Economic and Social Determinants of Military Labor Supply: Essays on the Effects of Local Labor Market Conditions and the Opioid Crisis and Service in the U.S. Army

by

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DEDICATION

To my family…I am grateful to be your son, humbled to be your brother, lucky to be your husband, and proud to be your father.

"Always remember there is nothing worth sharing, like the love that let us share our name."

- The Avett Brothers

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PREFACE

“A volunteer army, as we use the term today, fills its ranks through the use of the labor market ~ as do restaurants, banks, retail stores, and other businesses. The term volunteer is something of a misnomer. The volunteer army is not like a volunteer fire department, in which people serve without pay, or the local soup kitchen, where volunteer workers donate their time. It is a professional army in which soldiers work for pay. The soldiers are "volunteers" only in the sense that paid employees in any profession are volunteers. No one is conscripted, and the job is performed by those who agree to do so in exchange for money and other benefits.”

- Michael J. Sandel, Harvard University Law School

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LIST OF ABBREVIATIONS

AFQT	Armed Forces Qualification Test
AIT	advanced individual training
ASVAB	Armed Services Vocational Aptitude Battery
AVF	all volunteer force
BAH	basic allowance for housing
BAS	basic allowance for subsistence
BCT	basic combat training
CONUS	continental United States
CPS	Current Population Survey
DEP	Delayed Enlistment Program
DFAS	Defense Financial Accounting Service
DMDC	Defense Manpower Data Center
DoD	Department of Defense
ETS	expiration of term of service
FY	fiscal year
GWOT	global war on terrorism
HQ	high-quality
LOR	length of reenlistment
LQ	low-quality
MEPS	Military Entrance Processing Station

MGIB	Montgomery GI Bill
MOS	military occupational specialty
OEF	Operation Enduring Freedom
OIF	Operation Iraqi Freedom
PCS	permanent change of station
PPF	Production Possibilities Frontier
RMC	regular military compensation
TSC	test score category
USAREC	United States Army Recruiting Command

ABSTRACT

This dissertation contains three essays that use detailed administrative military data combined with social and economic information to explore the feasibility of estimating the enlistment elasticities of low-quality recruits and to answer questions related to modern determinants of military enlistment supply.

The first chapter explores the difficulty of estimating the influence of economic and social conditions on the total recruit population. I demonstrate at both the local (recruiting station) and national level, neither high low nor low-quality enlistment contracts are constrained by the Army. The Army's use of the Delayed Entry Program (DEP) allows recruiters to recruit beyond their assigned goals for low-quality soldiers. The result of this finding is that annual observational data on the total number of enlistment contracts (high-quality plus low-quality) does reflect the supply behavior of the population willing to sign an enlistment contract and not the Army's level of demand in the respective year. This finding validates the use of the entire potential recruit population to provide unbiased estimates of supply elasticities with respect to local labor market and social conditions.

The second chapter investigates the relationship between local labor market conditions and the willingness of individuals to enlist in the military. I provide the first causal estimates of the effect of these conditions on the type and quantity of recruits enlisting in the military at both the extensive and intensive margins of enlistment. I find that a one percentage point increase in the contemporaneous employment-to-population ratio results in a rate increase of two low-quality individuals per 100,000 eligible

population in the applicant pool, of which, one enters active duty. The size of the causal estimates in my findings indicates that the neglect of the correlation between changes in labor supply and economic conditions in previous studies likely underestimated the effect of labor demand shocks on the enlistment response. I also find the impact of labor market conditions in the year leading up to the enlistment decision is stronger than the effect of contemporaneous conditions and indicates the enlistment decision incorporates labor market information from many months prior to the actual decision.

The third chapter estimates the effect of opioid use on applicants for military service, on the composition of the applicant pool, and on active duty outcomes such as attrition in the first enlistment term. I use plausibly exogenous variation in Prescription Drug Monitoring Program implementation dates to instrument for access to opioids. Although one might expect to find opioid use reduces interest in military service or the ability to qualify for application, I find suggestive evidence to support the opposite conclusion. While my results vary or become non-significant in the presence of flexible state-specific trends or instrumenting, the magnitude and direction of the effects are largely stable and consistent with theory. They indicate opioid use in a county increases the rate of individuals that apply for military service and this increase in the applicant pool results in a higher rate of accessions. With respect to active duty soldiers, the results suggest the rate of individual attrition during the first enlistment term does appear to decrease while completion of the first term and reenlistment for a second term appears to increase. It does not appear opioid use negatively impacts military service through direct detrimental effects of abuse in young users, rather, I suggest opioid use in a county indirectly effects military enlistment by lowering the opportunity cost of military service (in a manner similar to poor labor market conditions) or through exposure to the negative externalities of opioid abuse.

CHAPTER 1

1.1 Background

Since the end of conscription and the advent of the all-volunteer Army in 1973, understanding the size, characteristics, and motivation of the supply of potential recruits has been a focus of both policy makers and academic researchers. The initial focus of this research agenda was understanding the relationship between the economic costs of the implicit tax levied on draftees and the budget costs of transitioning to an all-volunteer force. However, even before President Nixon formally ended conscription, the research agenda evolved to focus on estimating a supply curve for the pool of volunteers for military service (Altman and Fechter 1967, Fisher 1969, Cook, 1970, Gray 1970, Cook and White 1970, Borcherding 1970). Specifically, the literature sought to apply economic theory and understand how various supply-side factors (unemployment, relative military pay, and demographic conditions) impacted the size of the volunteer pool and the willingness of individuals to enlist. To this day, this remains the focus of most research on military enlistment.

The earliest studies immediately recognized an "identification problem" involved in a supply analysis of the total potential recruit population (Altman and Fechter 1967).[1]

[1] These "identification problems" are not unlike what economists understand as the identification problem where more than one set of parameters generates the same distribution of observations. The canonical example is the basic model of supply and demand where only equilibrium observations are observed, and it is unclear if observations are being generated by shifts in the demand curve or shifts in the supply curve, thus negating the ability of the researcher to "identify" the parameters describing the effect of a change in price on quantity.

This problem existed because Congress and the Army legally and administratively split this population into different categories based on their mental aptitude and placed different recruiting constraints on each type.[2] This led researchers to assume that because individuals in the highest mental aptitude categories (high-quality) have many opportunities in the labor market, fewer will be interested in enlisting but all those expressing interest will be accepted.[3] On the other hand, researchers assumed the supply of those in the lower aptitude categories ("low-quality") exceeds the Army's demand because they have fewer civilian options and are willing to enlist in essentially unlimited numbers.

Under the assumptions that the Army prefers high-quality recruits and restricts the proportion of low-quality recruits able to enlist, researchers estimating supply elasticities for the total population of potential recruits were concerned about biased results. If the overall population is a mixture of those high-quality individuals that are limited only by their willingness to serve (supply-limited) and another population of low-quality limited not by their desire to serve, but by the Army's fixed demand for their service (demand-constrained), it will be "difficult to separate variations in the number of new enlistees recruited caused by supply factors from those caused by demand factors" (Altman and Fechter 1967). This inability to identify the separate variation in supply and demand may

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[2] For the latest version of these restrictions, see Department of Defense Instruction 1145.01, Qualitative Distribution of Military Manpower, September 20, 2005, paragraph 4.1 at http://www.dtic.mil/whs/directives/corres/pdf/114501p.pdf.

[3] High-quality recruits are defined as high school graduates scoring in the top half of the aptitude distribution. Specifically, high-quality recruits are high school seniors or graduates in Armed Forces Test Score Category (TSC) I-IIIA ($51 \leq$ AFQT ≤ 100). Low-quality recruits are high school graduates in TSC IIIB-IV ($31 \leq$ AFQT ≤ 50) or a high school dropout in any test score category above 31. Recruits in TSC IV ($10 \leq$ AFQT ≤ 30) cannot exceed 4% of total recruits by Army mandate and congressional legislation forbids recruits in TSC V ($0 \leq$ AFQT ≤ 9) from enlisting. See Title 10, U.S. Code, Subtitle A, Part II, Chapter 31, paragraph 520.

result in downward biased estimates of elasticity to various supply variables if the total potential recruit population is used as the sample.

These assumptions regarding high and low-quality individuals' willingness to serve, combined with the Army's restrictions on the acceptable proportion of low-quality, resulted in the literature focusing almost exclusively on the high-quality population to estimate supply elasticities. This focus on high-quality recruits ostensibly avoids the "identification problem" by using a population for which their observed enlistment numbers are assumed to be a point on the supply curve, and not on the Army's demand curve, as would be the case with low-quality personnel.

In addition to focusing only on the high-quality population, most of the literature defines "recruit" as a signed enlistment contract. In other words, rather than using the number of applicants sent to a Military Entrance Processing Stations (MEPS) or the number of accessions that enter active duty service and ship to basic training, researchers focused on signed enlistment contracts as the outcome of interest in their analysis.[4] This was done largely due to data availability and because recruiting goals assigned to recruiters were historically expressed in contracts and not in applicants or accessions.

Using data from the United States Army Recruiting Command, this paper challenges the above assumptions and the resulting difficulty it creates in estimating the

[4] Specifically, an applicant is an individual that has demonstrated interest in enlisting in the Army, is pre-screened by a recruiter, sent to a MEPS to take the Armed Services Vocational Aptitude Battery, receives a medical and physical exam, and meets with a job counselor to select a military occupation but has not yet signed an enlistment contract. A "contract" is an individual who has passed all initial screening requirements at the MEPS, signed an enlistment contract, but is waiting in the Delayed Entry Program (DEP) to become an "accession". While in the DEP, the soldier returns home until they are to report back to the MEPS to become an accession. An "accession" is an individual who has passed all initial screening requirements, signed an enlistment contract, completed her time in the Delayed Entry Program (DEP), returned to the MEPS, taken the Oath of Enlistment, entered active duty, and shipped basic combat training. Due to attrition in the process, the number of applicants is greater than the number of contracts which is greater than the number of accessions.

influence of economic and social conditions on the total recruit population. I demonstrate at both the local (recruiting station) and national level, neither high nor low-quality enlistment contracts are constrained by the Army. While local and national goals exist for both high and low-quality contracts, these do not, in practice, serve as effective ceilings. The Army's use of the Delayed Entry Program (DEP) allows recruiters to recruit beyond their assigned goals for low-quality soldiers. If recruiters exceed their low-quality contract goals, the excess will increase the size of the DEP while still allowing the Army to control the number of annual accessions. The result of this finding is that annual observational data on the total number of enlistment contracts (high-quality plus low-quality) does reflect the behavior of the population willing to sign an enlistment contract and not the Army's level of demand in the respective year. This finding also validates the use of the entire potential recruit population (not just high-quality) to provide unbiased estimates of supply elasticities with respect to local labor market and social conditions (Crow 2019).[5] Finally, I address issues related to the use of enlistment contracts as the outcome of interest and propose using a more broadly defined category of applicants in recruiting analyses.

The remainder of this paper proceeds as follows. Section 2 provides a theoretical framework for thinking about the composition of the potential enlistment population. Section 3 reviews the existing literature and section 4 provides institutional background on how the Army determines its recruiting objectives. Section 5 describes the data and descriptive statistics necessary to place this problem in context. Section 6 examines the demand constrained assumption, the question of why low-quality contract goals are so often exceeded, and the issues surrounding use of signed enlistment contracts rather than

[5] This is not to say that estimating separate elasticities is not informative, especially if the factors that predict low and high quality differ in either degree or kind.

a more broadly defined population as the outcome of interest. Section 7 concludes with a discussion of the consequences of the results.

1.2 Theory

To investigate the estimation of population supply curves, it is important to understand recruiting and the enlistment decision at both the individual and market level. I begin with the enlistment decision at the individual level followed by a discussion of recruiting at the market level.

1.2.1 Individual Enlistment Decision

Occupational choice, along with post-secondary schooling, is one of the first and most fundamental decisions a person will make as a young adult. Those who do not attend college choose between entering the civilian labor market, enlisting in the U.S. military, or remaining out of the labor force altogether.[6] According to human capital theory, these individuals will weigh the potential benefits and costs of different occupational choices and select the one with the highest expected net return. Benefits include both potential earnings and non-pecuniary advantages of the occupation, while costs are either direct (training costs) or in the form of foregone opportunities.[7] In turn, these costs and benefits will depend on individual preferences, labor market and institutional constraints, information, and incentives (Fourage, Kriechel, and Dohmen 2014).

