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. Soldiers work in a diverse and varied set of military occupations, including non-combat roles like mechanics, legal services, financial specialists, cooks, dental hygienists, police officers, and network/computer specialists. Eligibility is determined by test score cutoffs which we leverage in a series of 43 regression discontinuity designs. We find that early career occupational experiences generate a substantial amount of path dependence, with point estimates that suggest a 20p.p. increase in the likelihood of being observed in the same occupation 11-15, and even 15-20 years later. We also find highly heterogeneous, yet predictable, effects on long-run wages. Implied changes in occupational earnings premia explain over 60% of the causal variation in earnings, with slope estimates that suggest improvements in average wage rates are tightly linked to actual causal effects on earnings. Changes in non-routine and routine task intensity also explain causal wage gains; however, educational attainment and union density do not. Taken together, our results highlight the importance of early career occupational experience as a key channel for promoting long run economic success among young adults who are not college bound.

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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; Wachter, 2020). 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 sources of inter-generational earnings transmission, and the role that high-quality job opportunities have in reducing economic inequality. In particular, understanding which *types* of occupations lead to prosperity is critical for the effective design of active labor market policy (e.g. Katz et al., 2022).

We study the causal effect of early career occupational experiences on labor market outcomes. The answer to this question is currently unknown. This is because it is empirically challenging to isolate the causal influence of occupation separately from other worker and firm characteristics. Simple observational comparisons exhibit clear scope for selection: workers with higher potential earnings likely choose higher paying careers. Existing work typically relies on survey data and leverages job transitions among observably similar workers for identification (e.g. Deming and Noray, 2020; Kambourov and Manovskii, 2009a,b; Topel and Ward, 1992). Natural experiments with transparent, quasi-random variation are hard to find. The scarcity of quasi-experimental estimates is due, in part, to the fact that it is rare to have high-quality administrative data that contains any reliable measure of occupation *at all*.[2]

To overcome these challenges, 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 larger than the population of Chicago, IL (2.86 million workers in 2022).[3] 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 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.[4] Thus military occupational experiences

[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] This literature frequently relies on publicly available surveys like the National Longitudinal Survey of Youth (as in Deming and Noray, 2020) or the Current Population Survey (as in Wachter, 2020).

[3] In fact, the military labor force is also 36% bigger than the largest private employer in the US, which is Walmart at 2.1 million employees.

[4] About 60% of soldiers in our data have non-combat roles. See appendix table B.1, which breaks out military occupa-

frequently have direct analogues in the civilian world. The military is also the rare example of a widely available pathway to opportunity for young adults who are not college bound. Currently, there are 7 million working age male veterans which equates to roughly 1 in 10 full time male workers in the US labor force. Thus, the military plays a dominant role in the early career development of skills and credentials for a huge swathe of the labor market, particularly those without a four-year degree (Greenberg et al., 2022). Therefore, specifically examining early career occupational experiences within the military is important for understanding the long-run well-being of the non-college educated, and particularly non-college educated young men, a population that is struggling both economically and socially (Case and Deaton, 2022).

The Army determines occupational eligibility via a unique natural experiment. In order to enlist, applicants must take a test known as the Armed Services Vocational Aptitude Battery (ASVAB). Sub-components of this test are then reformulated into 10 test scores known as "line-scores," which contain cutoffs that determine eligibility for specific occupations. For causal identification, we leverage these line-score thresholds in a series of 43 regression discontinuity designs. Much like sectoral job training, applicants induced into an Army occupation receive extensive training in the relevant skills, followed by anywhere from 2-5 years of practical, on-the-job experience.[5] By comparing applicants that barely cleared an eligibility threshold for a given occupation to those that did not, we can isolate variation in occupational experience that is orthogonal to other observable and unobservable confounders.

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, 20p.p. more likely to be in an identical or closely related occupation 11-15, and even 15-20 years later. Some of this effect is due to soldiers who choose to make a career out of the military.[6] However, for policy purposes, it is important to distinguish between path dependence that arises as the result of a durable connection with an employer, versus path dependence that arises as a result of skills, credentials, or information acquired on the job. To examine this second set of mechanisms, we also produce estimates that explicitly exclude retention effects by looking only at the impact of Army occupational experience

tions across several broad categories known as "Career Management Fields" among first term soldiers.

[5]Sectoral job training is a form of active labor market policy that seeks to jump start the careers of individuals who are marginally attached to the labor force by providing them with occupational training in fields that are in demand in their local labor market. After training is complete, these programs also typically facilitate durable connections with local employers via job placement services. Unlike other other job training models, where the evidence is quite mixed (e.g. Heckman and Smith, 2000), sectoral job training has generated improvements in economic outcomes across a small number of randomized controlled trials. See Katz et al. (2022) for an overview.

[6]Empirically, the number of soldiers who make a career out of military service is small. In our data, 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 (see appendix figure B.1).

on career paths at civilian (i.e. non-military) employers. We find that the average early career experience causes a 10.5p.p. increase in the likelihood of continuing on that career trajectory as a civilian 11-15, and even 15-20 years later. This suggests that at least half of our baseline effect is due to the skills, credentialing, and/or information channels.

Early career occupational experiences also have consequential, yet highly heterogeneous, effects on long-run wages. For example, we find that cutoffs that induce individuals to enter military occupations like signal support (i.e. computer networking) cause large increases in earnings of $12,833 per year. On the other hand, we find that cutoffs which induce individuals to enter military careers related to logistics management[7] actually *reduce* earnings by $12,422 per year. And for many of the military occupations, we find no evidence of an effect at all. What drives this heterogeneity?

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 the simple heuristic of examining average earnings differences across occupations can serve as good career guidance. We also find that skill based measures of occupational task content can explain a non-trivial amount of the heterogeneity in wage effects; however, education levels and union density do not.

We conclude by asking *which specific* military occupations put young adults on the path to success. Answering this question is a challenging econometric exercise for two reasons. First, as highlighted previously, we note that individual military occupations can "pull" soldiers out of counterfactual careers with very different wage rates. Thus it is unclear if the wage effects are different across cutoffs because the occupation itself has high monetary returns, or if the counterfactual occupation simply has lower wages on average. Second, as is often the case with regression discontinuity designs, many of our individual RD point estimates are imprecisely estimated. This will make it difficult to distinguish signal from noise when comparing the impact of different cutoffs to one another. To address these challenges, we develop a partially-pooled multiple endogenous variable two-stage least squares model of early career occupational experience. Under strong assumptions about the nature of treatment effect heterogeneity, this approach will allow us to isolate the impact of groups of similar Army occupations relative to a common counterfactual

[7]These are occupations that involve working in warehouses.

and with a reasonable degree of precision. We find that Army careers in fields like information technology, law enforcement, and healthcare can substantially improve long-run earnings. However, Army careers in logistics management that involve extensive work in warehouses can lead to lower relative earnings in the long-run.

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; Roys and Taber, 2019; Sanders and Taber, 2012). This literature generally relies on survey data to elicit and control for worker preferences. To our knowledge, this is the first paper to use large-scale, administrative data and leverage a natural experiment for identification. Recent work has also explored the role 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. Other strands of related work abstract from specific occupations and, instead, focus on the underlying tasks and skills (e.g. Acemoglu and Autor, 2011; Autor et al., 2003; Autor and Handel, 2013; Gathmann and Schönberg, 2010; Deming, 2017).

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 gain occupational training paired with extended on the job experience across a wide array of "blue-collar" careers. It is clear that – among college graduates – educational quality and field of study are important for long-run earnings (Kirkeboen et al., 2016; Zimmerman, 2019; Autor et al., 2020; Mountjoy, 2022); however, there is less consensus on how to improve long-run outcomes for those who struggle in a traditional classroom environment. For example, the potential for occupation and job training to cultivate success has a long history of study in labor economics; however, randomized evaluations have generally yielded disappointing results (Heckman and Smith, 2000; Crépon et al., 2013). An exception is the small number of evaluations that examine sectoral job training which is a model that, much like the military, involves an initial period of occupational training paired with subsequent on-the-job experience (Katz et al., 2022). There is also a related, and substantial, literature documenting the impact of macroeconomic events on long-run career outcomes; however, none of this work directly explores the causal effects of initial occupation. For example, Oreopoulos et al. (2012), Altonji et al. (2016) and Kahn (2010) show the long-run effects of graduating from college and entering the labor market during economic downturns. Huckfeldt (2022) pairs a novel theoretical model with descriptive, stylized facts to argue that the "scarring" effect of recessions documented in this body of work is actually

the result of workers accepting jobs in lower-skill occupations, which in turn results in less valuable human capital development. Additional 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). Our findings provide causal evidence that is consistent with Huckfeldt (2022).

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 service members 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.[8] For context, this is roughly half as large as the 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 occupations 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 enlist in one of these careers in our sample. This is large compared to the size of the enlisted force concentrated in CMFs that are 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

[8] 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/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.

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). In fact, the modal soldier in our data (≈60%) is employed in a non-combat occupation. See Table B.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.[9] 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 B.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 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 Services Vocational Aptitude Battery (ASVAB). Once completed, qualified applicants pick their occupation (more detail on this in the next section), sign an enlistment contract, and begin their Army career.

[9] 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.

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 disqualifies them from service.[10] 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 perform during their term of service. 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 test scores known as "line-scores." These scores are derived from the Armed Services 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 B.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 B.4).

Every Army occupation has a set of occupation specific cutoffs that applicants must clear in order to enlist in that occupation. For example, to join as a military police officer, applicants must have a score of 91 on the ST line score. On the other hand, applicants 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 (called "waivers") to these occupation specific line score requirements.

There is substantial scope for the line scores to shape which occupations applicants choose upon enlisting. In practice, while soldiers may enter the MEPS with an MOS in mind, applicants 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

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

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, applicants often arrive at the MEPS prepared to ship out to basic training, something that can occur soon after signing an enlistment contract.[11] At this point, they also spent two days at the MEPS going through the process. Choosing 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 applicants take a practice test prior to their MEPs appointment so that they do not arrive to the MEPs station with unrealistic expectations about the occupations 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 B.5 – B.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.[12] 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

[11] 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.

[12] 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.

1-3 months.[13]

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."[14]

Army occupational training most closely resembles sectoral job training. 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 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 B.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.[15]

At or near the conclusion of their first enlistment contract, most soldiers choose to leave the military (see figure B.1). Among soldiers with 2-4 year terms 39% remain 5 years out. Among soldiers

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

[14] 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.

[15] 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.

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 an 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 Military Data Sources, Line Scores, 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 the split sample.[16] 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.

Our regression discontinuity analysis relies on the ASVAB line scores as running variables. The line scores are built from a series of "standard scores" derived from the ASVAB. Since the Army maintains the standard scores in it's official personnel records, we are able to use the standard scores and official Army documents to reconstruct the line-scores from these underlying standard scores (see Appendix A for full detail). We note here that one consequence of the way line scores are constructed is that, with one exception, the post-2004 line scores are continuous, but prior to 2002 scores are discrete and exhibit a sawtooth pattern (see e.g. figures B.9–B.10).[17] The fact that the line-scores from the earlier period are discrete will have implications for bandwidth selection

[16] 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.

[17] 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.

in the regression discontinuity analysis (see section 4.1 for more detail).

3.2 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 of 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 sample (as zeros) but exclude (as missing) Army applicants who have earned income but no linked SOC.[18]

3.3 Outcomes

The main outcomes in our analysis are career trajectories 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).

[18] 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.

3.3.1 Career trajectories

Our primary method for measuring the impact of early career experiences on career trajectories is via the notion of occupational persistence, which we define as 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 either identical or closely related to the corresponding occupations at a given line score occupational qualification cutoff.[19]

This requires linking Army occupations to their closely related civilian counterparts. To do so, we create a Military Occupational Specialty (MOS) to three digit SOC crosswalk. The crosswalk is constructed using the results of several internal studies commissioned by the Army that were meant to determine potential career paths for soldiers. We supplement these internal studies 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 occupations 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.[20] 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 generic military SOC (55-0). This crosswalk allows us to explore whether an individual continues in the career implied by their initial MOS, either because they are still in a related Army occupation or because they are in a related civilian occupation.

Since each line score cutoff can determine eligibility for multiple military occupations, we construct cutoff-specific, occupation-group outcomes. The natural way to do this is to create the outcome based on whether the individual is in any of the primary, secondary, or supervisory occupations corresponding to the full set of military occupations "unlocked" 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.[21] 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 (denoting career continuation), otherwise it is 0.

[19] These cutoffs are important for our empirical strategy, which we will discuss shortly in section 4.

[20] For example, the "49" category of SOC codes contain installation, maintenance, and repair occupations. Within that broad category, there are numerous, more specific occupations. One of those more specific three digit SOC occupations is code 49-1 which denotes "Supervisors of installation, maintenance, and repair workers." Thus, if we link an Army occupation to a three digit SOC code in the 49 broad category, we additionally retain the supervisory category in our crosswalk in order to capture natural career progression.

[21] 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.

3.3.2 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 are exempt from taxation for servicemembers, we follow Greenberg et al. (2022) and use the Army personnel records to add these additional forms of compensation into our measure of income for individuals who are on active duty.[22]

3.3.3 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.

3.4 Summary Statistics

Summary statistics for all U.S. Army applicants in our two key samples (1992-2001 and 2004-2014) are presented in Table B.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

[22]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. Military pay not subject to taxation accounts for 17-25% of servicemembers' *total* compensation (see Appendix B of Greenberg et al. (2022)).

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 B.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.[23] 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 B.3 and B.4 zoom in on select entry MOS. Figure B.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 B.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.

The descriptive occupational path dependence could certainly be driven by selection: those with a specific interest computers are presumably are more likely to both choose that occupation upon enlisting in the Army, and to continue to choose similar occupations in the long-run after they have exited the service. In the remaining sections of this paper, we will explore how much of this path dependence can be explained as a causal effect due to the initial, military occupation itself.

[23] 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.

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 applicants who barely cleared one of these cutoffs to applicants 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 occupation, 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 applicant 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);[24] X_i is applicant i's line score from the relevant subtest; $Z_i = \mathbb{1}(X_i > c)$ is a binary variable indicating whether applicant i's line score cleared the cutoff (c);[25] and ϵ_i is a residual. The parameter of interest from equation 1 is γ. It represents the predicted difference in mean outcomes for applicants with a line score at the RD threshold.

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.

[24] 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.

[25] 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.

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.[26] However, our key findings are robust to varying the bandwidth and the order of the polynomial, including to using all quadratic polynomials (see appendix table B.8). 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 an occupation 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.[27]

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

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

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

Where D_i is an indicator that takes a value of 1 if the soldier enlists in the army in an occupation 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

[26] 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.

[27] 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.

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, occupation 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 also 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 B.5 through B.8 provide graphical evidence of strong first-stage effects. In addition to the graphical evidence, Table B.5 provides the estimated first-stage coefficients and their standard errors 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).[28] The largest first stages are observed at the following 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 occupational assignment.

[28] 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 et al., 2022); however, in all of our preferred specifications, we use just-identified IV which is median unbiased even in finite sample and hence less subject to these concerns (Angrist and Kolesár, 2024).

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 B.9 through B.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 "look-up" tables rather than a smooth 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 continuous, 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 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 there are 43 cutoffs checked across nine covariates, the resulting table is excessively large and is included in table B.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 1. Consistent with a balanced treatment, the distribution of p-values appears uniform. This interpretation is further supported by a joint test of balance across all covariates and cutoffs, which fails to reject ($p = 0.16$, see appendix table B.6). Thus, the data are consistent with the RD variation exhibiting balanced across observable, pre-service 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 of 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 of 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 2 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. We then turn to wages, where we find a substantial amount of heterogeneity that is well predicted by differences in occupational wage premium. Implied variation in non-routine and routine task intensity across occupations also explain non-trivial amounts of the variation in long-run causal wage effects; however, we find limited evidence that changes in educational attainment or rates of unionization are important predictors.

5.1 Path dependence in the labor market

Career trajectories. 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 later life outcomes in a number of ways, a natural starting point is to measure how these experiences change the likelihood of continuing along the relevant career path. In other words, does eligibility for an occupation increase the likelihood that individuals will be in an identical or

closely related occupation 15 years later?

To quantify this, 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).[29] 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 the date that they took the ASVAB test.

For policy purposes, it is important to distinguish between two possible mechanisms that could lead to path dependence in our setting. First, it could be that path dependence arises as the result of a durable connection with an employer. For example, some of the applicants who are quasi-randomly assigned to the mechanic occupation could find that they enjoy working as a mechanic in the Army during their initial term of service. Thus, the cutoff may cause them to stay in that occupation for the same employer for an extended period of time. These "retention effects" are real causal consequences of our treatment and, as such, our baseline estimates will incorporate them. However, a second channel that could lead to path dependence would be the accumulation of occupation specific skills / human capital, credentials, or information. Since these channels are not specific to the employer, we might expect them to extend across firms in the labor force in a more general way. To explore the second channel, we also estimate treatment effects on the likelihood an applicant is in an occupation unlocked by the cutoff 15 years later at a *non-military employer*.[30] We expect this to be a lower bound on the skills / information / credentialing channels, since these undoubtedly apply to the within employer channel as well – it is just not possible for us to completely separate them out using our experiment.

Panels (a) and (b) of figure 2 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

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

[30] More precisely, when incorporating retention effects, we define the outcome variable as "years spent in the relevant set of occupations, after crosswalking Army occupations 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 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.

cutoff. The y-axis corresponds to the reduced form estimate from our regression discontuity model (equation 1) where the outcome variable is 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 B.7 for the point estimates used to generate figure 2.

The V-IV slope from panels (a) and (b) of figure 2 is our preferred way to summarize the consequences for career paths that we find across different cutoffs. Up to a weighting, the V-IV slope in panels (a) and (b) of figure 2 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.[31] Another natural way to summarize the persistence is by directly examining the individual IV estimates. Panels (c) and (d) of figure 2 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 path dependence. The V-IV slope on the estimates that include persistence within the military suggest that early life occupational experiences cause a 20.4p.p. increase the likelihood of being found in a closely related occupation 11-15 years later. Retention within employer accounts for approximately half of this effect; however, even excluding retention we find a 10.5p.p. increase in the likelihood of being found in a corresponding occupation for a civilian employer 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 23.3p.p. with retention, and 10.5p.p. without retention. Panel (a) of table 1 summarises the key point estimates and provides corresponding standard errors.[32]

[31] 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.

[32] We also report results on our preferred V-IV measure of occupational persistence for Black and white subsamples in table B.10. Results, as expected, are substantially noisier, but overall 11-15 occupational persistence is generally not

Another intriguing feature of these estimates is that they suggest relatively limited heterogeneity (given our sampling variance) in the impact on career path across cutoffs. There are two ways to note this. First, in the V-IVs, following Angrist and Hull (2023), we can conduct a classic over-identification test. This is a joint test of instrument validity (i.e. exclusion) and functional form that will fail if there is heterogeneity across instruments not captured by the model specification (e.g. omitted interaction terms). 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 1). Thus, path dependence appears to be relatively constant across occupations, perhaps suggesting that information about the occupation (e.g. job satisfaction) plays an important role, since we expect levels of human capital acquired "on-the-job" and credentials (two other leading channels) to be quite heterogeneous across different military occupations. However, this interpretation of the lack of heterogeneity is necessarily speculative – we cannot be definitive on this point using the variation at our disposal.

Our main findings in this section (as well as our key findings pertaining to wages, discussed in Section 5.2), are robust to varying bandwidth and polynomial order. Appendix table B.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. In all cases, the results are robust to these modeling choices.

Dynamics. Figure 3 plots our preferred summary measure of the impact on career path 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 of the causal effect on pursuing a closely related career. Triangles correspond to estimates that exclude military occupations and therefore represent the causal effect of pursuing a closely related career 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 a 71% increase in the share of years spent in a closely related occupation; however, virtually all of this is due to the causal effect of crossing the threshold on entering military service in the relevant occupation. But by years 6-10, after everyone in our sample has had the opportunity to leave the

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).

Army, we see a large decline in the estimates that include employer retention effects coupled with a 9% increase in the causal effect on having closely related occupation at a non-military employer. 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 occupations for civilian employers dominates over long time horizons.

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.[33] 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.[34] In both panels, the dashed line is the 45 degree line. The solid line is the line of best fit.

[33] 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.

[34] 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).

These figures reveal clear and heterogeneous effects of these early career occupational experiences on wages. Cutoffs that shift people away from low-wage occupations and into high-wage occupations also cause large increases in realized earnings, and vice-versa. For example, at the top end we find that cutoffs that induce individuals to enter military occupations like the infantry/engineering corps and signal support (i.e. information technology) result in statistically significant increases in actual wages of $34,067 (P=0.003) and $12,833 (P=0.095), respectively.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).[35] 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 B.9. Table 1 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 1). 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 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. However, we cau-

[35]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 B.20).

tion against over-interpreting this result – the associated standard error of the slope is 0.133, and hence we do not have the precision necessary to rule out non-trivial amounts of forecast bias. We find similar patterns (both in terms of variance explained and forecast unbiasedness) for industry specific earnings premia.[36]

The finding that changes in occupational earnings premia can explain a substantial amount of the heterogeneity in wage effects begs a natural follow up: "What other occupational features predict economic sucess?" To answer this question, we draw on several, supplementary data sources including the ONet (Autor et al., 2003) database of occupation specific skills, the American Community Survey (ACS), and the Current Population Survey (CPS) to construct variables that capture other occupational features that could be relevant for earnings. These include non-routine task intensity (a proxy for high-skill work); routine task intensity (a proxy for low-skill work); measures of education, specifically the share of individuals employed in an occupation with four-year and two-year college degrees; and measures of bargaining power, specifically the share of workers in an occupation who belong to a union.

