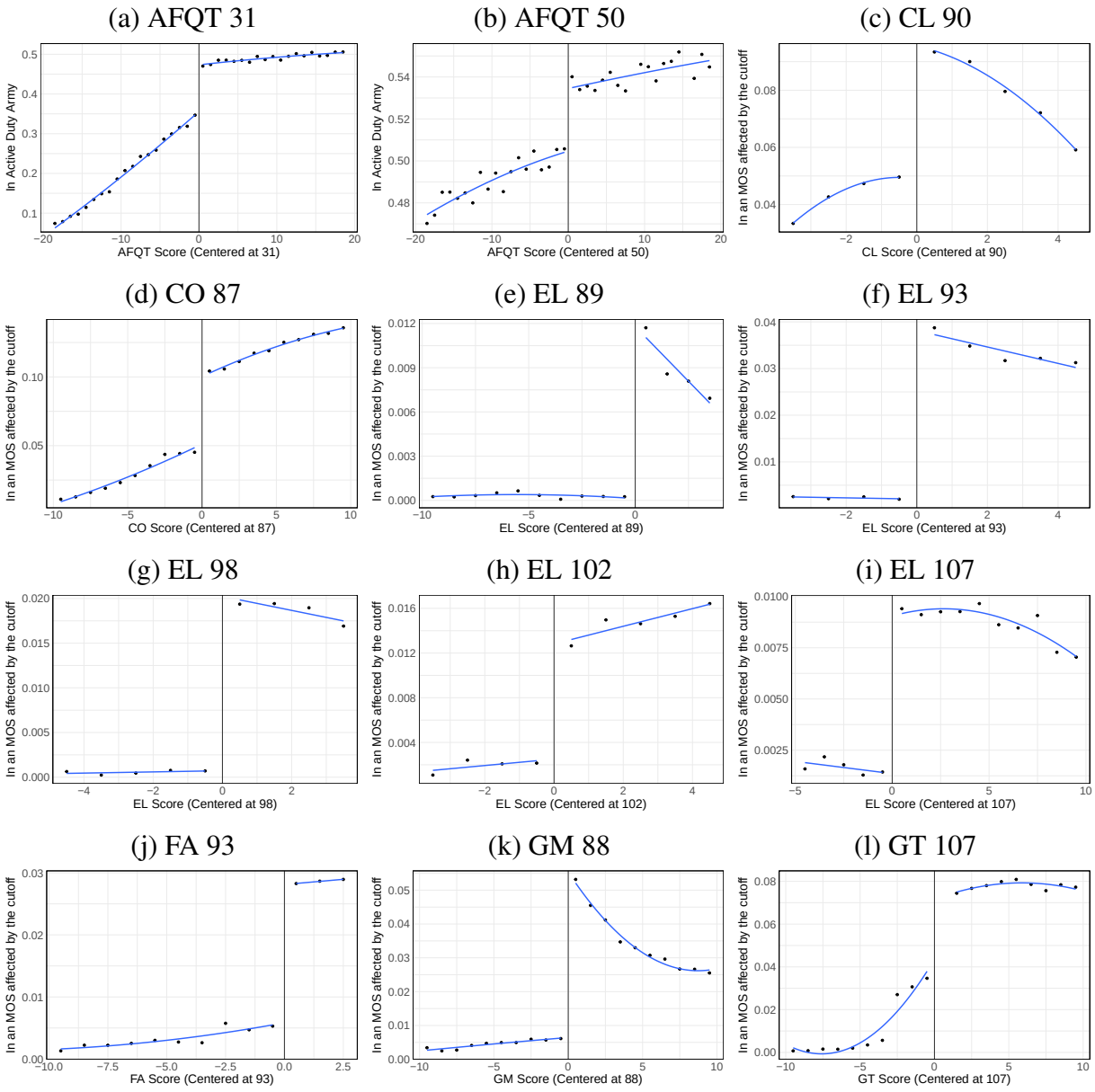
Figure A.6: 1992-2001 First Stage Plots



Notes: These figures depict the first stages around each 1992-2001 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table A.5.

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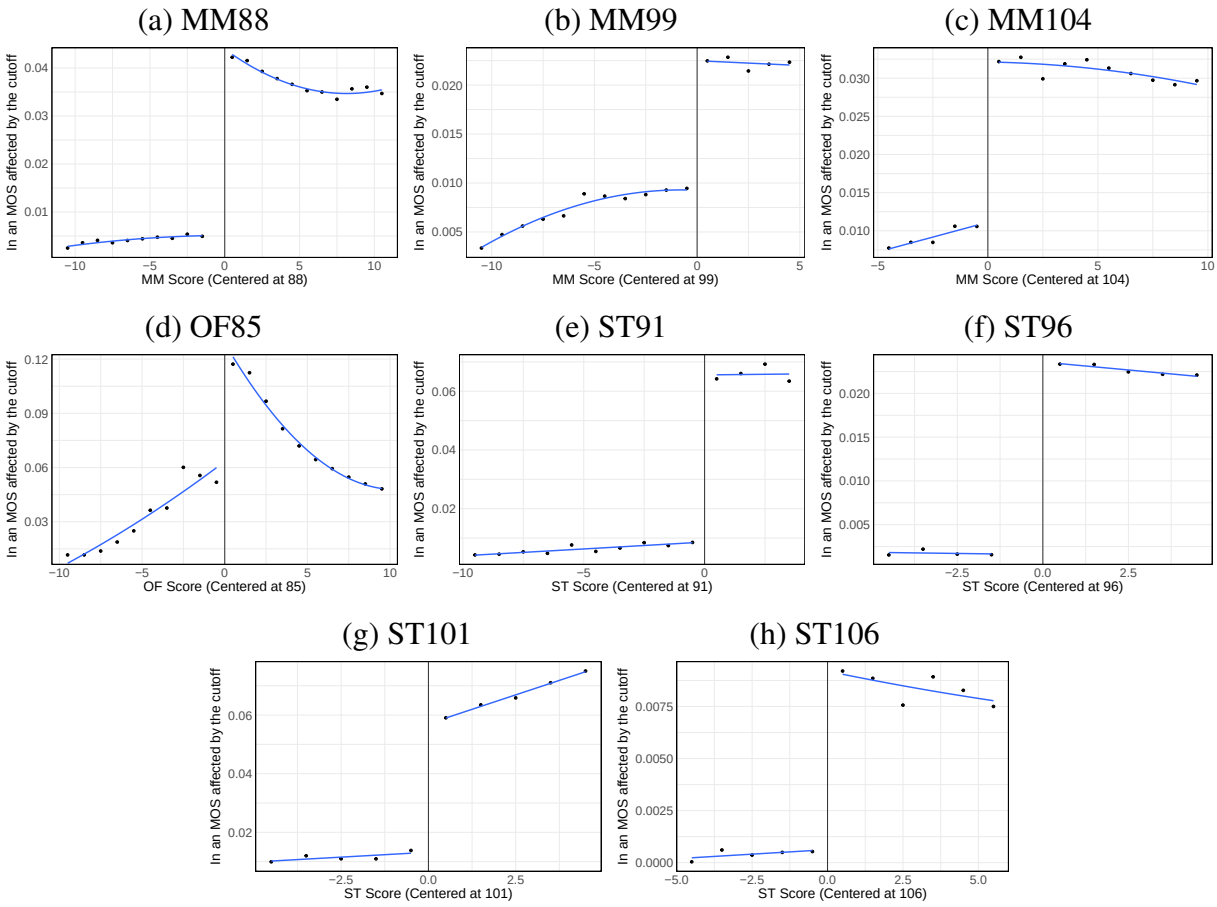
Figure A.7: 2004-2014 First Stage Plots



Notes: These figures depict the first stages around each 2004-2014 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table A.5.

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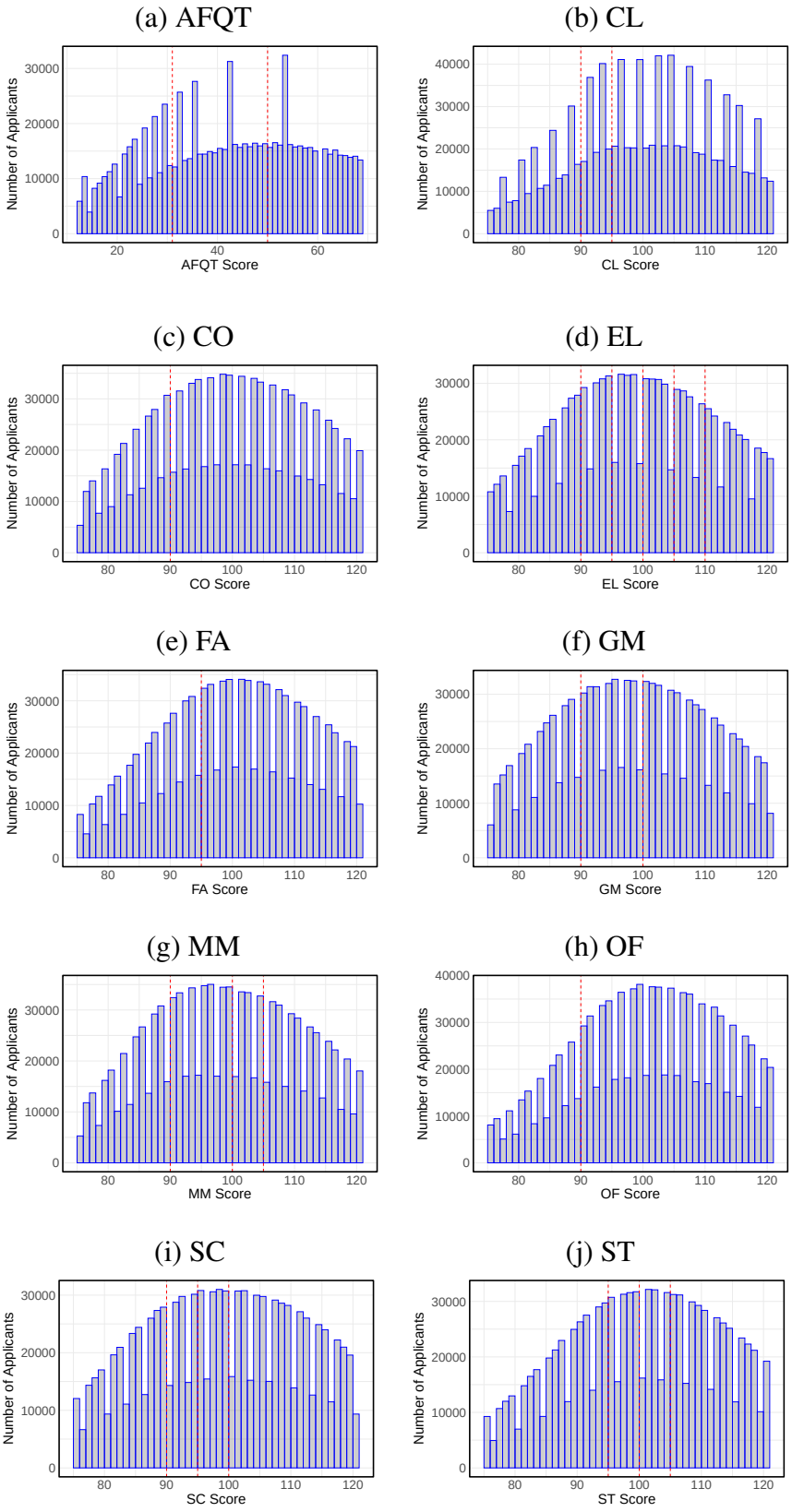
Figure A.8: 2004-2014 First Stage Plots



Notes: These figures depict the first stages around each 2004-2014 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table A.5.

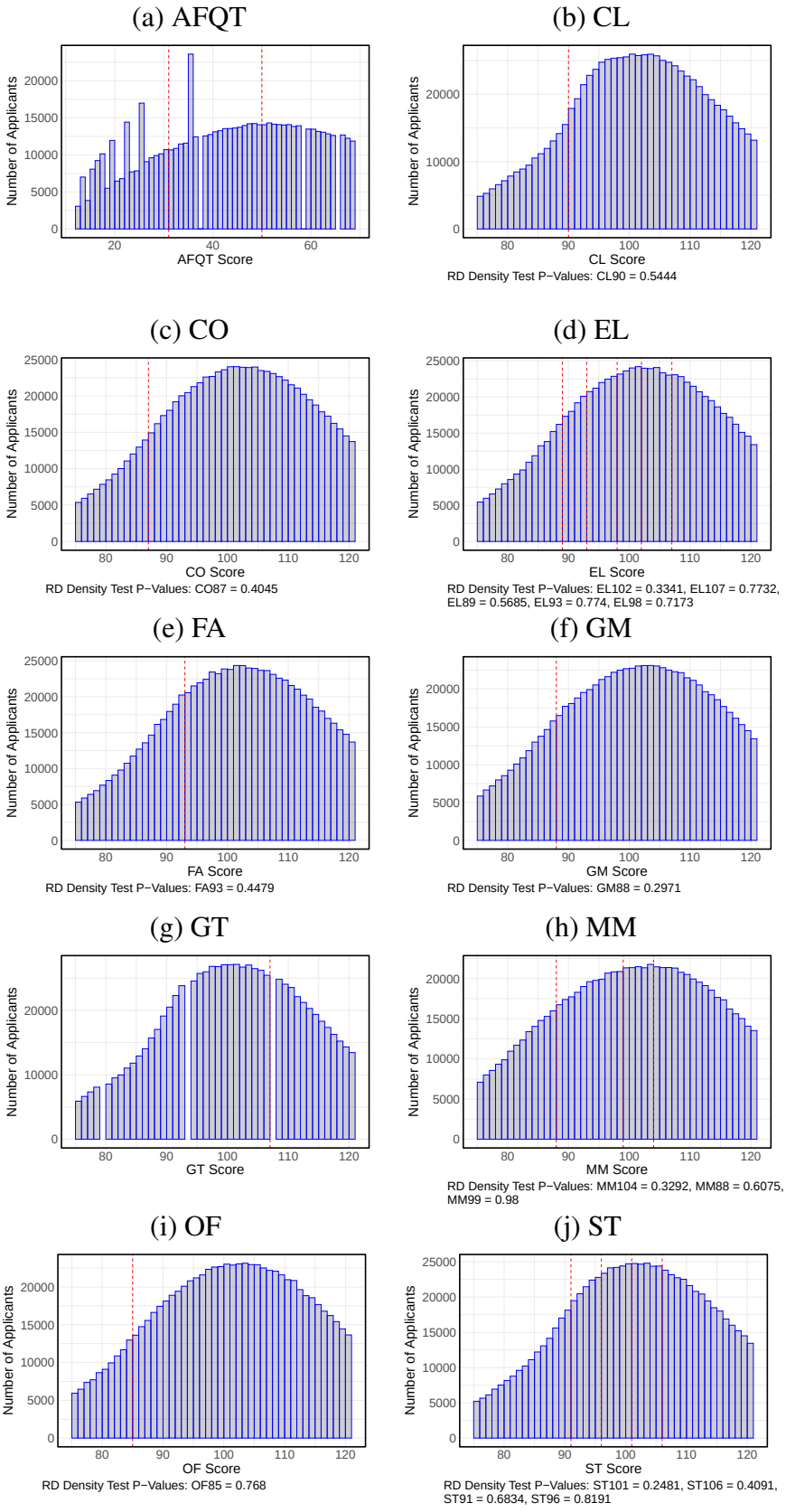
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Figure A.9: 1992-2001 Density Plots



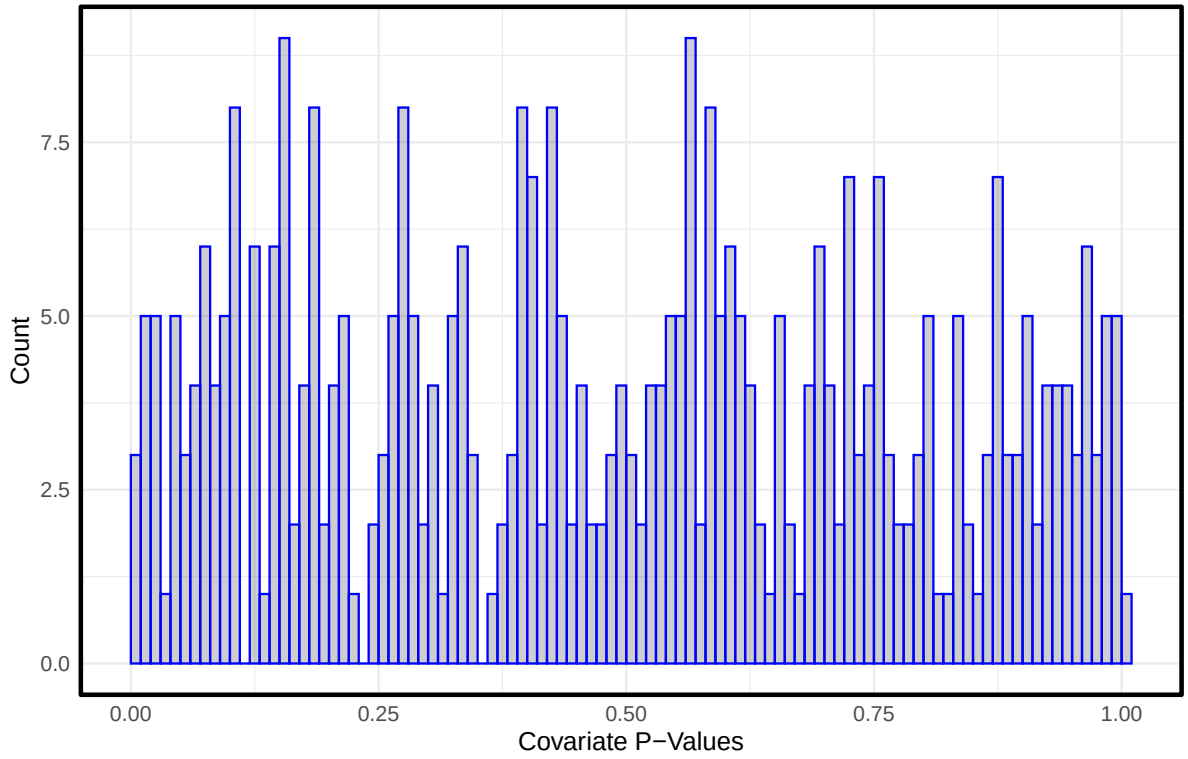
Notes: These figures show density plots for the 1992-2001 line scores. Red lines correspond to a cutoff used in our paper. Densities are discrete and lumpy due to the way that multiple raw test scores are converted, via two conversion tables, to final line scores, making some line scores more likely than others.