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[6] In 2015, there were 4 million 18-year-olds. 3.5 million graduated from high school and roughly 70 percent went on to attend college (2.4 million). The remaining 1.1 million young adults are faced with their first occupational choice. Roughly 4.3 percent of non-college bound high school graduates will enlist in military in a given year.
[7] See Becker (1964), Boskin (1974), and Mincer (1974).

Formally, the decision to enlist can be modeled using standard occupational choice theory (Rosen 1986) and the random utility model (McFadden 1983). The specific application of this concept to the enlistment decision was first demonstrated by Fisher (1969) and the following analysis adheres closely to his work and a review of his model in Warner and Asch (1995).

In this model, there are two sectors (civilian and military). An individual decides whether to join the military by comparing the pecuniary and non-pecuniary benefits of work in the military and civilian sector and chooses the sector with the larger overall benefits. The pecuniary portion of the decision can be thought of as comparing average civilian wages conditional on experience and ability in the civilian sector with regular military compensation (basic pay, allowances for housing and food, federal tax advantages).[8] As Altman (1969) identified in one of the earliest models of enlistment, military service has unique non-pecuniary costs and benefits. Not only does military service include the possibility of bodily injury or death, it also requires an individual to spend both her working and non-working hours in the same environment (on/around military bases), long separations from family, frequent moves, difficult working conditions, long hours, etc. On the other hand, individuals may derive psychic benefits from pride in serving one's country, the adventure of foreign travel, the challenge of physical trials, etc. In addition, many service members acquire skills that are directly transferrable to jobs in the civilian labor market following their enlistment.

For most individuals, enlistment in the military is a relatively short-term decision (approximately 65 percent exit the military at the end of their first term of enlistment). Abstracting from detailed present value calculations, I define W^M as the present value of

[8] In addition to a monthly military salary, service members are given money for food and housing that is based on their rank and duty location. These two allowances are not taxed by state or federal governments.

regular military compensation over the enlistment term and W^C as the present value of civilian wages over the same time horizon. If non-pecuniary benefits (i.e., tastes for each sector) are given by τ^M, τ^C then an individual will enlist in the Army if $W^M - W^C > \tau^C - \tau^M$. If $\tau^{net} = \tau^M - \tau^C$ is the net taste for military life, then we can write $W^M > W^C - \tau^{net}$. Assuming the individual can value her net taste for military life as a fraction t of her civilian wage, we can write the individual indifference condition as

$$W^{M^*} = W^C - W^C t = W^C(1-t) \quad \text{where } W^C t = \tau^{net}$$

In the aggregate, the distribution of both civilian earnings and the propensity for military service of young people are reasonably approximated by lognormal distribution.[9] After taking logs, the terms on the right side of the equation are now approximately normal and we can define a reservation military wage, W^*, as

$$W^* = \ln W^{M^*} = \ln W^C + \ln(1-t)$$

The distribution of t (taste for military life as fraction of civilian earnings potential) in the 17 to 24-year-old population and their civilian wage will determine the supply of applicants and the elasticity with respect to pay (Gray 1971).[10] In this case, the reservation military wage is normally distributed, and its probability density function and

[9] The Department of Defense Joint Advertising, Market Research and Studies (DoD-JAMRS) office has conducted a Youth Poll of high school students for the last 15 years. Historically, the answer to the question “How likely is it that you will be serving in the military in the next few years?” is distributed such that 60 percent answer “definitely not”, 30 percent answer “probably not”, 7 percent answer “probably” and only 3 percent answer “definitely.”

[10] Normality is not required in this case, rather, it is an assumption that allows us to conceptualize the probability density function and supply curve in ways that are familiar. See Figures 1.1, 1.2, and 1.3.

cumulative distribution function are shown in Figures 1.1 and 1.2.

Figure 1.1. Probability density function of reservation military wage

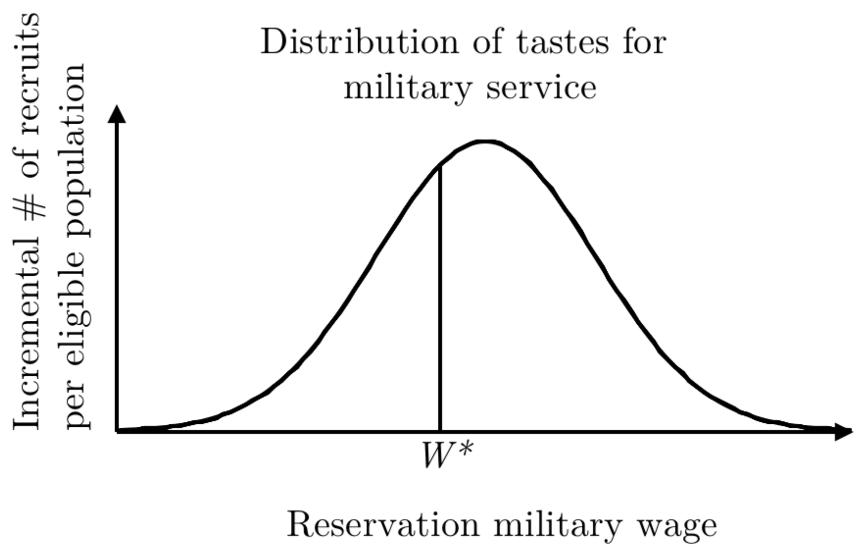
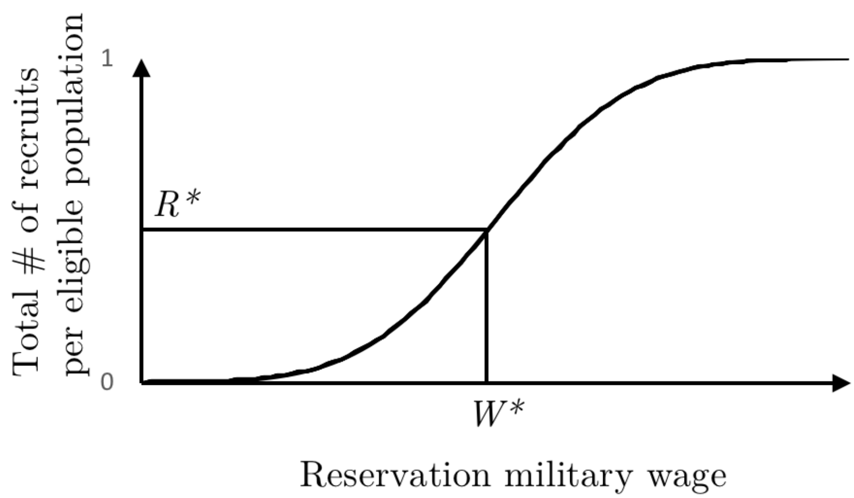
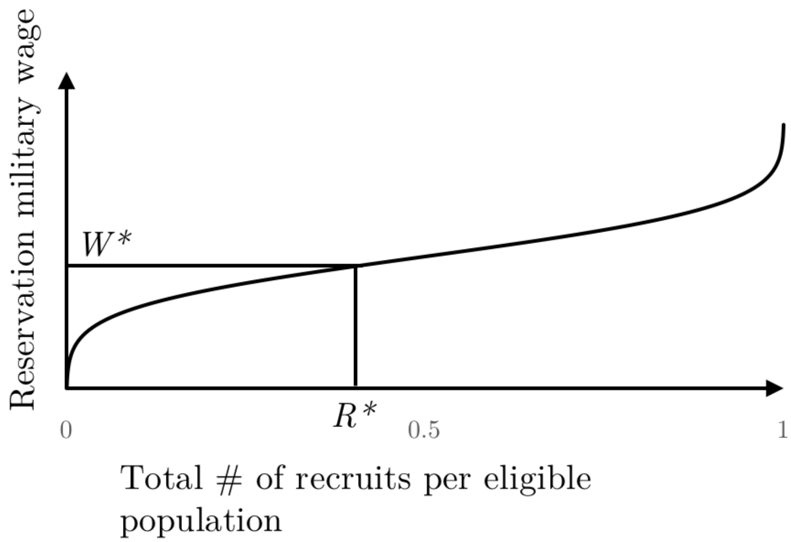


Figure 1.2. Cumulative distribution function of reservation military wage



This distribution of tastes for military service and civilian wages generates an aggregate supply curve with relatively low responsiveness to pay at the lower and upper ends of the wage range and high responsiveness in the middle of the wage distribution. The supply curve in Figure 1.3 represents the number of potential applicants (per eligible population) at each level of military wage holding constant the level of the applicant population quality. Given that only 4 percent of the non-college bound youth cohort enlists annually, applicants tend to come from the lower tail of the reservation wage distribution where taste for military services is relatively high.[11] Given this supply curve for applicants, we now consider the Army's demand and the market in which they participate.

Figure 1.3. Military applicant supply curve



1.2.2 Market for Military Manpower

The market for military applicants can be modeled using a variant of the supply and demand framework. However, in this market for applicants, the quantity demanded and wage are fixed annually by Congress and do not respond to current economic

[11] Increasing heterogeneity of tastes among the population, σ_t^2, will result in an overall less elastic applicant supply curve due to the shape of the normal distribution. If τ is uniformly distributed, then the CDF and the supply curve will be linear over the range of $W^C - t_{min}$ to $W^C - t_{max}$ and a change in pay will have the same effect at all points along that curve (Asch and Warner 1995).

conditions (notwithstanding marginal adjustments due to enlistment bonuses). This demand for military manpower is ultimately a product of the demand for military readiness as expressed by congressionally authorized end-strength requirements. It is inelastic in the short run and is expressed directly by the Army's high and low-quality recruiting goals.

Equilibrium in the market is obtained not by wage adjustments, but by accepting more or less low-quality recruits relative to the number of high-quality recruits. This mechanically adjusts the ratio of accepted high and low-quality recruits. The factors that shift the supply curve of military recruits can be categorized in two groups (Warner, Simon, and Payne 2001). The first group includes economic and demographic factors such as youth population, civilian and military pay, the unemployment rate, race, gender, age, college attendance levels, and contemporaneous military operations. The second category includes the recruiting resources employed by the military to attract and retain individuals. These include the number of recruiters, enlistment bonuses, educational benefits (G.I. Bill, Army College Fund, Tuition Assistance, etc.) and advertising budgets. A change in any one of these factors will induce a change in the aggregate net taste for military life, t, in the population which, in turn, will induce a shift in the supply curve and will impact the equilibrium wages and quantities at which the market for military labor clears.[12]

The Army uses measures of mental aptitude to categorize applicants by "quality" (high and low). A high-quality applicant is defined as a high school graduate scoring in the top half of the Armed Forces Qualification Test distribution (AFQT). A low-quality

[12] While not listed, it is possible that recruiter effort will change in response to changes in contract goals and this change in recruiting effort may lead to a change in the net taste for military life (e.g., through additional information about military life to recruits). See Dertouzos (1985 and 2006).

applicant is a high school graduate who scores between the 10th and 50th percentile on the AFQT or is an applicant in any test score category that fails to graduate high school. During weak economic conditions, the military can recruit and enlist a larger number of high-quality individuals relative to low-quality because civilian labor market alternatives are reduced for both groups. During strong economic conditions, fewer high-quality individuals are interested in joining the military (due to increased opportunity costs) and a relatively greater number of low-quality individuals will enlist. See Figure 1.4 and 1.5.