We find evidence that occupation specific measures of task-skill content explain a non-trivial share of the wage effect heterogeneity; however, other observable occupational features do not. To explore the connection between other occupation specific features and the wage heterogeneity, we estimate univariate regressions idential to those used to generate the results in the "Wages v. Occ Wages" column in panel (b) of table 1, except that the causal effect on "occupation-earnings" is replaced with the causal effect on the alternative occupational features described earlier in this section. Figure 5 contains the results. Each bar displays r-squared values from one of these regression. As a benchmark, the bar labeled "Occupation Wages" replicates the r-squared values from the "Wages v. Occ Wages" column in panel (b) of table 1. From the figure, we can see that 19% of the wage heterogeneity can be explained by cutoffs which move applicants from occupations with low levels of non-routine task content and into occupations with high levels of non-routine task content. Similarly, we see that cutoffs which move individuals from occupations with a high share of routine tasks and into occupations with a lower share of routines tasks also explain a non-trivial amount of the variation in wages effects. On the other hand, we find that measures of education, like the share of workers in an occupation with four- and two-year college degrees, as well as proxies for bargaining power like the share of workers in occupation that are unionized, do not have much explanatory power.

[36]Table B.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 B.27 shows that ultimate IV wage gains are not tightly linked to causal IV effects on years of service or army service.

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 occupations that applicants are shifted away from, there tends to be large impacts on career path over the long-run; and ii) cutoffs that move individuals out of low-wage occupations and into high-wage occupations lead to large improvements in realized earnings. One remaining question is what are the characteristics of the initial occupations that put young adults on the pathway to success? We address this in two ways. First, we will explore connections between short-run features of the military careers soldiers are induced to enter by the cutoffs and their long-run career outcomes. This will allow us to better understand the *types* of early career occupations that improve long-run well-being without imposing any additional assumptions or structure. Second, we will estimate a "partially pooled" multiple endogenous variable model of the causal effect of military occupations on long run outcomes. Under strong assumptions about the nature of treatment effect heterogeneity, this will allow us to identify the impact of *specific* military careers on long run outcomes relative to a consistently defined counterfactual.

Short-run military occupation features and long-run wage effects. The first way we will explore this question is to compare the cutoff-specific IV effects on wages to the corresponding causal effect of crossing that threshold on initial MOS-level characteristics (treating non-Army as a single MOS).This is effectively the same approach we took in the "long-run" analysis conducted in section 5.2, except that instead of using "long-run" occupational features from years 11-15 to explore wage effects, we will use short-run features of the military occupation instead. Figure B.28 plots the causal effects on wages, 11-15 years out, at each cutoff against the causal effects on various entry MOS-specific characteristics, like implied long-run MOS wages, average AFQT in that MOS, average initial terms, average months deployed, and average eventual years served and post-secondary educational attainment. Consistent with our earlier results, we find that the implied career earnings of an applicant's initial MOS are highly predictive of eventual, long-run wages, explaining roughly 17% of the long run variation 15-20 years later (see panel (f) of appendix figure B.28). However, across the board, there is no statistically significant link between how the cutoffs shift these other MOS-level characteristics and how they shifts long-run wages. Thus, implied changes in average wage rates (both initially, and in the long-run) appear to be a key summary measure of how career choices relate to prosperity.

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.

A "partially-pooled" multiple endogenous variable model of the long-run impact of military occupations on earnings. To this point, we have used our rich data on occupational characteristics to characterize the *types* of occupations that are most closely connected to economic well-being. However, this approach does not allow us to directly compare military occupations to one another, since differences across cutoffs could be due to *either* real treatment effect heterogeneity (i.e. different occupations have different long run effects) *or* the heterogeneous nature of the counterfactual (i.e. different cutoffs pull applicants out of counterfactual occupations with higher / lower wages). This complication is compounded by the fact that, as with most regression discontinuity designs, a number of our cutoff specific estimates have large standard errors, which will make it difficult to distinguish signal from noise when comparing across cutoffs.

In this section, we address both of these challenges by developing a "partially-pooled" multiple endogenous variable model of the impact of specific military occupations. Under strong assumptions about the nature of treatment effect heterogeneity (which we discuss in more detail below), the jointly estimated two-stage least squares model will deliver treatment effect estimates that are "normed" to a consistent counterfactual career – in our case, the reference will be individuals who remain civilians. In addition, to improve power, we will also "average" the effects of similar occupations[37] into a small number of more precise point estimates. To accomplish this second goal, we group the military occupations in our data that are causally effected by our cutoffs into 8 mutually exclusive career paths: Warehouse Operations; Petroleum Supply / Cooks; Mechanics & Maintenance; Infantry; Construction; Military Police / Medical Careers; Information Technology, and Other Army Job. We then define treatment variables for each of these 8 mutually exclusive groups that take a value of 1 if an applicant in our data enlists in any military occupation contained in that group. Thus, by "pooling" occupations into these larger groups, we hope to obtain more precise estimates at the cost of potentially abstracting away from important sources of heterogeneity. In practice, we will instrument for these 8 treatment variables using the 43 line-score cutoffs.[38]

[37] In practice, we identify "similar occupations" both by their official occupations descriptions and by whether they are impacted by common cutoffs. The latter is a reasonable criteria from a theoretical perspective since, in theory, the ASVAB line scores are meant to measure occupational aptitude. Hence, similar qualification requirements should imply similar occupational duties. It also has the practical benefit of aligning our occupation "groups" closely with the underlying variation in the instruments that will identify them.

[38] Specifically, we estimate the model $Y_i = \boldsymbol{\beta D_i} + f(\boldsymbol{X_i}) + \epsilon_i$ where Y_i is earnings; $\boldsymbol{D_i} = \{D_{ig}\}$ is a vector of 8 treatment indicators, one for each of the 8 mutually exclusive occupation groups (g) with "remaining a civilian" constituting the omitted category; $\boldsymbol{X_i}$ is a vector of 11 line scores; and f maps line scores into the series of piecewise linear and quadratic polynomials around the various RD thresholds as implied by our baseline, individual RD models. We instrument for the treatment variables with 8 first stage equations of the form: $D_{ig} = \boldsymbol{\Pi_g Z_i} + h_g(\boldsymbol{X_i}) + \eta_{ig}$ where D_{ig} takes a value of 1 if applicant i enlists in any occupation contained in group g; $\boldsymbol{Z_i}$ is a vector of 43 indicators that take a value of one if individual i crosses the relevant line score threshold; and h_g maps line scores into the series of piecewise linear and quadratic polynomials around the various RD thresholds as implied by our

Our model is identified under strong assumptions. In addition to the standard RD assumptions outlined earlier in our analysis of the individual thresholds, this approach also requires that treatment effects as defined by our occupation groups are constant and linear. This assumption could fail in two ways. First, it could be that different occupations within a career path have different causal effects. If different instruments move individuals across occupations within a group, this would then create violation of the implicit exclusion restriction embedded in our constant linear effects assumption, since it would imply that our instruments generate causal impacts on earnings through a channel not captured by any of our endogenous variables. Second, it could be that treatment effects are heterogeneous in ways that are not captured by the 8 treatment variables we have defined. This would be a form of model mis-specification, since it implies a violation of the functional form assumption (i.e. linearity) imposed by our model.[39]

Figure 6 displays the results. Each bar in this figure is the estimated causal effect from our multiple endogenous variable model on average long-run occupational earnings with the civilian mean ($37,144) added back-in – thus the height of each bar is interpreted as the long run average wages implied by the career paths of different military occupations, with causal effects encoded in differences between bar heights. Consistent with our individual RD analysis, we find that careers in healthcare and information technology, which have higher average annual earnings and require more non-routine tasks, put soldiers on the path to long-run success. On the other hand, careers that pay less on average and that involve a higher share of routine tasks like warehousing and cooking, lead to lower levels of long-run well-being.

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 Army occupations use different line score cutoffs to determine an enlistee's eligibility for a given Army occupation. 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, with initial occupations leading to a 20p.p. increase in the likelihood an individual winds up in an identical, or closely related career 20 years later. This high and relatively homogeneous effect 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

baseline, individual RD models.

[39] In ongoing work, we seek to both relax these assumptions and also test them more formally. However, this analysis is not complete at this time.

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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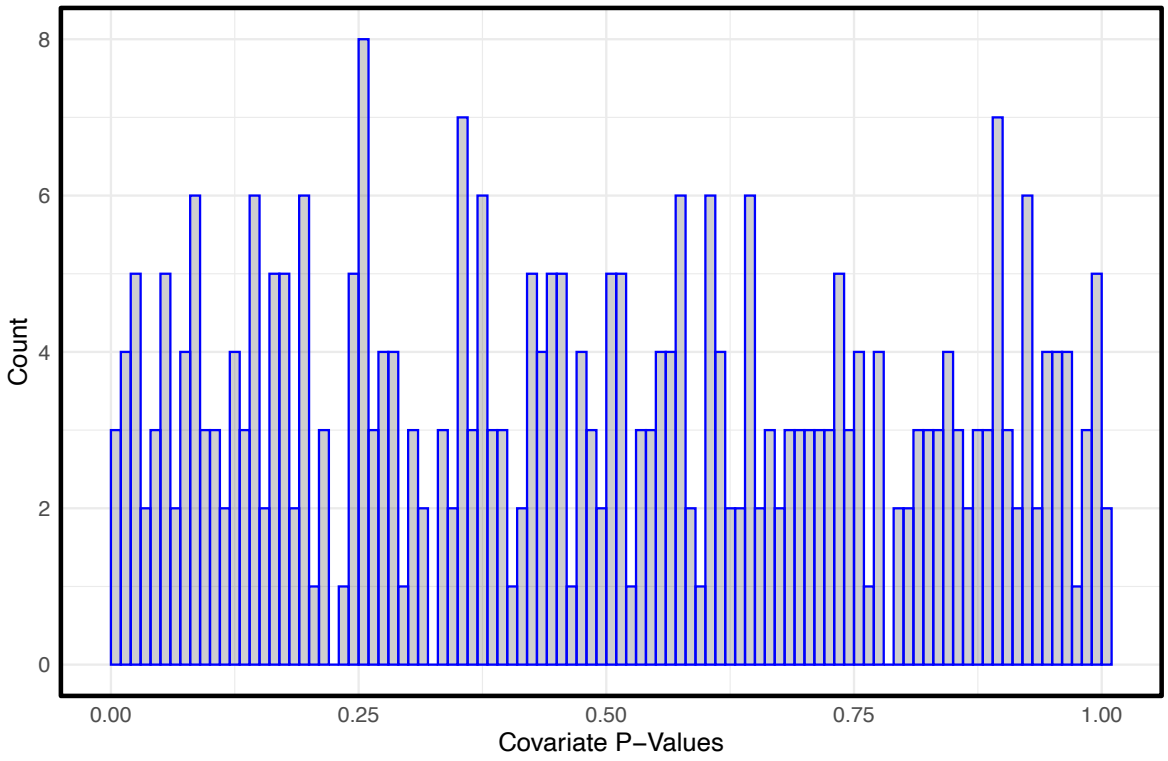
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Figures

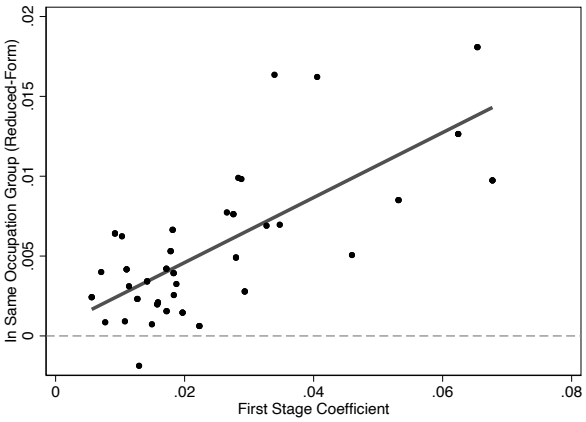
Figure 1: Balance: Covariate P-Values



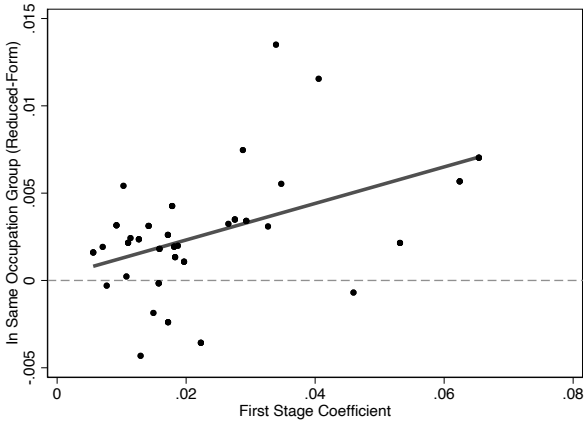
Notes: This Figure plots the 43×9 p-values for the reduced-form effects of crossing each of the 43 cutoffs on each of the 9 balance covariates. The underlying point estimates and standard errors are reported in Table B.6.

Figure 2: Causal Effects on Career Path 11-15 Years Later

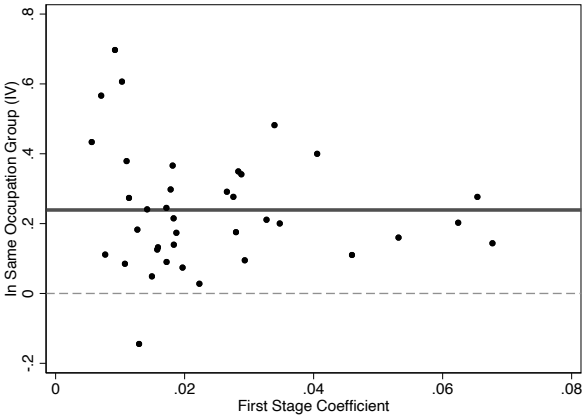
(a) Military + civilian occupations (V-IV)



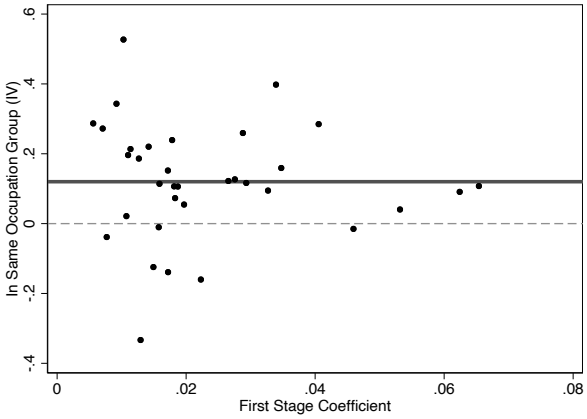
(b) Civilian occupations only (V-IV)



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

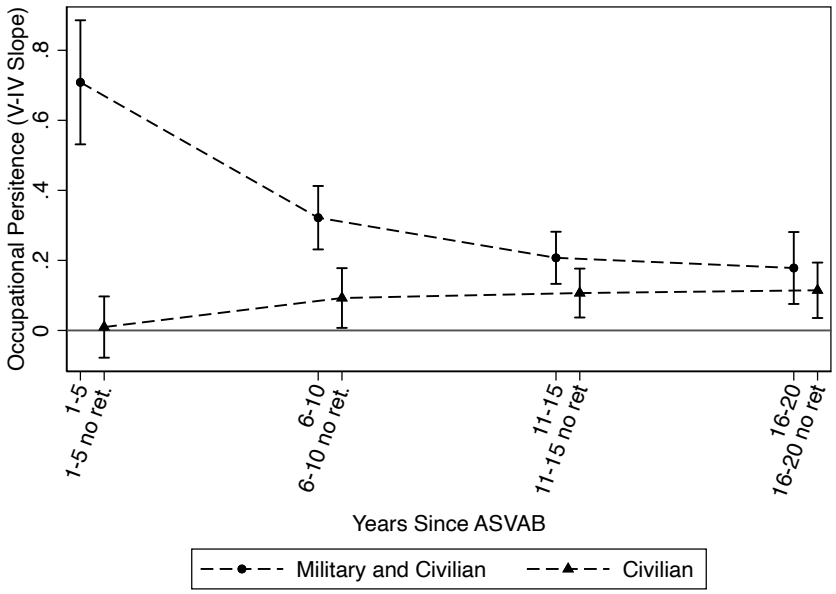


(d) Civilian occupations only (mean-IV)



Notes: Panels (a) and (b) plot the cutoff-specific, estimated reduced form effects on our preferred measure of path dependence against the first stage effects at that same cutoff. The outcome is measured as the share of years 11-15 post-AFQT that an individual is observed in closely related occupation that is linked by our cross-walk to the corresponding Army occupations affected by each relevant cutoff. The path dependence effects in panel (a) encompass both military and civilian careers, while those in panel (b) correspond to exclusively post-Active Duty Army careers at a civilian employer. 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.

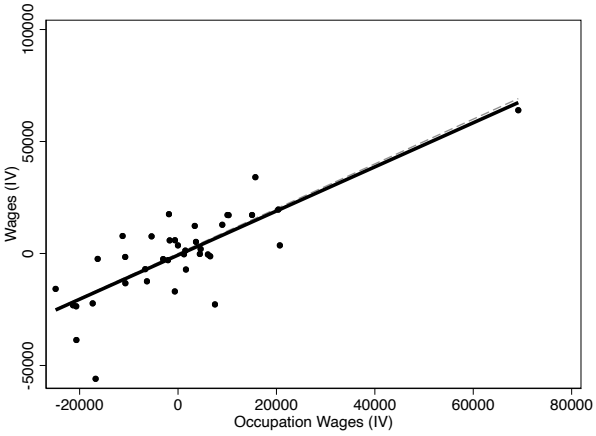
Figure 3: The Dynamics of Path Dependence



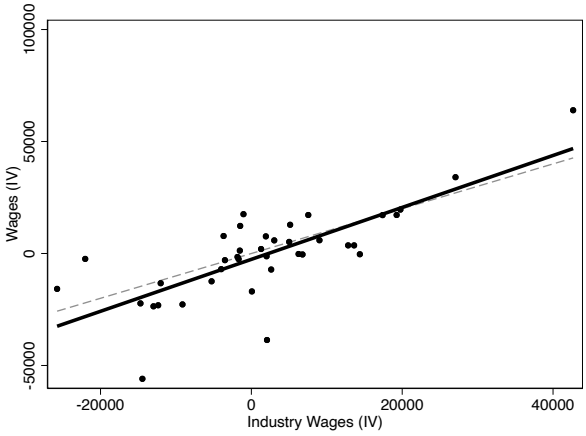
Notes: This figure plots our preferred measure of impact on career paths (V-IV slope) for different time horizons: 1-5 years, 6-10 years, 11-15 years (these correspond to the slopes in Figure 2 panels (a) and (b)), and 16-20 years post-ASVAB. The circles represent effects across either civilian or military careers. The triangles represent the effects on civilian careers. 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 careers, 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.

Figure 4: Occupations, Industries, and Wages

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

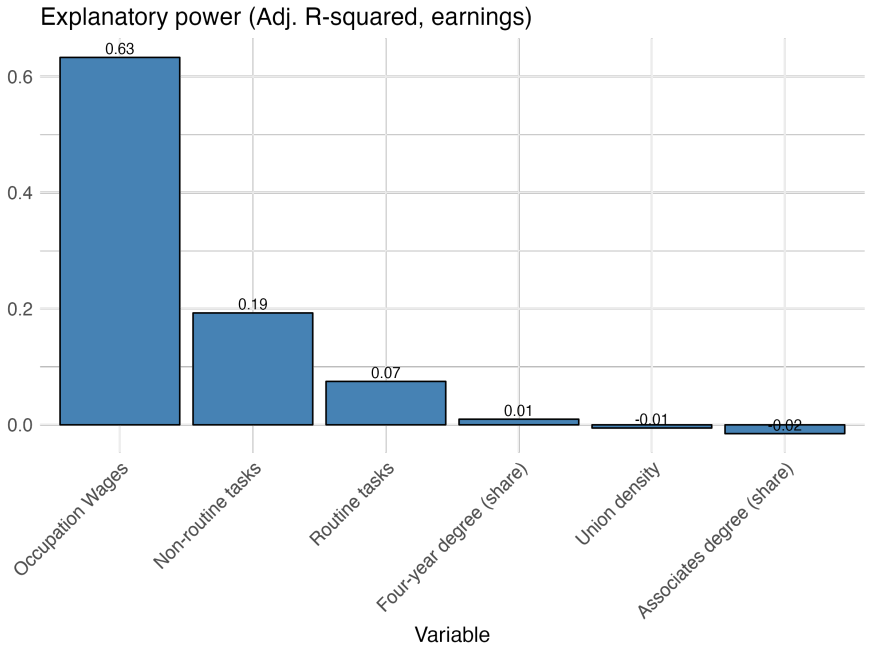


(b) Wage vs. Industry Wage Effects (IVs)



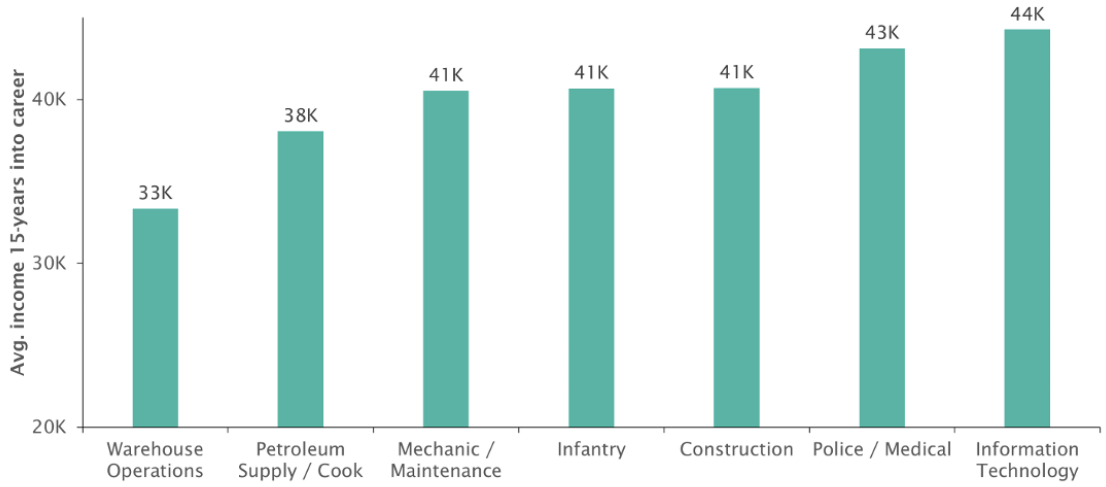
Notes: This figure plots the correlation between the cutoff-specific IV effect on 11-15 average own wages and, in panel (a), the 11-15 IV effect on average (leave-out) occupation wages. Panel (b) plots the IV effects on own wages against the IV effect on average (leave-out) industry wages. Occupation 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 2, 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.