Figure A.10: 2004-2014 Density Plots



Notes: These figures show density plots for the 2004-2014 line scores. Red lines correspond to a cutoff used in our paper. For the densities that that have a non-discrete, non-lumpy running variable, we report the p-values from the Cattaneo et al. (2018) density test using their optimal bandwidth and a local linear functional form.

Figure A.11: Balance: Covariate P-Values

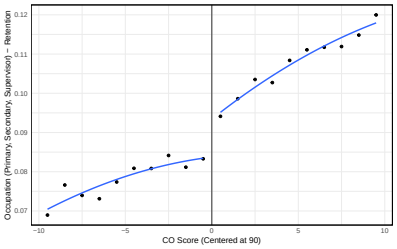


Notes: This Figure plots the 43×9 p-values for the reduced-form effects of crossing each of the 43 cutoffs on each of the 9 balance covariates. The underlying point estimates and standard errors are reported in Table A.6.

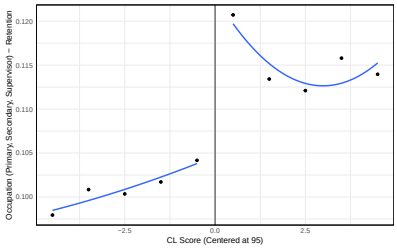
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Figure A.12: Reduced-Form Occ. Persistence Plots (Military & Civilian)

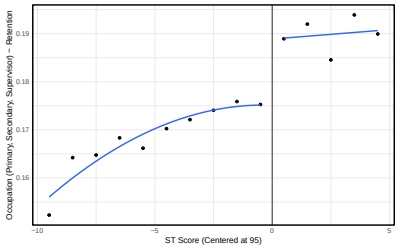
(a) CO90_pre



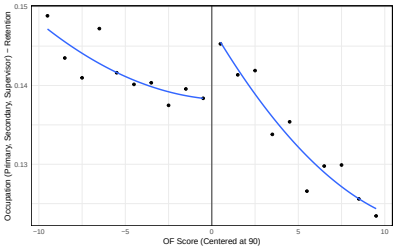
(b) CL95_pre



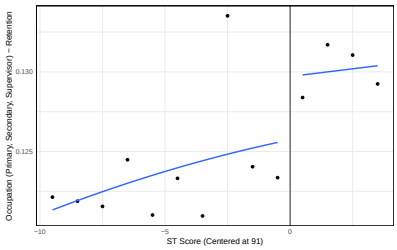
(c) ST95_pre



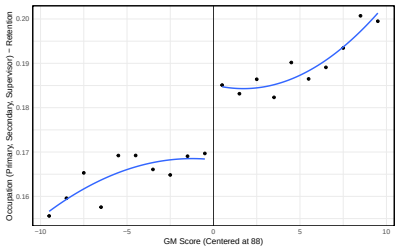
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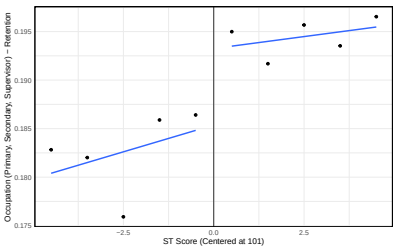
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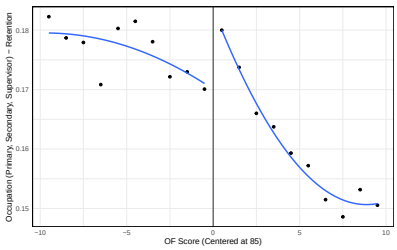
(f) GM88_post



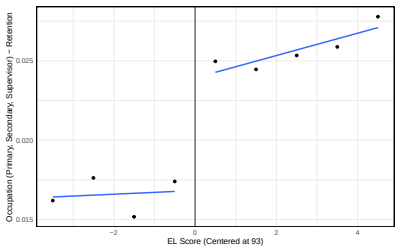
(g) ST101_post



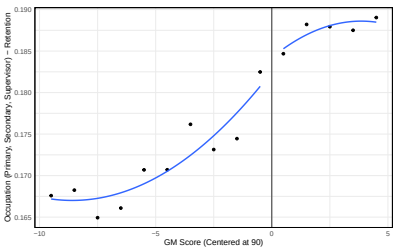
(h) OF85_post



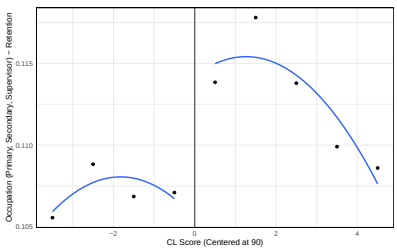
(i) EL93_post



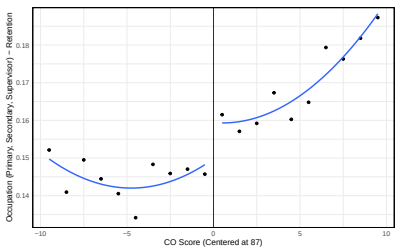
(j) GM90_pre



(k) CL90_post



(l) CO87_post

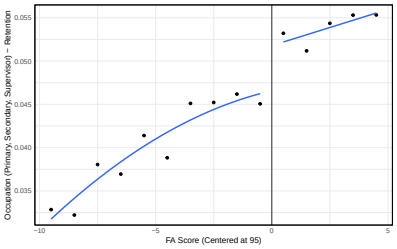


Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds. They are sorted by first stage for this 11-15 sample and show the top 20 cutoffs.

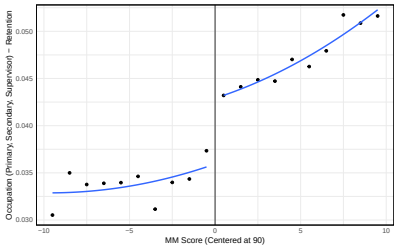
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Figure A.13: Reduced-Form Occ. Persistence Plots (Military & Civilian)

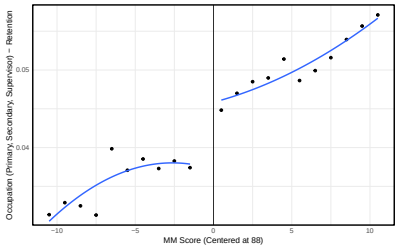
(a) FA95_pre



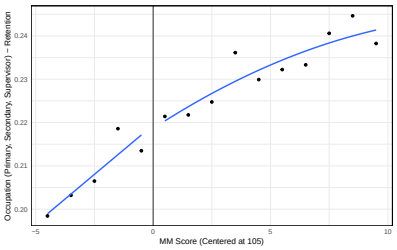
(b) MM90_pre



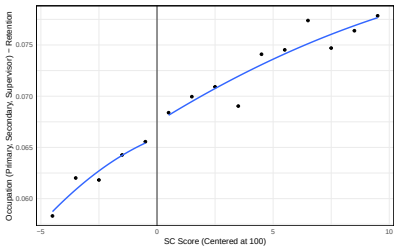
(c) MM88_post



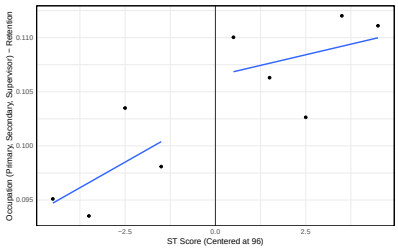
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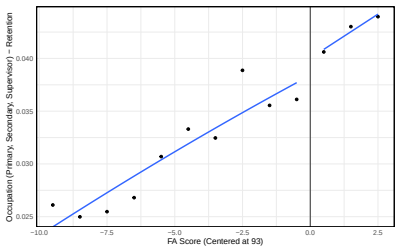
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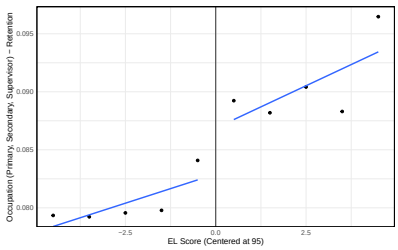
(f) ST96_post



(g) FA93_post



(h) EL95_pre

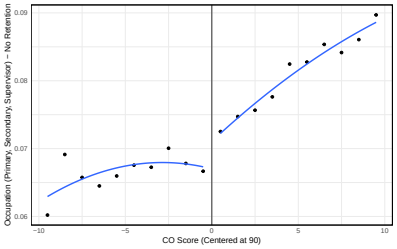


Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds. They are sorted by first stage for this 11-15 sample and show the top 20 cutoffs.

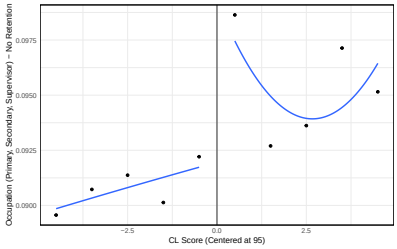
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Figure A.14: Reduced-Form Occ. Persistence Plots (Civilian only)

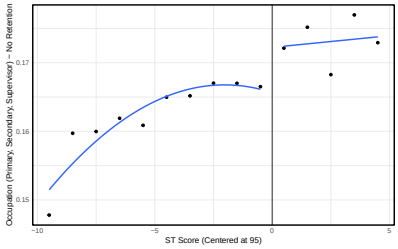
(a) CO90_pre



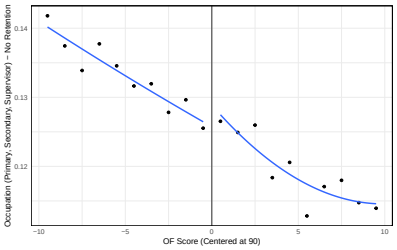
(b) CL95_pre



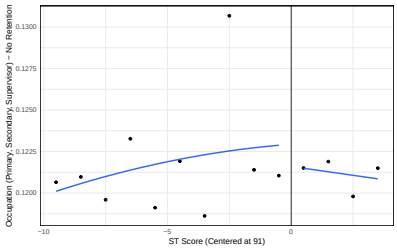
(c) ST95_pre



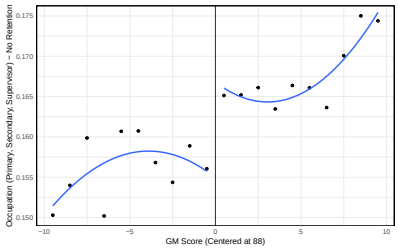
(d) OF90_pre



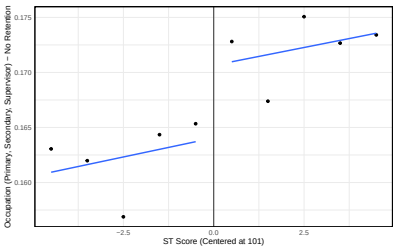
(e) ST91_post



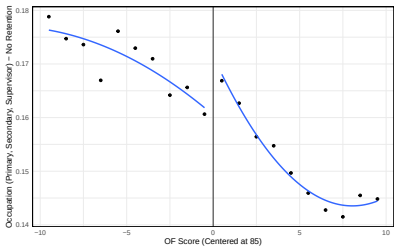
(f) GM88_post



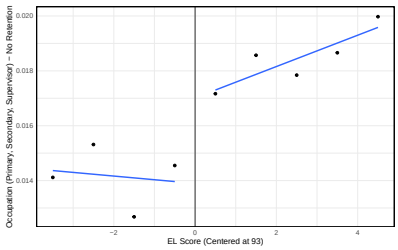
(g) ST101_post



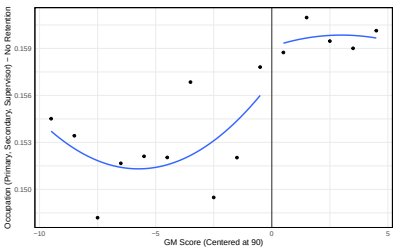
(h) OF85_post



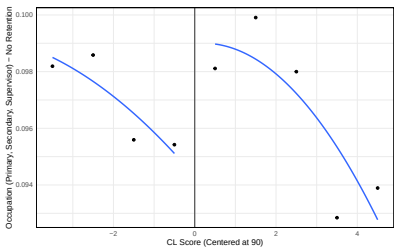
(i) EL93_post



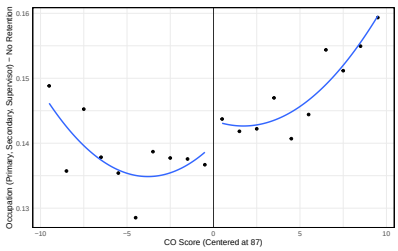
(j) GM90_pre



(k) CL90_post



(l) CO87_post

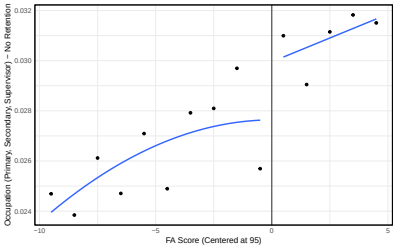


Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds, for persistence in civilian jobs only. They are sorted by first stage for this 11-15 sample and show the top 20 cutoffs.

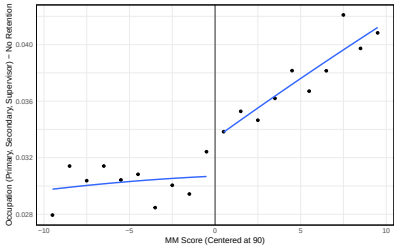
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Figure A.15: Reduced-Form Occ. Persistence Plots (Civilian only)

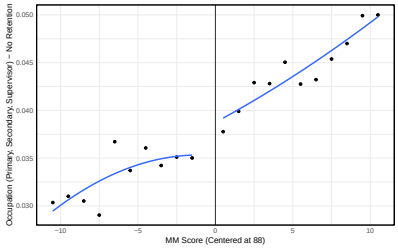
(a) FA95_pre



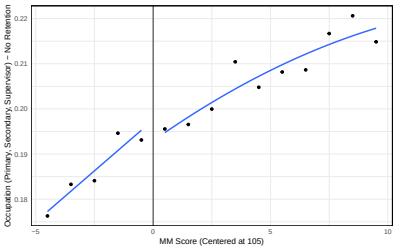
(b) MM90_pre



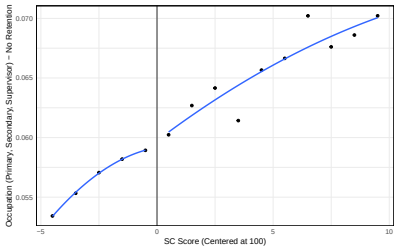
(c) MM88_post



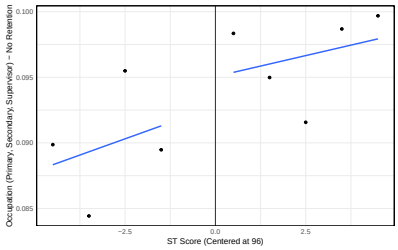
(d) MM105_pre



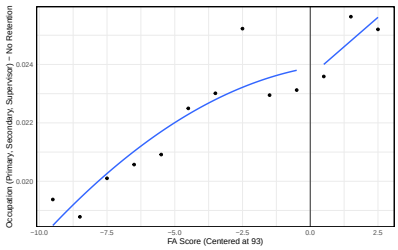
(e) SC100_pre



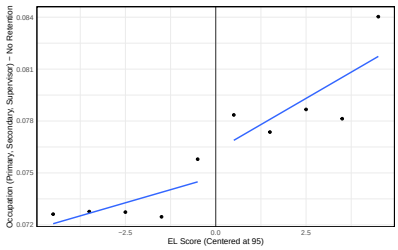
(f) ST96_post



(g) FA93_post



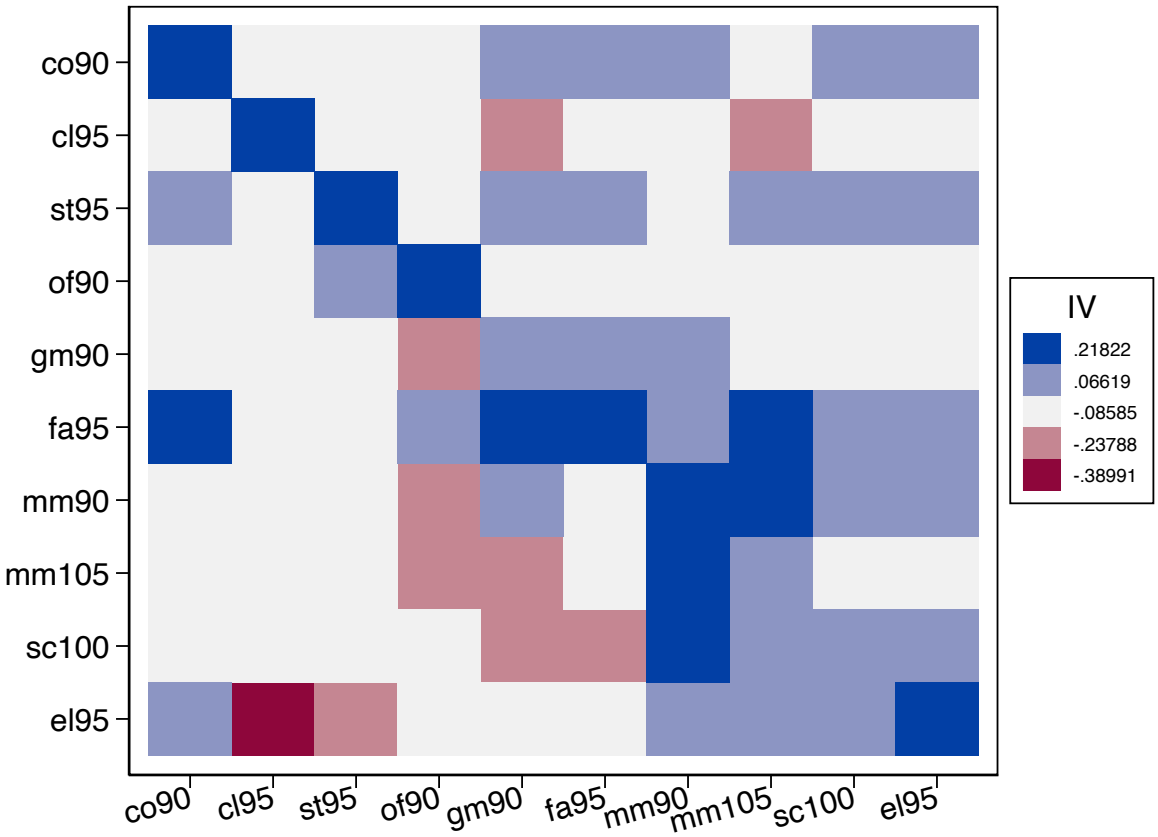
(h) EL95_pre



Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds, for persistence in civilian jobs only. They are sorted by first stage for this 11-15 sample and show the top 20 cutoffs.