Figure 1.4. Average Applicant AFQT Scores and Unemployment Rate

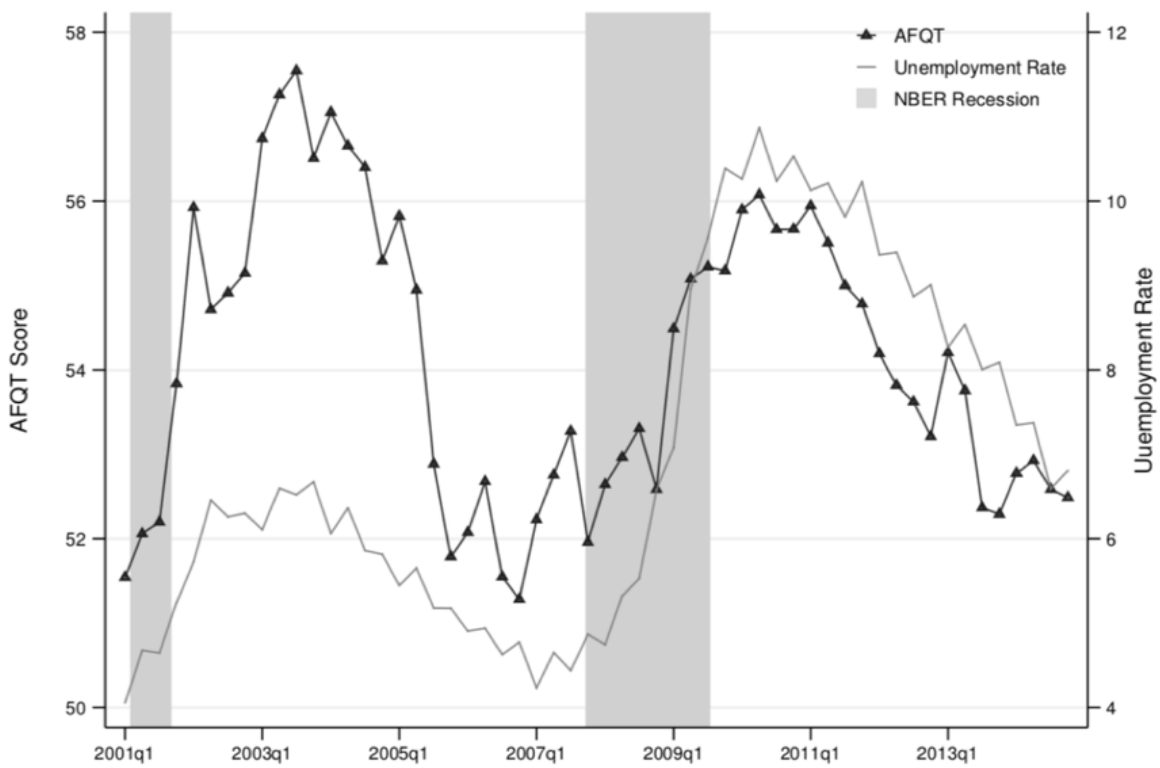
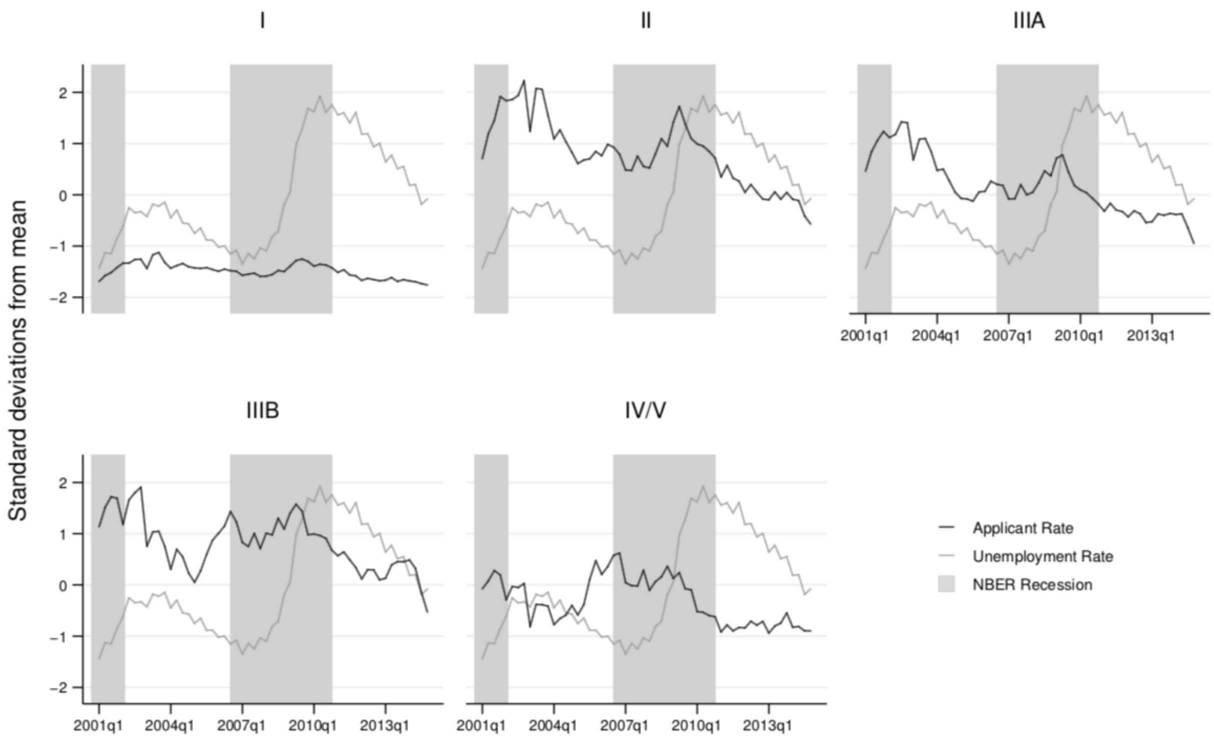
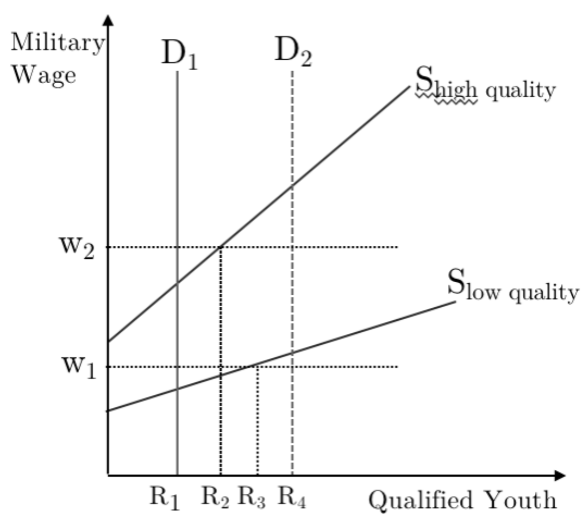


Figure 1.5. Standardized applicant rates by AFQT Test Score Category



Abstracting from the actual shape of the supply curve for expositional simplicity, Figure 1.6 represents the "identification problem" discussed above. At a common military wage, low and high-quality individuals are assumed to have different supply curves based on different underlying tastes for military life and different opportunities in the civilian economy. The identification problem is due to the presence of the population of low-quality individuals for whom *it is assumed* the Army's demand is fixed and less than the number willing to enlist. This results in the biased estimation of elasticities of supply for the total population of individuals interested in military service (combined number of high and low-quality). As illustrated in Figure 1.6, it is assumed that high-quality individuals require relatively higher wages to enlist and the Army's demand for them is rarely met. Low-quality individuals are assumed to be willing to enlist in large numbers but constrained by the Army's limited demand for them due to its preference for high-quality individuals. This results in an excess supply of low-quality individuals at nearly any wage/demand combination. The observed number of low-quality applicants to the Army is thought to be jointly determined by the military's annual recruiting goal and by the enlistment decisions of high-quality individuals. In most recruiting years, wages and demand are set at levels conceptually similar to W_2 and D_2 and the Army demands R_4 total contracts. In this case, the Army accepts R_2 high-quality contracts and low-quality individuals fill the remaining need for recruits by supplying R_4 - R_2. This example demonstrates how researchers have traditionally viewed low-quality individuals as demand constrained and a "residual" population in recruiting.

Figure 1.6. Market for high and low-quality individuals

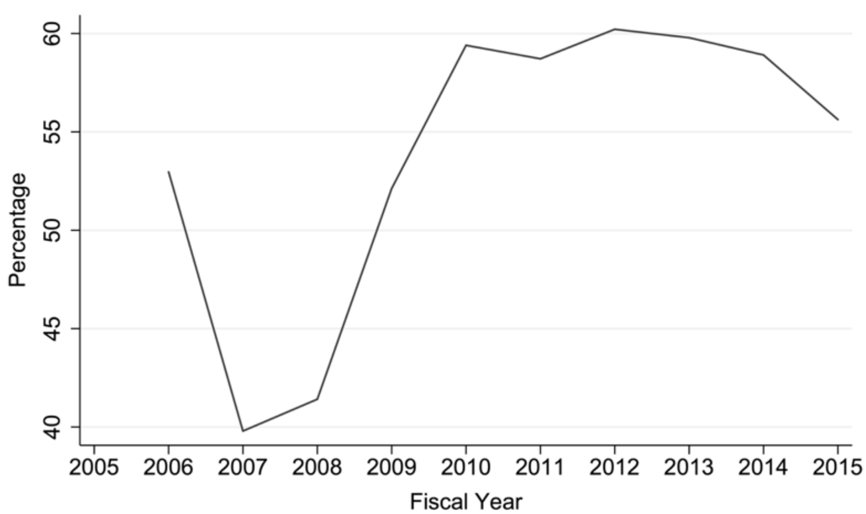


	Quantity of individual willing to enlist	
	High-quality	Low-quality
W_1 & D_1	0 (S.C.)	R_1 (D.C.)
W_1 & D_2	0 (S.C.)	R_3 (S.C.)
W_2 & D_1	R_1 (D.C.)	0 (D.C.)
W_2 & D_2	R_2 (S.C.)	R_4 - R_2 (D.C.)

* S.C. ≡ Supply-constrained; D.C. ≡ Demand-constrained

Efforts to avoid the "identification problem" created the fundamental limitation in the existing literature on military recruiting: the neglect of low-quality contracts. The common approach to analyzing enlistment supply has been to split the contract population into high and low-quality in line with the military's recruitment categories and assume that high-quality contracts are supply-constrained and low-quality contracts are demand-constrained. The researcher then focuses solely on high-quality contracts assumed to have an observable supply curve.[13] Unfortunately, this method of analysis ignores roughly half of the contract population and results in an incomplete understanding of the entire cohort. Although the Department of Defense mandates that at least 60 percent of an annual accessions cohort is high-quality (i.e., the 60/40 rule), historically, low-quality individuals often comprise much more than 40 percent of a cohort (Figure 1.7).[14] This makes low-quality contracts an important yet understudied component of military enlistment.

Figure 1.7. High-quality Contracts as percent of all Enlistment Contracts (Army)



[13] Previous research also shows high-quality recruits with high school degrees and higher AFQT scores are more likely to retain and perform better. See Are Smart Tankers Better? AFQT and Military Productivity by Scribner, Smith, and Baldwin 1986.
[14] See Department of Defense Instruction 1145.01, Qualitative Distribution of Military Manpower, September 20, 2005, paragraph 4.1 at http://www.dtic.mil/whs/directives/corres/pdf/114501p.pdf.

1.3 Literature Review

The literature on military labor supply focuses almost exclusively on the supply elasticities of economic and social determinants of enlistment (as defined by contracts).[15] Specifically, these studies focus on high-quality contracts that are assumed to be supply constrained (in excess demand), and thus, have a supply curve that is visible to the researcher and can be estimated without bias (Asch, Hosek, and Warner 2007). These studies are observational in nature except for an early paper examining the Army's enlistment bonus experiment in the early 1980s (Polich and Dertouzos 1986).

The literature can be categorized into three different generations of models and econometric specifications. The first dates to the late 1960s and the work of the President's Commission on an All-Volunteer Armed Force (Gates Commission). President Richard Nixon established the Gates Commission to examine the social and economic costs of ending military conscription. Early work by Altman and Fechter (1967), Fisher (1969), Altman (1969), Cook and White (1970), Gray (1970), and Cook (1971) examined the theoretical foundations of enlistment supply and attempted the first empirical estimates of enlistment and retention supply elasticities. Prominent economists such as Walter Oi and Milton Friedman contributed to this effort which resulted in the Gates Commission final report recommending the end of conscription and the creation of the All-Volunteer Force in 1973.