Figure 5: Occupational Features and Long-run Wage Heterogeneity



Notes: This figure displays r-squared values from univariate regressions that explain variation in the cutoff-specific IV effect on 11-15 average earnings with the corresponding cutoff specific IV effect on various long-run occupational features. For example, the bar labeled "Occupation Wages" replicates the r-squared values from the "Wages v. Occ Wages" column in panel (b) of table 1; the r-squared values of the remaining bars are generated identically, except that the causal effect on "occupation-earnings" is replaced with the causal effect on an alternative occupational feature. "Non-routine task" intensity (a proxy for high-skill work) and "Routine task" intensity (a proxy for low-skill work) are constructed from the ONet database as described in Autor et al. (2003). "Four-year degree" and "Associates degree" are taken from the ACS and measures the share of individuals employed in an occupation with four-year and two-year college degrees, respectively. "Union density" is taken from the CPS and measures the share of workers in an occupation who belong to a union.

Figure 6: Implied Long-run Earnings for Military Occupations from Joint Model



Notes: This figure displays estimates from the model $Y_i = \boldsymbol{\beta D_i} + g(\boldsymbol{X_i}) + \epsilon_i$ where Y_i is earnings; $\boldsymbol{D_i}$ is a vector of 8 treatment indicators, one for each of the 8 occupation groups with "remaining a civilian" constituting the omitted category; $\boldsymbol{X_i}$ is a vector of 11 line scores; and f maps line scores into the series of piecewise linear and quadratic polynomials around the various RD thresholds as implied by our baseline, individual RD models. We instrument for the treatment variables with 8 first stage equations of the form: $D_{ig} = \boldsymbol{\Pi_g Z_i} + h_g(\boldsymbol{X_i}) + \eta_{ig}$ where D_{ig} takes a value of 1 if applicant i enlists in any occupation contained in group g; $\boldsymbol{Z_i}$ is a vector of 43 indicators that take a value of one if individual i crosses the relevant line score threshold; and h_g maps line scores into the series of piecewise linear and quadratic polynomials around the various RD thresholds as implied by our baseline, individual RD models. Each bar in this figure is the estimated causal effect from our multiple endogenous variable model with the civilian mean ($37,144) added back-in for interpretability – thus the height of each bar represents the long run earnings of each military occupation, and causal effects are encoded in differences between bar heights. We omit "Other Army Job" from the figure ($39,724).

Tables

Table 1: Summary of Key Results

	Panel (a): Career Path	
	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)
Mean IV:		
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 results for career paths. 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 2 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 2, 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.

Online Appendix

A Details of 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.[40]

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 B.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.[41]

Line scores are then constructed based on different combinations of the standard scores. Table B.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 $\approx$ $0.24 \cdot GS + 0.46 \cdot AR + 0.45 \cdot MK + 0.29 \cdot MC + 0.30 \cdot EI + 0.50 \cdot AS + 0.22 \cdot (WK + PC) - 23.36$.

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 B.9–B.10).[42]

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.[43]

[40] 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.

[41] 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.

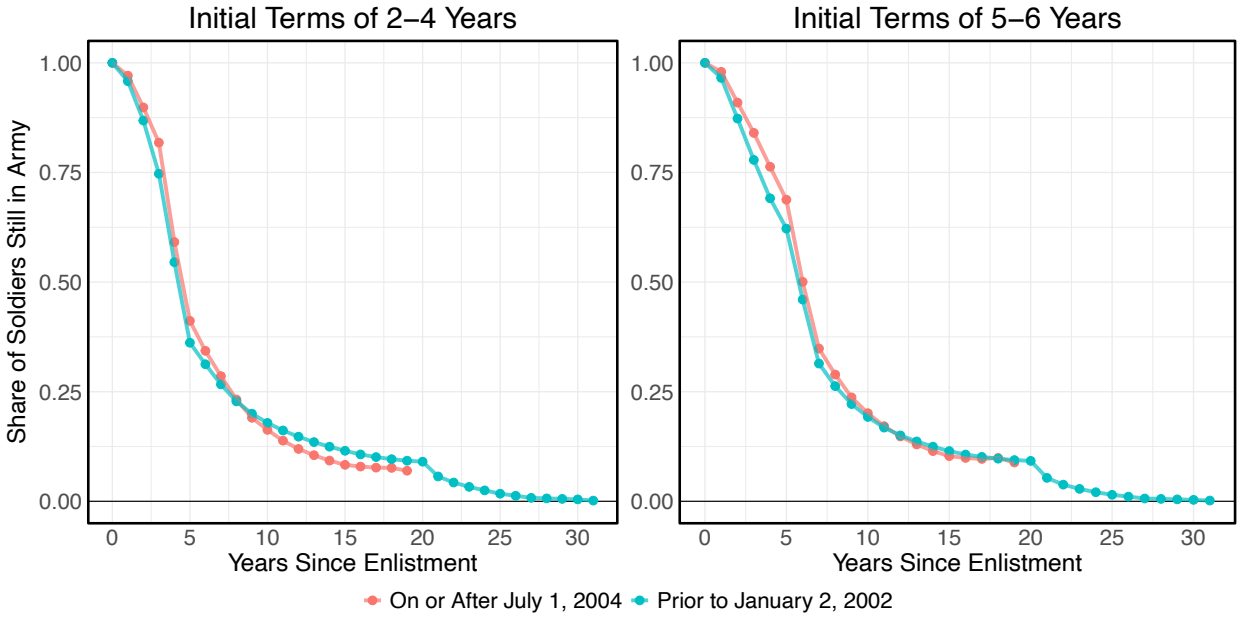
[42] Given that the underlying standard scores prior to 2002 are also generated from conversion tables and are discrete, there is no way to construct a more continuous line score. The AFQT score percentiles in all periods and the GT score post-2004, which is based off on only the sum of VE and AR, are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

[43] In practice many cutoffs either apply to very uncommon or small, singleton jobs, or apply to jobs for which another

B Appendix Figures and Tables

Appendix Figures

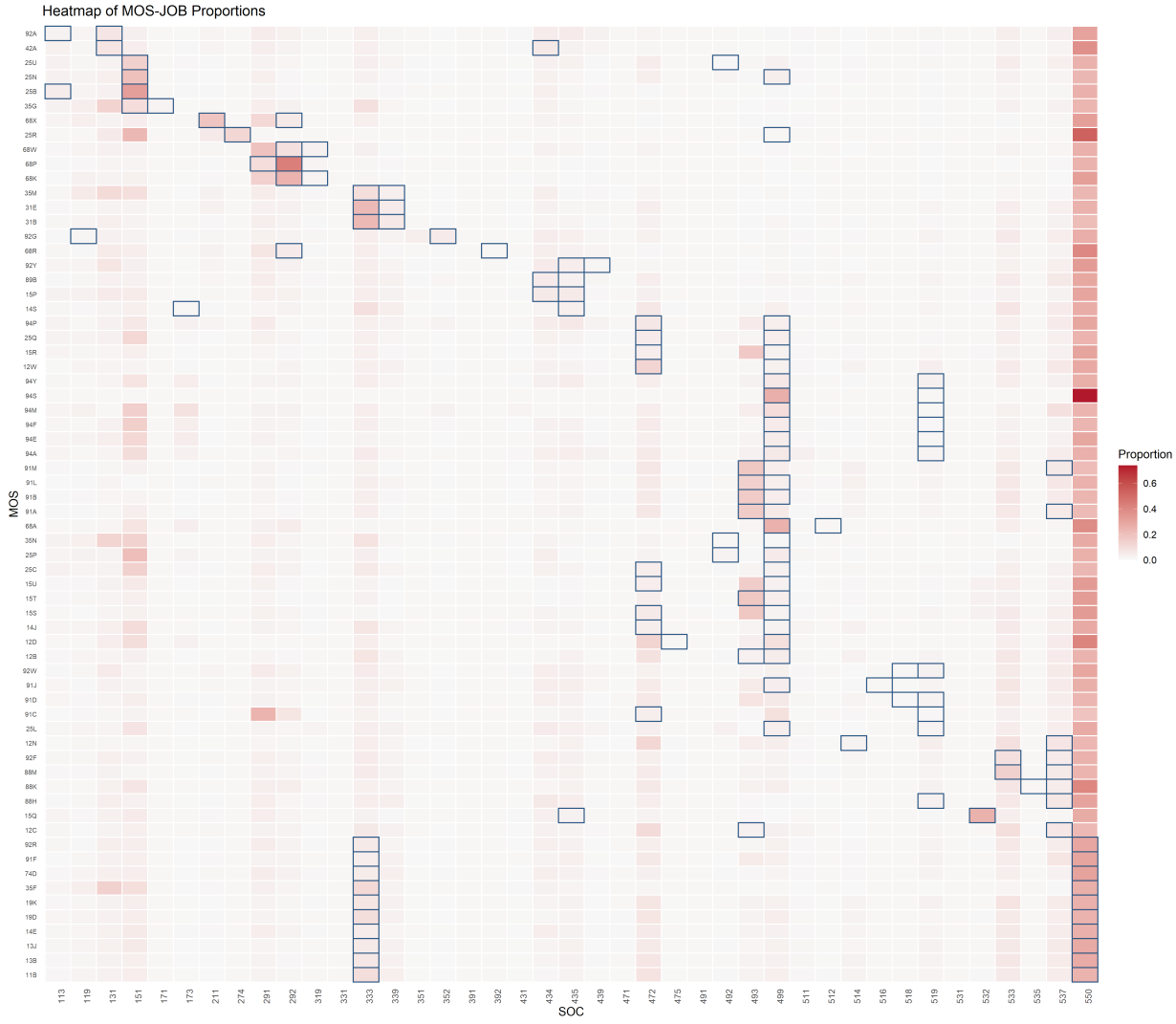
Figure B.1: Years in Army



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.

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.

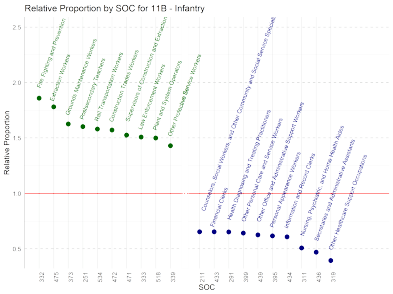
Figure B.2: Distribution of Occupations 15 Years Post-ASVAB by Entry MOS



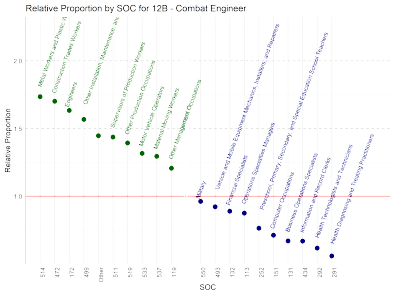
Notes: Each cell represents the proportion of Soldiers within that row's MOS who are in the corresponding SOC by 15 years after the ASVAB. The sample includes all enlisted soldiers in both the 1992-2001 and 2004-2014 samples. Cells outlined in blue indicate the primary and secondary SOC codes we have 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.

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

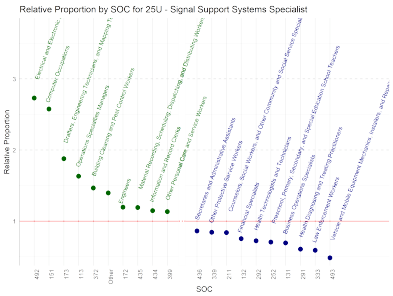
(a) 11B - Infantry



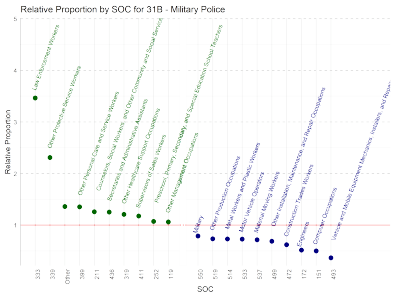
(b) 12B - Combat Engineer



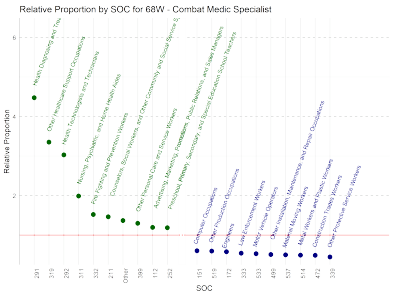
(c) 25U - Signal Support Specialist



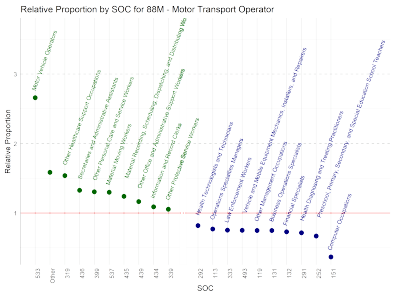
(d) 31B - Military Police



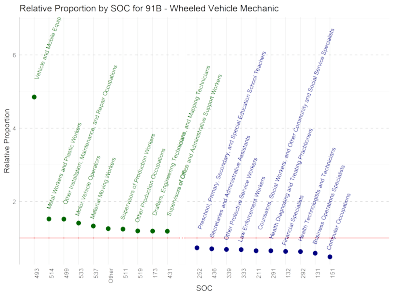
(e) 68W - Combat Medic Specialist



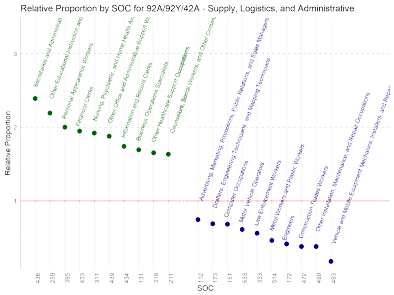
(f) 88M - Motor Transport Operator



(g) 91B - Wheeled Vehicle Mechanic



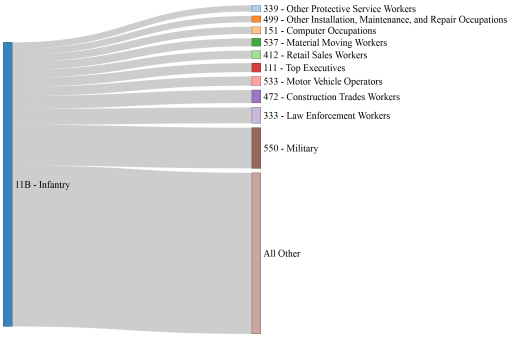
(h) 92A/92Y/42A - Logistics and HR



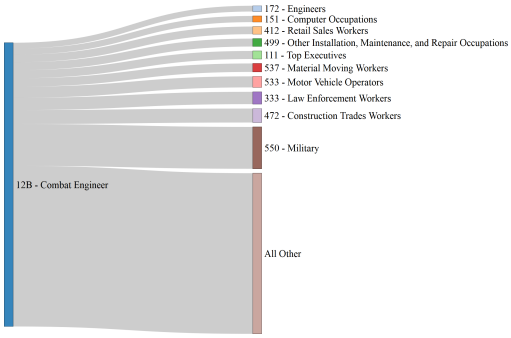
Notes: The relative proportions are calculated as (Fraction of MOS in SOC)/(Fraction of Sample in SOC), where the sample is all enlisted within our dataset, both from the 1992-2001 and 2004-2014 samples, and the SOC codes are measured as of 15 years after the ASVAB. This measure provides an easy view 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.