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Figure A.16: Heatmap of IV effects on Occupation Groups (1992-2001)

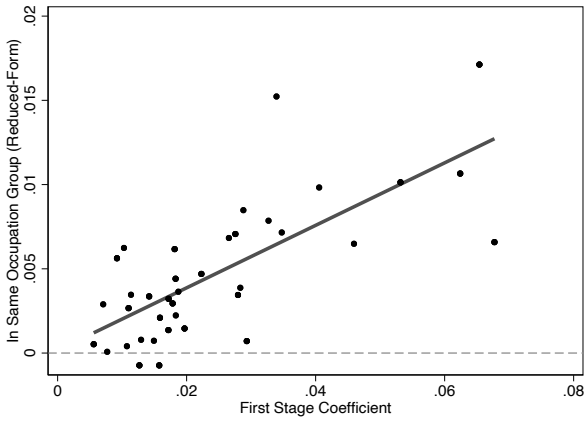


Notes: The heatmap is the 1992-2001 analogue of Figure 3. It depicts IV effects on being in a given occupation group 11-15 years post-AFQT for the ten 1992-2001 cutoffs with the largest first stages. The diagonal shows persistence in the focal occupations (i.e. the estiamtes plotted in Figure 1 panel (c)). The off-diagonals represent persistence in the focal occupations of other cutoffs (which are not necessarily mutually exclusive). The legend value corresponds to the midpoint of the bin (with the exception of the top and bottom bin, bins are 0.152 units wide).

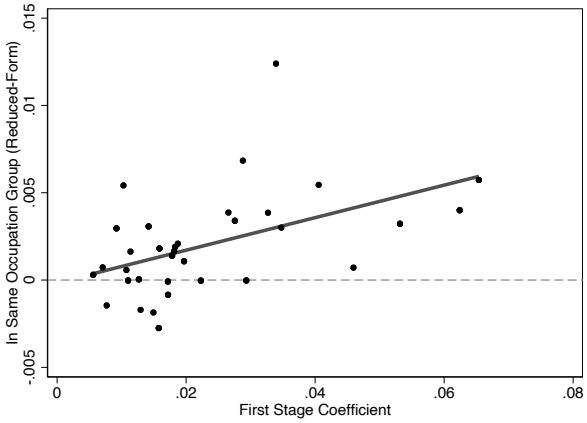
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Figure A.17: Occupational Persistence - Primary and Supervisors Only

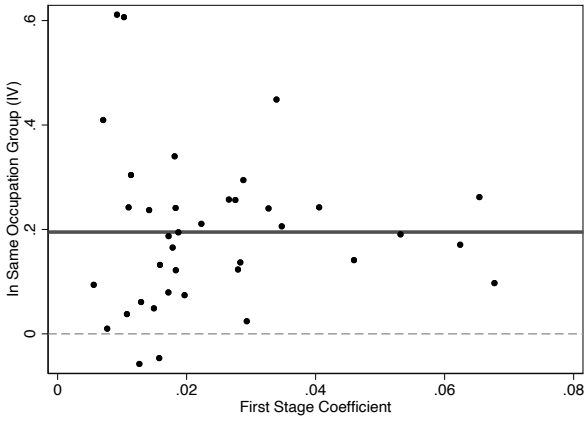
(a) Military + civilian occupations (V-IV)



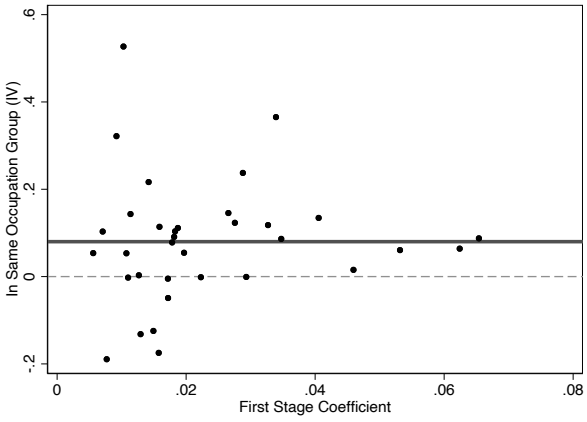
(b) Civilian occupations only (V-IV)



(c) Military + civilian occupations (mean-IV)



(d) civilian occupations (mean-IV)

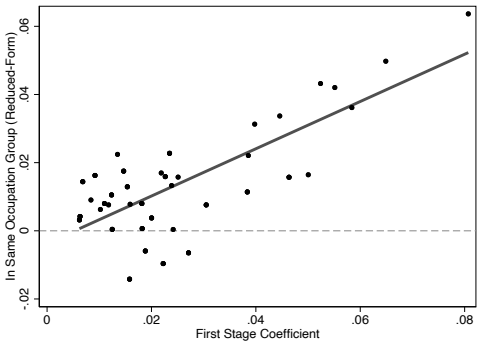


Notes: These figures are analogous to those in Figure 1 except that we now construct the outcome — in the focal occupation group — using only on the primary three digit SOC (and corresponding supervisor SOC) in our crosswalk (as opposed to any of the primary, secondary, or corresponding supervisory SOCs).

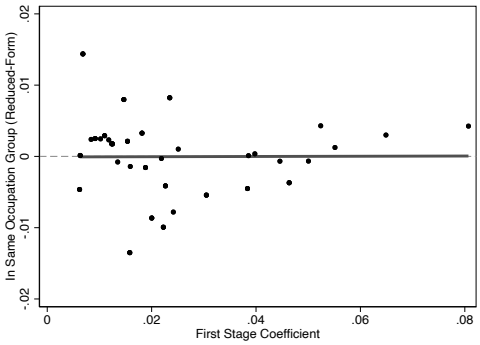
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Figure A.18: V-IV Figures Over Different Time Horizons

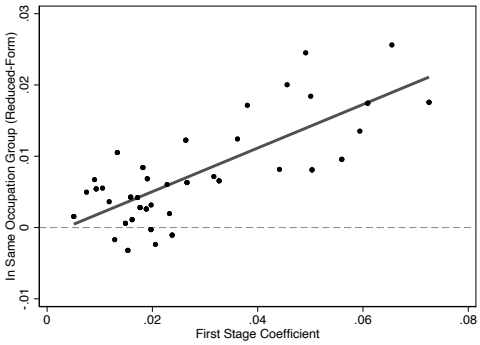
(a) 1-5, Mil. & Civ.



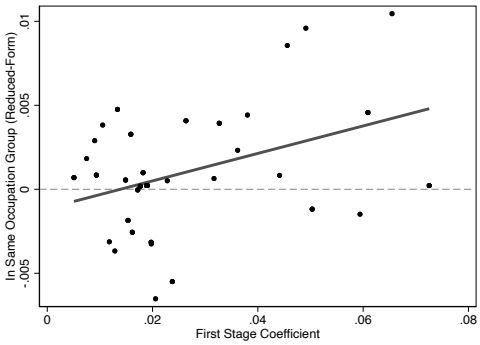
(b) 1-5, Civ. only



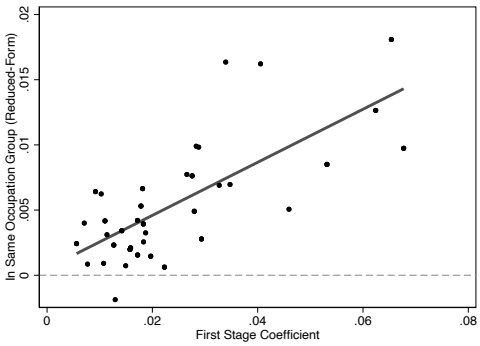
(c) 6-10, Mil. & Civ.



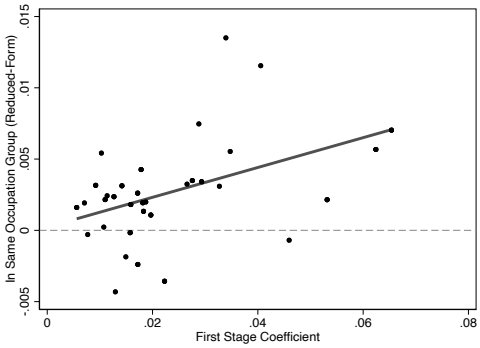
(d) 6-10, Civ. only



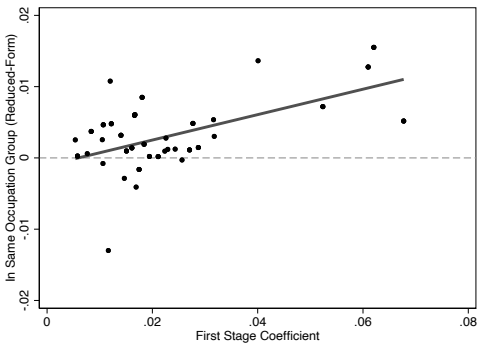
(e) 11-15, Mil. & Civ.



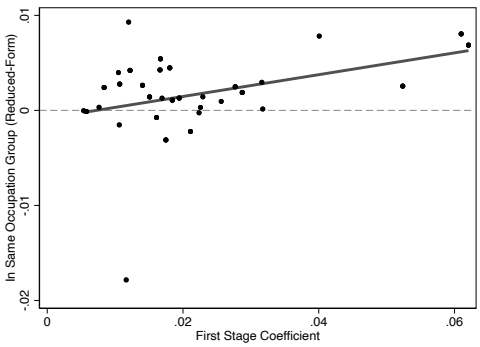
(f) 11-15, Civ. only



(g) 16-20, Mil. & Civ.



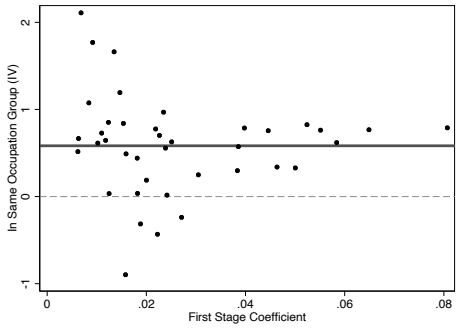
(g) 16-20, Civ. only



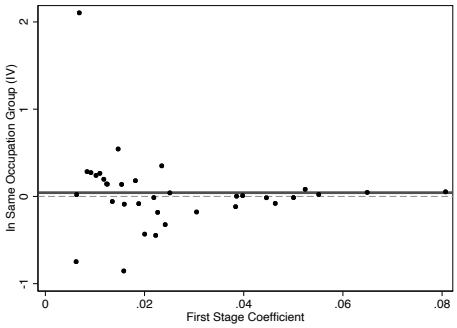
Notes: This figure reports the analogous V-IV figures from Figure 1 panels (a) and (b) for all the different time horizons: 1-5, 6-10, 11-15, and 6-20 years after ASVAB.

Figure A.19: mean-IV Figures Over Different Time Horizons

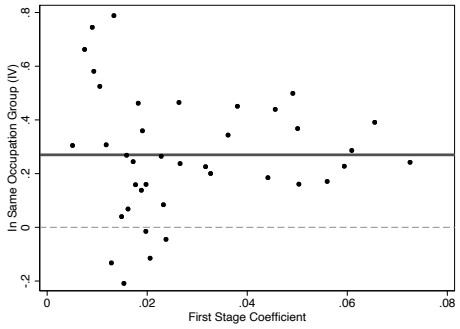
(a) 1-5, Mil. & Civ.



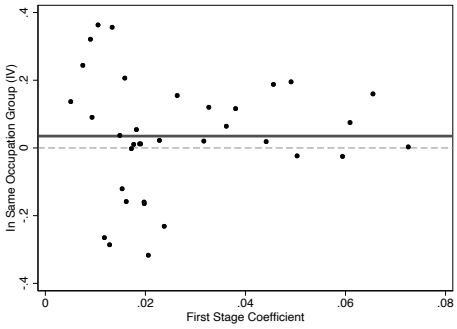
(b) 1-5, Civ. only



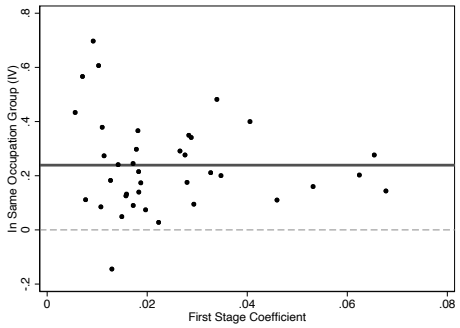
(c) 6-10, Mil. & Civ.



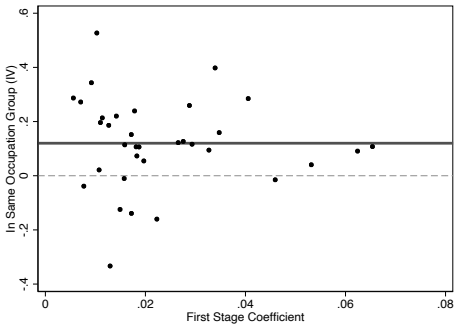
(d) 6-10, Civ. only



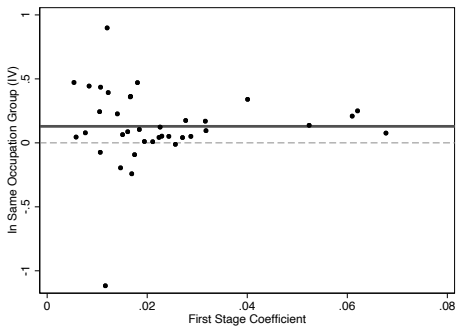
(e) 11-15, Mil. & Civ.



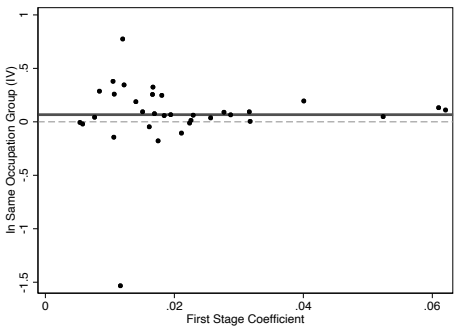
(f) 11-15, Civ. only



(g) 16-20, Mil. & Civ.



(h) 16-20, Civ. only

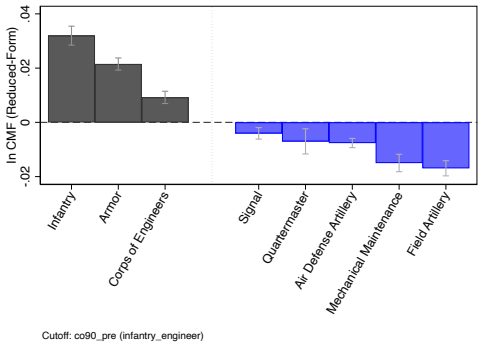


Notes: This figure reports the analogous mean-IV figures from Figure 1 panels (c) and (d) for all the different time horizons: 1-5, 6-10, 11-15, and 6-20 years after ASVAB.