The second generation of models dates to the early 1980s and focuses on reduced form models estimating supply elasticities without regard recruiting resources. These are best represented by studies by Ash, Udis, and McNown (1983), Dale and Gilroy (1983) and Brown (1985). The third and most recent generation of models began in the mid-

[15] Some recent literature also focused on improving recruiter performance and evaluation (Dertouzos and Garber 2003, 2006; Dertouzos 2008)

1980s and continues until today with both structural and reduced form models that endogenize military recruiting goals and recruiter effort. The studies are best exemplified by those of Dertouzos (1985), Daula and Smith (1985), and Berner and Daula (1993).

Since the late 1980s, the literature has focused on enlistment supply elasticities (aggregate data) and enlistment propensity (individual data) as defined by the number of observed high-quality contracts. Aggregate enlistment studies used panel data (e.g., state*quarter) to examine the impact of military pay (Hansen 2005, Asch et al. 2007, Asch et al. 2010), educational benefits (Warner, Simon, and Payne 2001; Simon, Negrusa, and Warner 2010), recruiters (Dertouzos and Garber 2003, 2006), cash bonuses (Polich and Dertouzos 1986; Asch et al. 2010), and the unemployment rate (Gilroy 1983, Arkes 2014). Enlistment propensity studies use cross-sectional data and focus on estimating individual enlistment probabilities given a variety of socioeconomic and demographic factors. Three comprehensive surveys of the literature on enlistment and reenlistment have been completed in the last twenty years; Asch and Warner (1995) and Asch, Hosek, and Warner (2007) cover the pre-drawdown and post-drawdown periods, respectively. The third survey was written in support of the 2012 Department of Defense Quadrennial Defense Review by Warner (2012). The discussion that follows adheres closely to Warner in summarizing results from the above literature.

First, military pay relative to civilian labor market pay positively impacts the number of signed high-quality contracts. The literature finds overall pay elasticities for high-quality contracts average approximately 0.7 to 1.15 for the enlistment decision (Goldberg 2001). Second, the number of recruiters has been found to positively impact high-quality contract supply with elasticities ranging from 0.45 to 0.65 (Dertouzos and Garber 2006). Third, there is a strong relationship in the data between the civilian unemployment rate and the number of high-quality contracts. Previous studies find the elasticity with respect to unemployment to be approximately 0.1 to 0.3 for all armed services personnel. Fourth, enlistment bonuses also positively impact the number of high-quality contracts. These effects are estimated to be a 0.5 to 1.7 percent increase in contracts for a 10 percent increase in enlistment bonuses (Asch et al 2010). Similarly, education benefits (GI Bill, Tuition Assistance, Army College Fund) attract individuals but may also have the unintended consequence of incentivizing them to leave the service to use the benefits (e.g., the GI Bill). In fact, some early studies (Smith, Sylwester, and Villa 1991) find that higher educational benefits will lower first term reenlistment in the Army, but the data is less clear for the other military services. Lastly, the effects of advertising are explored, especially in the 1980s and 1990s. Results from early papers find the effects of advertising to be small (elasticities of 0.01 to 0.05) and not precisely estimated. A lack of recent advertising data collection has made updating this line of inquiry difficult.

1.4 Institutional Background

1.4.1 Determining Army recruiting goals

The number of new soldiers needed to enter active duty each year is based on annual changes in the Army's size (authorized end strength) and the rate at which it retains current soldiers.[16] This is the Army's "accessions" goal which it assigns to its own internal recruiting organization, the US Army Recruiting Command (USAREC).[17]

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[16] The Army's authorized end strength is mandated by congressional legislation and is based largely on operational requirements and fiscal constraints. Approximately 15 percent of an accession cohort will separate prior to end of their first term and roughly 30 percent of an annual accession cohort will reenlist at the end of their first term.

[17] USAREC is organized into six brigades which are roughly the size of census divisions. These brigades are further sub-organized into battalions (roughly the size of states), companies (multi-county elements), and finally, nearly 1,000 recruiting centers where over 8,000 recruiters work. A typical recruiting center has between 2 to 5 recruiters and will average between 3 to 10 recruits per month.

USAREC uses weighted averages of past Army and other military services' recruiting success along with a measure of the qualified and military available population in each area to convert this annual accession goal into an annual contract goal to be assigned to recruiters across the country.[18] The annual contract goals are generally set to be about 110 percent of the accessions goals to account for attrition that occurs between the time an individual signs an enlistment contract, "accesses" onto active duty, and ships to basic training (typically 1 to 12 months).[19] USAREC divides the annual contract goals into high and low-quality categories (based on historical recruiting performance) and subordinate recruiting units are given an annual contract goal divided into monthly contract goals as a guide. Recruiting centers do not have to meet/exceed every monthly goal, rather, their year-to-date cumulative progress needs to keep pace with the annual contract goals determined by USAREC.

As described above, an "accession" is an individual who has passed all initial screening requirements, signed an enlistment contract, completed the oath of enlistment, spent time in the Delayed Entry Program (DEP), and shipped to basic combat training. A "contract" is an individual who has passed all initial screening requirements, signed an enlistment contract, and enters the Delayed Entry Program waiting to access. While in the Delayed Entry Program, the soldier returns home until they are to report back to the processing station, take the Oath of Enlistment to enter active duty, and ship to basic

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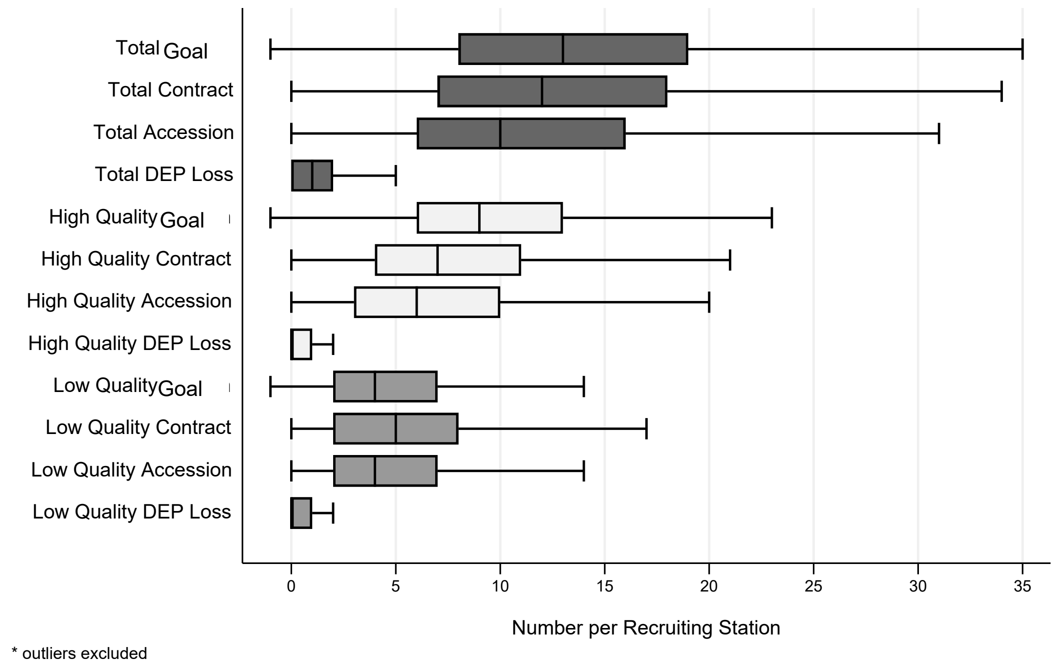
[18] Qualified Military Available (QMA) is defined as the number of youth who are eligible and available for enlisted military service without a waiver. It is normally the size of the population aged 17-24 reduced by number who have disqualifying characteristics in one or more of the following: physical/medical, overweight, mental health, drugs, criminal conduct, dependent family members, mental aptitude. See DoD Instruction 1304.26, Qualification Standards for Enlistment, Appointment, and Induction and DoD Instruction 6130.03 Medical Standards for Appointment, Enlistment, or Induction in the Military Services.
[19] The Army's accession goal given to USAREC is the only accession goal. All subordinate recruiting units base their recruiting efforts on the contract goal where contract goals = accession goals + estimated Delayed Entry Program loss.

training.

The Delayed Entry Program is used to smooth the flow of new accessions to training bases due to the uneven distribution of contract signings over the course of a year (large surge in summer/fall months with dearth in winter/spring months). Most individuals will spend between one and twelve months in the Delayed Entry Program before shipping to basic training. During their time in the DEP and before they swear the oath of enlistment to enter active duty, individuals can break their enlistment contract without consequence. This might happen because they fail to graduate high school, conduct themselves in a manner not conducive to military service, or simply reconsider their original enlistment decision. These individuals are known as DEP losses and the requirement for their contract is added back into their respective recruiting center's annual contract goal.[20] Figure 1.8 shows the distribution of goals, contracts, accessions, and DEP Loss for recruiting stations for fiscal quarters 2003 to 2016.

[20] As mentioned above, contracts goals = accession goals + estimated Delayed Entry Program loss.

Figure 1.8. Recruiting Station Performance for Fiscal Quarters 2003 to 2016



1.4.2 Adjustment of recruiting goals

Enlistment contract goals are typically set in June and July for the upcoming fiscal year and there are no regular adjustments once they are set. Recruiting units subordinate to USAREC (brigades, battalions, companies, and stations) are not allowed to adjust goals unless approved by the recruiting command. Changes are rare and are made only if the recruiting command receives an accession goal change sometime in the middle of the fiscal year due to external events (such as mid-year Congressional changes in authorized end strength, which happened in 2014).[21]

Figures A 1.1 and A 1.2 (in appendix) emphasize the relative infrequency and small size of goal adjustments that do occur each year.[22] Low and high-quality goals

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[21] If this occurs, the recruiting command is forced to issue a change to recruiters in the field and the assigned change will vary by subordinate units.

[22] 2014 is an outlier as that's the year the Army was given direction mid-way through the year to shrink to pre-WWII levels. Excluding 2014, the percentage of goal adjustments (total, high-quality, low-quality) that

remain unadjusted 97 percent of the time. When goals are adjusted, they are generally for low-quality contracts and they are adjusted downward (Figure A 1.3). The next most frequent adjustment is high-quality goals being adjusted downward.

USAREC distributes recruiters to recruiting centers across the country in a manner almost identical to for distributing recruiting goals. Examining the data, about 80 percent of recruiting stations in a given year see no recruiter number changes (Figure A 1.4). Of the changes, 96 percent are +/- 1 recruiter and 99 percent are +/-2 recruiters. Moreover, the changes are mostly balanced between increase and decreases in recruiters (Figure A 1.5).

1.5 Data

The data for this project comes from the U.S. Army Recruiting Command and the U.S. Military Entrance Processing Command (USMEPCOM). It comprises individual records containing monthly demographic, medical, physical, aptitude, and enlistment contract information, for all applicants to the Army from January 1, 2003 to September 30, 2016. The observations contain the results of physical, medical, and aptitude screening (to include ten ASVAB subtest composite scores and the AFQT) and, for those that sign a contract, the terms of each contract (occupation, contract length, bonus, educational benefits, term length, etc.). I condition the sample to include only non-prior service enlisted individuals that signed a contract within the United States. I exclude the small fraction of Soldiers that enlist at recruiting stations overseas or in U.S. territories such as Guam, Puerto Rico or the Virgin Islands[23].

The data also includes recruiter quantities, monthly high and low-quality recruiting

are zero go up by another 1 percent.

[23] Less than 2 percent of all recruits.

contract goals, and enlistment contracts signed by the other armed services (Air Force, Navy, Marine Corps). The analysis is constrained to the period from October 2005 to September 2016 due to limitations in matching recruiting stations and enlistment contract production to U.S. counties.[24] Finally, I link the recruiting data to county FIPS codes and collapse this data by month and county FIPS codes to obtain a panel dataset of observations for each county by month.[25] The combined panel data represents nearly 122,000 county*quarters between fiscal years 2006 and 2016 and identifies the number and characteristics of total applicants and enlistment contracts signed for each county*quarter.

These military datasets are taken from databases used by DoD to calculate pay and promotion information for soldiers and to monitor, adjust, and reward recruiting performance. The information in these datasets are used on a day-to-day basis by the military and incentives exist for all parties (soldiers, recruiters, and military) to ensure their accuracy. Consequently, measurement error is assumed to be minimal.