Figure B.4: Sankey Plots

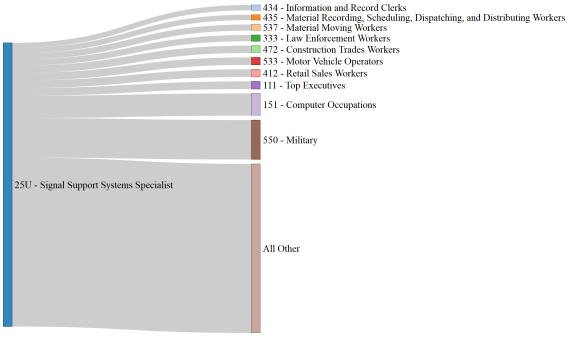
(a) 11B - Infantry



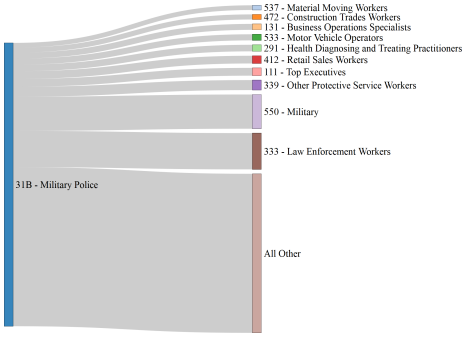
(b) 12B - Combat Engineer



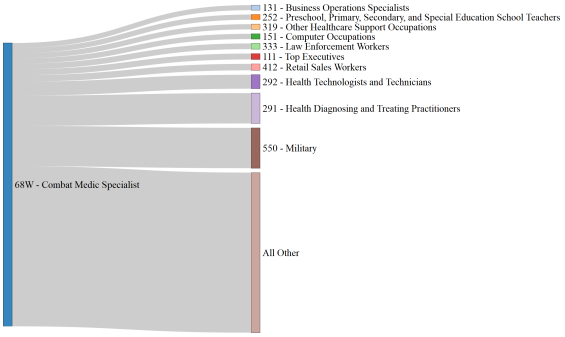
(c) 25U - Signal Support Specialist



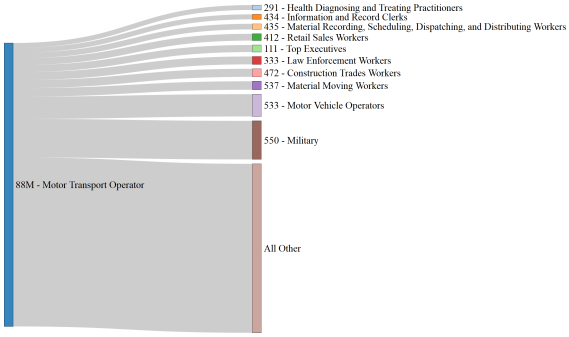
(d) 31B - Military Police



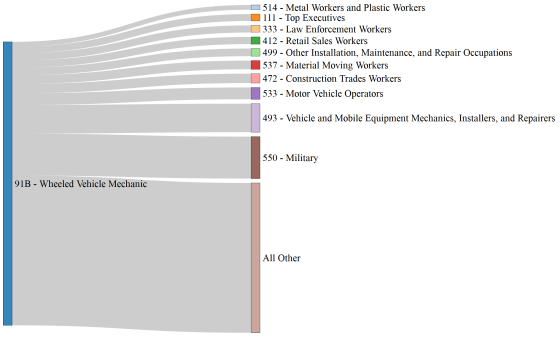
(e) 68W - Combat Medic Specialist



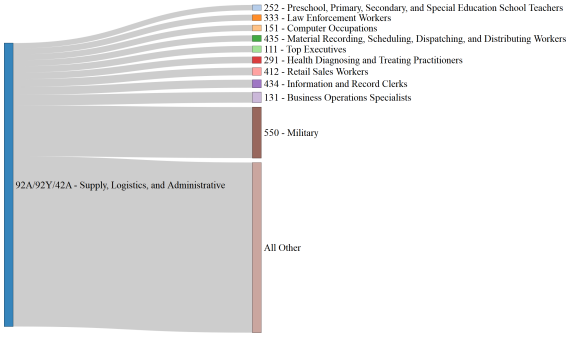
(f) 88M - Motor Transport Operator



(g) 91B - Wheeled Vehicle Mechanic

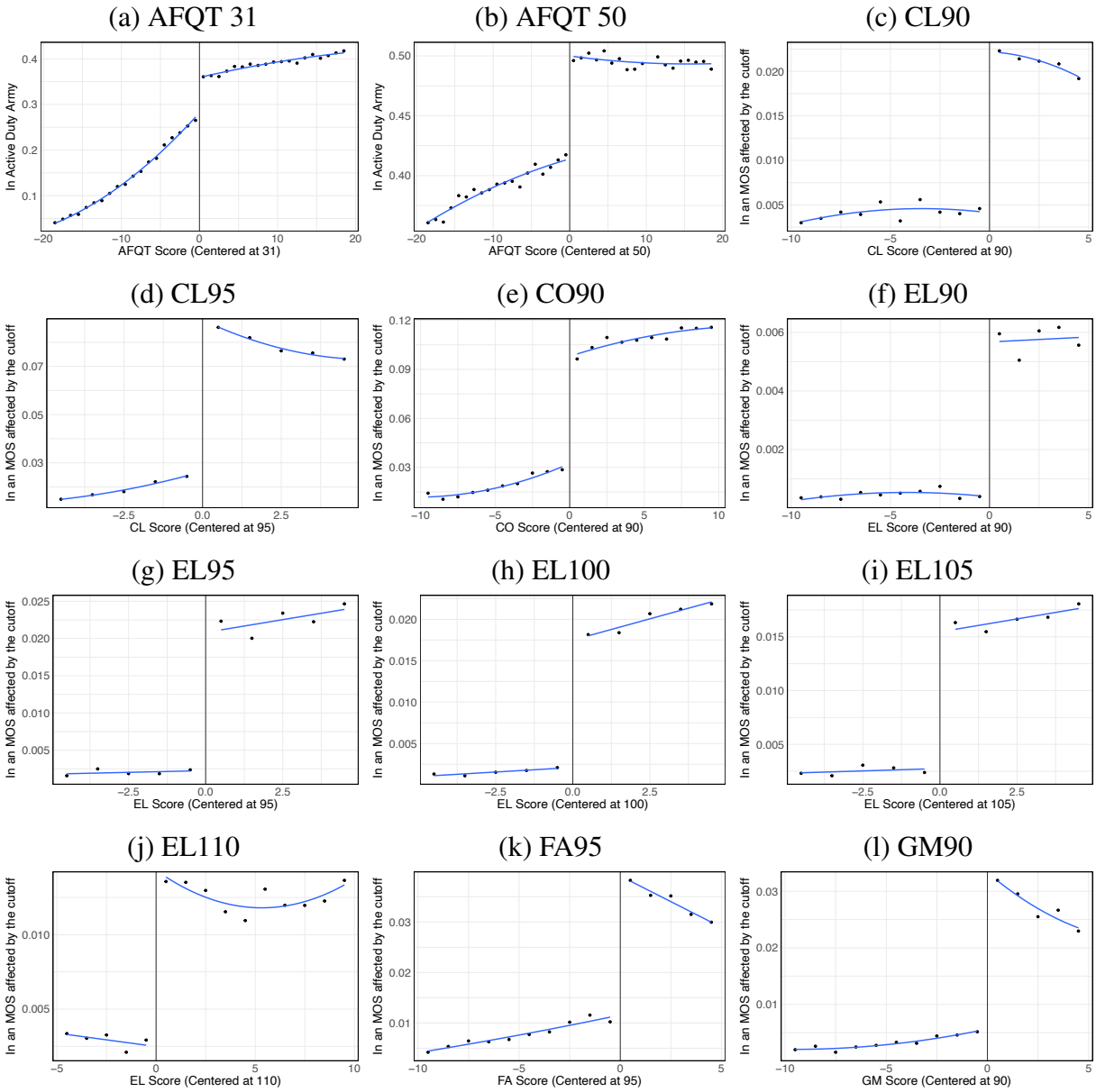


(h) 92A/92Y/42A - Logistics and HR



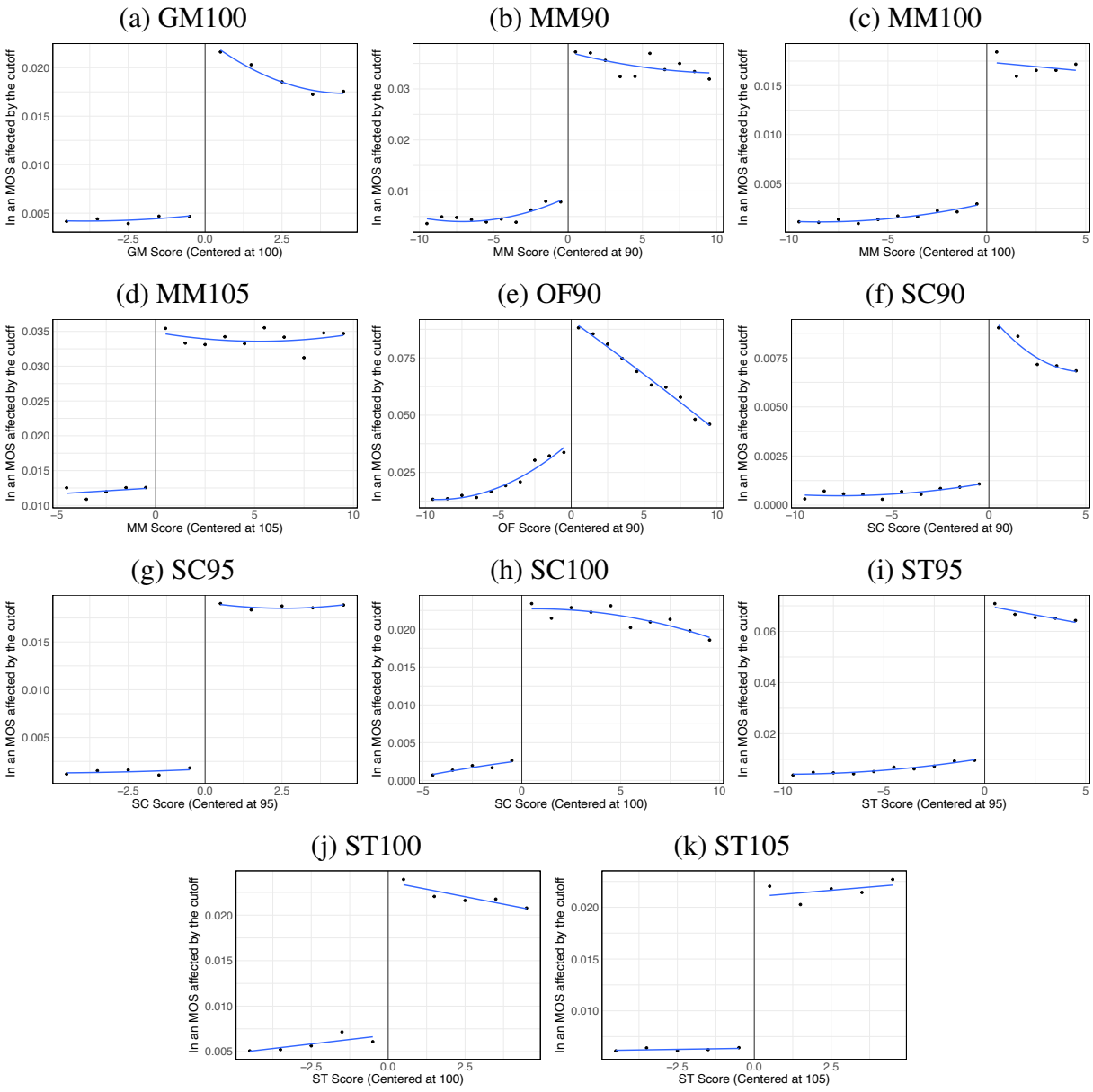
Notes: These plots demonstrate the distribution of jobs 11 years after enlistment for each MOS. The top 10 jobs for each MOS are shown, while all other jobs are grouped together. The sample combines both the 1992-2001 and 2004-2014 samples. Eventual occupations (three digit SOC) are measured as of 15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

Figure B.5: 1992-2001 First Stage Plots



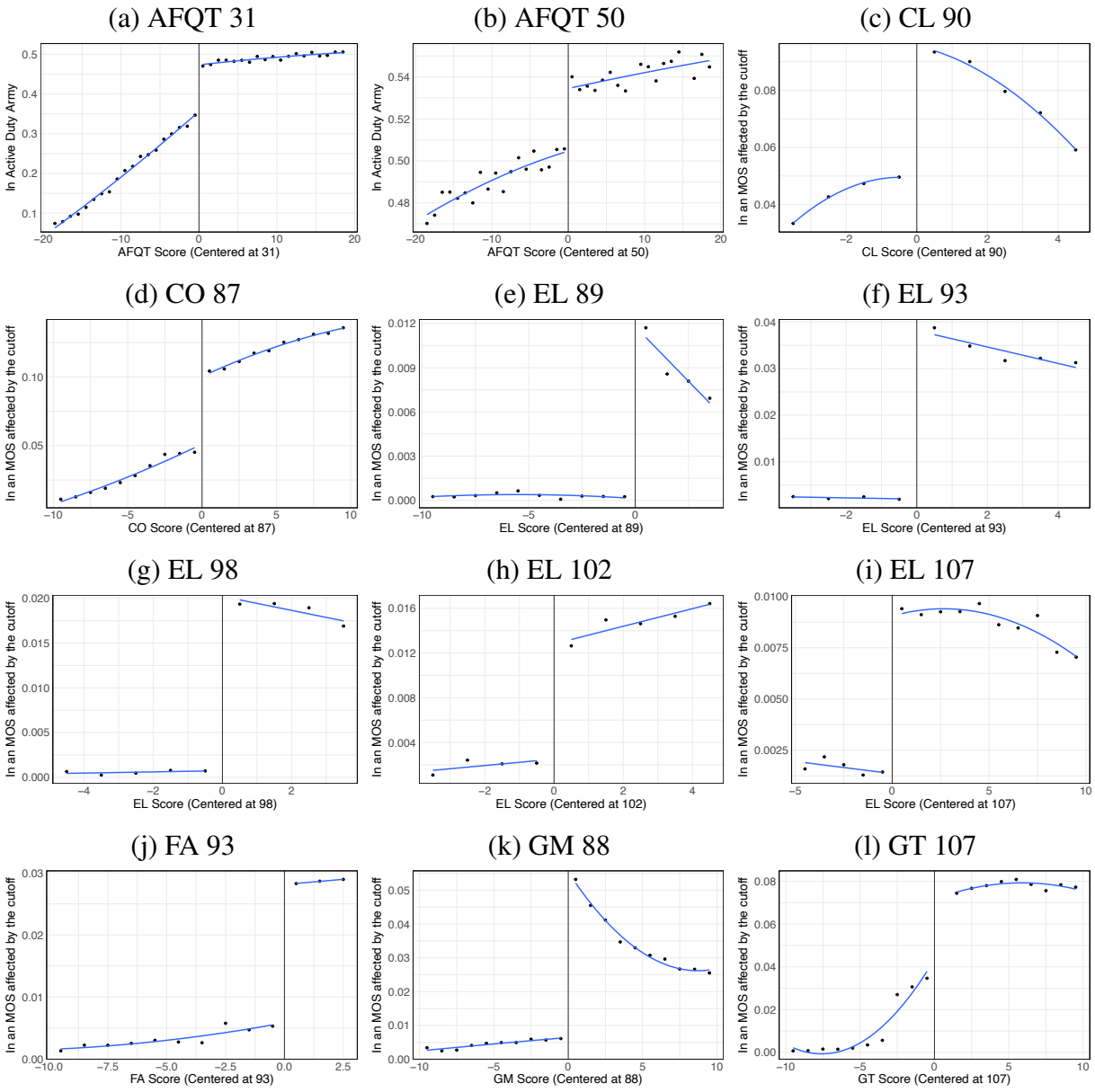
Notes: These figures depict the first stages around each 1992-2001 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table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

Figure B.6: 1992-2001 First Stage Plots



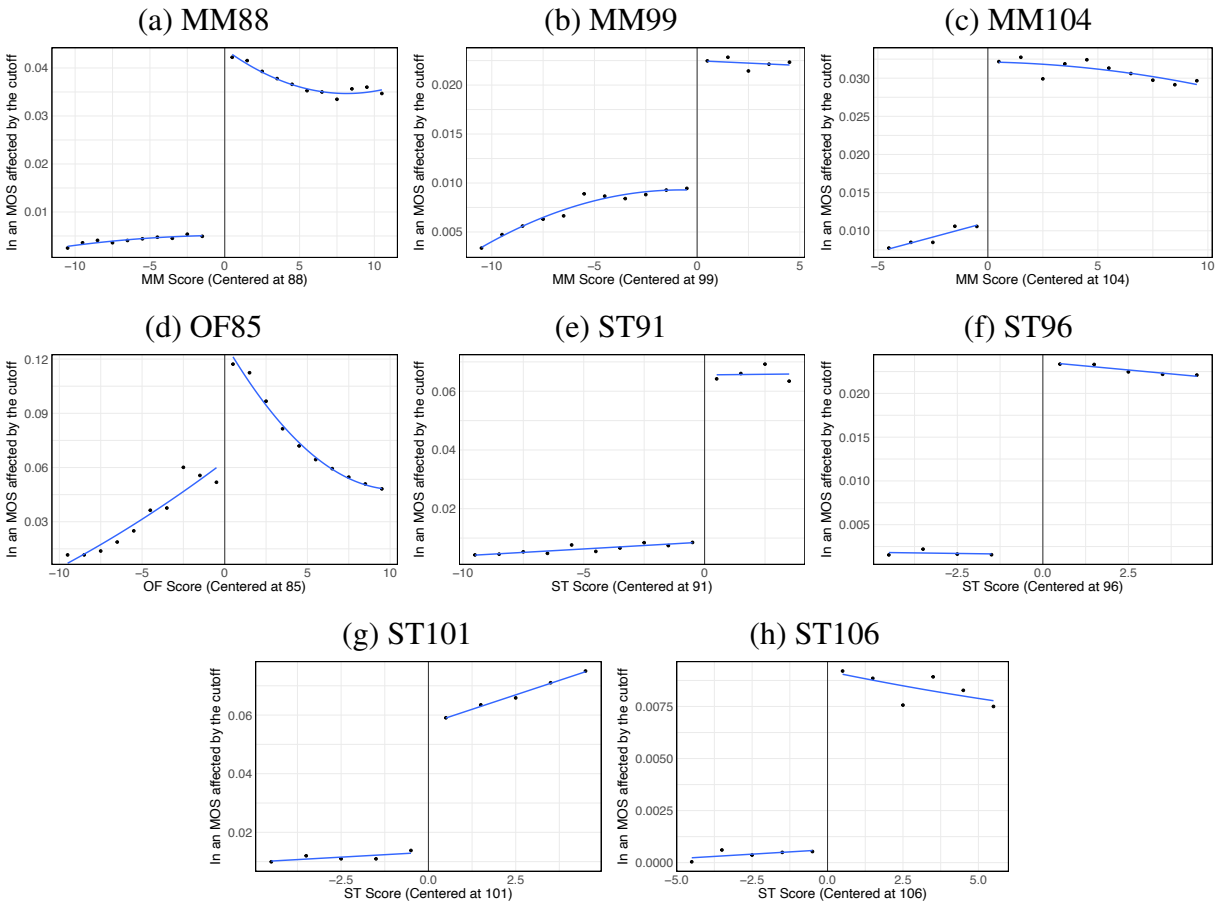
Notes: These figures depict the first stages around each 1992-2001 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table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

Figure B.7: 2004-2014 First Stage Plots



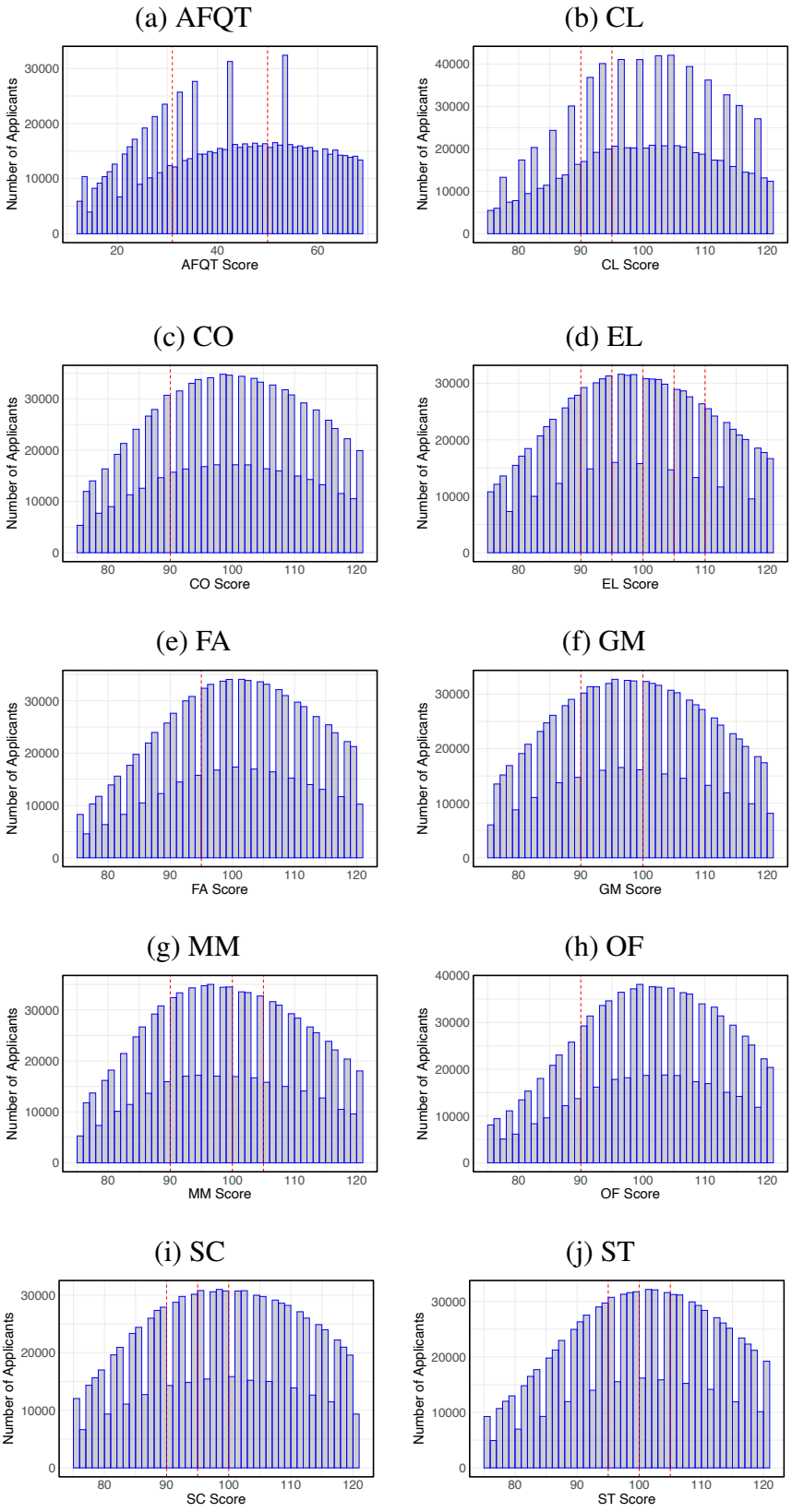
Notes: These figures depict the first stages around each 2004-2014 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table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

Figure B.8: 2004-2014 First Stage Plots



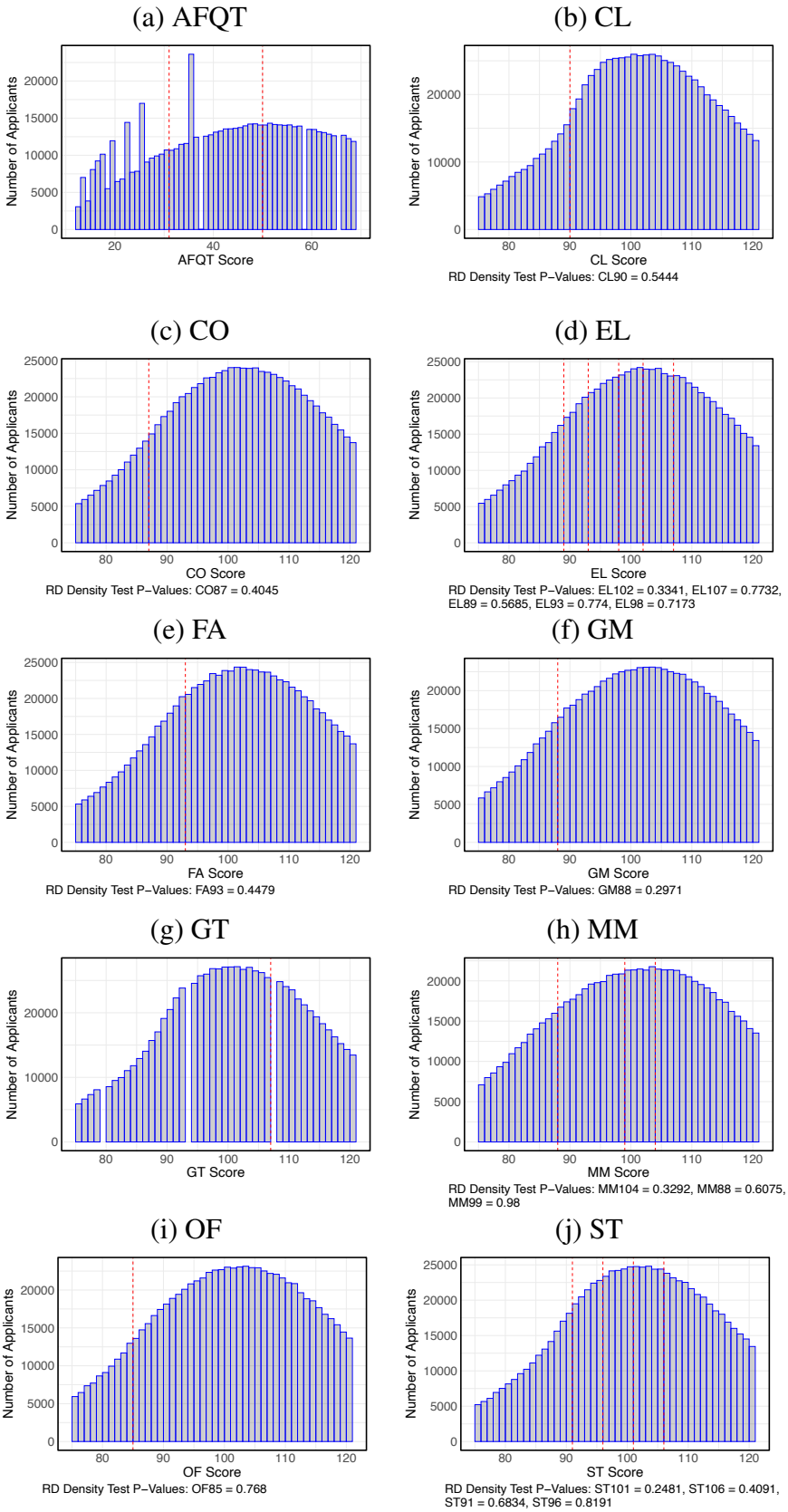
Notes: These figures depict the first stages around each 2004-2014 period cutoff. In each case, the y-axis represents the share of applicants who join an Army MOS that is affected by the given cutoff. Bandwidth and linear/quadratic fits follow our baseline specification. Estimates are reported in Table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

Figure B.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.