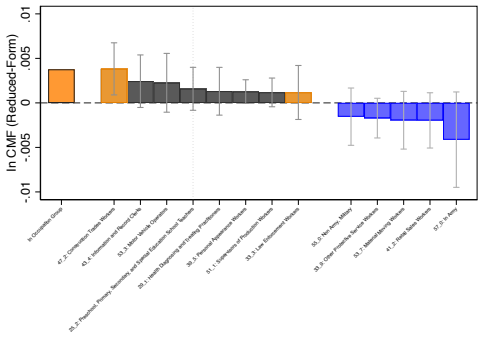
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Figure A.20: Additional Case Studies (1)

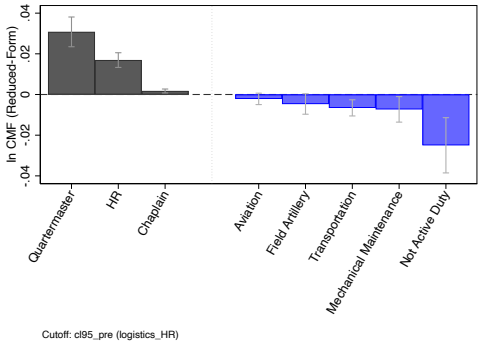
(a) CO90 Pre (CMFS)



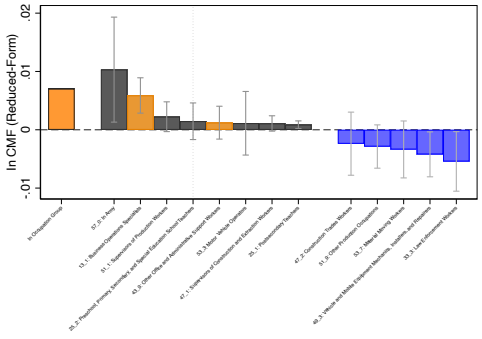
(b) CO90 Pre (SOCS)



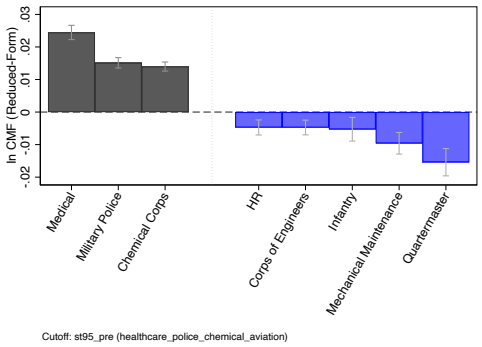
(c) CL95 Pre (CMFS)



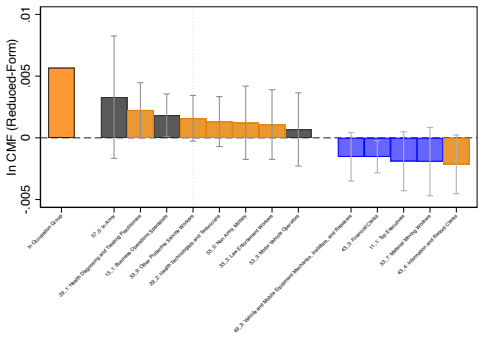
(d) CL95 Pre (SOCS)



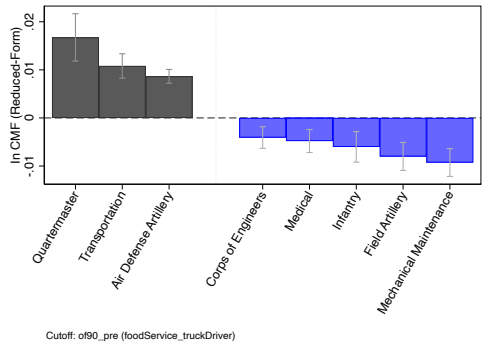
(e) ST95 Pre (CMFS)



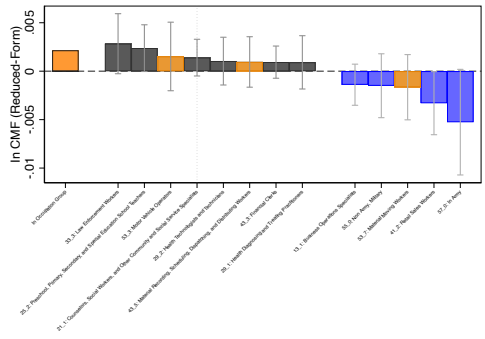
(f) ST95 Pre (SOCS)



(g) OF90 Pre (CMFS)



(h) OF90 Pre (SOCS)

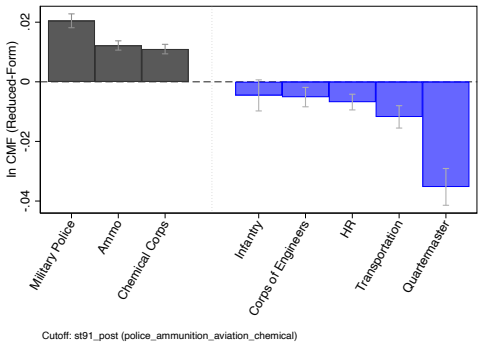


Notes: These figures plot the same exhibits as in figure 5 for different cutoffs. See notes to that exhibit for details.

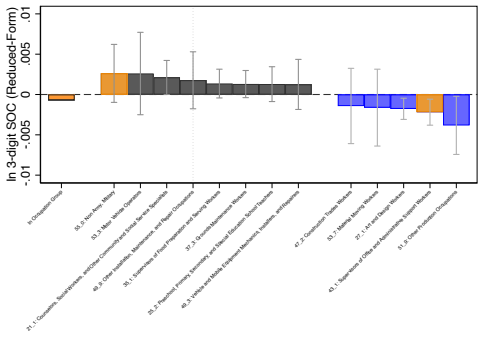
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Figure A.21: Additional Case Studies (2)

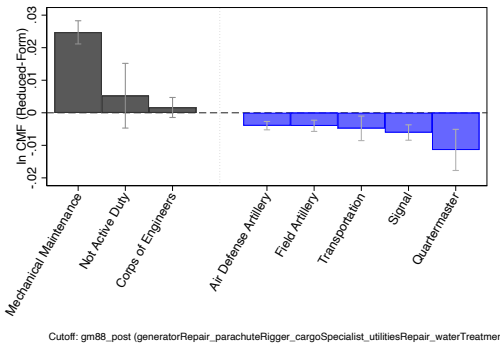
(a) ST91 Post (CMFS)



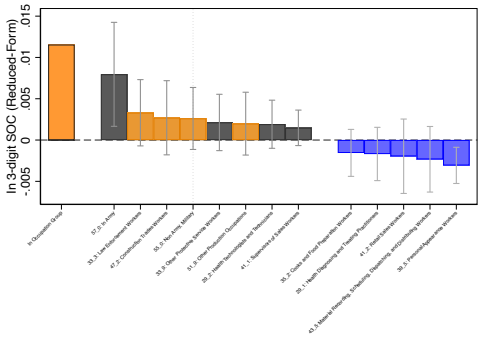
(b) ST91 Post (SOCS)



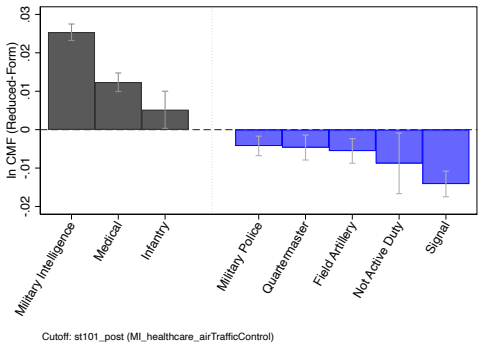
(c) GM 88 Post (CMFS)



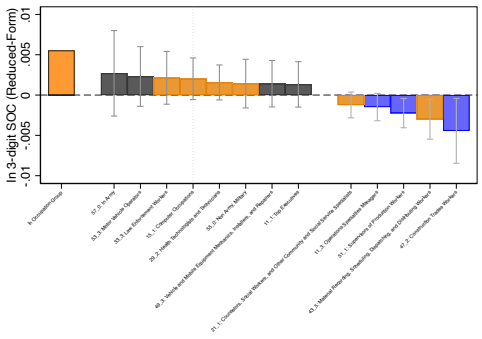
(d) GM 88 Post (SOCS)



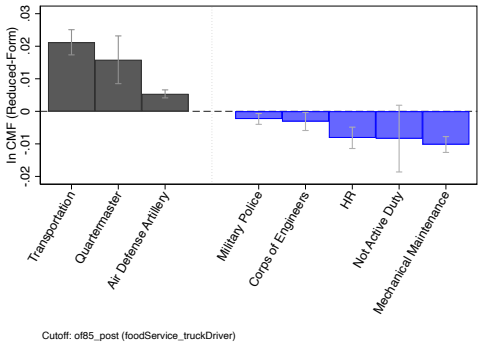
(e) ST 101 Post (CMFS)



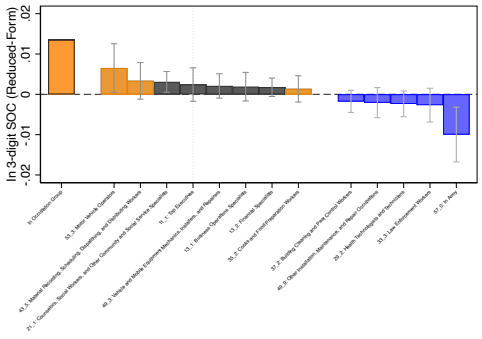
(f) ST 101 Post (SOCS)



(g) OF 85 Post (CMFS)



(h) OF 85 Post (SOCS)

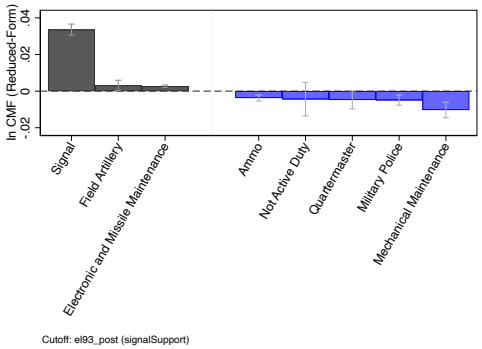


Notes: These figures plot the same exhibits as in figure 5 for different cutoffs. See notes to that exhibit for details.

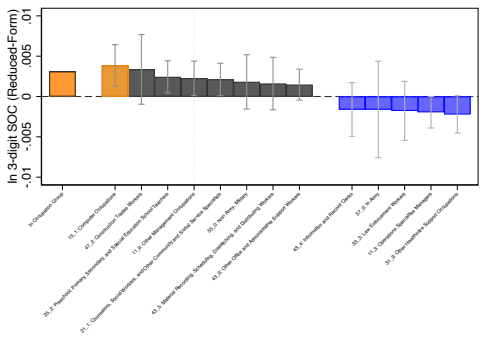
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Figure A.22: Additional Case Studies (3)

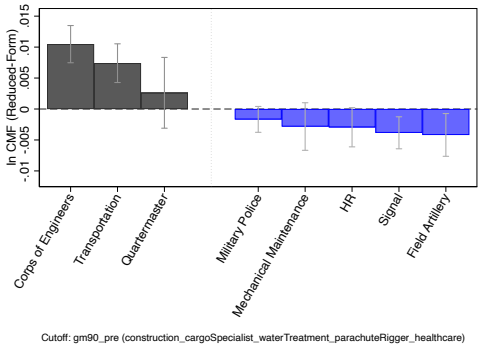
(a) El93 Post (CMFS)



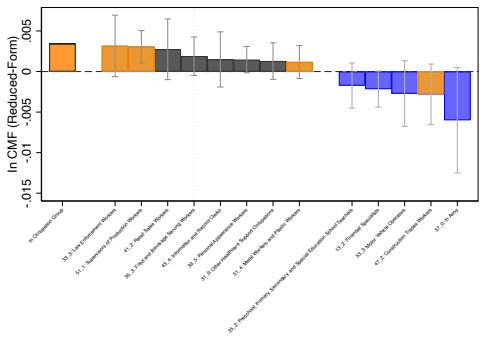
(b) El93 Post (SOCS)



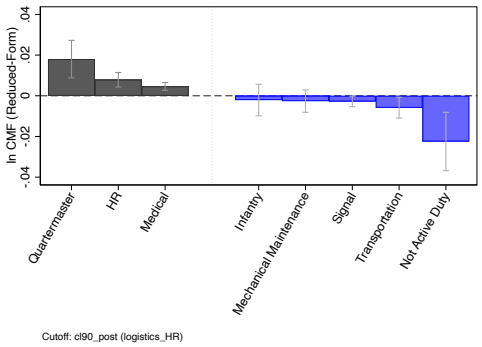
(c) GM90 Pre (CMFS)



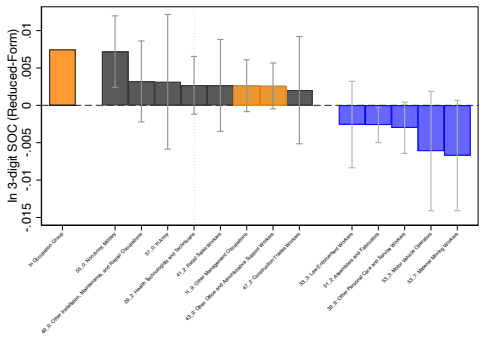
(d) GM90 Pre (SOCS)



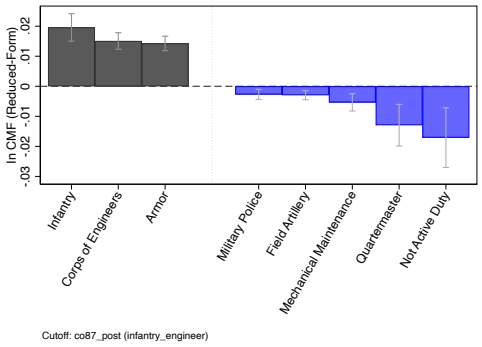
(e) CL90 Post (CMFS)



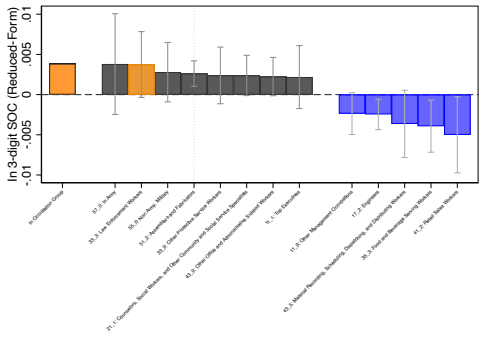
(f) CL90 Post (SOCS)



(g) CO87 Post (CMFS)



(h) CO87 Post (SOCS)

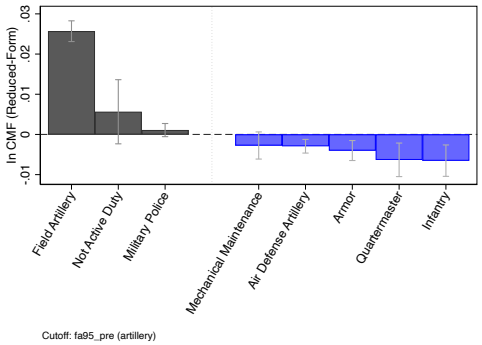


Notes: These figures plot the same exhibits as in figure 5 for different cutoffs. See notes to that exhibit for details.

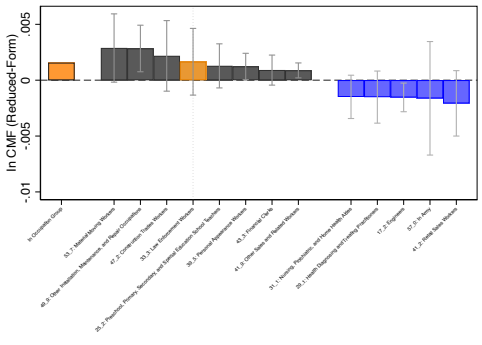
Approved for limited disclosure. Not for public distribution.

Figure A.23: Additional Case Studies (4)

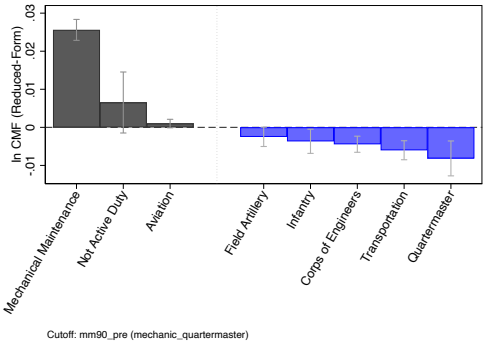
(a) FA95 Pre (CMFS)



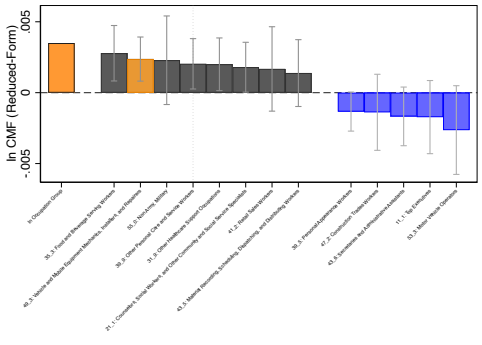
(b) FA95 Pre (SOCS)



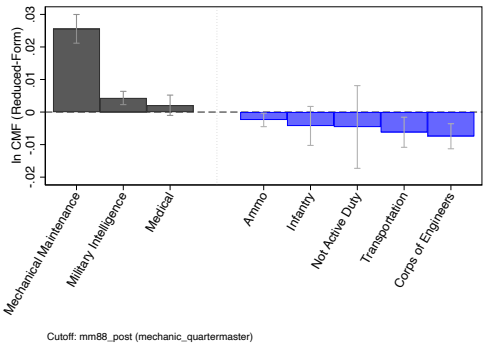
(c) MM90 Pre (CMFS)



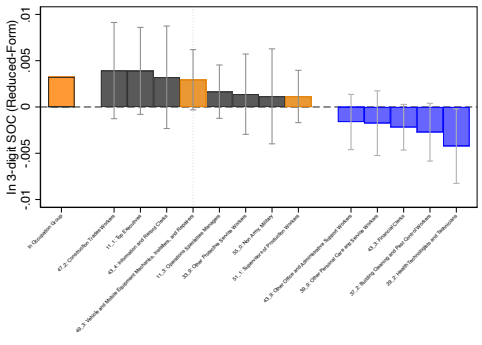
(d) MM90 Pre (SOCS)



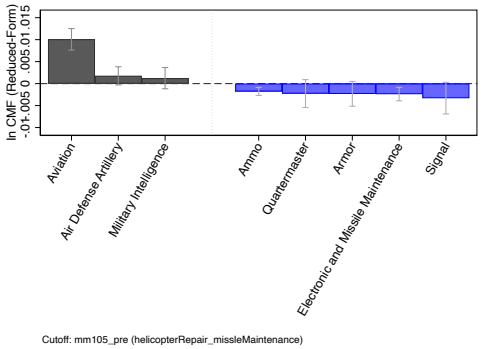
(e) MM88 Post (CMFS)



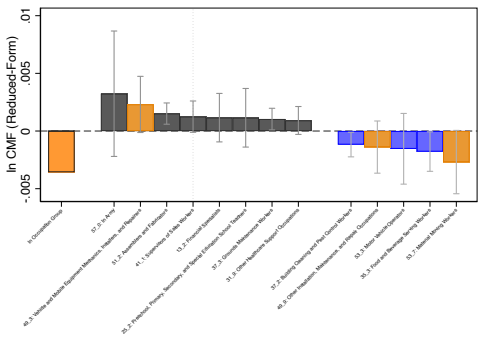
(f) MM88 Post (SOCS)



(g) MM105 Pre (CMFS)



(h) MM105 Pre (SOCS)

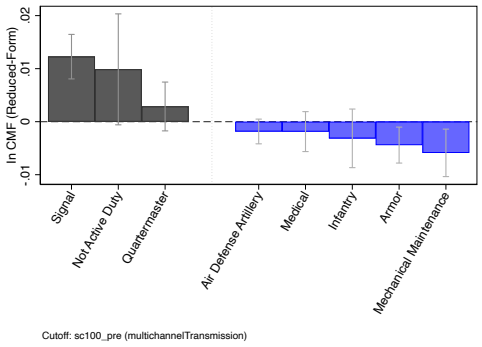


Notes: These figures plot the same exhibits as in figure 5 for different cutoffs. See notes to that exhibit for details.