1.5.1 Descriptive Statistics

Since the advent of the All-Volunteer Force in 1973, the active duty Army has ranged in size from nearly 800,000 Soldiers at the end of Vietnam to roughly 470,000 soldiers at the depth of the draw down following the end of the Cold War in the 1990s. In my sample from 2003 to 2016, the Army ranged in size from 493,000 to 561,000 with the peak occurring in 2010 and 2011 (see Figure 1.9).

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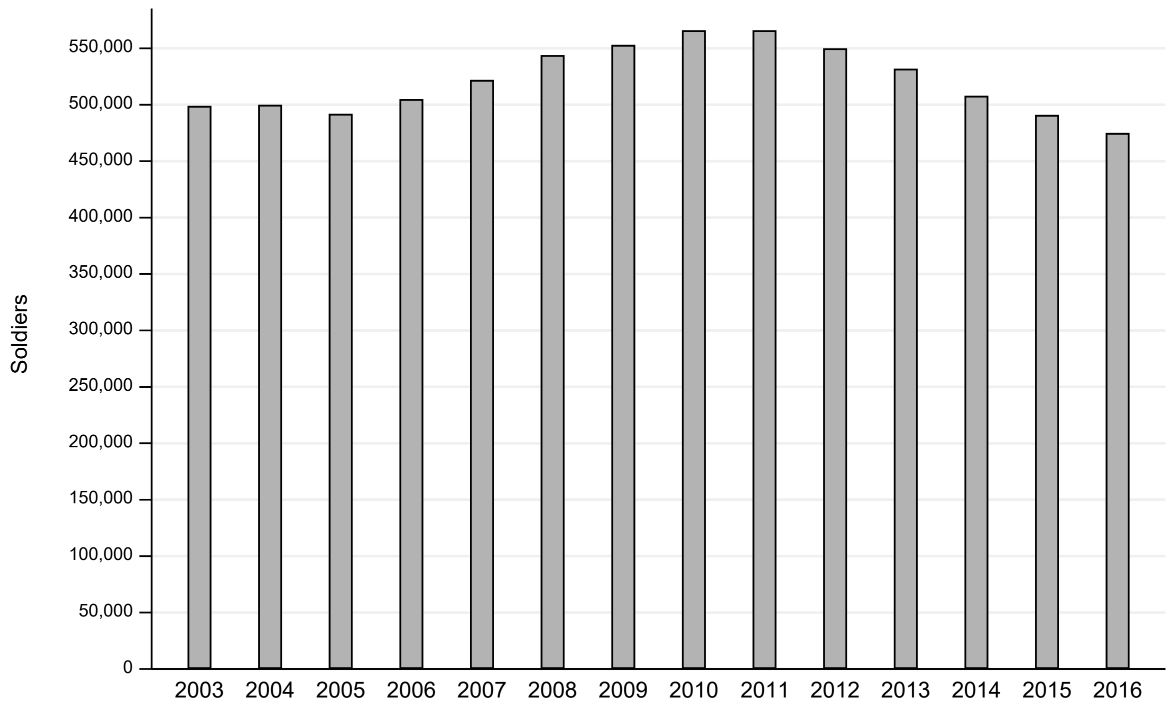
[24] The crosswalk file for matching recruiting stations to counties from the US Army Recruiting Command does not extend back beyond October 2005.

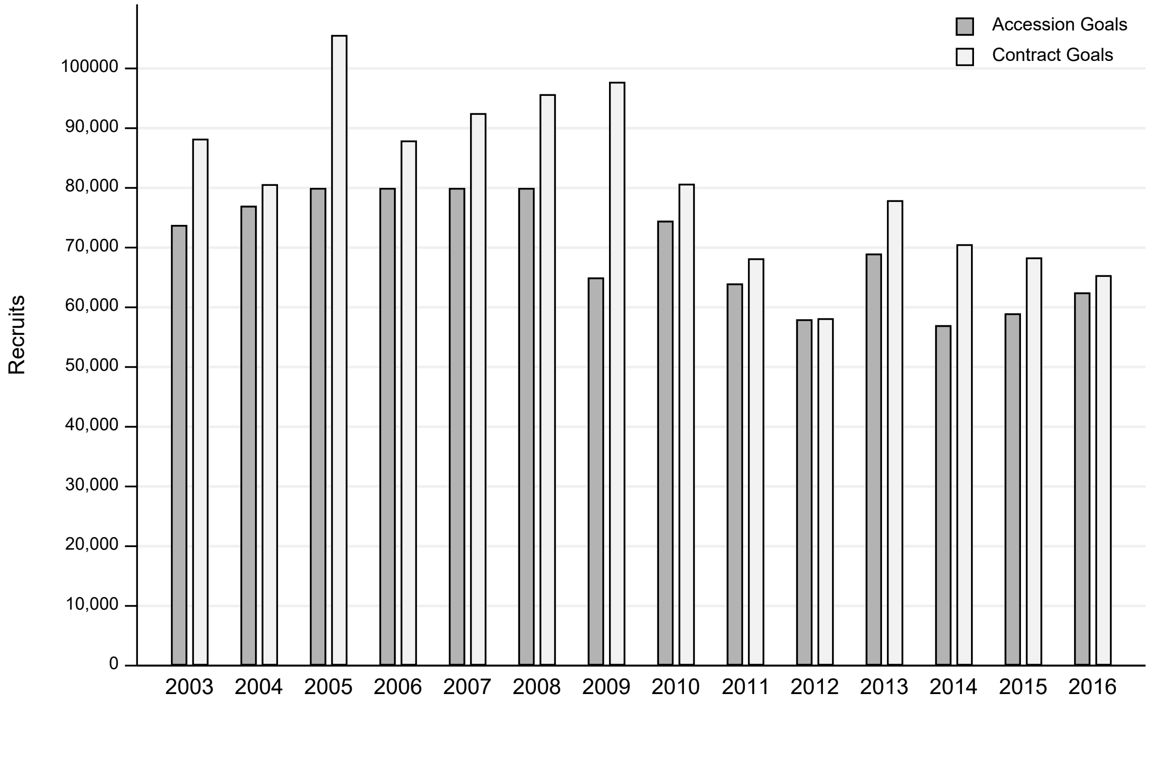
[25] To apportion the recruiting data to counties (rather than recruiting stations), I used the Census' intercensal estimates of county resident population and the fraction of zip codes each recruiting station was responsible for in each county to apportion the recruiters, recruiting goals, and DoD contract data to individual counties.

Figure 1.9. Army Authorized End Strength for Fiscal Years 2003 to 2016



To maintain the Army's size, the annual accession goals ranged from 59,000 to 80,000 and contract goals ranged from 59,000 to 110,000. During this period, contract goals average roughly 110 percent of the respective accessions goal to account for annual DEP loss (see Figure 1.10).

Figure 1.10. Accession and Contract Goals for Fiscal Years 2003 to 2016



With respect to accessions goals, the Army met or exceeded its annual accessions goal every year since 2003 except for during the height of fighting in Iraq and low unemployment in 2005 (see Figure 1.11). In terms of contracts, the Army met or exceeded its goals much less frequently than accessions with contracts exceeding contract goals in only 2009 through 2012 (depths of the Great Recession and aftermath – see Figure 1.12).

Figure 1.11. Accession Achievement for Fiscal Years 2003 to 2016

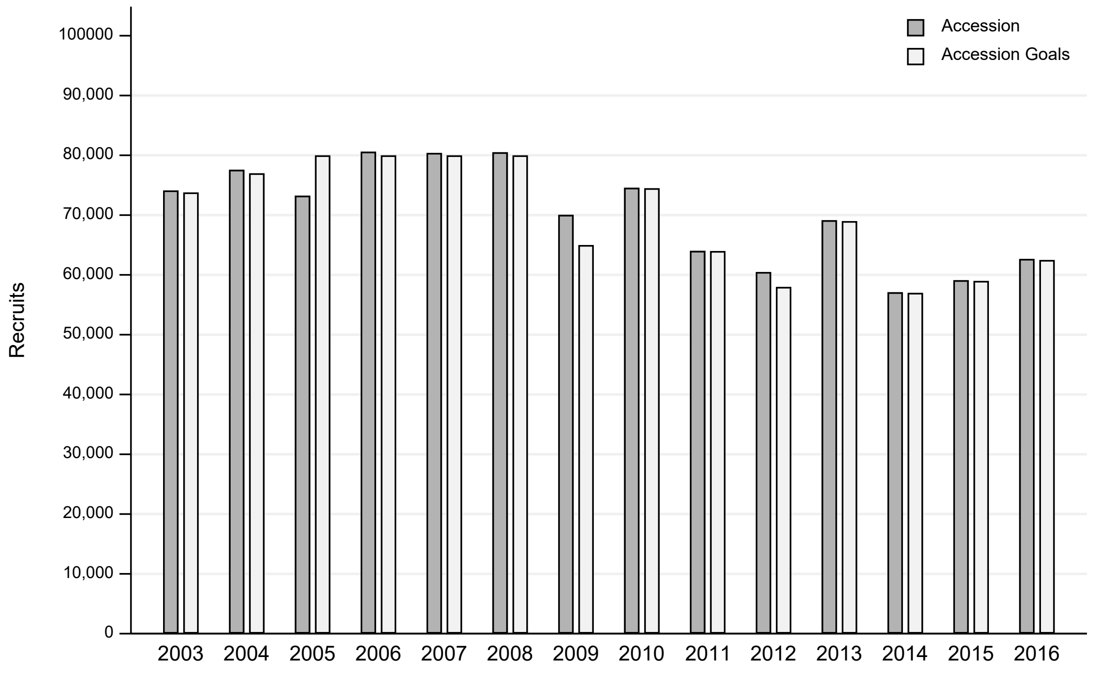
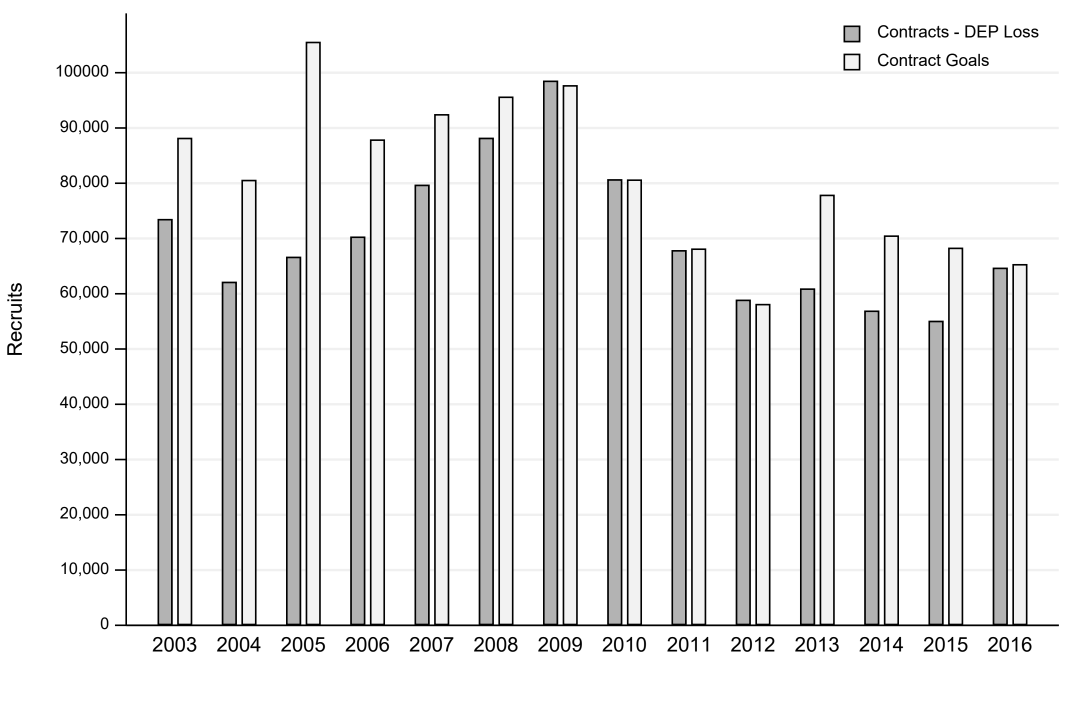
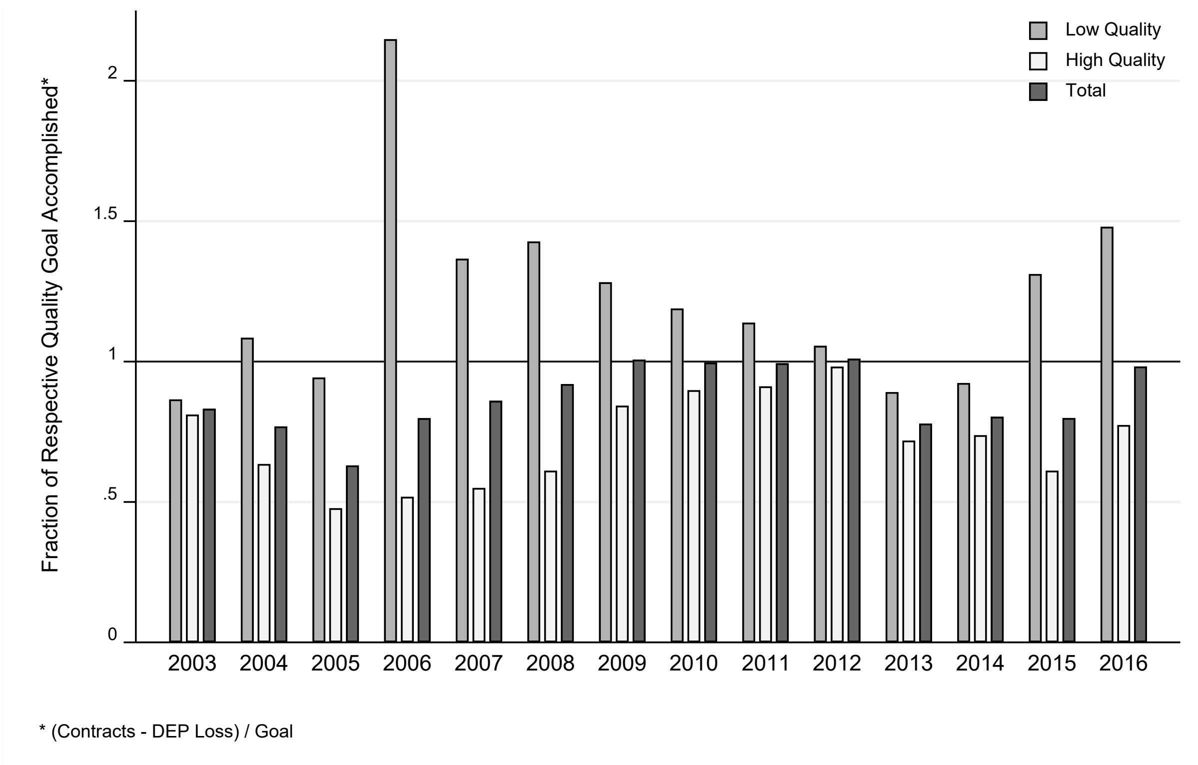