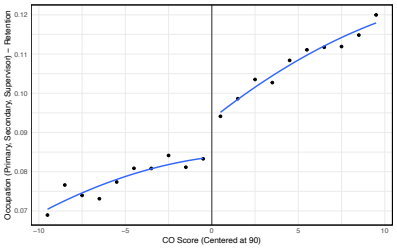
Figure B.10: 2004-2014 Density Plots



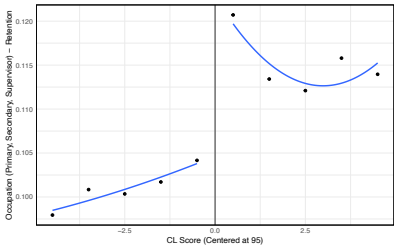
Notes: These figures show density plots for the 2004-2014 line scores. Red lines correspond to a cutoff used in our paper. For the densities that that have a non-discrete, non-lumpy running variable, we report the p-values from the Cattaneo et al. (2018) density test using their optimal bandwidth and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

Figure B.11: Reduced-Form Occ. Persistence Plots (Military & Civilian)

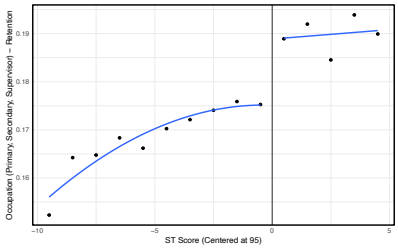
(a) CO90_pre



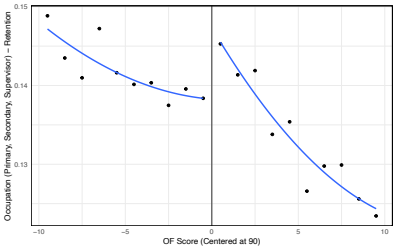
(b) CL95_pre



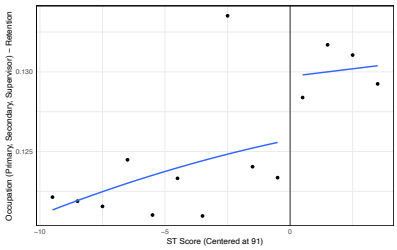
(c) ST95_pre



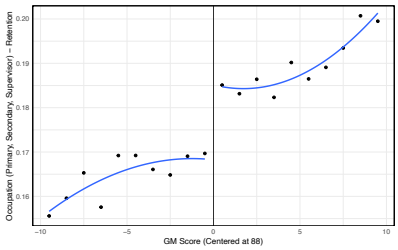
(d) OF90_pre



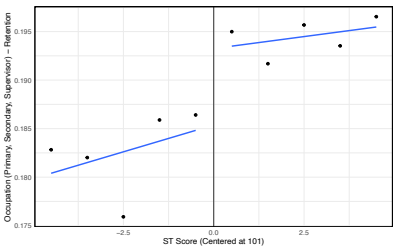
(e) ST91_post



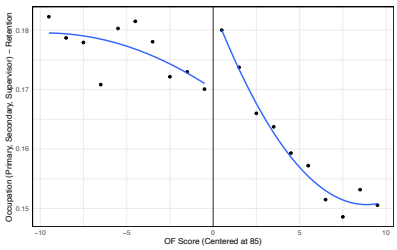
(f) GM88_post



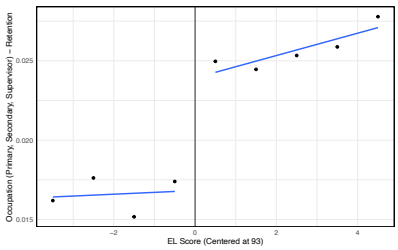
(g) ST101_post



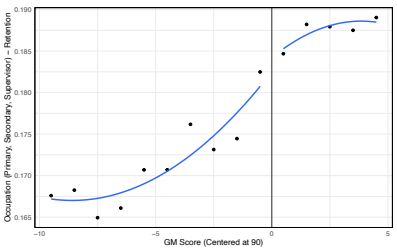
(h) OF85_post



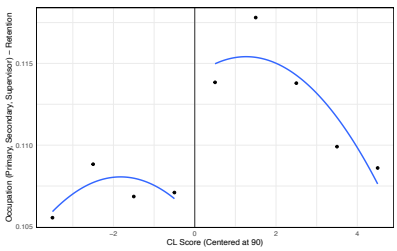
(i) EL93_post



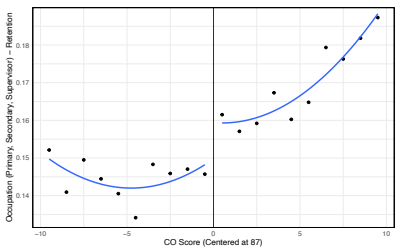
(j) GM90_pre



(k) CL90_post



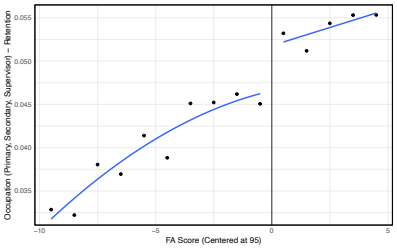
(l) CO87_post



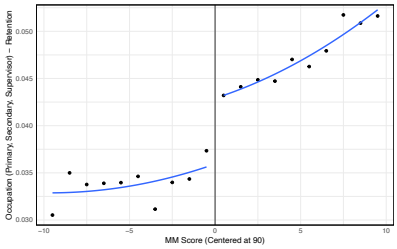
Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds. They are sorted by first stage for this 11-15 sample and show the top 20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

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

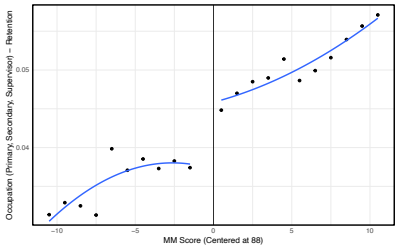
(a) FA95_pre



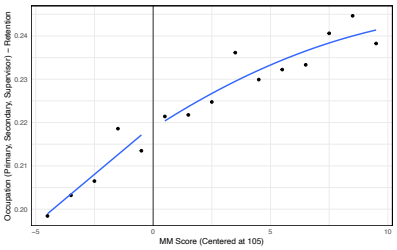
(b) MM90_pre



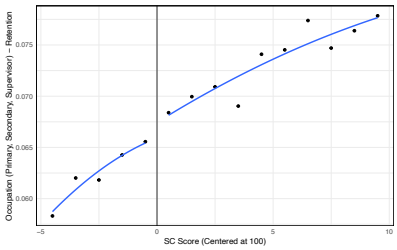
(c) MM88_post



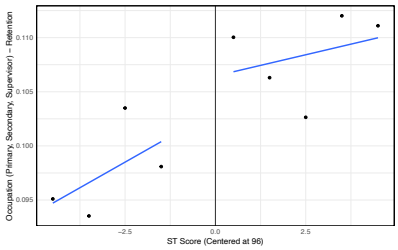
(d) MM105_pre



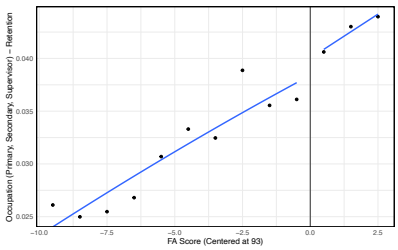
(e) SC100_pre



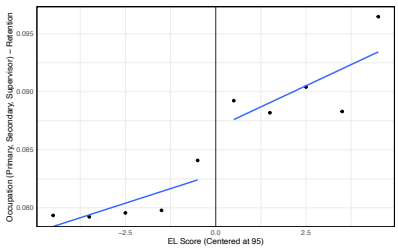
(f) ST96_post



(g) FA93_post



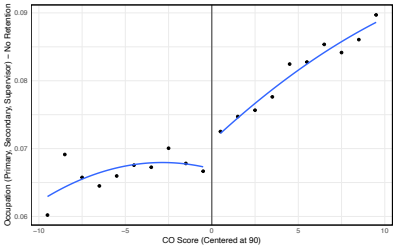
(h) EL95_pre



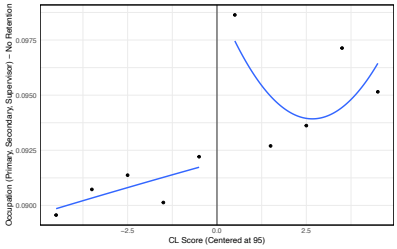
Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds. They are sorted by first stage for this 11-15 sample and show the top 20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

Figure B.13: Reduced-Form Occ. Persistence Plots (Civilian only)

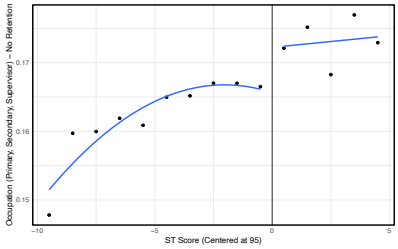
(a) CO90_pre



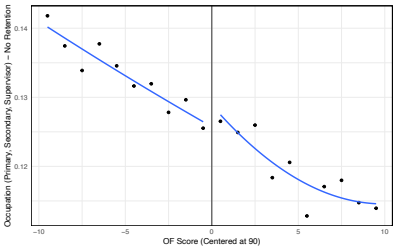
(b) CL95_pre



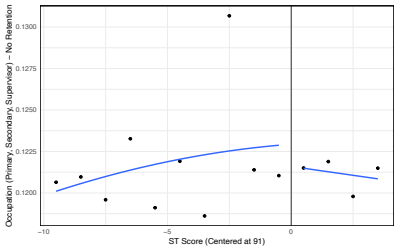
(c) ST95_pre



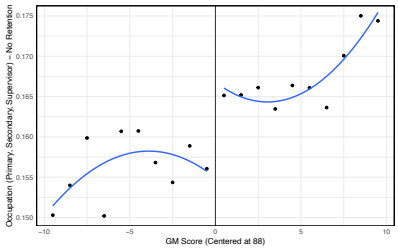
(d) OF90_pre



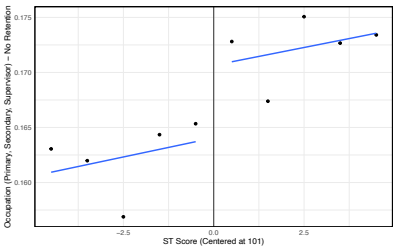
(e) ST91_post



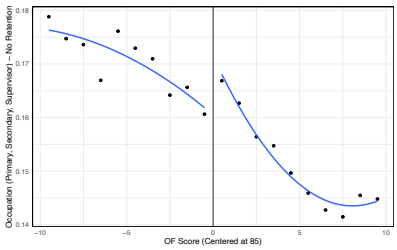
(f) GM88_post



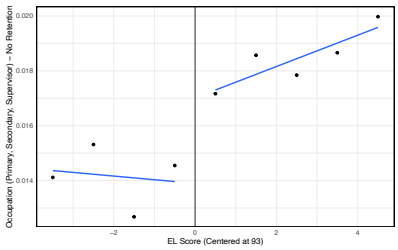
(g) ST101_post



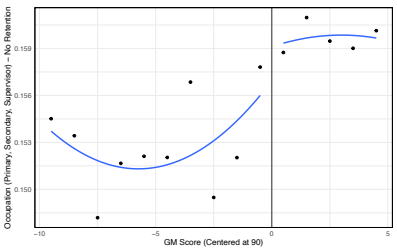
(h) OF85_post



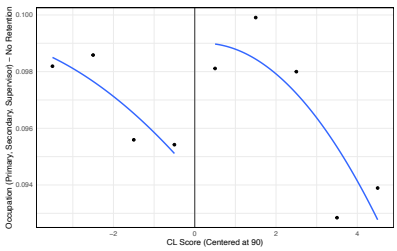
(i) EL93_post



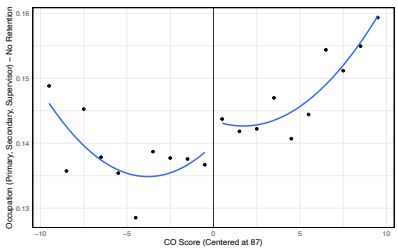
(j) GM90_pre



(k) CL90_post



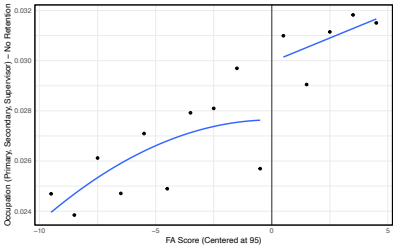
(l) CO87_post



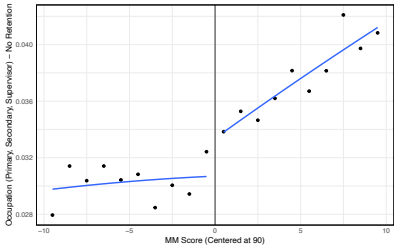
Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds, for persistence in civilian jobs only. They are sorted by first stage for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

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

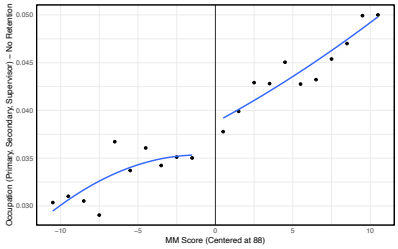
(a) FA95_pre



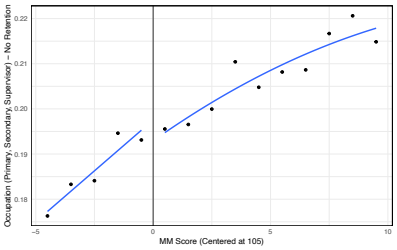
(b) MM90_pre



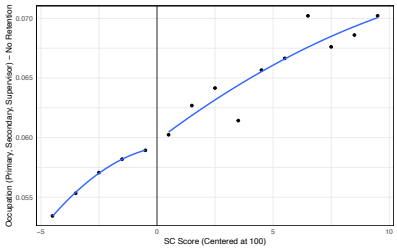
(c) MM88_post



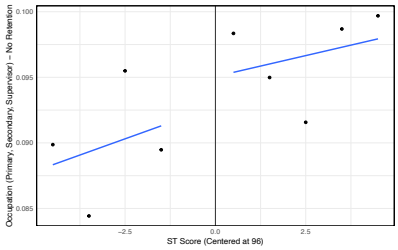
(d) MM105_pre



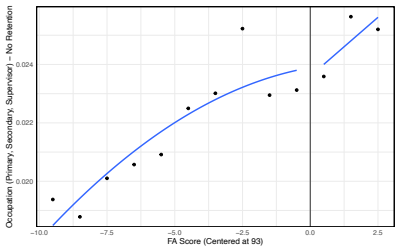
(e) SC100_pre



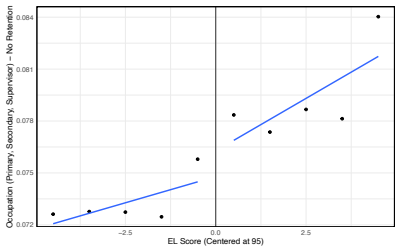
(f) ST96_post



(g) FA93_post

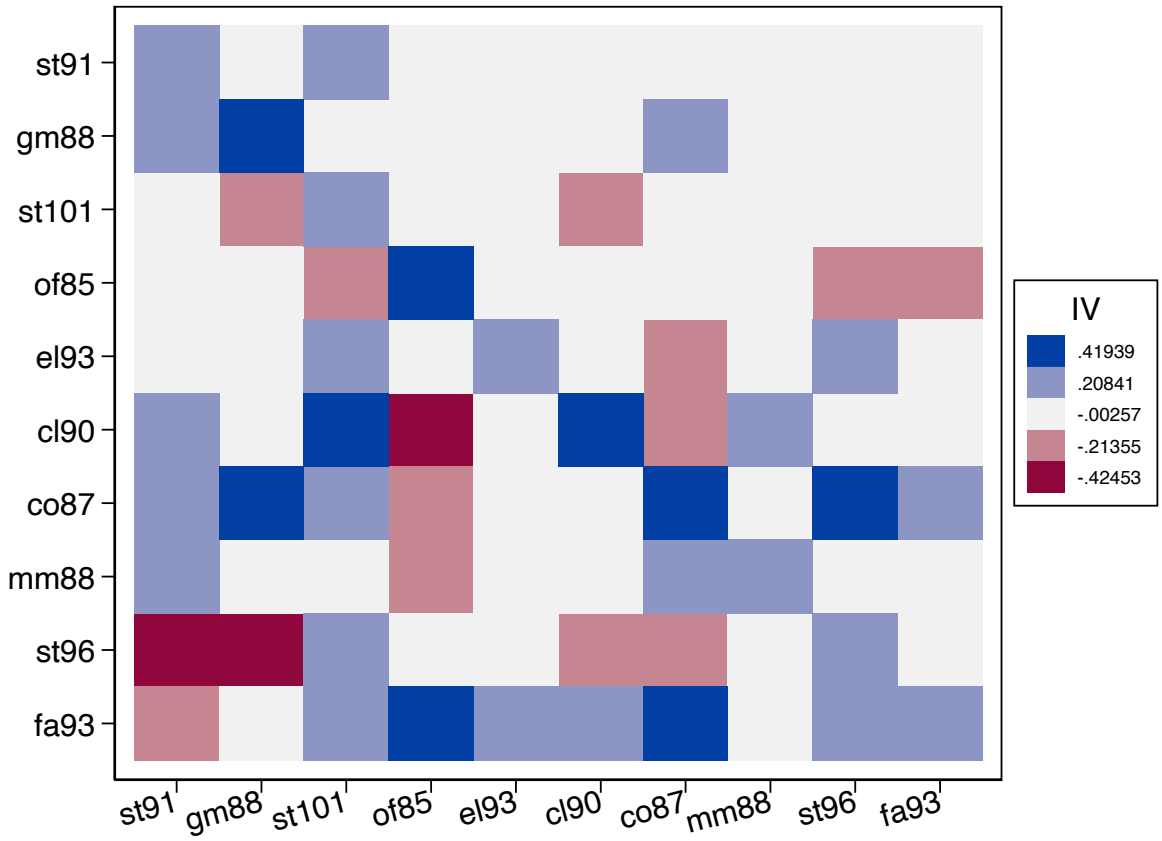


(h) EL95_pre



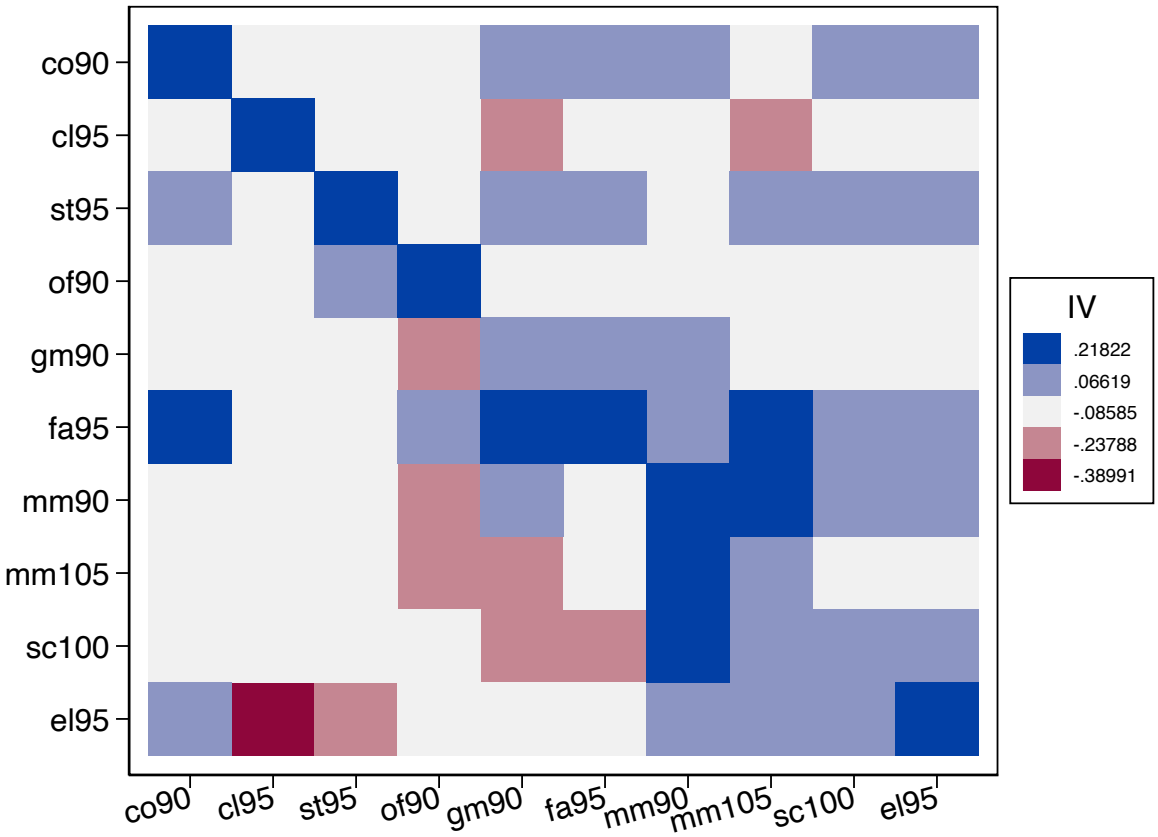
Notes: These figures show the reduced-form relationship between our occupational persistence outcome (share of years 11-15 that you are in one of the occupations linked to the cutoff by our crosswalk) and the various thresholds, for persistence in civilian jobs only. They are sorted by first stage for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

Figure B.15: 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 2 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 B.16 shows the analogous set of results for the top ten 1992-2011 cutoffs.

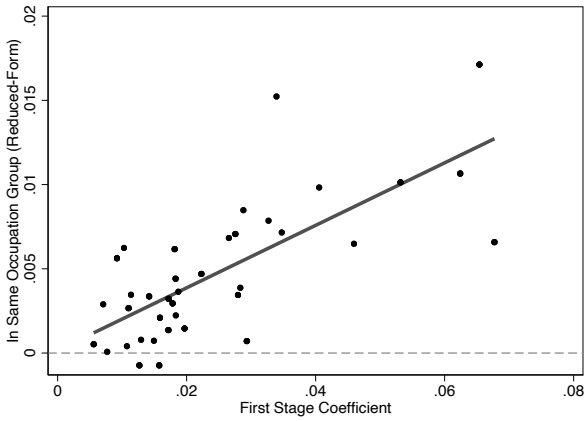
Figure B.16: Heatmap of IV effects on Occupation Groups (1992-2001)



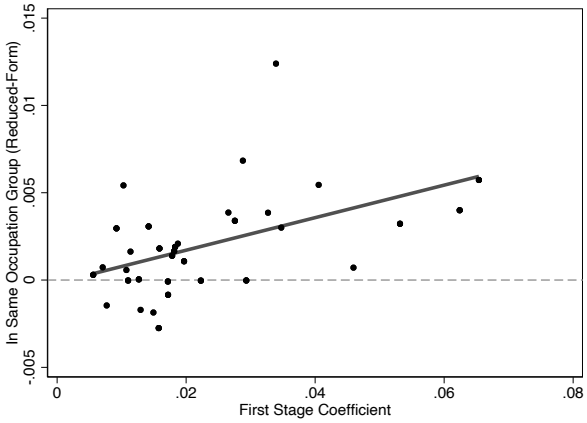
Notes: The heatmap is the 1992-2001 analogue of Figure B.15. It depicts IV effects on being in a given occupation group 11-15 years post-AFQT for the ten 1992-2001 cutoffs with the largest first stages. The diagonal shows persistence in the focal occupations (i.e. the estiamtes plotted in Figure 2 panel (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).