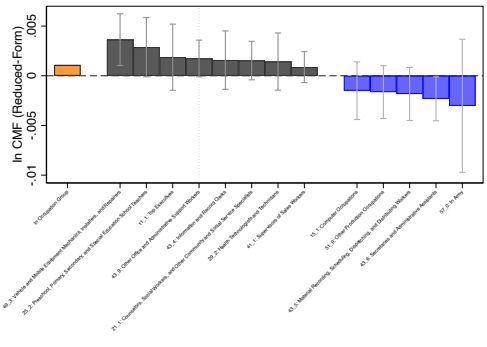
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Figure A.24: Additional Case Studies (5)

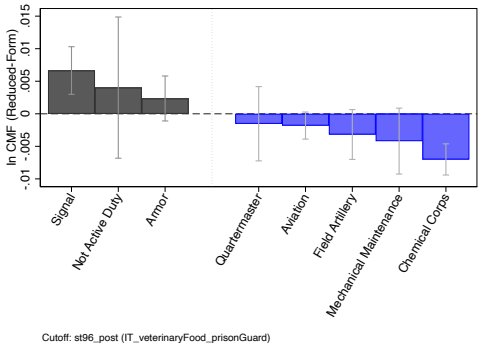
(a) SC100 Pre (CMFS)



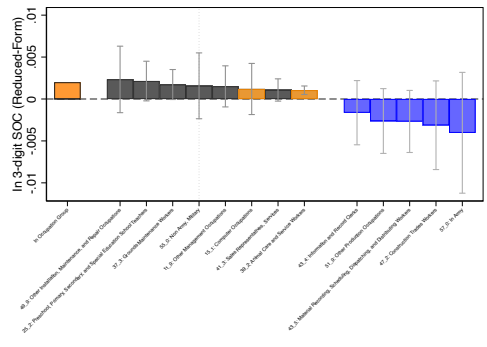
(b) SC100 Pre (SOCS)



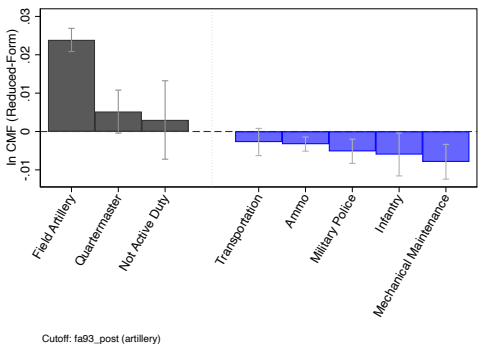
(c) ST96 Post (CMFS)



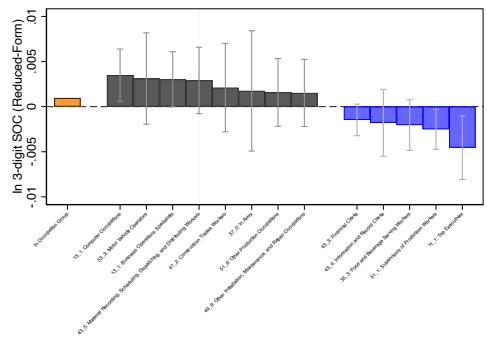
(d) ST96 Post (SOCS)



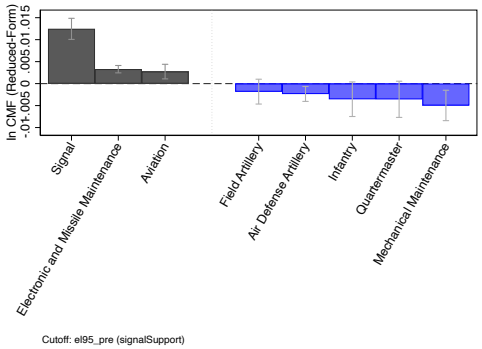
(e) FA93 Post (CMFS)



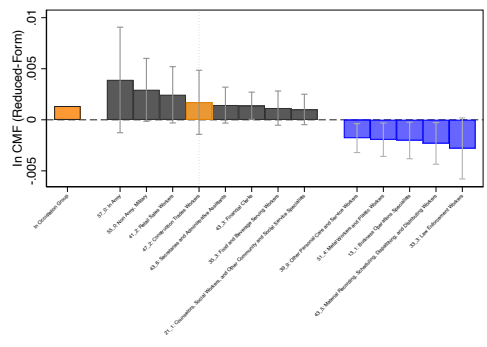
(f) FA93 Post (SOCS)



(g) EL95 Pre (CMFS)



(h) EL95 Pre (SOCS)

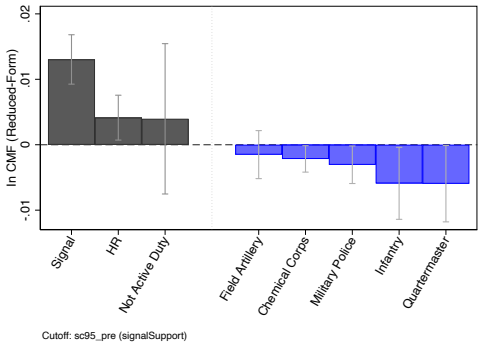


Notes: These figures plot the same exhibits as in figure 5 for different cutoffs. See notes to that exhibit for details.

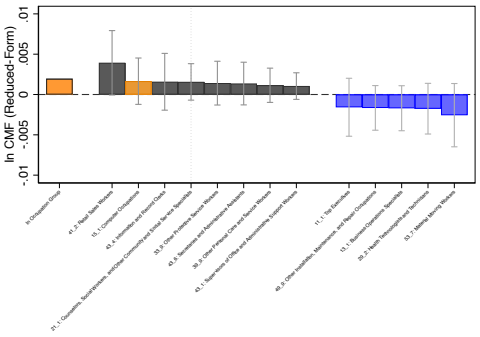
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Figure A.25: Additional Case Studies (6)

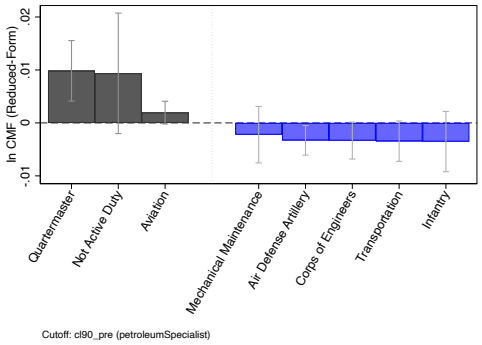
(a) SC95 Pre (CMFS)



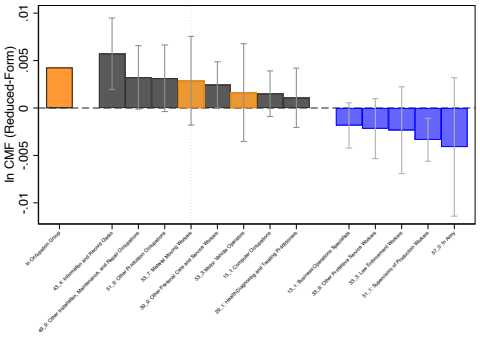
(b) SC95 Pre (SOCS)



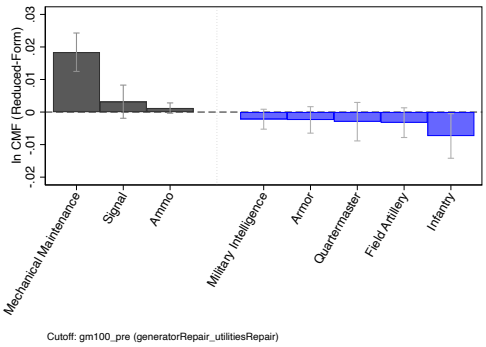
(c) CL90 Pre (CMFS)



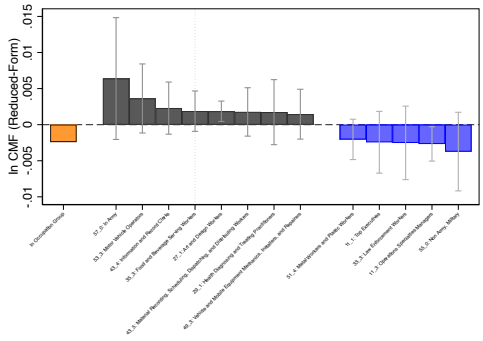
(d) CL90 Pre (SOCS)



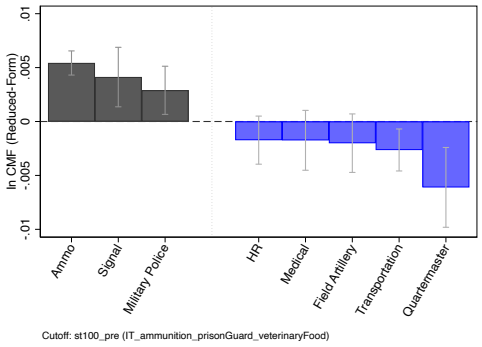
(e) GM 100 Pre (CMFS)



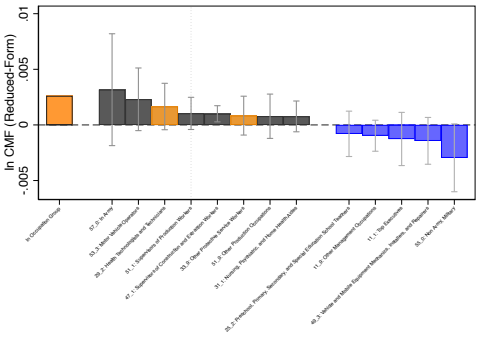
(f) GM 100 Pre (SOCS)



(g) ST 100 Pre (CMFS)



(h) ST 100 Pre (SOCS)

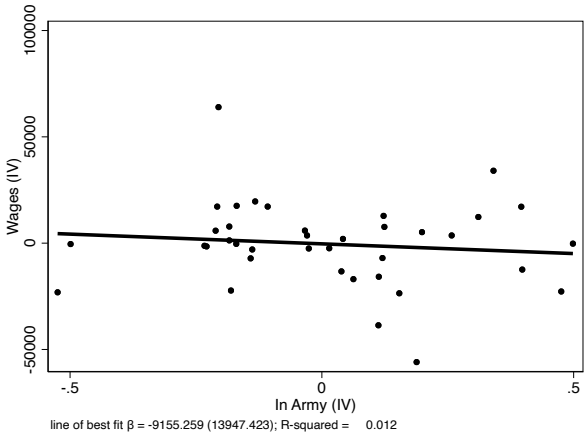


Notes: These figures plot the same exhibits as in figure 5 for different cutoffs. See notes to that exhibit for details.

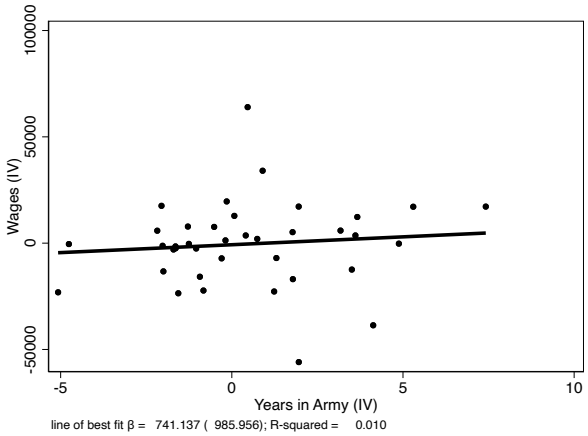
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Figure A.26: Wages and Persistence vs. Years Served

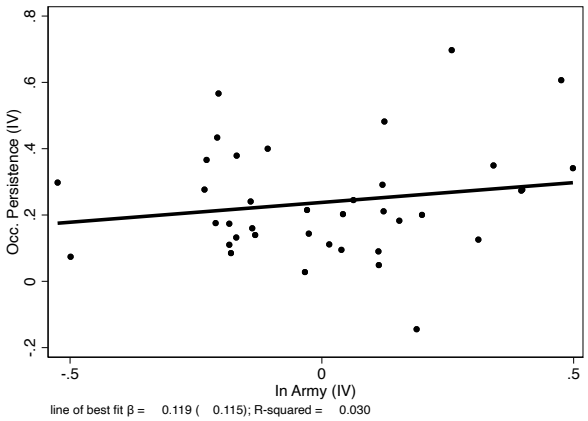
(a) Wage vs. In Army (IVs)



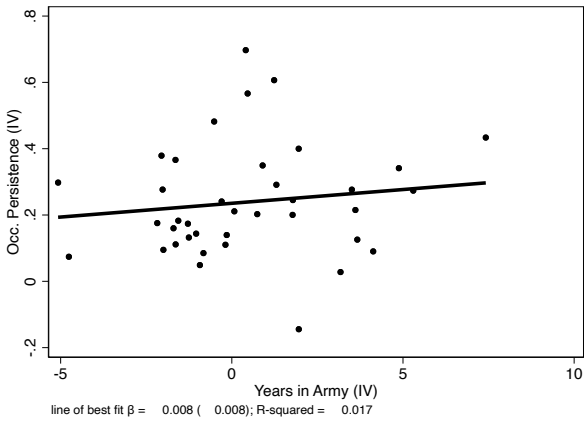
(b) Wage vs. Years Army (IVs)



(c) Persistence vs. In Army (IVs)



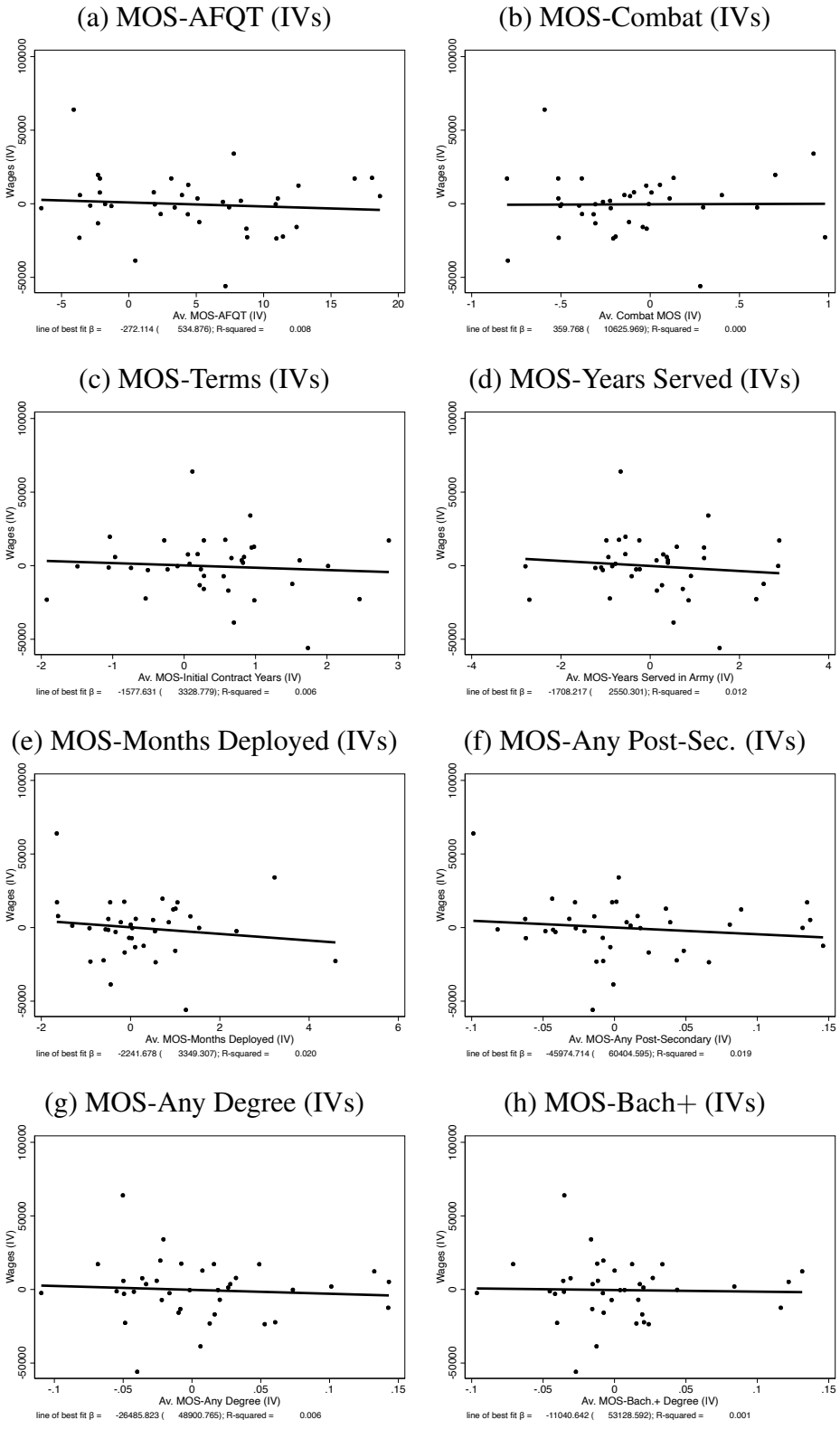
(d) Persistence vs. Years Army (IVs)



Notes: This figure plots IV effects on own wages (panels (a) and (b)) and occupational persistence (panels (c) and (d)) at each cutoff versus the corresponding IV effects on other outcomes on the x-axis. In panel (a) the x-axis variable is the IV effect on ever in the active duty Army. In panel (b) the x-axis variable is the IV effect on years in the army (until 2024), which combines a service effect and a retention effect at the cutoffs. In panels (c) and (d) the y-axis is the IV effect on occupational persistence (civilian + military, defined as in Figure 1 and the x-axis remains the same as in panels (a) and (b) respectively.