Figure 1.12. Contract Achievement for Fiscal Years 2003 to 2016



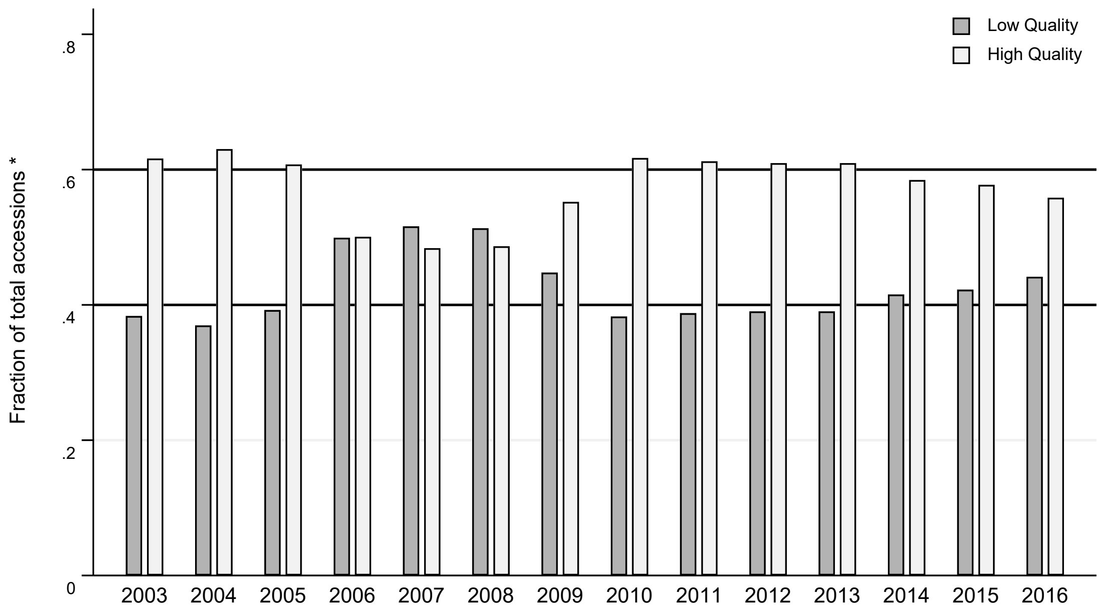
Decomposing the contract goals by quality, the low-quality contract goal was met or exceeded ten times during the sample period while the high-quality contract goal was never exceeded (see Figure 1.13).

Figure 1.13. Contract Goal Achievement for Fiscal Years 2003 to 2016



In addition to total contract volume, the Army is also concerned about the quality composition of the recruiting cohort. The Army has missed its own goal of 60 percent of each cohort comprising high-quality accessions eight times from 2003 to 2016 (see Figure 1.14). As one would expect, the quality composition goals for contract goals are closely related to the quality composition of accessions goals (see Figure 13b) with the years 2005-2009 and 2014-2016 reflecting recruiting difficulty.

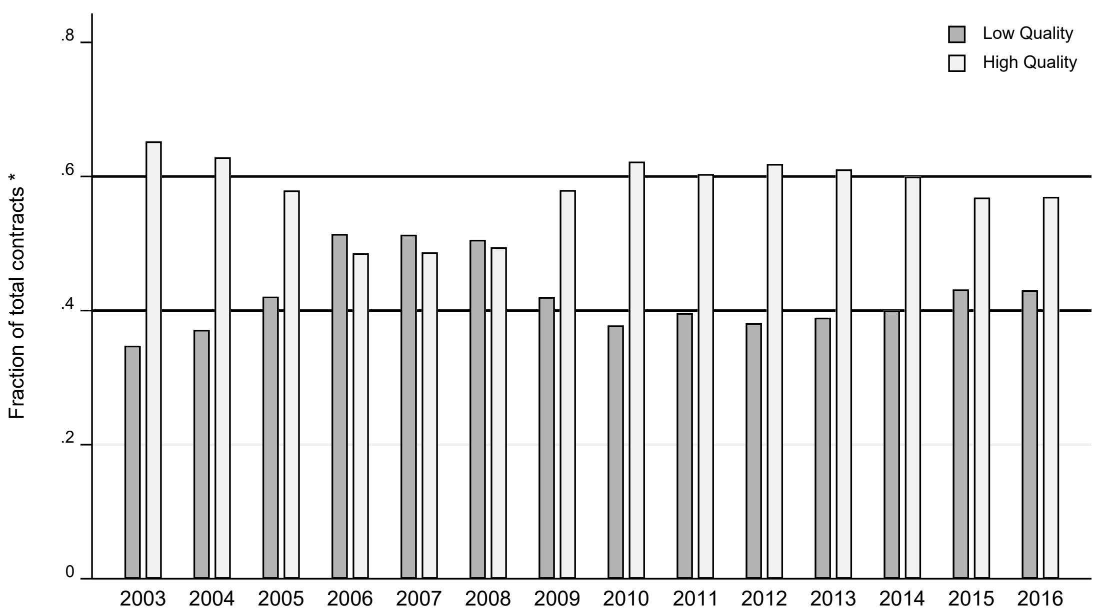
Figure 1.14. Accession Quality Composition for Fiscal Years 2003 to 2016



* (Acessions) / (Total Accesions)

** DoD mandates fraction of LQ accessions is capped at 40% and fraction of HQ accessions must exceed 60%

Figure 1.15. Contract Quality Composition for Fiscal Years 2003 to 2016



* (Contracts - DEP Loss) / (Total Contracts - Total DEP Loss)

** DoD mandates fraction of LQ contracts is capped at 40% and fraction of HQ contacts must exceed 60%

As described above, the Delayed Entry Program is used to smooth the flow of new accessions to training bases and to provide a pool of contracts from which to draw accessions in tough recruiting environments. The size of this pool at the start of each fiscal year determines the amount of flexibility the Army has with respect to recruiting shortfalls. From 2003 to 2016, the Delayed Entry Program start pool (size of DEP at beginning of the fiscal year) has varied from nearly 40,000 contracts in 2003 to less than 10,000 contracts in 2007 (see Figure 1.16). The Army prefers to hold approximately 30-35 percent of an annual accessions requirement in the DEP start pool as a hedge against uncertain recruiting environments (Peterson and Quester 2013). In the sample, the size of the DEP as a fraction of the annual accessions goal ranged from a high of 55 percent in 2003 to a low of 9 percent in 2007 (Figure 1.17 and 1.18).

Figure 1.16. Delayed Entry Program Size at beginning of Fiscal Years 2003 to 2016

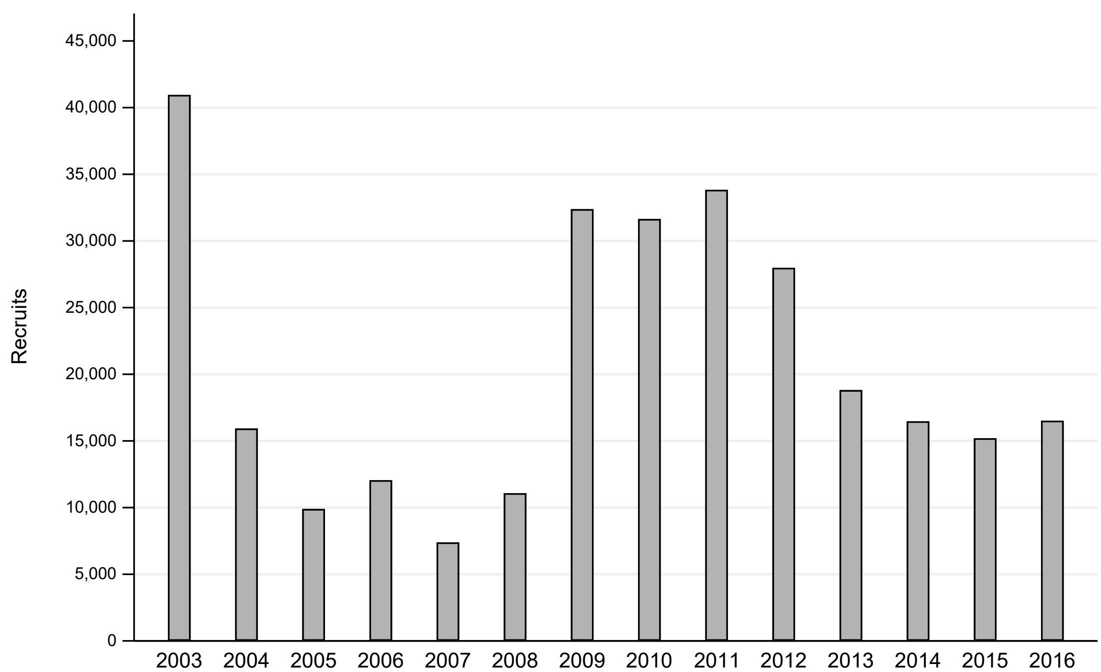


Figure 1.17. Delayed Entry Program Loss in DEP by Contract Type for Fiscal Years 2003 to 2016