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

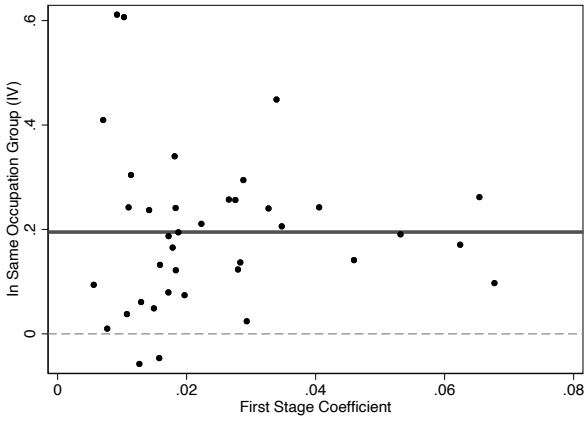
(a) Military + civilian occupations (V-IV)



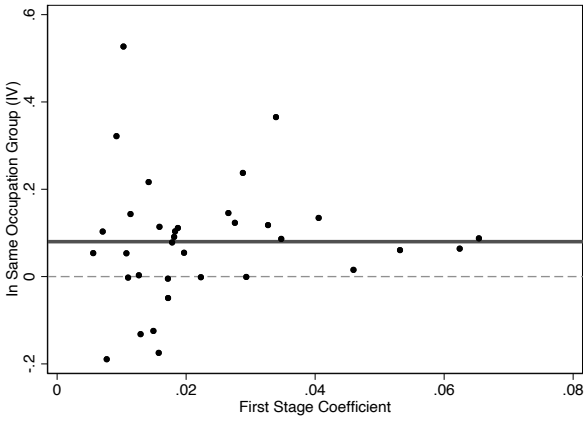
(b) Civilian occupations only (V-IV)



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



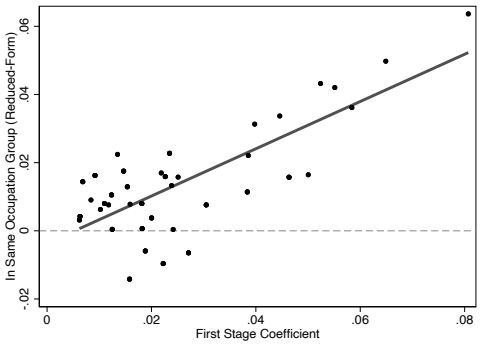
(d) civilian occupations (mean-IV)



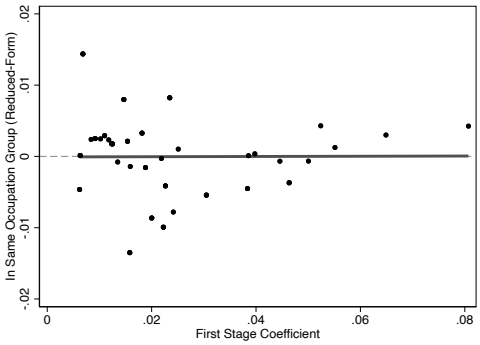
Notes: These figures are analogous to those in Figure 2 except that we now construct the outcome — in the focal occupation group — using only on the primary three digit SOC (and corresponding supervisor SOC) in our crosswalk (as opposed to any of the primary, secondary, or corresponding supervisory SOCs).

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

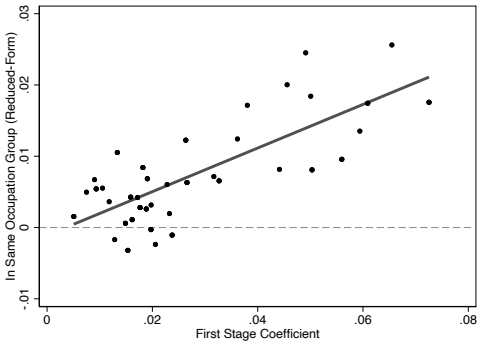
(a) 1-5, Mil. & Civ.



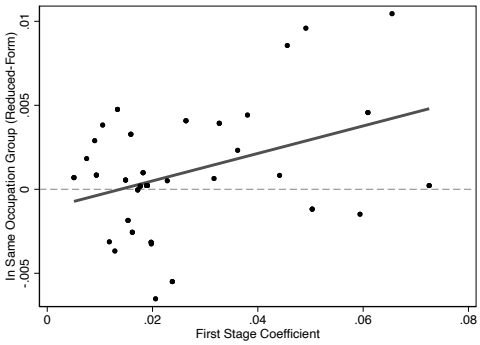
(b) 1-5, Civ. only



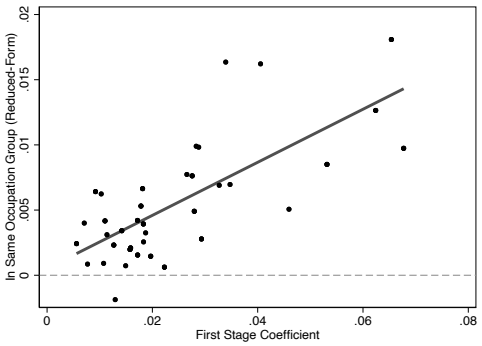
(c) 6-10, Mil. & Civ.



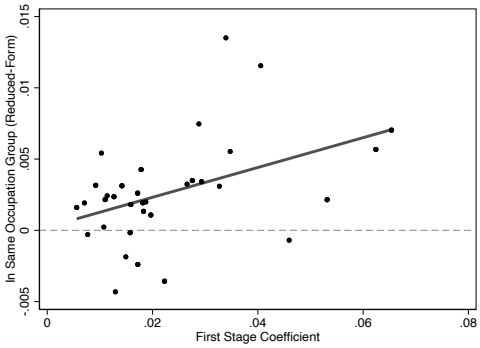
(d) 6-10, Civ. only



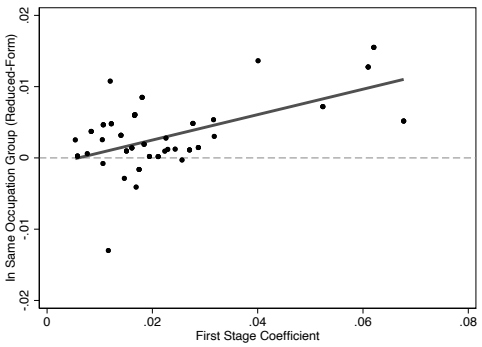
(e) 11-15, Mil. & Civ.



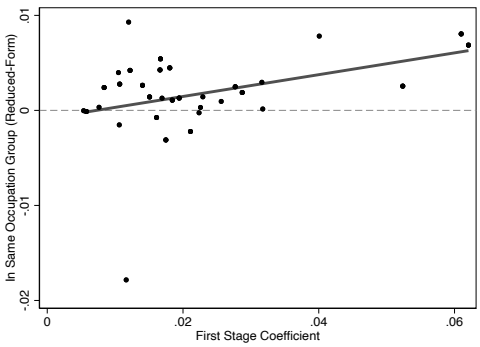
(f) 11-15, Civ. only



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



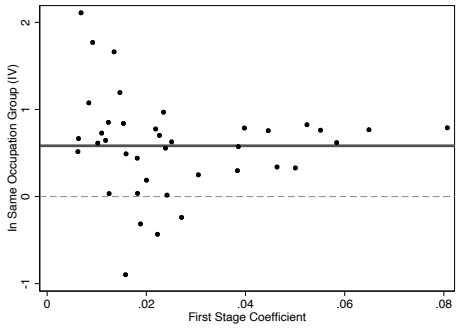
(g) 16-20, Civ. only



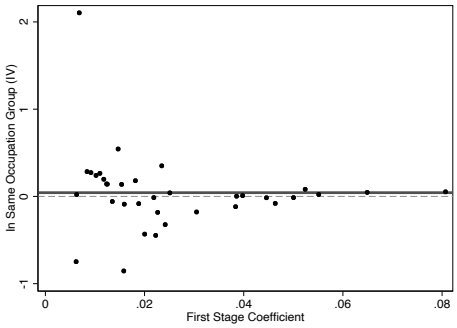
Notes: This figure reports the analogous V-IV figures from Figure 2 panels (a) and (b) for all the different time horizons: 1-5, 6-10, 11-15, and 6-20 years after ASVAB.

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

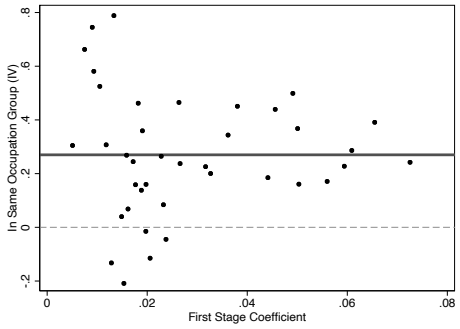
(a) 1-5, Mil. & Civ.



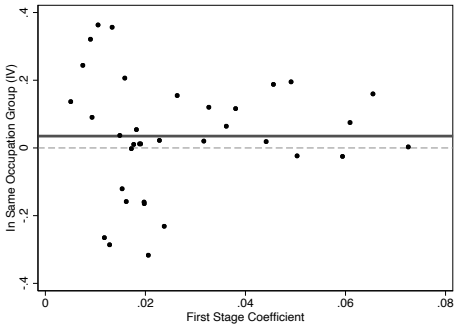
(b) 1-5, Civ. only



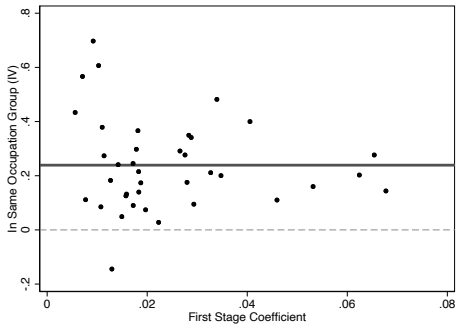
(c) 6-10, Mil. & Civ.



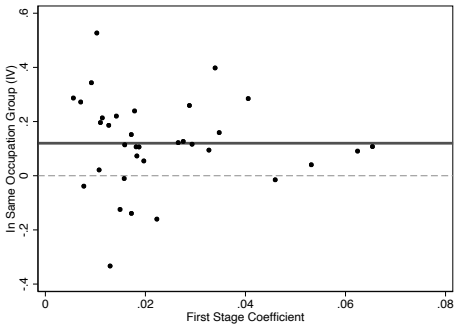
(d) 6-10, Civ. only



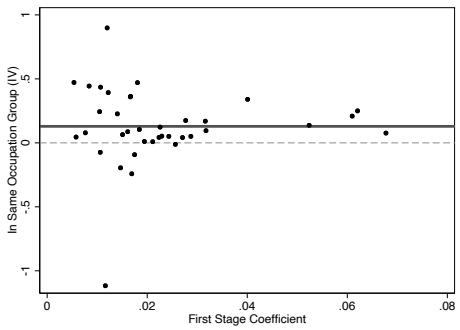
(e) 11-15, Mil. & Civ.



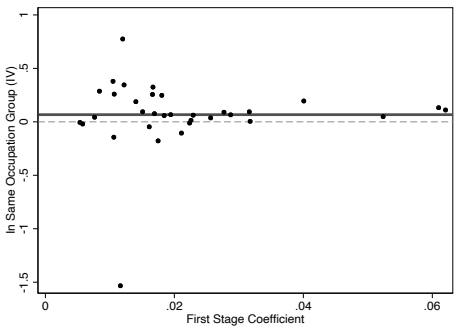
(f) 11-15, Civ. only



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



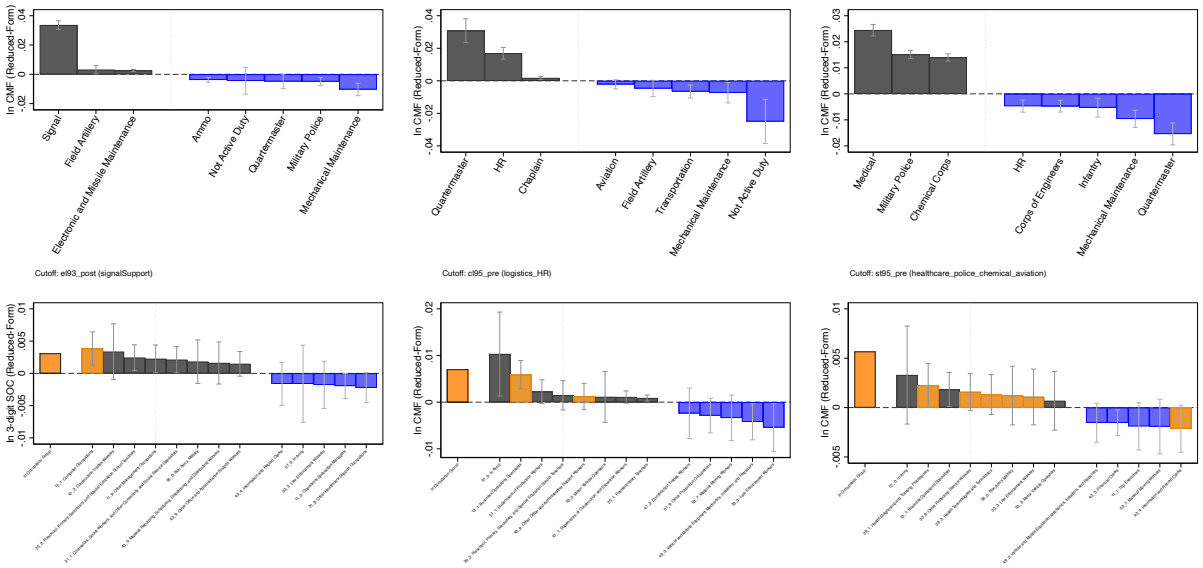
(h) 16-20, Civ. only



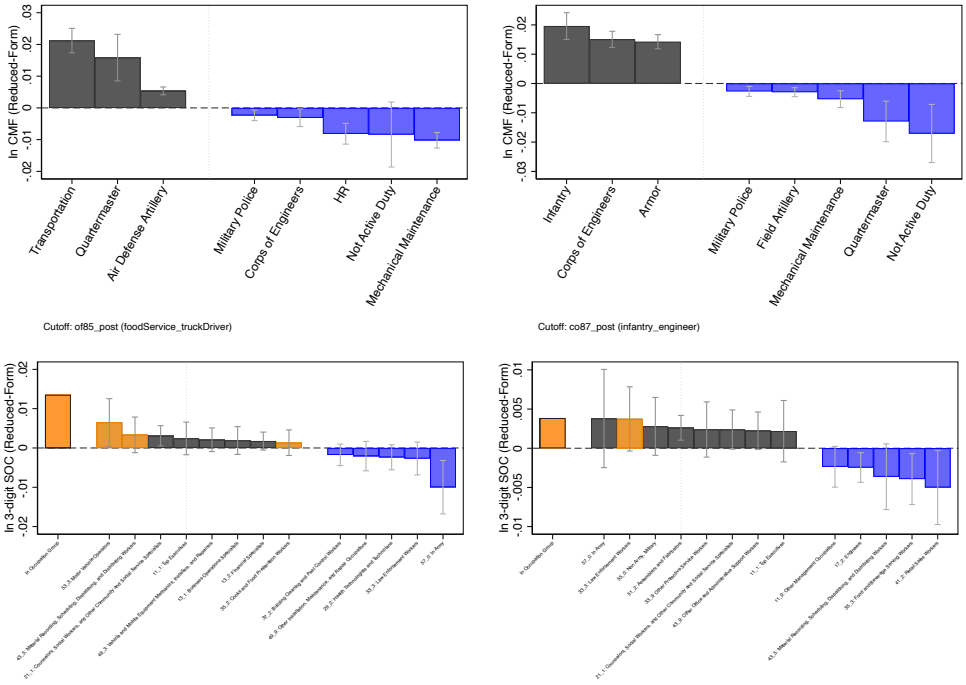
Notes: This figure reports the analogous mean-IV figures from Figure 2 panels (c) and (d) for all the different time horizons: 1-5, 6-10, 11-15, and 6-20 years after ASVAB.

Figure B.20: Case Studies

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



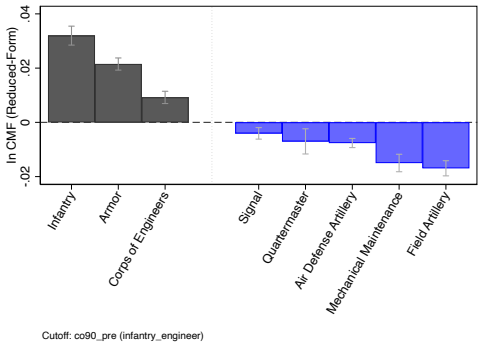
(d) Transport, Food (OF85_post) (e) Infantry/Eng./Armor (CO87_post)



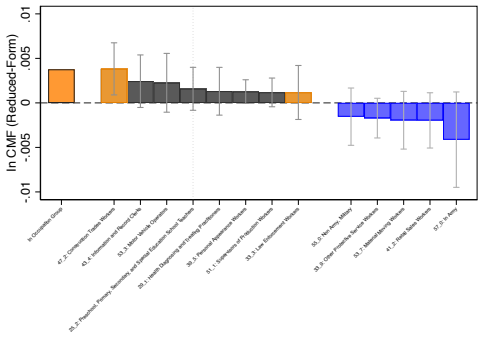
Notes: Each panel of this figure focuses on a different cutoff and shows two subfigures. The first plots top 3 and bottom 5 reduced-form effects of crossing the threshold on various military CMFs, to show which job groups enlistees are pulled from. The bottom subfigure in each panel plots reduced-form 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).

Figure B.21: Additional Case Studies (1)

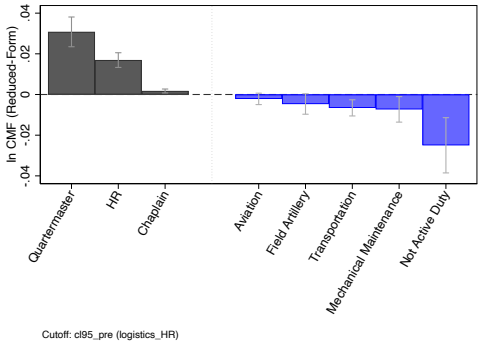
(a) CO90 Pre (CMFS)



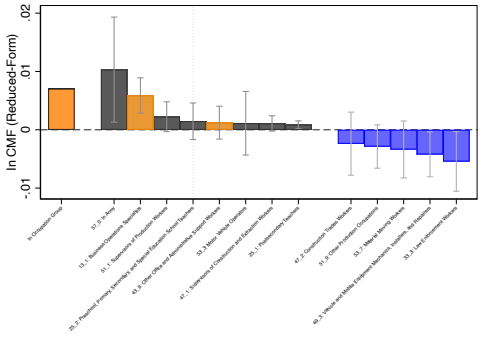
(b) CO90 Pre (SOCS)



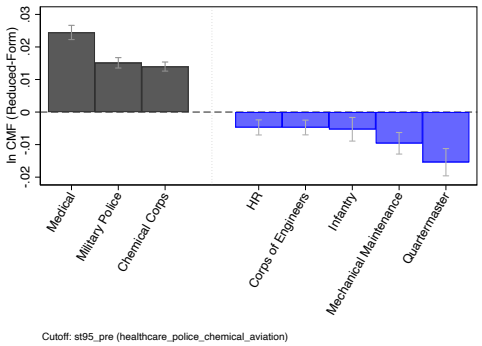
(c) CL95 Pre (CMFS)



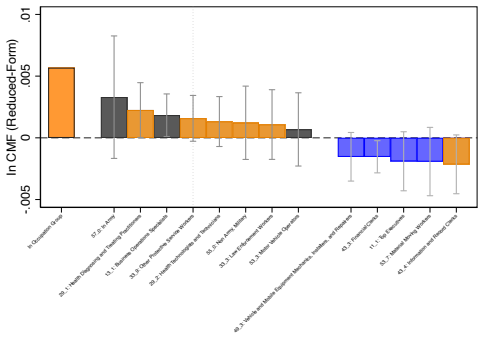
(d) CL95 Pre (SOCS)



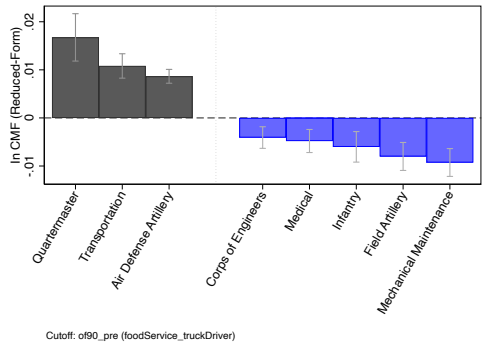
(e) ST95 Pre (CMFS)



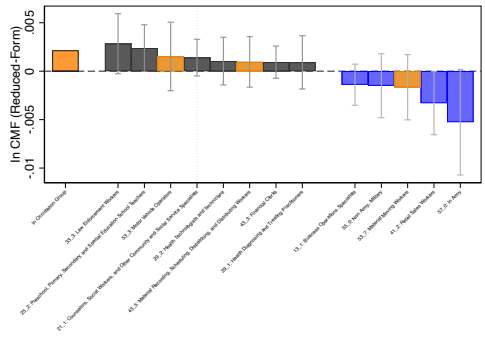
(f) ST95 Pre (SOCS)



(g) OF90 Pre (CMFS)



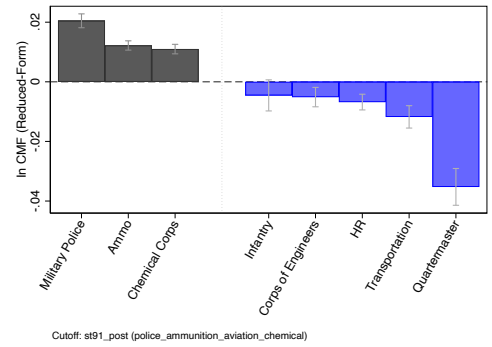
(h) OF90 Pre (SOCS)



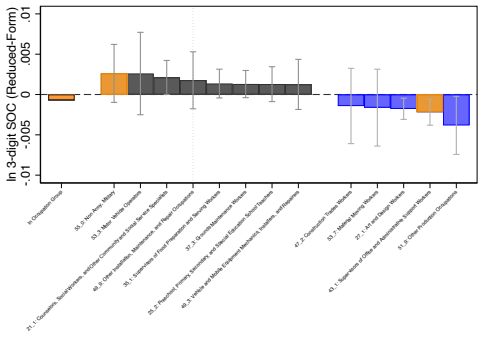
Notes: These figures plot the same exhibits as in figure B.20 for different cutoffs. See notes to that exhibit for details.