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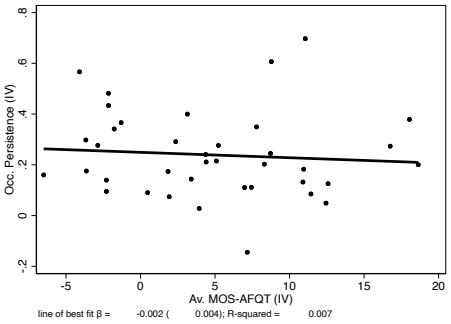
Figure A.27: Wages vs. Initial MOS Characteristics



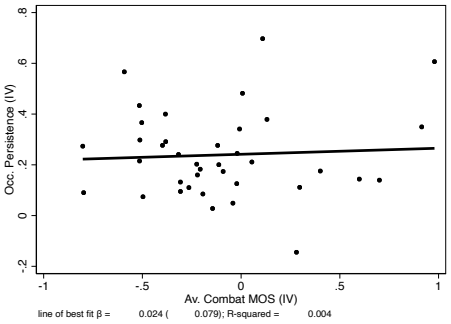
Notes: This figure plots IV effects on own wages at each cutoff versus the corresponding IV effects on various entry MOS-specific outcomes. From (a) to (h), the IV effects on the x-axis are: average MOS-based AFQT, average of dummies for a combat MOS, average MOS-based initial contract years, average MOS-based years served, average MOS-based months deployed within first 4 years, average MOS-based any post-secondary by 2020 (NSC), average MOS-based any degree by 2020 (NSC), average MOS-based any Bachelors or higher degree by 2020 (NSC). All averages are leave-out means and are calculated within period (1992-2001 and 2004-2014).

Figure A.28: Persistence vs. Initial MOS Characteristics

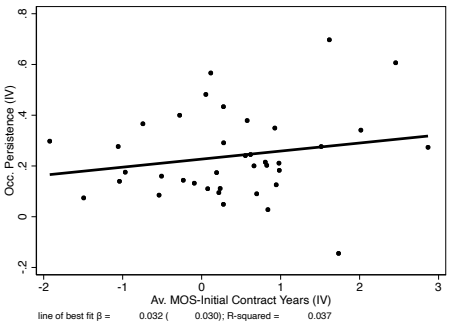
(a) MOS-AFQT (IVs)



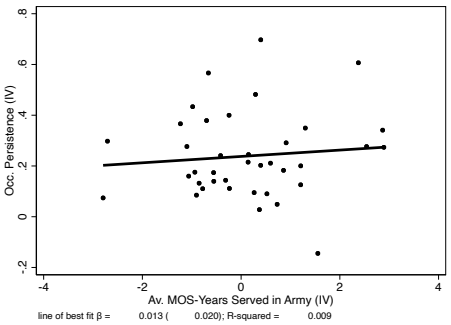
(b) MOS-Combat (IVs)



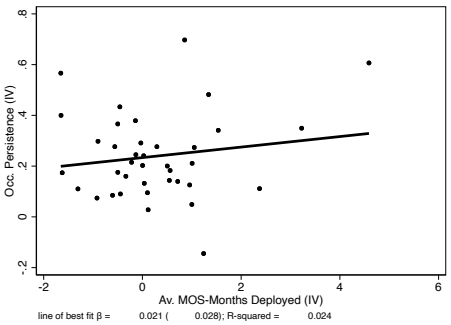
(c) MOS-Terms (IVs)



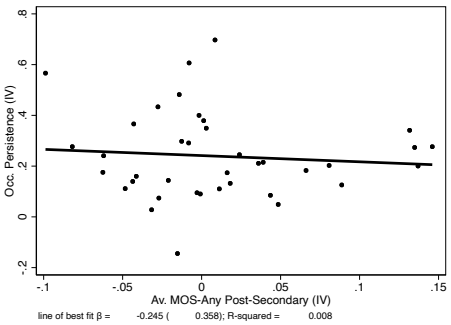
(d) MOS-Years Served (IVs)



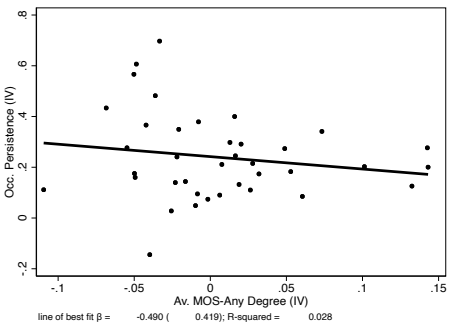
(e) MOS-Months Deployed (IVs)



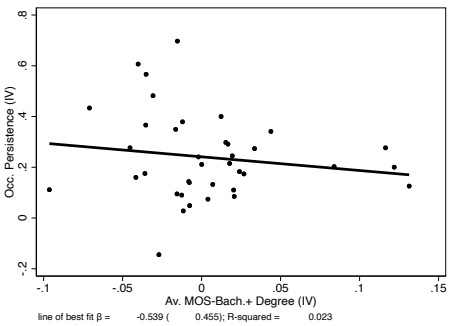
(f) MOS-Any Post-Sec. (IVs)



(g) MOS-Any Degree (IVs)



(h) MOS-Bach+ (IVs)



Notes: Similar to figure A.27, this figure plots IV effects on occupational persistence (civilian + military, measured as in Figure 1) on entry MOS-specific outcomes. See notes to figure A.27 for more details.

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Table A.1: CMF Summary

CMF Number	CMF Title	Number of Soldiers	Percentage of Soldiers
11	Infantry	30,096	18.39%
92	Quartermaster Corps	18,264	11.16%
91	Mechanical Maitenance	14,626	8.94%
68	Medical	12,080	7.38%
25	Signal Corps	11,977	7.32%
13	Field Artillery	9,137	5.58%
19	Armor	8,164	4.99%
12	Corps of Engineers	7,229	4.42%
35	Military Intelligence	7,138	4.36%
15	Aviation	6,672	4.08%
88	Transportation	6,642	4.06%
31	Military Police	6,451	3.94%
42	Adjutant General Corps (Human Resources)	4,849	2.96%
09	Officer Candidates	3,988	2.44%
14	Air Defense Artillery	3,788	2.31%
89	Ammunition	2,672	1.63%
74	Chemical Corps	2,314	1.41%
94	Electronic and Missile Maintenance	2,279	1.39%
99	Other	2,118	1.29%
18	Special Forces	1,253	0.77%
36	Finance and Comptroller	628	0.38%
27	JAG	516	0.32%
56	Chaplain	481	0.29%
37	Psychological Operations	162	0.10%
46	Public Affairs	158	0.10%

Notes: This table reports the share of soldiers in each military CMF for all those who enlist in our sample, sorted from largest to smallest CMFs. "Other" includes recruitment, civil affairs, cyber operations/warfare, interpreters/translators, musicians, special duty assignments, and trainees.

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Table A.2: Summary Stats

	All		*Enlisted Active Duty Army*	
	1992-2001	2004-2014	1992-2001	2004-2014
Total Observations	1,186,775	977,629	452,045	438,621
In Army	0.38	0.45	1.00	1.00
Years in Army			5.94	5.49
Initial Contract Term			3.73	3.77
Distinct MOS			148	152
Line Scores:				
AFQT	50.59	52.16	57.80	59.02
CL	101.75	102.55	106.91	107.15
CO	100.37	102.67	105.05	107.28
EL	100.03	102.45	105.12	107.08
FA	102.48	102.78	107.39	107.41
GM	98.91	102.33	103.68	106.88
GT	100.79	101.74	105.90	106.21
MM	99.46	101.88	103.83	106.12
OF	100.84	102.30	105.51	106.86
SC	99.50	102.71	104.57	107.37
ST	101.45	102.57	106.79	107.24
Covariates:				
Age	20.34	21.22	20.29	21.00
Male	0.76	0.81	0.81	0.85
White	0.60	0.57	0.64	0.62
Black	0.25	0.18	0.22	0.16
Hispanic	0.10	0.13	0.09	0.12
In HS	0.29	0.19	0.23	0.19
No HS Diploma	0.13	0.16	0.12	0.14
HS Diploma	0.52	0.55	0.59	0.57
Some College+	0.06	0.09	0.06	0.10

Notes: This table reports covariate means from the Army applicant data (regardless of whether or not individuals matched to the tax data), split into the February 1992-December 2001 and July 2004-September 2014 periods. The 10 line scores are normed to have a mean of 100 and a standard deviation of 50, which we approximately replicate in our sample. Mutually exclusive education categories are defined as follows: still in High School refers to those still enrolled in high school at the time of application; No HS Diploma refers to those no longer in high school with a GED, credential near completion, or less than high school completion; HS Diploma are those who have earned a high school diploma but not attended any college, and Some College+ includes anyone who has attended at least one semester of college.

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Table A.3: ASVAB Standard Scores and Descriptions

Abbreviation	Full Name	Description
AR	Arithmetic Reasoning	Measures the ability to solve arithmetic word problems
AI	Auto Information	Assesses knowledge of automobile technology, tools, and terminology
SI	Shop Information	Evaluates knowledge of tools, shop practices, and building materials
EI	Electronic Information	Assesses knowledge of electrical current, circuits, devices, and electronic systems
GS	General Science	Measures knowledge of physical and biological sciences
MC	Mechanical Comprehension	Assesses understanding of mechanical principles and ability to apply them
MK	Mathematics Knowledge	Evaluates knowledge of high school mathematics principles
PC	Paragraph Comprehension	Measures the ability to obtain information from written passages
WK	Word Knowledge	Assesses the ability to understand the meaning of words and how they are used

Notes: The ASVAB is a timed multi-aptitude test developed and maintained by the Department of Defense. The test currently consists of 10 subtests, including the 9 standard scores listed above and the Assembling Objects (AO) subtest, which does not contribute to any of these standard scores. The entire test takes approximately 2-3 hours to complete.

In the past, there were additional subtests and scores, such as Numerical Operations (NO), which measured the speed and accuracy of simple arithmetic computations, and Coding Speed (CS), which measured the ability to quickly and accurately assign code numbers to words based on a key. These subtests were removed from the ASVAB in 2002. Additionally, before 2002, the Auto Information (AI) and Shop Information (SI) scores were combined into a single score called Auto & Shop Information (AS). In 2002, the AS score was split into the separate AI and SI scores.

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Table A.4: Army ASVAB Line Scores

Abbreviation	Full Name	Description
AFQT	Armed Forces Qualification Test	Measures general cognitive ability, including verbal and math skills, and is used to determine overall eligibility for military service
CL	Clerical	Assesses abilities in administrative tasks, data management, and attention to detail; related to roles such as human resources specialists and administrative assistants
CO	Combat Operations	Evaluates skills needed for combat roles, such as situational awareness, decision-making under pressure, and physical fitness
EL	Electronics	Measures knowledge of electronic systems, circuits, and equipment maintenance, necessary for jobs such as avionics technicians and computer network specialists
FA	Field Artillery	Assesses abilities relevant to field artillery roles, including mathematical reasoning, spatial visualization, and mechanical comprehension
GM	General Maintenance	Evaluates skills in troubleshooting, repairing, and maintaining various equipment, which are necessary for roles such as general purpose vehicle mechanics and construction equipment repairers
GT	General Technical	Measures overall technical aptitude, problem-solving skills, and the ability to learn and apply new information; related to many technical jobs
MM	Mechanical Maintenance	Assesses knowledge of mechanical systems, tools, and equipment maintenance, important for roles such as wheeled vehicle mechanics
OF	Operators and Food	Evaluates skills relevant to equipment operation and food service roles, such as attention to detail, multitasking, and following procedures
SC	Surveillance and Communications	Measures abilities related to gathering and communicating information, necessary for jobs like intelligence analysts and signal support systems specialists
ST	Skilled Technical	Assesses overall technical knowledge and skills needed for various specialized technical roles, such as medical laboratory specialists and geospatial intelligence imagery analysts

Notes: While the ASVAB is a series of tests measuring the subjects in Table A.3, this table demonstrates the different scores used to determine eligibility to join the Army (AFQT) and the line scores used to determine eligibility for different MOS within the Army. Calculating these scores requires a combination of some or all of the standard scores in Table A.3, where more relevant standard scores are weighted more heavily.

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Table A.5: First Stages

cutoff	cutoff_label	First Stage Coef	N	Dep. Var Mean
1990-2001:				
firstafqt31_pre	in army	0.078 (0.003)***	557571	0.293
firstafqt50_pre	in army	0.086 (0.004)***	614852	0.440
cl90_pre	petroleumSpecialist	0.018 (0.002)***	300180	0.012
cl95_pre	logistics_HR	0.063 (0.003)***	276551	0.050
co90_pre	infantry_engineer	0.068 (0.002)***	464767	0.071
el90_pre	cableSystems	0.005 (0.000)***	341358	0.003
el95_pre	signalSupport	0.018 (0.001)***	262539	0.012
el100_pre	multichannelTransmission	0.015 (0.001)***	263013	0.011
el105_pre	electronicsRepair	0.013 (0.001)***	261522	0.009
el110_pre	electronicsRepair_biomedicalEquipment	0.012 (0.001)***	317713	0.009
fa95_pre	artillery	0.027 (0.001)***	362792	0.019
gm90_pre	construction_cargoSpecialist_waterTreatment_parachuteRigger_healthcare	0.028 (0.002)***	351193	0.013
gm100_pre	generatorRepair_utilitiesRepair	0.018 (0.001)***	272281	0.012
mm90_pre	mechanic_quartermaster	0.028 (0.001)***	491921	0.023
mm100_pre	medicalEquipment_helicopterRepair_watercraftOperator	0.014 (0.001)***	423185	0.006
mm105_pre	helicopterRepair_missleMaintenance	0.022 (0.001)***	363189	0.026
of90_pre	foodService_truckDriver	0.052 (0.002)***	452754	0.051
sc90_pre	cableSystems	0.009 (0.001)***	320233	0.003
sc95_pre	signalSupport	0.017 (0.001)***	256171	0.011
sc100_pre	multichannelTransmission	0.020 (0.001)***	391579	0.014
st95_pre	healthcare_police_chemical_aviation	0.060 (0.002)***	368010	0.029
st100_pre	IT_ammunition_prisonGuard_veterinaryFood	0.017 (0.001)***	268533	0.013
st105_pre	MI	0.015 (0.001)***	264522	0.014
2004-2014:				
firstafqt31_post	in army	0.119 (0.005)***	410550	0.380
firstafqt50_post	in army	0.030 (0.004)***	470894	0.516
cl90_post	logistics_HR	0.045 (0.004)***	159423	0.066
co87_post	infantry_engineer	0.050 (0.003)***	289502	0.091
el89_post	cableSystems	0.012 (0.001)***	190813	0.004
el93_post	signalSupport	0.036 (0.001)***	183569	0.021
el98_post	multichannelTransmission	0.019 (0.001)***	204026	0.009
el102_post	electronicsRepair	0.010 (0.001)***	213179	0.009
el107_post	electronicsRepair_biomedicalEquipment	0.008 (0.001)***	321500	0.006
fa93_post	artillery	0.023 (0.001)***	216753	0.011
gm88_post	generatorRepair_parachuteRigger_cargoSpecialist_utilitiesRepair_waterTreatment	0.049 (0.002)***	310660	0.023
gt107_post	healthcare	0.034 (0.002)***	457671	0.039
mm88_post	mechanic_quartermaster	0.038 (0.002)***	329681	0.025
mm99_post	helicopterRepair	0.014 (0.001)***	317504	0.012
mm104_post	helicopterRepair_missleMaintenance	0.021 (0.001)***	311019	0.023
of85_post	foodService_truckDriver	0.068 (0.003)***	264642	0.060
st91_post	police_ammunition_aviation_chemical	0.058 (0.002)***	212988	0.030
st96_post	IT_veterinaryFood_prisonGuard	0.022 (0.001)***	204425	0.014
st101_post	MI_healthcare_airTrafficControl	0.044 (0.002)***	243653	0.039
st106_post	healthcare_diver	0.009 (0.001)***	257560	0.005

Notes: This table reports the first stages for our 43 cutoffs. The endogenous variables correspond to whether the person enters any of the mos for which that cutoff potentially applies. * $p < .10$, ** $p < .05$, *** $p < .01$

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Table A.6: Balance Table - All Cutoffs