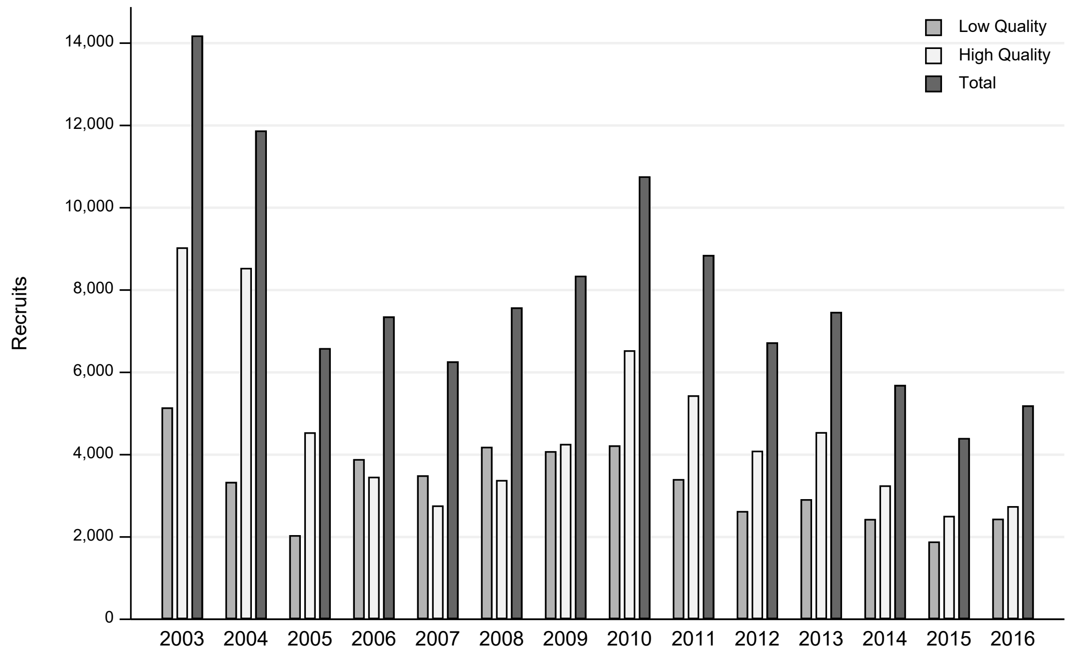
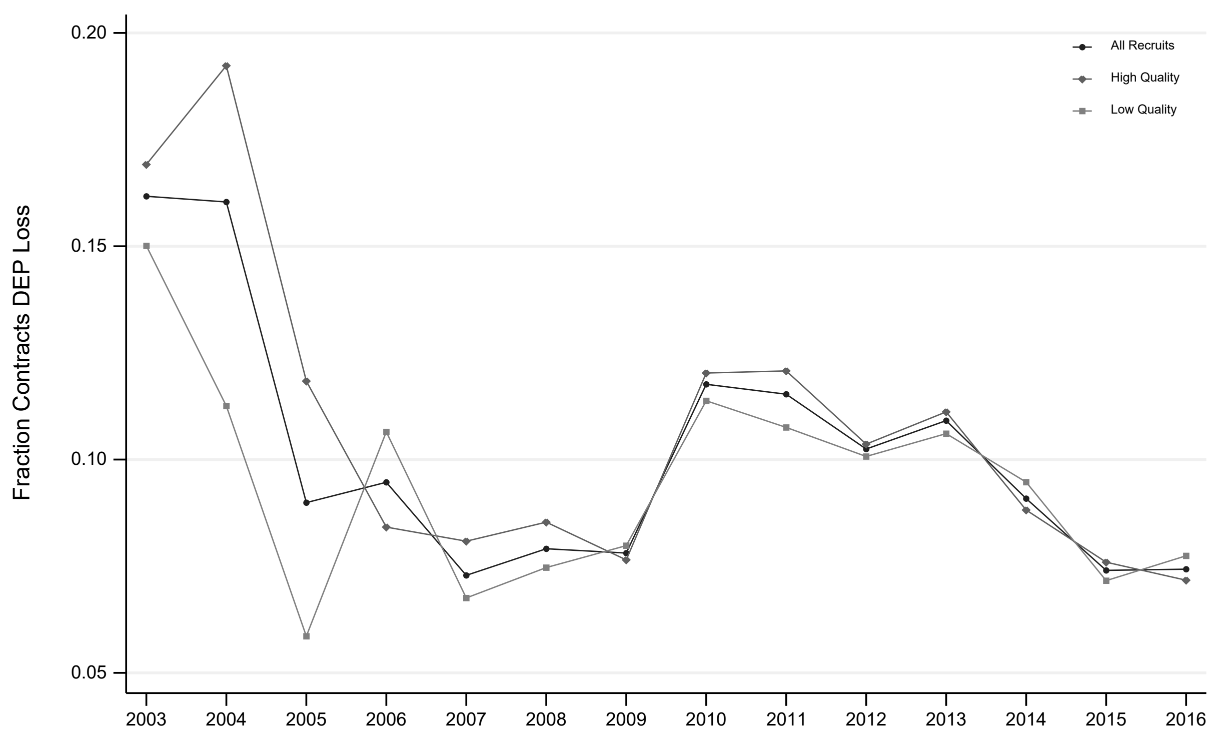


Figure 1.18. Delayed Entry Program Fraction lost in DEP by Contract Type for Fiscal Years 2003 to 2016



1.6 Analysis

Using Army enlistment data from 2003 to 2016, I demonstrate that low-quality contracts are not constrained by the Army. Recruiters routinely exceed low-quality contract goals, both when high-quality contracts are in short supply and when high-quality contract goals are exceeded during “good” recruiting periods. This indicates that recruiters don’t view low-quality contracts as a poor substitute for high-quality contracts in tough recruiting environments, nor do they view low-quality contracts as a “residual” population to be recruited to make up for the remaining contracts needed each month after accounting for high-quality contracts. Rather, it appears low-quality contracts are a complement to high-quality contracts and are influenced by economic and social factors in similar ways.

The results also indicate it is the use of the DEP that allows recruiters to recruit beyond their assigned goals. Given that recruiting is both a *national* effort undertaken by geographically disparate recruiting stations and an *annual* effort broken up into monthly and quarterly milestones, the analysis below shows the results hold in both dimensions (spatial and time). This means researchers should be able to estimate supply elasticities for the total population of individuals willing to contract. Finally, I explore reasons why low-quality goals are so often exceeded when the Army is centrally managing the recruiting process. While the data cannot directly answer this question, I hypothesize the Army and its recruiting force maximize related, but different, constrained objective functions which potentially leads to divergent goals and uncertainty in the recruiting process, geographic and temporal dispersion of recruiting units, and a focus on volume over quality composition combine to incentivize recruiters to exceed low-quality contract goals when possible.

1.6.1 Low-quality contract goals independent of high-quality contracts

Assuming low-quality contracts are demand-constrained implies the number of observed low-quality contracts is the result of the Army's requirement for these contracts (as represented by low-quality contract goals) and not the actual supply of low-quality recruits. If low-quality contracts were constrained by the Army's demand, then the observed number would always equal low-quality contract goals, $C_L = G_L^C$. However, on average, only 13 percent of recruiting stations in a given fiscal quarter achieve *exactly* their low-quality contract goal. Another 49 percent of recruiting stations exceed their low-quality contract goal while 38 percent fall short.

Table 1.1. Recruiting Station Contract Goal Performance by Contract Type for Fiscal Quarters 2003 to 2016[26]

	Not reached	*Achieved*	*Exceeded*
Low quality Goals	0.38	0.13	0.49
High quality Goals	0.70	0.07	0.23

One might imagine that due to the natural variance in recruiting, seasonality of recruit availability, or intertemporal choices made by recruiters, recruiting stations might fail to achieve their goal in one quarter but, on average, exactly achieve their goals for the fiscal year. However, this is also not the case. On average, in a fiscal year, recruiting stations achieve their low-quality contract goals only six percent of the time and exceed it 55 percent of the time. Moreover, 39 percent of all recruiting stations fail to achieve their low-quality contract goals.

[26] This also remains true if DEP losses are not subtracted from contract achievement. The values for low quality goals are 0.33, 0.13, and 0.54. The values for high quality goals are 0.63, 0.09, and 0.28.

Table 1.2. Recruiting Station Contract Goals Performance by Type for Fiscal Years 2003 to 2016 [27]

	Not reached	*Achieved*	*Exceeded*
Low quality Goals	0.39	0.06	0.55
High quality Goals	0.80	0.02	0.18

Combining "achieved" and "exceeded" within fiscal quarters (Table 1.1) or fiscal years (Table 1.2) respectively, one can see contracts were greater than or equal to contract goals approximately 60 percent of the time.

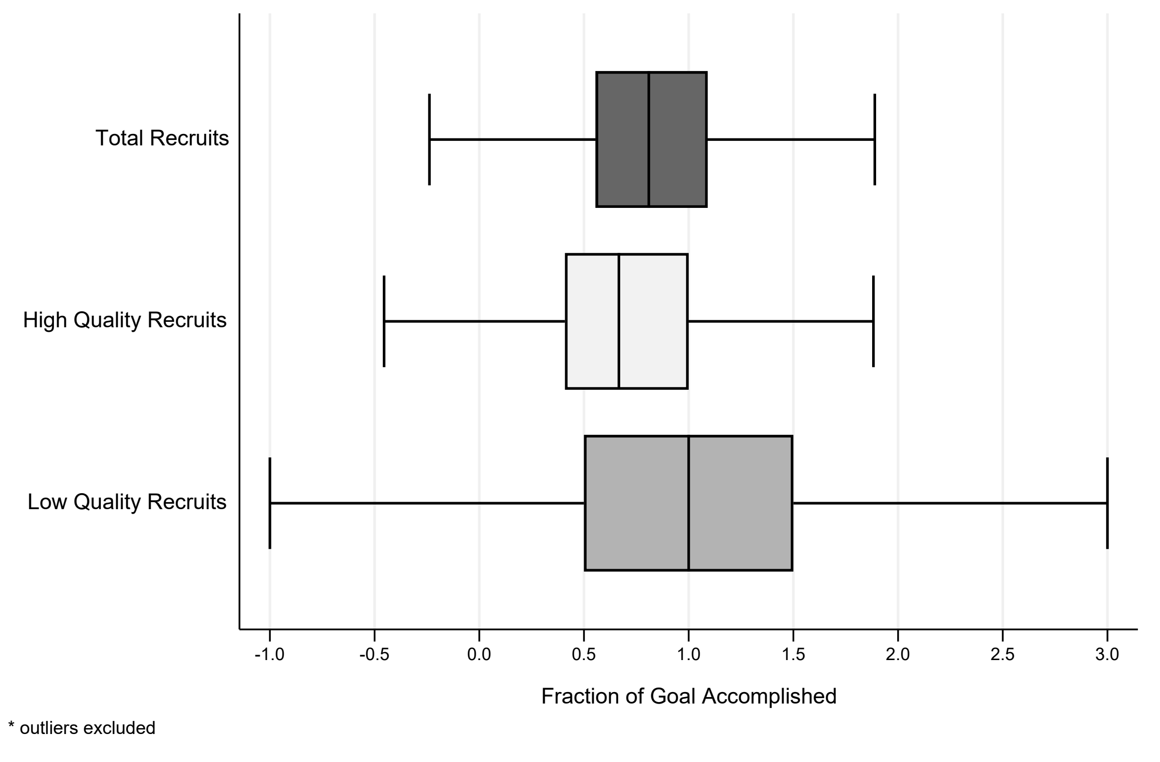
Due to the geographically disparate nature of recruiting, it is also possible some recruiting stations might fail to achieve their low-quality contract goals, while others achieve or even exceed them, and in the aggregate for a given period, the Army still exactly achieves its low-quality contract goal (i.e., constraining its demand for low-quality contracts). However, this is not supported by aggregated data at each geographic level of recruiting (recruiting stations, companies, battalions, brigades, or the entire Army) in a given period. In fact, the achievement of low-quality contract goals follows the same pattern with roughly 38 percent of recruiting entities (stations, companies, battalions, brigades) failing to achieve the low-quality goal and 62 percent exceeding the low-quality contract goal.