Figure B.22: Additional Case Studies (2)

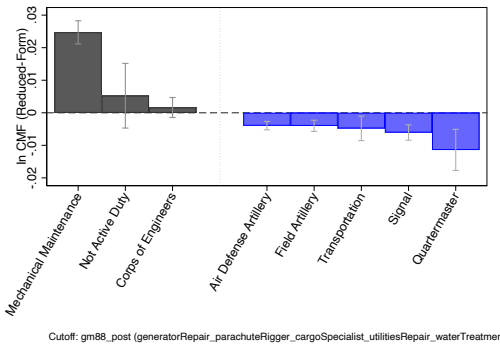
(a) ST91 Post (CMFS)



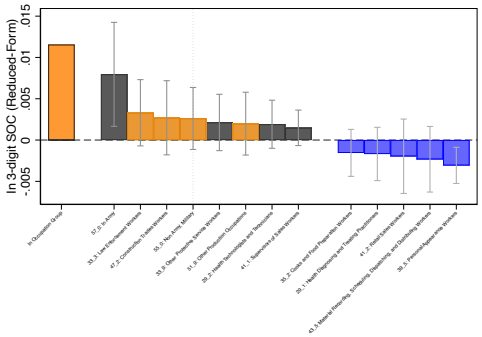
(b) ST91 Post (SOCS)



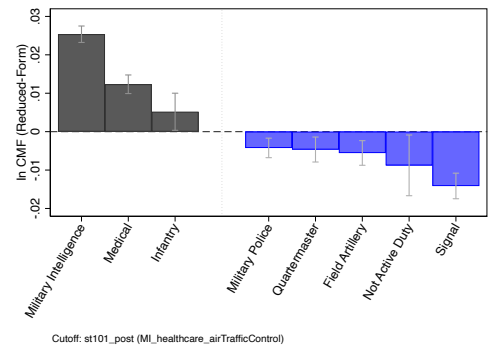
(c) GM 88 Post (CMFS)



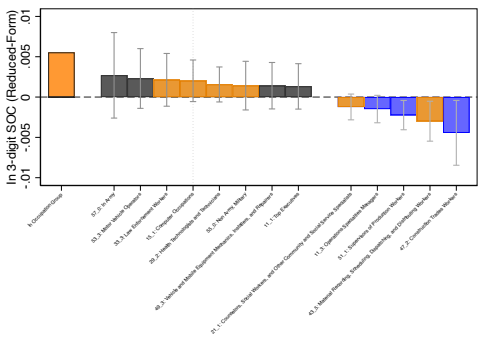
(d) GM 88 Post (SOCS)



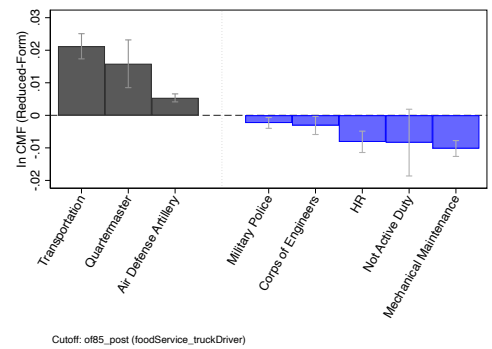
(e) ST 101 Post (CMFS)



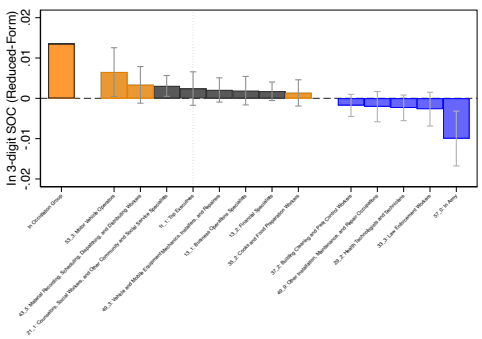
(f) ST 101 Post (SOCS)



(g) OF 85 Post (CMFS)



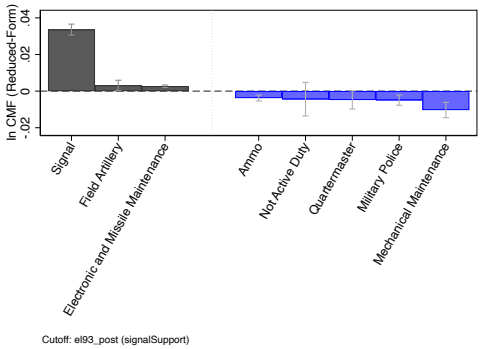
(h) OF 85 Post (SOCS)



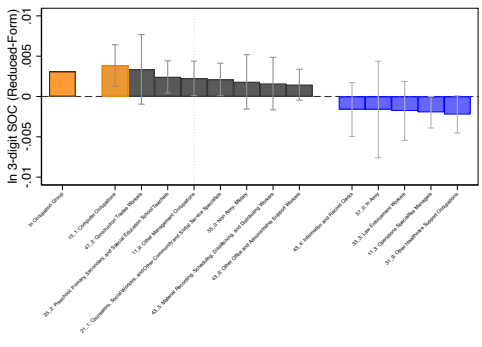
Notes: These figures plot the same exhibits as in figure B.20 for different cutoffs. See notes to that exhibit for details.

Figure B.23: Additional Case Studies (3)

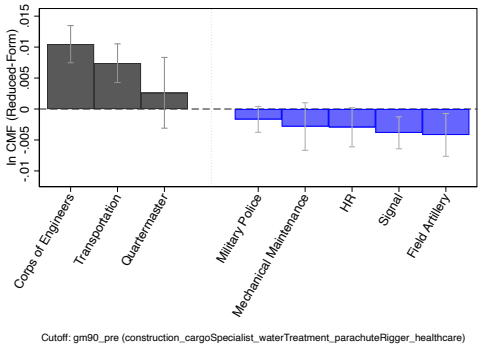
(a) El93 Post (CMFS)



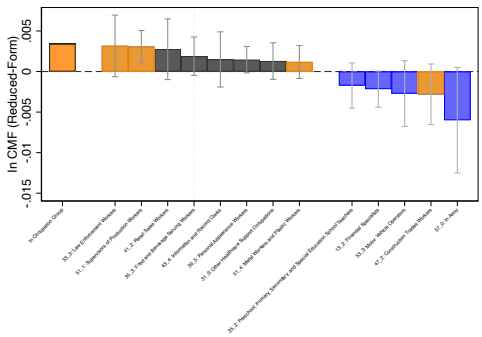
(b) El93 Post (SOCS)



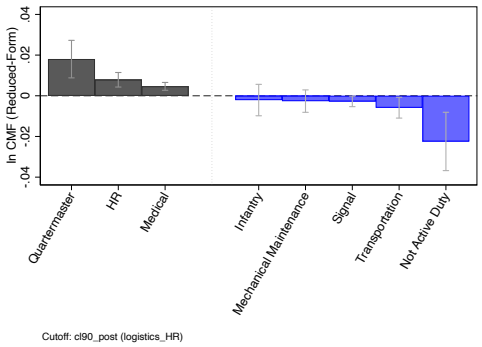
(c) GM90 Pre (CMFS)



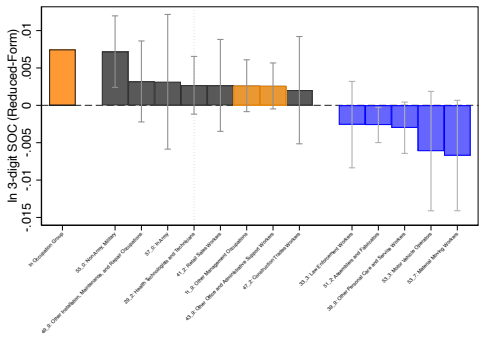
(d) GM90 Pre (SOCS)



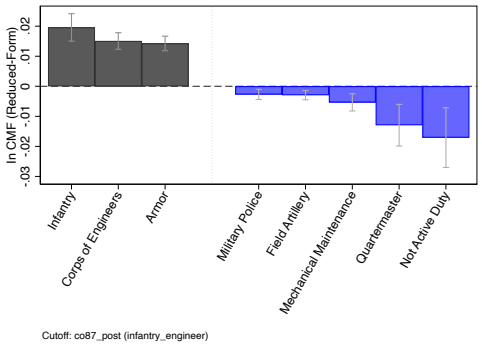
(e) CL90 Post (CMFS)



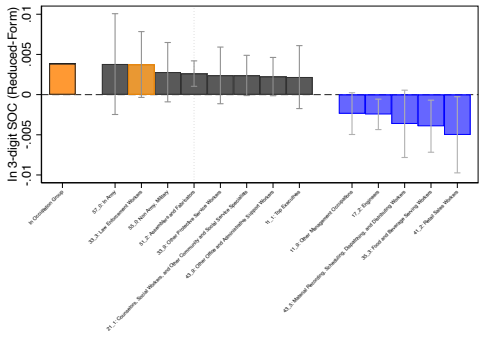
(f) CL90 Post (SOCS)



(g) CO87 Post (CMFS)



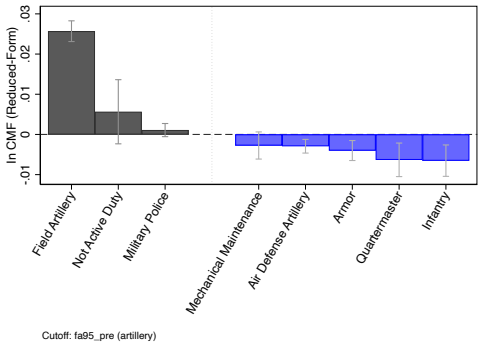
(h) CO87 Post (SOCS)



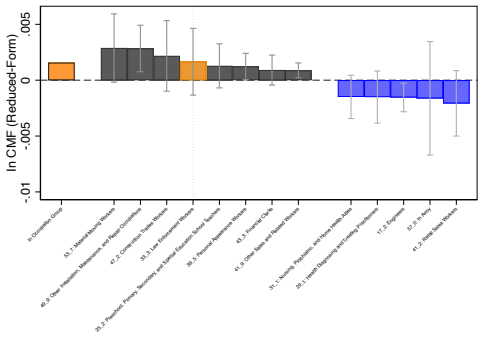
Notes: These figures plot the same exhibits as in figure B.20 for different cutoffs. See notes to that exhibit for details.

Figure B.24: Additional Case Studies (4)

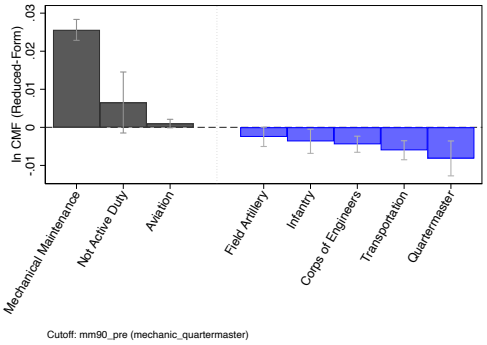
(a) FA95 Pre (CMFS)



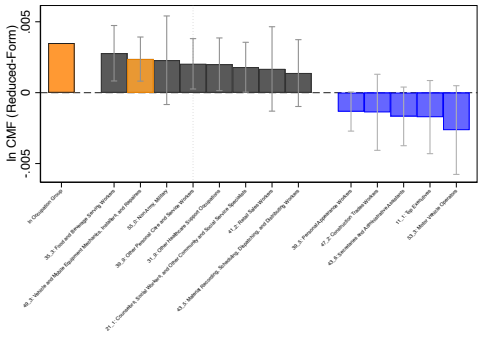
(b) FA95 Pre (SOCS)



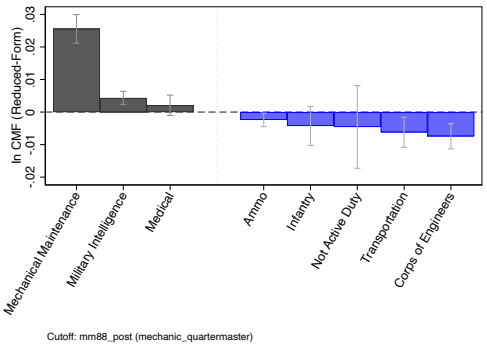
(c) MM90 Pre (CMFS)



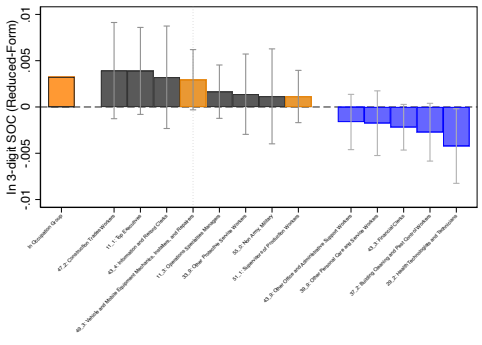
(d) MM90 Pre (SOCS)



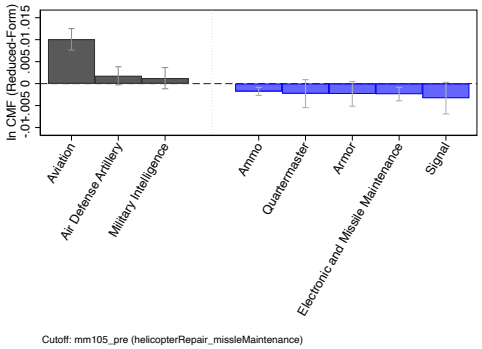
(e) MM88 Post (CMFS)



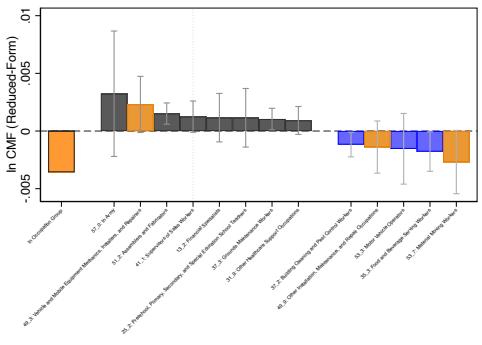
(f) MM88 Post (SOCS)



(g) MM105 Pre (CMFS)



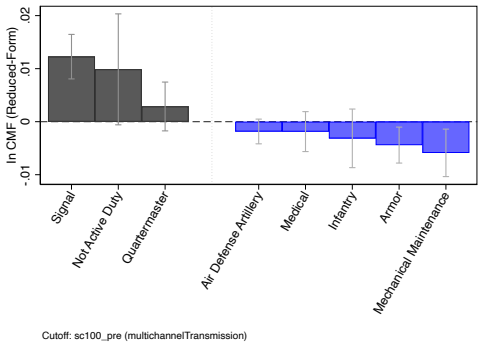
(h) MM105 Pre (SOCS)



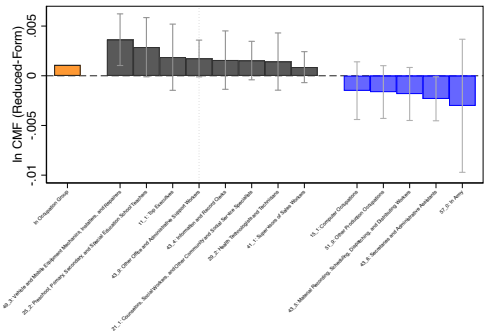
Notes: These figures plot the same exhibits as in figure B.20 for different cutoffs. See notes to that exhibit for details.

Figure B.25: Additional Case Studies (5)

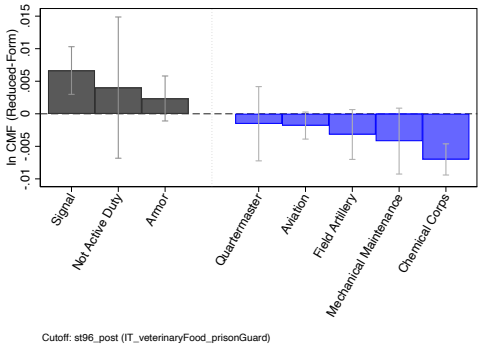
(a) SC100 Pre (CMFS)



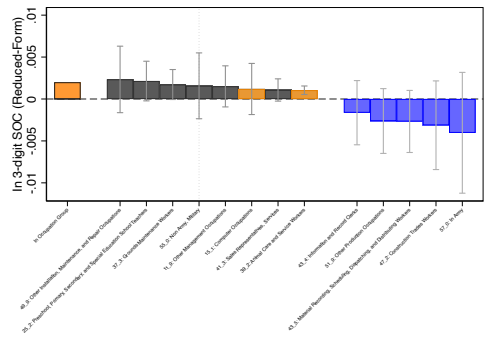
(b) SC100 Pre (SOCS)



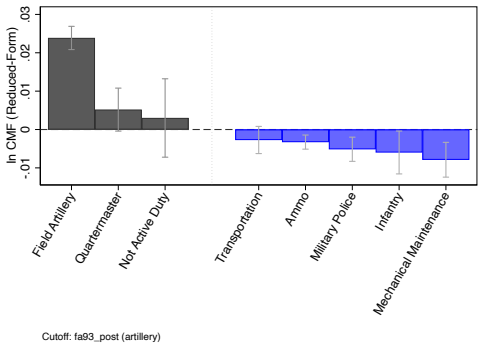
(c) ST96 Post (CMFS)



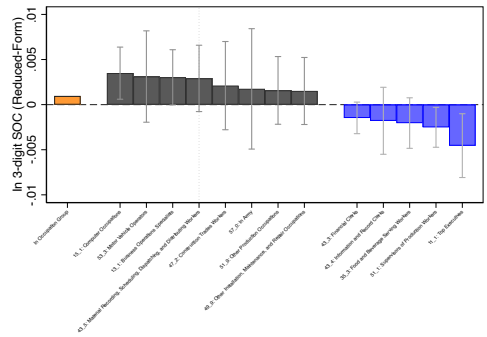
(d) ST96 Post (SOCS)



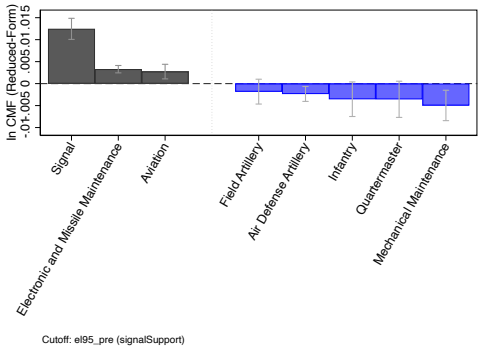
(e) FA93 Post (CMFS)



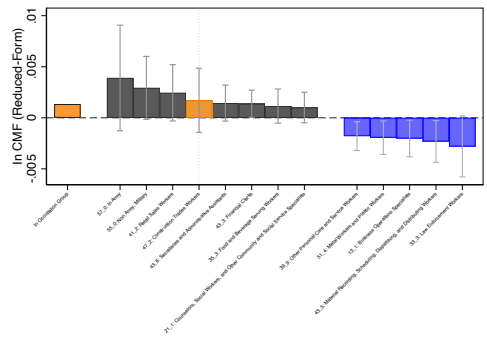
(f) FA93 Post (SOCS)



(g) EL95 Pre (CMFS)



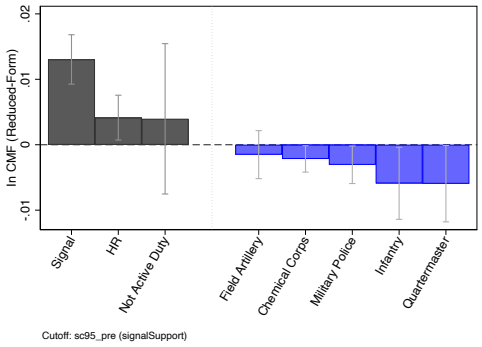
(h) EL95 Pre (SOCS)



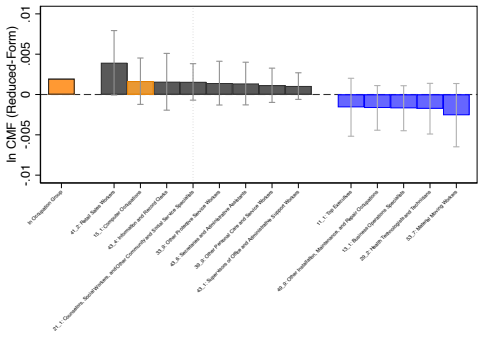
Notes: These figures plot the same exhibits as in figure B.20 for different cutoffs. See notes to that exhibit for details.