	Age	Male	White	Black	Hisp.	In HS	<HS	HS Dip.	Some College+
Pre-2002 Period:									
firstafqt_31	0.01410	-0.00634*	-0.00485	0.00254	0.00186	0.00682*	-0.00148	-0.00638	0.00101
	(0.02500)	(0.00345)	(0.00385)	(0.00375)	(0.00266)	(0.00358)	(0.00268)	(0.00389)	(0.00137)
firstafqt_50	0.02086	-0.00387	-0.00300	0.00316	0.00037	-0.00056	-0.00341	0.00241	0.00159
	(0.02463)	(0.00337)	(0.00372)	(0.00328)	(0.00230)	(0.00352)	(0.00295)	(0.00383)	(0.00147)
cl_90	-0.02846	0.00179	-0.00657	0.00264	0.00405	0.00954*	-0.00265	-0.00659	-0.00006
	(0.04213)	(0.00564)	(0.00636)	(0.00612)	(0.00424)	(0.00578)	(0.00455)	(0.00637)	(0.00230)
cl_95	0.02770	-0.00840	-0.00245	0.00483	-0.00211	-0.00935	-0.00771	0.01301*	0.00399
	(0.04576)	(0.00628)	(0.00709)	(0.00662)	(0.00463)	(0.00647)	(0.00524)	(0.00710)	(0.00260)
co_90	-0.01794	-0.00240	-0.00356	0.00007	0.00109	-0.00117	-0.00165	0.00467	-0.00173
	(0.02901)	(0.00436)	(0.00447)	(0.00445)	(0.00311)	(0.00423)	(0.00296)	(0.00455)	(0.00175)
el_90	0.00702	-0.00425	-0.00732*	0.00246	0.00385	0.00155	-0.00175	0.00045	-0.00011
	(0.02659)	(0.00379)	(0.00408)	(0.00395)	(0.00278)	(0.00373)	(0.00290)	(0.00410)	(0.00151)
el_95	0.02662	-0.00763**	-0.00238	0.00681*	-0.00203	-0.00204	-0.00396	0.00511	0.00116
	(0.02609)	(0.00370)	(0.00409)	(0.00373)	(0.00265)	(0.00375)	(0.00304)	(0.00411)	(0.00153)
el_100	0.02687	-0.00329	-0.00402	0.00377	0.00082	0.00572	0.00045	-0.00692*	0.00086
	(0.02614)	(0.00367)	(0.00408)	(0.00358)	(0.00259)	(0.00383)	(0.00316)	(0.00418)	(0.00161)
el_105	-0.01373	-0.00008	-0.00639*	0.00009	0.00374	0.00781**	-0.00120	-0.00838**	0.00186
	(0.02592)	(0.00349)	(0.00387)	(0.00324)	(0.00239)	(0.00380)	(0.00310)	(0.00413)	(0.00169)
el_110	0.07718***	-0.00096	-0.00047	0.00022	-0.00195	-0.00782**	0.00018	0.00594	0.00157
	(0.02733)	(0.00348)	(0.00379)	(0.00302)	(0.00228)	(0.00397)	(0.00308)	(0.00432)	(0.00196)
fa_95	-0.00812	0.00392	0.00488	-0.00022	-0.00175	-0.00531	-0.00267	0.00753*	0.00028
	(0.02776)	(0.00391)	(0.00430)	(0.00408)	(0.00282)	(0.00393)	(0.00312)	(0.00430)	(0.00159)
gm_90	0.02779	-0.00957*	-0.01351**	0.00987*	0.00206	-0.00062	0.00415	-0.00283	-0.00073
	(0.03484)	(0.00521)	(0.00544)	(0.00531)	(0.00373)	(0.00503)	(0.00376)	(0.00548)	(0.00207)
gm_100	0.02375	0.00225	-0.01286*	0.00638	0.00322	0.00677	-0.00562	0.00229	-0.00355
	(0.04309)	(0.00590)	(0.00658)	(0.00568)	(0.00410)	(0.00627)	(0.00504)	(0.00682)	(0.00277)
mm_90	0.00994	-0.00174	-0.00542	0.00227	0.00290	-0.00144	0.00012	-0.00252	0.00406**
	(0.02762)	(0.00425)	(0.00426)	(0.00428)	(0.00297)	(0.00406)	(0.00276)	(0.00436)	(0.00170)
mm_100	-0.01771	-0.00697**	0.00413	0.00149	-0.00647***	0.00120	-0.00034	-0.00154	0.00061
	(0.02514)	(0.00343)	(0.00385)	(0.00332)	(0.00244)	(0.00367)	(0.00283)	(0.00399)	(0.00169)
mm_105	0.02244	-0.00364	-0.01113***	0.01037***	0.00057	-0.00282	0.00047	0.00226	0.00010
	(0.02779)	(0.00330)	(0.00392)	(0.00310)	(0.00247)	(0.00403)	(0.00322)	(0.00439)	(0.00195)
of_90	-0.06650**	-0.00658	0.00601	-0.00210	-0.00374	0.00477	-0.00334	0.00187	-0.00310*
	(0.03021)	(0.00458)	(0.00452)	(0.00470)	(0.00334)	(0.00443)	(0.00295)	(0.00473)	(0.00180)
sc_90	0.07043*	-0.00105	-0.00555	0.00545	0.00203	-0.00666	0.00107	0.00333	0.00208
	(0.04163)	(0.00619)	(0.00641)	(0.00633)	(0.00445)	(0.00601)	(0.00421)	(0.00649)	(0.00253)
sc_95	-0.03333	0.00291	0.00888	-0.00913*	0.00231	0.01029*	-0.00458	-0.00771	0.00193
	(0.03821)	(0.00551)	(0.00596)	(0.00550)	(0.00392)	(0.00551)	(0.00411)	(0.00597)	(0.00241)
sc_100	0.05518	-0.01050**	0.00450	-0.00287	0.00072	0.00265	-0.00057	-0.00284	0.00061
	(0.03393)	(0.00466)	(0.00519)	(0.00443)	(0.00333)	(0.00496)	(0.00390)	(0.00539)	(0.00224)
st_95	-0.01572	-0.00119	-0.00205	0.00312	-0.00199	0.00077	0.00037	-0.00349	0.00240
	(0.02584)	(0.00368)	(0.00401)	(0.00377)	(0.00266)	(0.00366)	(0.00290)	(0.00401)	(0.00153)
st_100	-0.01632	-0.00240	0.00381	-0.00652*	0.00206	-0.00091	-0.00241	0.00709*	-0.00366**
	(0.02516)	(0.00354)	(0.00390)	(0.00347)	(0.00247)	(0.00362)	(0.00296)	(0.00396)	(0.00154)
st_105	-0.04092*	0.00073	0.00563	-0.00300	-0.00076	0.00303	-0.00165	-0.00067	-0.00066
	(0.02411)	(0.00332)	(0.00365)	(0.00311)	(0.00226)	(0.00353)	(0.00291)	(0.00384)	(0.00157)
Post-2004 Period:									
firstafqt_31	-0.00519	-0.00590	-0.00261	0.00414	0.00002	0.00538	0.00164	-0.00941**	0.00261
	(0.03240)	(0.00402)	(0.00473)	(0.00420)	(0.00356)	(0.00385)	(0.00373)	(0.00472)	(0.00187)
firstafqt_50	-0.00132	0.00828**	0.00272	-0.00542*	0.00089	0.00086	-0.00026	-0.00132	0.00059
	(0.02882)	(0.00336)	(0.00412)	(0.00320)	(0.00285)	(0.00340)	(0.00333)	(0.00417)	(0.00193)
cl_90	0.11202**	-0.00416	-0.00650	0.00714	0.00718	-0.00083	-0.00212	0.00119	0.00182
	(0.05331)	(0.00693)	(0.00777)	(0.00718)	(0.00586)	(0.00628)	(0.00611)	(0.00777)	(0.00310)
co_87	-0.09544**	0.00757	-0.00200	0.00057	0.00591	0.00077	-0.00151	0.00252	-0.00168
	(0.03839)	(0.00530)	(0.00542)	(0.00538)	(0.00437)	(0.00458)	(0.00413)	(0.00556)	(0.00234)
el_89	0.01628	0.00262	0.00086	-0.00005	-0.00297	0.00597	-0.00140	-0.00574	0.00122
	(0.03612)	(0.00502)	(0.00526)	(0.00510)	(0.00421)	(0.00447)	(0.00395)	(0.00535)	(0.00224)
el_93	0.00508	-0.00027	0.00186	-0.00606	0.00176	0.00154	0.00201	-0.00220	-0.00122
	(0.03170)	(0.00419)	(0.00468)	(0.00420)	(0.00360)	(0.00388)	(0.00359)	(0.00468)	(0.00206)
el_98	-0.04296	0.00430	0.00258	-0.00014	-0.00016	0.00035	0.00504	-0.00726	0.00198
	(0.03014)	(0.00368)	(0.00441)	(0.00354)	(0.00322)	(0.00363)	(0.00349)	(0.00442)	(0.00205)
el_102	-0.01865	0.00554	0.00172	-0.00123	-0.00032	-0.00007	0.00239	-0.00166	-0.00066
	(0.03008)	(0.00341)	(0.00425)	(0.00312)	(0.00297)	(0.00354)	(0.00346)	(0.00433)	(0.00212)
el_107	0.00714	-0.00157	-0.00308	0.00128	0.00084	-0.00594*	-0.00163	0.00749*	0.00011
	(0.03043)	(0.00311)	(0.00410)	(0.00269)	(0.00274)	(0.00346)	(0.00340)	(0.00432)	(0.00232)
fa_93	0.00009	-0.00304	-0.00037	-0.00150	-0.00339	-0.00242	-0.00384	0.00779	-0.00156
	(0.03603)	(0.00473)	(0.00526)	(0.00476)	(0.00404)	(0.00434)	(0.00405)	(0.00526)	(0.00229)
gm_88	-0.04495	0.00423	0.00110	0.00352	-0.00222	0.00578	-0.00591	-0.00325	0.00339
	(0.03599)	(0.00500)	(0.00515)	(0.00505)	(0.00417)	(0.00441)	(0.00385)	(0.00528)	(0.00231)
gt_107	0.00282	0.00515	0.01085**	-0.00018	-0.00315	0.00514	-0.00406	-0.00120	0.00004
	(0.03433)	(0.00357)	(0.00453)	(0.00312)	(0.00295)	(0.00374)	(0.00371)	(0.00475)	(0.00265)
mm_88	0.02248	-0.00509	-0.01015	0.00752	-0.00020	0.00375	0.00157	-0.00426	-0.00091
	(0.04479)	(0.00649)	(0.00650)	(0.00647)	(0.00537)	(0.00571)	(0.00469)	(0.00673)	(0.00309)
mm_99	-0.00027	0.00031	-0.00094	-0.00411	0.00242	-0.00358	0.00066	0.00355	-0.00071
	(0.02999)	(0.00356)	(0.00436)	(0.00332)	(0.00316)	(0.00363)	(0.00338)	(0.00439)	(0.00225)
mm_104	-0.02846	0.00271	0.00152	0.00167	0.00035	0.00274	-0.00139	0.00039	-0.00192
	(0.03097)	(0.00319)	(0.00428)	(0.00283)	(0.00294)	(0.00360)	(0.00349)	(0.00445)	(0.00242)
of_85	0.02303	0.00660	-0.00465	0.00622	0.00049	-0.00393	0.00242	0.00775	-0.00624**
	(0.03939)	(0.00562)	(0.00556)	(0.00569)	(0.00461)	(0.00488)	(0.00409)	(0.00579)	(0.00246)
st_91	-0.00543	0.00343	-0.00043	0.00065	-0.00527	0.00173	0.00514	-0.00746	0.00042
	(0.03440)	(0.00461)	(0.00502)	(0.00472)	(0.00393)	(0.00419)	(0.00384)	(0.00506)	(0.00213)
st_96	0.01825	0.00089	0.00713	-0.00062	-0.00735*	-0.00017	0.00013	-0.00197	0.00193
	(0.03716)	(0.00480)	(0.00553)	(0.00481)	(0.00417)	(0.00456)	(0.00431)	(0.00552)	(0.00239)
st_101	-0.06509**	-0.00175	0.00234	-0.00412	0.00251	0.00478	-0.00459	-0.00101	0.00095
	(0.02793)	(0.00322)	(0.00398)	(0.00303)	(0.00281)	(0.00329)	(0.00323)	(0.00403)	(0.00191)
st_106	0.03450	0.00235	0.00586	-0.00564*	0.00272	0.00240	-0.00334	-0.00133	0.00226
	(0.03458)	(0.00367)	(0.00471)	(0.00320)	(0.00318)	(0.00397)	(0.00390)	(0.00491)	(0.00255)

Notes: This table reports the covariate balance (reduced-form) results for our 43 cutoffs 9 balance covariates.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table A.7: Occupational Persistence Estimates

cutoff		FS	RF	IV	RF (civ. only)	IV (civ. only)
co90_pre	infantry_engineer	0.068	0.010	0.144		
			(0.003)***	(0.040)***		
cl95_pre	logistics_HR	0.065	0.018	0.277	0.007	0.108
			(0.004)***	(0.066)***	(0.004)*	(0.060)*
st95_pre	healthcare_police_chemical_aviation	0.062	0.013	0.203	0.006	0.091
			(0.003)***	(0.050)***	(0.003)*	(0.048)*
of90_pre	foodService_truckDriver	0.053	0.009	0.160	0.002	0.040
			(0.003)***	(0.061)***	(0.003)	(0.058)
st91_post	police_ammunition_aviation_chemical	0.046	0.005	0.110	–0.001	–0.015
			(0.004)	(0.089)	(0.004)	(0.087)
gm88_post	generatorRepair_parachuteRigger_cargoSpecialist_utilitiesRepair_waterTreatment	0.041	0.016	0.400	0.012	0.285
			(0.005)***	(0.126)***	(0.005)**	(0.119)**
st101_post	MI_healthcare_airTrafficControl	0.035	0.007	0.200	0.006	0.159
			(0.004)*	(0.111)*	(0.004)	(0.104)
of85_post	foodService_truckDriver	0.034	0.016	0.482	0.014	0.398
			(0.005)***	(0.165)***	(0.005)***	(0.161)**
el93_post	signalSupport	0.033	0.007	0.211	0.003	0.095
			(0.002)***	(0.050)***	(0.001)**	(0.043)**
gm90_pre	construction_cargoSpecialist_waterTreatment_parachuteRigger_healthcare	0.029	0.003	0.095	0.003	0.116
			(0.004)	(0.148)	(0.004)	(0.136)
cl90_post	logistics_HR	0.029	0.010	0.341	0.007	0.259
			(0.006)*	(0.200)*	(0.005)	(0.189)
co87_post	infantry_engineer	0.028	0.010	0.349		
			(0.005)**	(0.178)*		
fa95_pre	artillery	0.028	0.005	0.176		
			(0.002)**	(0.073)**		
mm90_pre	mechanic_quartermaster	0.028	0.008	0.277	0.003	0.127
			(0.002)***	(0.060)***	(0.001)**	(0.054)**
mm88_post	mechanic_quartermaster	0.027	0.008	0.291	0.003	0.122
			(0.003)**	(0.123)**	(0.003)	(0.116)
mm105_pre	helicopterRepair_missleMaintenance	0.022	0.001	0.028	–0.004	–0.160
			(0.004)	(0.168)	(0.004)	(0.159)
sc100_pre	multichannelTransmission	0.020	0.001	0.074	0.001	0.055
			(0.003)	(0.137)	(0.003)	(0.128)
st96_post	IT_veterinaryFood_prisonGuard	0.019	0.003	0.174	0.002	0.106
			(0.004)	(0.225)	(0.004)	(0.214)
fa93_post	artillery	0.018	0.003	0.140		
			(0.003)	(0.149)		
el95_pre	signalSupport	0.018	0.004	0.215	0.001	0.073
			(0.002)*	(0.127)*	(0.002)	(0.118)
sc95_pre	signalSupport	0.018	0.007	0.366	0.002	0.107
			(0.002)***	(0.104)***	(0.002)	(0.087)
cl90_pre	petroleumSpecialist	0.018	0.005	0.298	0.004	0.239
			(0.004)	(0.211)	(0.004)	(0.198)
gm100_pre	generatorRepair_utilitiesRepair	0.017	0.002	0.090	–0.002	–0.139
			(0.004)	(0.208)	(0.003)	(0.202)
st100_pre	IT_ammunition_prisonGuard_veterinaryFood	0.017	0.004	0.245	0.003	0.152
			(0.003)	(0.180)	(0.003)	(0.170)
el100_pre	multichannelTransmission	0.016	0.002	0.132	0.002	0.114
			(0.002)	(0.135)	(0.002)	(0.127)
st105_pre	MI	0.016	0.002	0.126	0.000	–0.010
			(0.003)	(0.161)	(0.002)	(0.148)
el98_post	multichannelTransmission	0.015	0.001	0.049	–0.002	–0.124
			(0.003)	(0.189)	(0.003)	(0.183)
mm100_pre	medicalEquipment_helicopterRepair_watercraftOperator	0.014	0.003	0.241	0.003	0.220
			(0.003)	(0.183)	(0.002)	(0.171)
mm104_post	helicopterRepair_missleMaintenance	0.013	–0.002	–0.144	–0.004	–0.333
			(0.004)	(0.321)	(0.004)	(0.305)
el105_pre	electronicsRepair	0.013	0.002	0.183	0.002	0.186
			(0.002)	(0.187)	(0.002)	(0.169)
el89_post	cableSystems	0.011	0.003	0.274	0.002	0.213
			(0.003)	(0.267)	(0.003)	(0.254)
el110_pre	electronicsRepair_biomedicalEquipment	0.011	0.004	0.379	0.002	0.196
			(0.002)**	(0.191)**	(0.002)	(0.169)
gt107_post	healthcare	0.011	0.001	0.085	0.000	0.021
			(0.002)	(0.220)	(0.002)	(0.202)
mm99_post	helicopterRepair	0.010	0.006	0.607	0.005	0.527
			(0.003)**	(0.277)**	(0.003)**	(0.266)**
sc90_pre	cableSystems	0.009	0.006	0.697	0.003	0.343
			(0.003)**	(0.318)**	(0.003)	(0.285)
el102_post	electronicsRepair	0.008	0.001	0.111	0.000	–0.038
			(0.002)	(0.322)	(0.002)	(0.307)
el107_post	electronicsRepair_biomedicalEquipment	0.007	0.004	0.566	0.002	0.272
			(0.003)	(0.380)	(0.002)	(0.354)
el90_pre	cableSystems	0.006	0.002	0.434	0.002	0.287
			(0.002)	(0.323)	(0.002)	(0.305)

Notes: This table reports IV and RF effects on our preferred measure of occupational persistence at all 38 cutoffs (the share of years 11-15 one is in an occupation linked to the cutoff as determined by our crosswalk). These estimates underlie the points in Figure 1. The first two RF and IV columns show estimates on military+civilian persistence, while the latter two show estimates for civlian persistence only. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A.8: Robustness of Key Results

Panel (a): Occupational Persistence

	(1) Baseline	(2) Baseline	(3) Quad.	(4) Quad.	(5) BW≤5	(6) BW≤5	(7) Lin., BW≤5	(8) Lin., BW≤5
	Military & Civ.	Civilian Only	Military & Civ.	Civilian Only	Military & Civ.	Civilian Only	Military & Civ.	Civilian Only
V-IV:								
Slope Coef.	0.204	0.105	0.215	0.118	0.242	0.118	0.184	0.079
	(0.034)	(0.038)	(0.038)	(0.043)	(0.044)	(0.047)	(0.029)	(0.033)
Slope Coef. (no constant)	0.219	0.111	0.223	0.114	0.214	0.088	0.196	0.086
	(0.021)	(0.023)	(0.022)	(0.025)	(0.026)	(0.028)	(0.018)	(0.019)
IV Persistence Effects:								
Average IV Effect	0.233	0.105	0.231	0.101	0.181	0.051	0.200	0.078
	(0.032)	(0.029)	(0.037)	(0.034)	(0.037)	(0.034)	(0.029)	(0.027)
$P(H_0 : \beta_c = 0 \; \forall c)$	< 0.0001	0.009	< 0.0001	0.069	< 0.0001	0.327	< 0.0001	0.083
$P(H_0 : \beta_c = \beta \; \forall c)$	0.792	0.797	0.686	0.938	0.966	0.952	0.968	0.879

Panel (b): IV Wage Effects

	(1) Baseline	(2) Quad.	(3) BW≤5	(4) Lin., BW≤5
	Wages	Wages	Wages	Wages
$P(H_0 : \beta_c = 0 \; \forall c)$	0.003	0.005	0.006	0.015
$P(H_0 : \beta_c = \beta \; \forall c)$	0.002	0.004	0.004	0.013
Slope Coef. on Wages v. Occ Wages	0.985	0.924	0.882	1.015
	(0.109)	(0.126)	(0.167)	(0.082)
R^2	0.633	0.551	0.516	0.659

Notes: This table reports robustness checks on the main results in table 2. In panel (a), the first two columns simply restate our baseline for comparisons purposes, the next two columns report results when we use all quadratic polynomials for all RDs, the next two columns use a maximum bandwidth of 5 and our baseline functional forms, and the last two use all linear polynomials and a maximum bandwidth of 5. For each, we report all occupational persistence the results from table 2 panel (a). In panel (b) we report the p-values relating to wage IV effects and the slope coefficient on wages versus occupation-wages for the baseline, followed by the same three alternative specifications as in panel (a).