Figure B.26: Additional Case Studies (6)

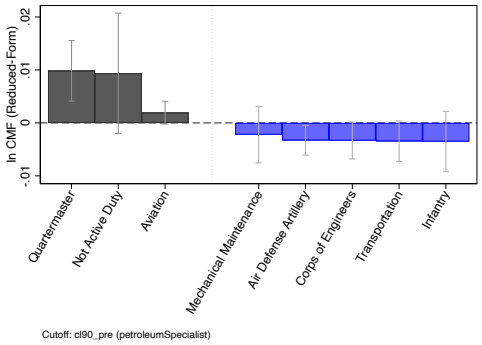
(a) SC95 Pre (CMFS)



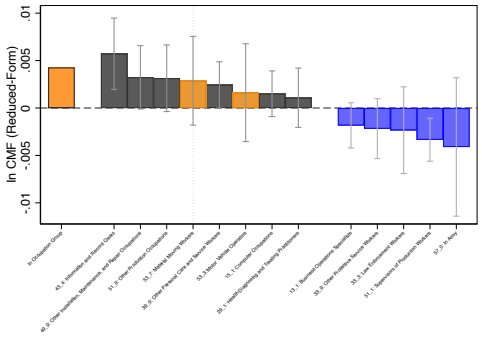
(b) SC95 Pre (SOCS)



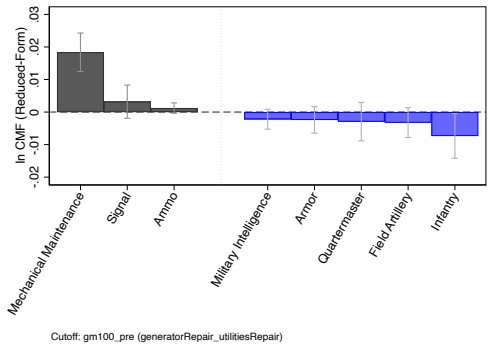
(c) CL90 Pre (CMFS)



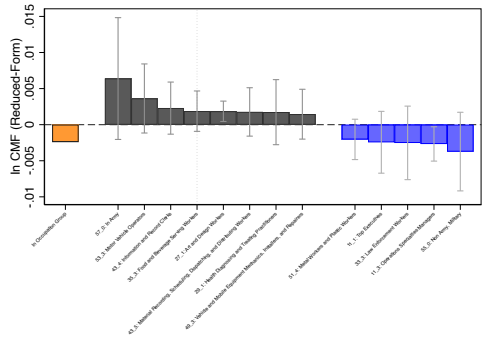
(d) CL90 Pre (SOCS)



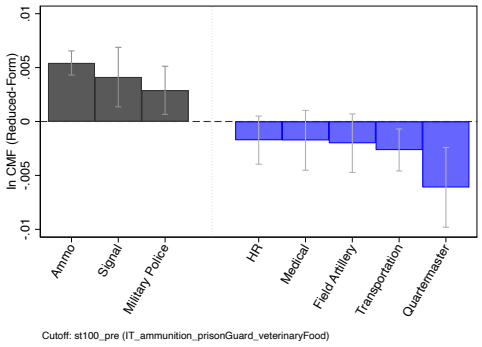
(e) GM 100 Pre (CMFS)



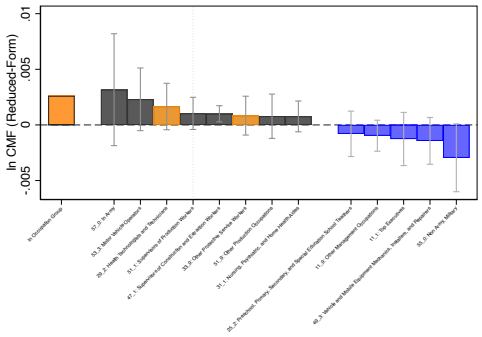
(f) GM 100 Pre (SOCS)



(g) ST 100 Pre (CMFS)



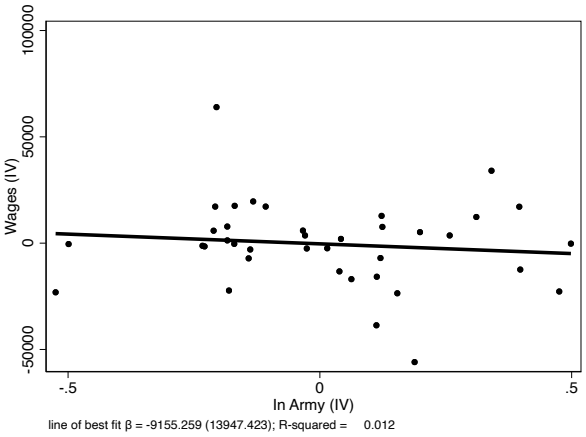
(h) ST 100 Pre (SOCS)



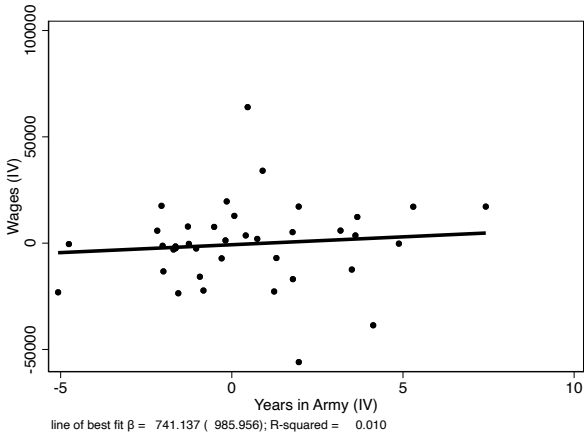
Notes: These figures plot the same exhibits as in figure B.20 for different cutoffs. See notes to that exhibit for details.

Figure B.27: Wages and Persistence vs. Years Served

(a) Wage vs. In Army (IVs)



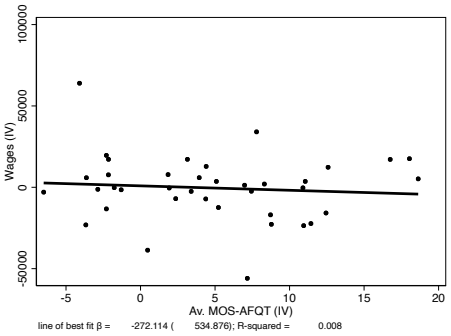
(b) Wage vs. Years Army (IVs)



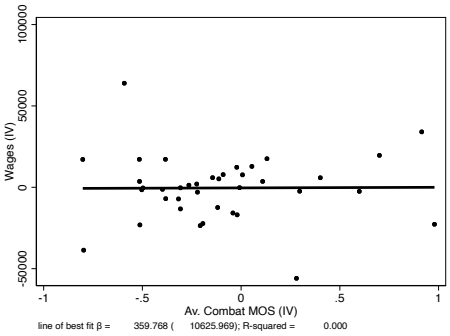
Notes: This figure plots IV effects on own wages at each cutoff versus the corresponding IV effects on other outcomes on the x-axis. In panel (a) the x-axis variable is the IV effect on ever in the active duty Army. In panel (b) the x-axis variable is the IV effect on years in the army (until 2024), which combines a service effect and a retention effect at the cutoffs.

Figure B.28: Wages vs. Initial MOS Characteristics

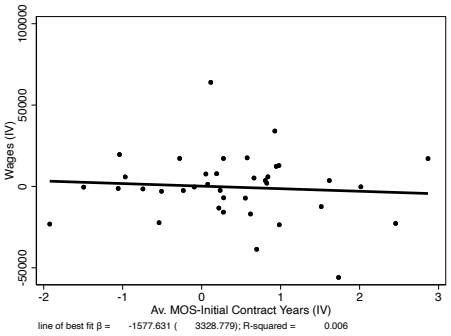
(a) MOS-AFQT (IVs)



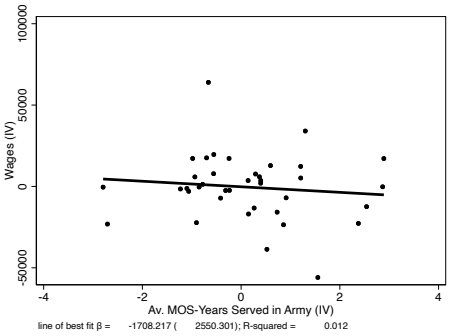
(b) MOS-Combat (IVs)



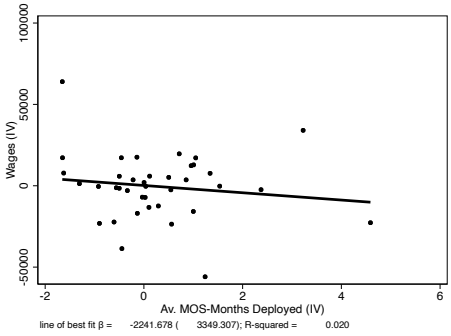
(c) MOS-Terms (IVs)



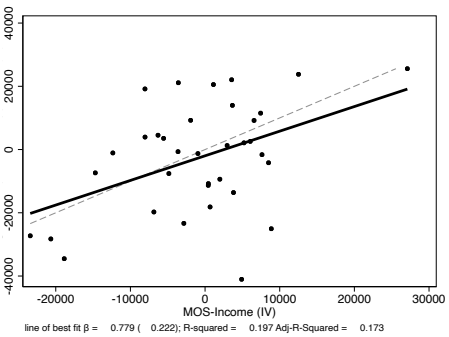
(d) MOS-Years Served (IVs)



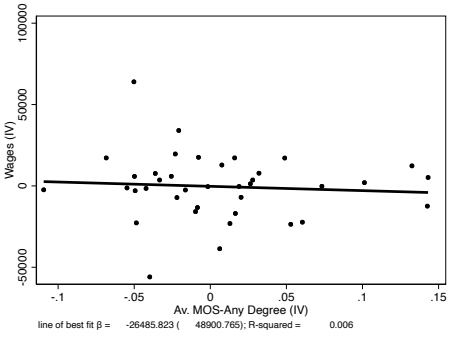
(e) MOS-Months Deployed (IVs)



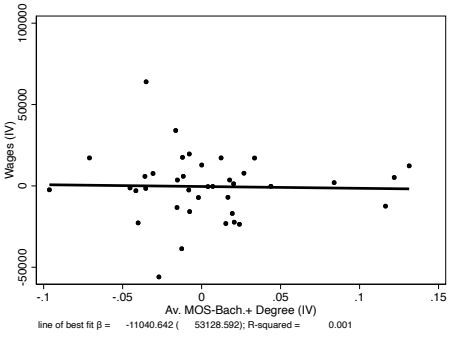
(f) MOS-average wages (IVs)



(g) MOS-Any Degree (IVs)



(h) MOS-Bach+ (IVs)



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).

Table B.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.

Table B.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.

Table B.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.

Table B.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 B.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 B.3, where more relevant standard scores are weighted more heavily.

Table B.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. * $p < .10$, ** $p < .05$, *** $p < .01$

Table B.6: Balance Table - All Cutoffs

	Age	Male	White	Black	Hisp.	In HS	<HS	HS Dip.	Some College+
Pre-2002 Period:									
cl_90	-0.02645	0.00214	-0.00746	0.00315	0.00411	0.00900	-0.00296	-0.00566	-0.00013
	(0.04211)	(0.00564)	(0.00636)	(0.00611)	(0.00424)	(0.00578)	(0.00455)	(0.00637)	(0.00229)
cl_95	0.02650	-0.00830	-0.00266	0.00498	-0.00197	-0.00980	-0.00736	0.01319*	0.00391
	(0.04574)	(0.00627)	(0.00709)	(0.00662)	(0.00463)	(0.00647)	(0.00523)	(0.00709)	(0.00260)
co_90	-0.01620	-0.00213	-0.00388	0.00003	0.00136	-0.00143	-0.00156	0.00473	-0.00163
	(0.02900)	(0.00435)	(0.00447)	(0.00445)	(0.00311)	(0.00423)	(0.00296)	(0.00455)	(0.00174)
el_95	0.02556	-0.00740**	-0.00214	0.00682*	-0.00201	-0.00140	-0.00412	0.00455	0.00124
	(0.02607)	(0.00370)	(0.00408)	(0.00373)	(0.00265)	(0.00375)	(0.00304)	(0.00410)	(0.00153)
el_100	0.02508	-0.00325	-0.00368	0.00361	0.00077	0.00640*	0.00047	-0.00774*	0.00100
	(0.02612)	(0.00367)	(0.00408)	(0.00358)	(0.00258)	(0.00383)	(0.00316)	(0.00418)	(0.00160)
el_105	-0.01480	-0.00034	-0.00612	0.00004	0.00368	0.00812**	-0.00127	-0.00869**	0.00192
	(0.02592)	(0.00349)	(0.00387)	(0.00324)	(0.00239)	(0.00380)	(0.00309)	(0.00413)	(0.00169)
el_110	0.07739***	-0.00072	-0.00089	0.00030	-0.00163	-0.00777*	0.00019	0.00594	0.00150
	(0.02731)	(0.00348)	(0.00379)	(0.00302)	(0.00228)	(0.00397)	(0.00308)	(0.00432)	(0.00195)
el_120	0.05305	-0.00192	0.00063	-0.00027	0.00141	0.00056	-0.00116	-0.00797	0.00862***
	(0.03633)	(0.00395)	(0.00417)	(0.00299)	(0.00243)	(0.00501)	(0.00320)	(0.00547)	(0.00321)
fa_95	-0.00726	0.00348	0.00481	0.00007	-0.00218	-0.00539	-0.00250	0.00752*	0.00021
	(0.02773)	(0.00390)	(0.00429)	(0.00408)	(0.00282)	(0.00393)	(0.00312)	(0.00430)	(0.00158)
gm_90	-0.00752	-0.01351**	-0.01960***	0.01270*	0.00339	0.00302	0.00048	-0.00159	-0.00183
	(0.04501)	(0.00675)	(0.00706)	(0.00689)	(0.00484)	(0.00652)	(0.00487)	(0.00711)	(0.00270)
gm_100	0.02516	0.00298	-0.01307**	0.00654	0.00311	0.00704	-0.00589	0.00219	-0.00345
	(0.04309)	(0.00590)	(0.00658)	(0.00567)	(0.00410)	(0.00627)	(0.00504)	(0.00682)	(0.00277)
mm_90	0.00996	-0.00199	-0.00485	0.00177	0.00273	-0.00127	0.00006	-0.00257	0.00399**
	(0.02759)	(0.00425)	(0.00426)	(0.00428)	(0.00297)	(0.00406)	(0.00276)	(0.00436)	(0.00170)
mm_100	-0.01485	-0.00710**	0.00412	0.00158	-0.00673***	0.00100	-0.00042	-0.00117	0.00054
	(0.02514)	(0.00342)	(0.00385)	(0.00332)	(0.00244)	(0.00367)	(0.00283)	(0.00398)	(0.00169)
mm_105	0.02366	-0.00387	-0.01103***	0.01043***	0.00034	-0.00299	0.00060	0.00229	0.00010
	(0.02778)	(0.00330)	(0.00392)	(0.00310)	(0.00247)	(0.00403)	(0.00321)	(0.00439)	(0.00195)
of_90	-0.06212**	-0.00600	0.00625	-0.00221	-0.00366	0.00501	-0.00339	0.00169	-0.00311*
	(0.03019)	(0.00458)	(0.00452)	(0.00470)	(0.00334)	(0.00443)	(0.00295)	(0.00473)	(0.00180)
sc_95	-0.03207	0.00286	0.00841	-0.00866	0.00232	0.00972*	-0.00390	-0.00783	0.00194
	(0.03821)	(0.00551)	(0.00596)	(0.00550)	(0.00392)	(0.00551)	(0.00411)	(0.00597)	(0.00241)
sc_100	0.04143	-0.01024*	0.00000	0.00145	0.00193	0.00502	0.00175	-0.00652	-0.00038
	(0.04389)	(0.00601)	(0.00669)	(0.00571)	(0.00428)	(0.00639)	(0.00506)	(0.00694)	(0.00287)
st_95	-0.01686	-0.00125	-0.00227	0.00324	-0.00193	0.00052	0.00005	-0.00302	0.00249
	(0.02583)	(0.00368)	(0.00401)	(0.00377)	(0.00266)	(0.00365)	(0.00290)	(0.00401)	(0.00153)
st_100	-0.01663	-0.00238	0.00354	-0.00636*	0.00221	-0.00064	-0.00274	0.00718*	-0.00368**
	(0.02515)	(0.00354)	(0.00390)	(0.00347)	(0.00247)	(0.00362)	(0.00296)	(0.00396)	(0.00154)
st_105	-0.03909	0.00079	0.00568	-0.00303	-0.00066	0.00314	-0.00165	-0.00081	-0.00063
	(0.02411)	(0.00332)	(0.00365)	(0.00311)	(0.00226)	(0.00352)	(0.00291)	(0.00384)	(0.00156)
Post-2004 Period:									
cl_90	0.11219**	-0.00488	-0.00679	0.00740	0.00705	-0.00032	-0.00197	0.00045	0.00190
	(0.05319)	(0.00692)	(0.00775)	(0.00716)	(0.00585)	(0.00627)	(0.00609)	(0.00775)	(0.00310)
co_87	-0.09059**	0.00691	-0.00328	0.00071	0.00560	0.00018	-0.00193	0.00368	-0.00184
	(0.03832)	(0.00528)	(0.00540)	(0.00536)	(0.00434)	(0.00457)	(0.00411)	(0.00554)	(0.00233)
el_89	0.01404	0.00307	0.00073	-0.00037	-0.00248	0.00670	-0.00136	-0.00663	0.00135
	(0.03610)	(0.00501)	(0.00524)	(0.00508)	(0.00419)	(0.00446)	(0.00393)	(0.00534)	(0.00223)
el_93	0.00717	-0.00091	0.00177	-0.00590	0.00166	0.00171	0.00192	-0.00241	-0.00107
	(0.03167)	(0.00418)	(0.00467)	(0.00419)	(0.00359)	(0.00388)	(0.00358)	(0.00468)	(0.00206)
el_98	-0.04183	0.00432	0.00301	-0.00065	-0.00007	0.00051	0.00516	-0.00769*	0.00212
	(0.03012)	(0.00368)	(0.00441)	(0.00354)	(0.00322)	(0.00362)	(0.00349)	(0.00441)	(0.00205)
el_102	-0.01674	0.00562*	0.00149	-0.00133	-0.00029	0.00019	0.00258	-0.00215	-0.00063
	(0.03007)	(0.00341)	(0.00425)	(0.00312)	(0.00296)	(0.00354)	(0.00346)	(0.00433)	(0.00212)
fa_93	0.00469	-0.00246	-0.00037	-0.00095	-0.00377	-0.00293	-0.00335	0.00775	-0.00150
	(0.03601)	(0.00473)	(0.00525)	(0.00475)	(0.00403)	(0.00434)	(0.00404)	(0.00526)	(0.00228)
gm_88	-0.04063	0.00409	0.00364	0.00123	-0.00077	0.00793*	-0.00630	-0.00423	0.00255
	(0.03652)	(0.00506)	(0.00523)	(0.00510)	(0.00422)	(0.00447)	(0.00390)	(0.00535)	(0.00235)
gt_107	0.00325	0.00521	0.01088**	-0.00023	-0.00316	0.00507	-0.00410	-0.00103	-0.00003
	(0.03432)	(0.00357)	(0.00453)	(0.00312)	(0.00295)	(0.00374)	(0.00371)	(0.00475)	(0.00264)
mm_88	0.03498	-0.00437	-0.01112*	0.00739	-0.00044	0.00247	0.00185	-0.00308	-0.00107
	(0.04475)	(0.00647)	(0.00647)	(0.00645)	(0.00534)	(0.00570)	(0.00467)	(0.00671)	(0.00308)
mm_99	-0.00083	0.00022	-0.00101	-0.00430	0.00218	-0.00342	0.00070	0.00339	-0.00074
	(0.02998)	(0.00356)	(0.00436)	(0.00331)	(0.00316)	(0.00363)	(0.00338)	(0.00439)	(0.00225)
mm_104	-0.02714	0.00290	0.00136	0.00159	0.00015	0.00279	-0.00137	0.00059	-0.00218
	(0.03096)	(0.00319)	(0.00428)	(0.00283)	(0.00294)	(0.00360)	(0.00348)	(0.00445)	(0.00242)
of_85	0.02205	0.00607	-0.00444	0.00576	0.00088	-0.00348	0.00293	0.00659	-0.00603**
	(0.03930)	(0.00560)	(0.00554)	(0.00567)	(0.00458)	(0.00486)	(0.00407)	(0.00577)	(0.00245)
sc_98	0.06904**	0.00642	-0.00595	0.00567	-0.00154	-0.00489	0.00311	-0.00060	0.00241
	(0.03509)	(0.00430)	(0.00512)	(0.00417)	(0.00375)	(0.00421)	(0.00407)	(0.00511)	(0.00226)
st_91	-0.00330	0.00377	-0.00084	0.00117	-0.00513	0.00195	0.00482	-0.00727	0.00034
	(0.03436)	(0.00460)	(0.00501)	(0.00471)	(0.00392)	(0.00418)	(0.00383)	(0.00505)	(0.00212)
st_96	0.02106	0.00098	0.00634	-0.00066	-0.00733*	-0.00004	0.00031	-0.00202	0.00169
	(0.03713)	(0.00480)	(0.00553)	(0.00481)	(0.00417)	(0.00456)	(0.00430)	(0.00552)	(0.00239)
st_101	-0.06513**	-0.00202	0.00256	-0.00422	0.00260	0.00482	-0.00433	-0.00135	0.00098
	(0.02793)	(0.00322)	(0.00398)	(0.00303)	(0.00281)	(0.00329)	(0.00322)	(0.00403)	(0.00191)
All Covariates and Cutoffs:	0.201								

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

Table B.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 2. 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 B.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	0.985	0.924	0.882	1.015
Wages v. Occ Wages	(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 1. 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 1 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).

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

****Table Suppressed Pending Disclosure****

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. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table B.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 1, 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 1 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 2, 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.

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

****Table Suppressed Pending Disclosure****

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. * $p < .10$, ** $p < .05$, *** $p < .01$.