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Table A.9: IV Effects on wages (all cutoffs), 11-15 years out

cutoff		First Stage (11-15)	wages	ln(wages)	work	occ wags	ind wages
co90_pre	infantry_engineer	0.068	–2,505	–0.141	0.008	–3,023	–1,691
			(2,866)	(0.133)	(0.042)	(2,516)	(1,948)
cl95_pre	logistics_HR	0.063	–12,422	–0.397	–0.163	–6,317	–5,275
			(4,918)**	(0.225)*	(0.070)**	(4,129)	(3,300)
st95_pre	healthcare_police_chemical_aviation	0.060	2,003	0.056	0.034	4,586	1,289
			(2,933)	(0.132)	(0.041)	(2,427)*	(1,945)
of90_pre	foodService_truckDriver	0.052	–2,979	–0.089	–0.021	–2,043	–3,506
			(3,812)	(0.178)	(0.057)	(3,313)	(2,625)
st91_post	police_ammunition_aviation_chemical	0.045	1,291	0.000	0.029	1,488	–1,529
			(6,062)	(0.299)	(0.096)	(4,257)	(4,134)
gm88_post	generatorRepair_parachuteRigger_cargoSpecialist_utilitiesRepair_waterTreatment	0.039	17,200	0.815	0.275	15,046	19,261
			(7,243)**	(0.361)**	(0.115)**	(5,081)***	(4,959)***
st101_post	MI_healthcare_airTrafficControl	0.035	5,181	0.136	0.005	3,646	5,014
			(6,600)	(0.281)	(0.094)	(4,530)	(4,194)
of85_post	foodService_truckDriver	0.034	7,647	–0.064	0.027	–5,380	1,921
			(8,820)	(0.455)	(0.144)	(6,338)	(6,125)
el93_post	signalSupport	0.033	12,833	0.085	0.186	8,996	5,142
			(7,681)*	(0.369)	(0.120)	(5,624)	(5,176)
cl90_post	logistics_HR	0.029	–221	0.744	0.020	4,431	6,260
			(14,186)	(0.735)	(0.230)	(10,131)	(9,708)
mm90_pre	mechanic_quartermaster	0.028	–1,236	–0.125	0.136	6,539	2,014
			(6,689)	(0.307)	(0.096)	(5,900)	(4,487)
gm90_pre	construction_cargoSpecialist_waterTreatment_parachuteRigger_healthcare	0.028	–13,274	–0.661	–0.163	–10,704	–12,025
			(8,510)	(0.409)	(0.122)	(7,165)	(5,730)**
co87_post	infantry_engineer	0.028	34,067	1.300	0.521	15,719	27,068
			(11,308)***	(0.534)**	(0.186)***	(7,719)**	(7,989)***
fa95_pre	artillery	0.027	5,861	0.241	0.005	–1,695	3,035
			(6,800)	(0.313)	(0.099)	(5,831)	(4,616)
mm88_post	mechanic_quartermaster	0.025	–6,999	–0.148	–0.226	–6,668	–3,998
			(14,493)	(0.741)	(0.229)	(9,998)	(9,841)
mm105_pre	helicopterRepair_missleMaintenance	0.022	5,918	0.482	–0.089	–624	9,029
			(9,960)	(0.366)	(0.118)	(7,497)	(5,875)
sc100_pre	multichannelTransmission	0.020	–433	–0.905	0.182	6,069	6,781
			(12,910)	(0.516)*	(0.165)	(10,451)	(7,982)
st96_post	IT_veterinaryFood_prisonGuard	0.019	7,811	0.482	–0.168	–11,268	–3,684
			(16,398)	(0.741)	(0.252)	(11,612)	(10,964)
fa93_post	artillery	0.018	19,617	0.987	0.566	20,376	19,763
			(15,507)	(0.747)	(0.248)**	(11,398)*	(10,608)*
el95_pre	signalSupport	0.018	3,626	0.138	0.033	–17	12,831
			(9,992)	(0.443)	(0.139)	(8,535)	(6,600)*
gm100_pre	generatorRepair_utilitiesRepair	0.018	–38,626	–1.508	–0.072	–20,658	2,073
			(18,289)**	(0.753)**	(0.229)	(15,120)	(11,124)
cl90_pre	petroleumSpecialist	0.018	–23,120	–1.069	–0.114	–21,333	–12,354
			(15,032)	(0.794)	(0.225)	(13,530)	(10,355)
sc95_pre	signalSupport	0.017	–1,539	0.359	0.038	–10,735	–1,838
			(15,483)	(0.698)	(0.210)	(12,708)	(10,024)
st100_pre	IT_ammunition_prisonGuard_veterinaryFood	0.017	–16,930	–0.862	0.152	–651	69
			(10,952)	(0.449)*	(0.144)	(8,765)	(6,933)
el100_pre	multichannelTransmission	0.015	–335	–0.680	0.088	1,214	14,383
			(12,443)	(0.528)	(0.164)	(10,055)	(7,951)*
el98_post	multichannelTransmission	0.015	–15,796	–0.136	–0.575	–24,879	–25,756
			(16,902)	(0.731)	(0.250)**	(11,621)**	(11,060)**
st105_pre	MI	0.015	12,317	0.092	0.086	3,400	–1,481
			(12,455)	(0.505)	(0.156)	(9,282)	(7,657)
mm100_pre	medicalEquipment_helicopterRepair_watercraftOperator	0.014	–7,155	–0.375	0.064	1,607	2,629
			(13,642)	(0.538)	(0.173)	(10,743)	(8,401)
mm104_post	helicopterRepair_missleMaintenance	0.013	–55,942	–1.696	–0.416	–16,752	–14,447
			(21,458)***	(0.796)**	(0.280)	(13,440)	(12,634)
gt107_post	healthcare	0.013	–22,278	–0.342	–0.225	–17,345	–14,706
			(23,509)	(0.988)	(0.306)	(16,309)	(14,271)
el105_pre	electronicsRepair	0.013	–23,577	–0.577	–0.354	–20,693	–12,979
			(15,852)	(0.618)	(0.194)*	(12,472)*	(9,616)
el89_post	cableSystems	0.012	17,130	0.044	0.415	10,270	17,396
			(23,509)	(1.106)	(0.372)	(17,579)	(16,069)
el110_pre	electronicsRepair_biomedicalEquipment	0.012	17,558	0.559	–0.106	–1,847	–1,045
			(18,763)	(0.657)	(0.214)	(14,873)	(10,866)
mm99_post	helicopterRepair	0.011	–22,733	–0.927	–0.215	7,503	–9,134
			(23,665)	(0.994)	(0.337)	(16,489)	(14,944)
sc90_pre	cableSystems	0.009	3,624	0.988	0.108	20,690	13,622
			(32,229)	(1.509)	(0.460)	(27,236)	(21,564)
el102_post	electronicsRepair	0.008	–2,410	1.832	–0.661	–16,331	–22,030
			(33,025)	(1.429)	(0.473)	(22,169)	(21,069)
el107_post	electronicsRepair_biomedicalEquipment	0.007	63,969	3.996	0.597	69,157	42,667
			(36,888)*	(1.599)**	(0.489)	(25,381)***	(22,498)*
el90_pre	cableSystems	0.005	17,190	2.513	–0.150	10,055	7,547
			(31,634)	(1.513)*	(0.466)	(27,388)	(21,610)

Notes: This table reports IV estimates on various wage measures at all 38 cutoffs. These estimates underlie the points in Figure 4. See Section 3 for the 5 key variable definitions. * $p < .10$, ** $p < .05$, *** $p < .01$.

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Table A.10: Occupational Persistence (11-15) By Race

	All Military & Civ. (1)	All Civilian Only (2)	Black Military & Civ. (3)	Black Civilian Only (4)	White Military & Civ. (5)	White Civilian Only (6)
V-IV:						
Slope Coef.	0.204	0.105	0.156	0.031	0.183	0.140
	(0.034)	(0.038)	(0.059)	(0.051)	(0.063)	(0.085)
Slope Coef. (no constant)	0.219	0.111	0.167	0.033	0.219	0.170
	(0.021)	(0.023)	(0.031)	(0.030)	(0.038)	(0.044)

Notes: This Table shows how occupational persistence 11-15 years out varies across subsamples. As in table 2, we report the V-IV slopes and heteroskedasticity robust standard errors (constructed using the delta method and using the full covariance-variance matrix of reduced form and first stage estimates) for overall and civilian only persistence. Below this, we report the same objects but for a regression without a constant, which yields efficiency gains. Columns (1) and (2) copy the V-IV effects from the full sample in table 2 for comparison purposes. Columns (3) and (4) report the V-IV effects for the subsample of Black applicants, and columns (5) and (6) report the V-IV effects for the subsample of white applicants. The cutoffs off of which results are based are as in figure 1, except we additionally exclude the GT107_post cutoff for both the white and Black subsamples as its first stage falls below 0.005 for the Black subsample.

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Table A.11: IV Effects on other Army Service and Education (all cutoffs)

cutoff		First Stage (11-15)	in army	years army	any postsec	sharepostsec	any grad	share grad
co90_pre	infantry_engineer	0.068	–0.026	–1.041	–0.045	–0.036	0.012	0.001
			(0.064)	(0.655)	(0.066)	(0.025)	(0.036)	(0.008)
cl95_pre	logistics_HR	0.063	0.398	3.506	0.261	0.119	0.044	0.009
			(0.106)***	(1.130)***	(0.111)**	(0.039)***	(0.052)	(0.011)
st95_pre	healthcare_police_chemical_aviation	0.060	0.042	0.743	0.087	0.039	–0.006	0.002
			(0.064)	(0.669)	(0.065)	(0.024)	(0.034)	(0.007)
of90_pre	foodService_truckDriver	0.052	–0.138	–1.703	–0.003	–0.041	0.007	0.013
			(0.084)*	(0.870)*	(0.088)	(0.034)	(0.048)	(0.010)
st91_post	police_ammunition_aviation_chemical	0.045	–0.184	–0.185	–0.119	–0.099	–0.049	–0.010
			(0.087)**	(0.666)	(0.088)	(0.037)***	(0.035)	(0.009)
gm88_post	generatorRepair_parachuteRigger_cargoSpecialist_utilitiesRepair_waterTreatment	0.039	–0.108	1.954	0.072	–0.039	0.048	0.006
			(0.105)	(0.793)**	(0.107)	(0.046)	(0.046)	(0.012)
st101_post	MI_healthcare_airTrafficControl	0.035	0.199	1.775	0.173	0.017	–0.010	–0.010
			(0.090)**	(0.729)**	(0.089)*	(0.037)	(0.040)	(0.010)
of85_post	foodService_truckDriver	0.034	0.124	–0.515	–0.032	–0.005	0.017	0.004
			(0.075)*	(0.614)	(0.086)	(0.037)	(0.036)	(0.009)
el93_post	signalSupport	0.033	0.123	0.074	0.067	0.048	0.093	0.013
			(0.130)	(1.016)	(0.129)	(0.054)	(0.055)*	(0.014)
cl90_post	logistics_HR	0.029	0.499	4.880	–0.215	0.008	0.045	–0.010
			(0.152)***	(1.198)***	(0.176)	(0.068)	(0.063)	(0.015)
mm90_pre	mechanic_quartermaster	0.028	–0.233	–2.021	–0.306	–0.129	–0.075	–0.032
			(0.148)	(1.492)	(0.151)**	(0.059)**	(0.089)	(0.019)*
gm90_pre	construction_cargoSpecialist_waterTreatment_parachuteRigger_healthcare	0.028	0.039	–1.999	0.138	–0.053	0.058	0.001
			(0.186)	(1.912)	(0.191)	(0.072)	(0.104)	(0.022)
co87_post	infantry_engineer	0.028	0.341	0.900	0.055	0.014	0.025	0.008
			(0.095)***	(0.764)	(0.111)	(0.047)	(0.045)	(0.012)
fa95_pre	artillery	0.027	–0.211	–2.178	–0.144	–0.087	–0.003	0.006
			(0.154)	(1.564)	(0.158)	(0.056)	(0.076)	(0.016)
mm88_post	mechanic_quartermaster	0.025	0.120	1.302	0.121	–0.006	–0.009	–0.008
			(0.169)	(1.306)	(0.173)	(0.077)	(0.082)	(0.022)
mm105_pre	helicopterRepair_missleMaintenance	0.022	–0.034	3.176	0.011	–0.075	0.006	–0.010
			(0.201)	(2.036)	(0.195)	(0.073)	(0.120)	(0.026)
sc100_pre	multichannelTransmission	0.020	–0.499	–4.759	–0.193	–0.080	–0.259	–0.032
			(0.274)*	(2.805)*	(0.264)	(0.100)	(0.159)	(0.034)
st96_post	IT_veterinaryFood_prisonGuard	0.019	–0.184	–1.283	–0.316	–0.229	–0.122	–0.044
			(0.254)	(2.003)	(0.250)	(0.105)**	(0.105)	(0.027)
fa93_post	artillery	0.018	–0.132	–0.149	0.004	–0.004	0.055	–0.012
			(0.231)	(1.792)	(0.228)	(0.096)	(0.097)	(0.024)
el95_pre	signalSupport	0.018	–0.029	3.611	–0.033	0.116	0.158	0.073
			(0.223)	(2.312)	(0.221)	(0.082)	(0.116)	(0.025)***
gm100_pre	generatorRepair_utilitiesRepair	0.018	0.112	4.130	–0.011	0.027	–0.216	–0.044
			(0.378)	(3.867)	(0.369)	(0.141)	(0.219)	(0.047)
cl90_pre	petroleumSpecialist	0.018	–0.525	–5.074	–0.599	–0.136	–0.147	0.000
			(0.338)	(3.394)	(0.362)*	(0.118)	(0.146)	(0.030)
sc95_pre	signalSupport	0.017	–0.229	–1.645	0.287	0.025	–0.050	–0.006
			(0.341)	(3.495)	(0.332)	(0.128)	(0.195)	(0.042)
st100_pre	IT_ammunition_prisonGuard_veterinaryFood	0.017	0.063	1.784	0.009	0.119	–0.044	–0.003
			(0.237)	(2.464)	(0.231)	(0.087)	(0.129)	(0.027)
el100_pre	multichannelTransmission	0.015	–0.170	–1.255	0.013	0.049	–0.067	0.010
			(0.273)	(2.837)	(0.264)	(0.100)	(0.147)	(0.031)
el98_post	multichannelTransmission	0.015	0.113	–0.933	–0.121	0.033	0.069	0.001
			(0.227)	(1.812)	(0.223)	(0.094)	(0.100)	(0.026)
st105_pre	MI	0.015	0.311	3.666	–0.058	0.163	–0.111	–0.022
			(0.260)	(2.703)	(0.252)	(0.097)*	(0.150)	(0.032)
mm100_pre	medicalEquipment_helicopterRepair_watercraftOperator	0.014	–0.141	–0.297	–0.173	0.013	0.090	0.006
			(0.285)	(2.916)	(0.279)	(0.106)	(0.168)	(0.036)
mm104_post	helicopterRepair_missleMaintenance	0.013	0.188	1.957	0.164	–0.032	–0.218	–0.048
			(0.210)	(1.683)	(0.206)	(0.085)	(0.104)**	(0.027)*
gt107_post	healthcare	0.013	–0.181	–0.828	–0.044	–0.024	–0.044	–0.017
			(0.143)	(1.150)	(0.135)	(0.058)	(0.070)	(0.018)
el105_pre	electronicsRepair	0.013	0.154	–1.563	–0.677	–0.193	–0.415	–0.057
			(0.329)	(3.432)	(0.318)**	(0.122)	(0.191)**	(0.040)
el89_post	cableSystems	0.012	0.396	5.300	0.320	0.149	–0.027	–0.012
			(0.433)	(3.332)	(0.451)	(0.191)	(0.186)	(0.047)
el110_pre	electronicsRepair_biomedicalEquipment	0.012	–0.169	–2.054	–0.299	–0.230	–0.269	–0.063
			(0.375)	(3.875)	(0.351)	(0.140)	(0.235)	(0.050)
mm99_post	helicopterRepair	0.011	0.475	1.237	–0.164	0.128	–0.368	–0.082
			(0.319)	(2.522)	(0.315)	(0.134)	(0.157)**	(0.041)**
sc90_pre	cableSystems	0.009	0.258	0.407	–0.093	0.004	–0.097	–0.089
			(0.704)	(7.367)	(0.720)	(0.279)	(0.408)	(0.086)
el102_post	electronicsRepair	0.008	0.015	–1.641	–0.080	–0.098	0.045	–0.017
			(0.417)	(3.365)	(0.409)	(0.171)	(0.188)	(0.049)
el107_post	electronicsRepair_biomedicalEquipment	0.007	–0.205	0.462	–0.476	–0.062	0.357	0.077
			(0.559)	(4.537)	(0.547)	(0.229)	(0.272)	(0.071)
el90_pre	cableSystems	0.005	–0.208	7.419	0.262	0.338	0.080	0.024
			(0.702)	(7.251)	(0.739)	(0.263)	(0.351)	(0.073)

Notes: This table reports IV estimates on several outcomes at all 38 cutoffs: whether you enlisted in the army, years served in the army (data covers until Feb. 2024), and then several education outcomes from the tax data. * $p < .10$, ** $p < .05$, *** $p < .01$.