Rather than look at only averages across time (quarter to annual) or across geography (recruiting station up to Army), we could also inspect the distribution of recruiting station performance. In a given fiscal quarter, the median recruiting station accomplished its goal, but the distribution of performance is broad (see Figure 1.19). As

[27] As before, this also remains true if DEP losses are not subtracted from contract achievement. The values for low quality goals are 0.31, 0.05, and 0.64. The values for high quality goals are 0.71, 0.04, and 0.25.

before with average performance, this remains true when the data is aggregated up from recruiting stations, to recruiting battalions (roughly state size), to brigades (roughly census divisions), and to the Army as a whole for any given fiscal quarter in the sample. Finally, this pattern also holds for the distribution of recruiting performances aggregated across time from fiscal quarters to fiscal years (see Figure A 1.6 to Figure A 1.15 in the Appendix).

Figure 1.19. Distribution of Recruiting Station Performance in Fiscal Quarters 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)



In sum, the data shows the Army does not constrain low-quality contracts to be equal to the low-quality contract goal in any meaningful way. This result holds for both average recruiting performance and the distribution of recruiting performance when examined over time (a fiscal year) and geography (nationally for roughly 1,000 recruiting stations).

1.6.2 Low-quality contracts as a residual element in recruiting

The analysis above demonstrates that low-quality contracts, irrespective of high-quality contracts, are not constrained. However, it is possible low-quality contracts are constrained by the Army, but not in the absolute sense as investigated above ($C_L = C_L^G$), where C_L is the low-quality contracts signed and C_L^G is the Army's goal for low quality contracts in a certain location and period. Rather, low-quality contracts might be constrained to be a "residual" element in overall recruiting efforts. In other words, the Army might constrain the number of low-quality contracts to be exactly equal to the number necessary to achieve overall contract goals after accounting for high-quality contracts in the overall goal. In other words,

$$C_L = C_T^G - C_H \text{ where } C_H + C_L = C_T^G \qquad 1.1$$

where G represents goals, C represents contracts, L and H represent high and low-quality types, and T represents total. If this is the case, the number of low-quality contracts can exceed low-quality goals, but only in situations where high-quality goals are not being met. In this way, low-quality contracts act as a substitute for high-quality contracts when and where high-quality contracts are in short supply. If true, we would expect to see three possible outcomes in the data:

1) When high-quality contracts exceed high-quality goals, low-quality contracts should be constrained to less than low-quality goals. If $C_H > C_H^G \Rightarrow C_L < C_L^G$.
2) When high-quality contracts are short of high-quality goals, low-quality contracts should exceed low-quality goals to ensure total contract goals are met. If $C_H < C_H^G \Rightarrow C_L > C_L^G$
3) If high-quality contracts are equal to high-quality goals, then low-quality contracts should also be exactly equal to low-quality contract goals $C_H = C_H^G \Rightarrow C_L = C_H^G$

From the 2003 to 2016, when high-quality contract goals are not reached, low-quality contract goals are also achieved at lower rates. When high-quality contract goals are achieved or exceeded, low-quality contract goals are achieved or exceeded as well (see Table 1.3). In other words, the data does not support the hypothesis that low-quality contracts are a substitute for high-quality contracts, rather, the achievement of both low and high-quality contracts goals are positively correlated.

Table 1.3. Low-quality Contract Performance conditional on high-quality contract performance (Recruiting Stations in Fiscal Quarters 2003 to 2016)[28]

	Low Quality Goal Not reached	*Low Quality Goal Achieved*	*Low Quality Goal Exceeded*
High Quality Goal Not Reached	0.41	0.12	0.47
High Quality Goal Achieved	0.39	0.14	0.47
High Quality Goal Exceeded	0.32	0.12	0.56

As with the earlier investigation into low-quality contracts independent of the Army's progress in meeting high-quality contract goals, this pattern holds up when aggregating across both time and geography. Rather than low-quality contracts acting as a residual or substitute for high-quality contracts as recruiters strive to achieve their overall goals, it appears low-quality contracts are subject to the same economic, social, and demographic forces as high-quality contracts and achievement for high and low-quality contracts are positively, not negatively, correlated.

In personal communications with the author, former Army recruiters and analysts

[28] Finally, as before, this also remains true if DEP losses are not subtracted from contract achievement. The values for low quality goals when high quality goals are not achieved are 0.36, 0.12, and 0.52. The values for low quality goals when high quality goals are achieved are 0.28, 0.23, and 0.49. The values for low quality goals when high quality goals are exceeded are 0.27, 0.12, and 0.61.

from USAREC concurred that low-quality recruits, like high-quality contracts, are not meaningfully constrained, at least most of the time. [29] There are circumstances when the recruiting command will constrain a particular category (e.g., high school seniors scoring below 50 on the AFQT) until a recruiting station achieves its high-quality goal for the month. This would typically only occur in the last few of months of a fiscal year as the Army is closely managing its high/low-quality balance in the annual cohort to meet congressionally mandated ratios (e.g., the 60/40 rule). However, in most cases, the recruiting command does not constrain low-quality contracts. Instead, the marginal low-quality individual is encouraged to sign a contract irrespective of goal progress and is placed in the Delayed Entry Program until the next fiscal year. This means that during years when the Army is successfully achieving both their low and high-quality goals (positive recruiting environment), they do not reduce recruiting efforts or turn away low-quality applicants. The question then is how can low-quality contracts be unconstrained by the Army, yet the Army meets its annual requirement for accessions every year without vastly exceeding its recruiting objectives? The answer is the Army uses the DEP as a buffer to reconcile flows of contracts with flows of accessions when the two are unequal.

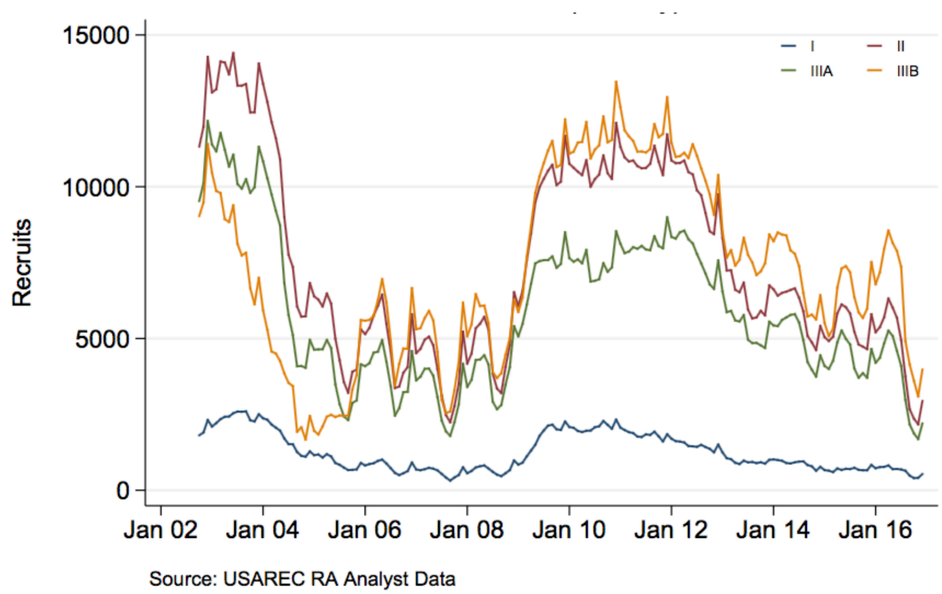
If the Delayed Entry Program is used a "buffer" for absorbing more low-quality contracts during positive recruiting periods (poor economic conditions, fewer active conflicts, etc.) or sending onto active duty more low-quality accessions during difficult recruiting periods (good economic conditions, high casualty conflicts, etc.), then the size of the Delayed Entry Program should increase during positive recruiting conditions and decrease during poor recruiting conditions. Moreover, the number of low-quality contracts moving into the DEP should increase more than high-quality since low-quality more often

[29] In-person interview on March 23, 2018 and email communication with author on July 21, 2017.

exceed contract goals.

Using individual soldier contract and accession dates (the difference between the two dates are the months they wait in the Delayed Entry Program), I examined Delayed Entry Program data by contract quality by month. Figure 1.20 illustrates that most of the movement in the Delayed Entry Program is coming from those with AFQT scores below 93.[30] This supports the hypotheses that the Delayed Entry Program is used as a buffer. Specifically, the size of the Delayed Entry Program decreases (for both high and low-quality) during the large contract shortfall in 2005, begins to increase in 2006 to 2008 as the low-quality contract shortfall closes, increases significantly during the period 2009 to 2012 when contract goals were met, and then begins to drop again during the contract shortfalls of 2013 to 2015 (refer to Figure 1.12 above for contract achievement).

Figure 1.20. Delayed Entry Program Size by Recruit Quality for fiscal years 2003 to 2016



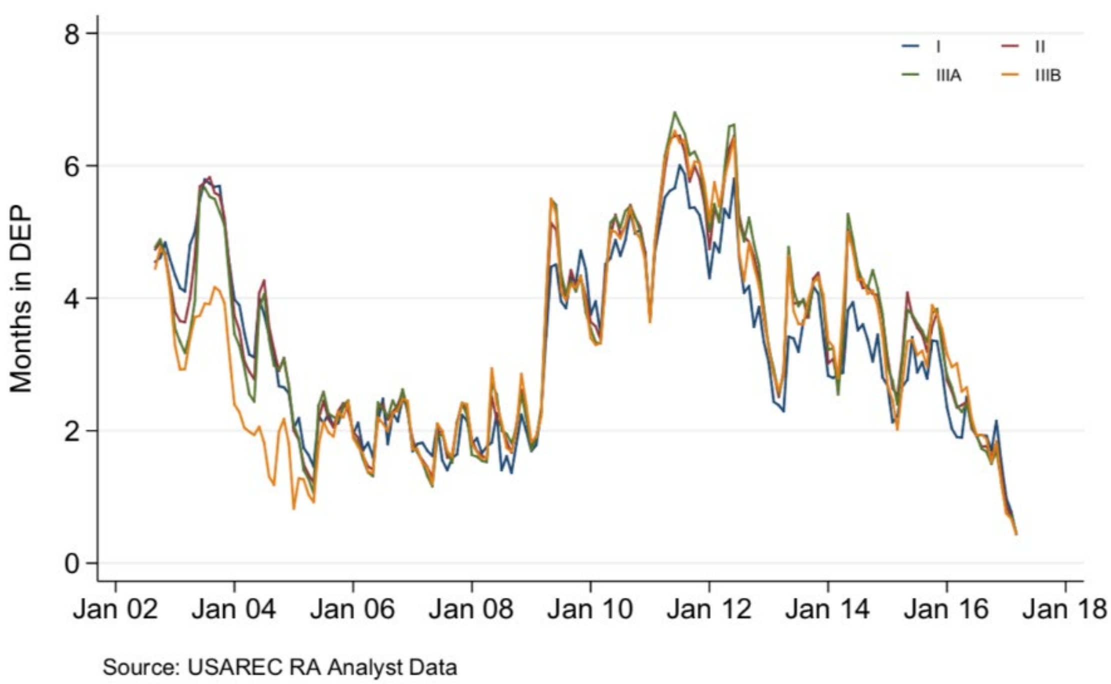
Looking at low-quality contracts specifically (Test Score Category IIIB), the

[30] Specifically, Test Score Categories II: 93 > AFQT ≥ 65; IIIA: 65 > AFQT ≥ 50; IIIB: 50 > AFQT ≥ 31

movement in DEP size is greatest for this population and it largely follows the same pattern. If low-quality individuals are used as a buffer to reconcile contracts with accessions, then we would expect to see relatively more movement into and out of the Delayed Entry Program by low-quality than high-quality contracts. We would also expect to see relatively longer Delayed Entry Program stays for low-quality contracts during bad economic times and shorter stays during good economic times. This is what we see in both Figure 1.20 above and Figure 1.21 below.

With respect to Delayed Entry Program duration (Figure 1.21), we expect to see a contract's stay in the DEP fluctuate more for low-quality than high-quality, increasing when the recruiting environment is favorable and decreasing in difficult periods. While they appear to move together in most cases, the duration for low-quality contracts (Test Score Category IIIB) does follow the expected trend.

Figure 1.21. Average Delayed Entry Program Stay by Recruit Quality for fiscal years 2003 to 2016



In summary, the number of observed high and low-quality contracts are determined by the youth population's willingness to enlist and not a demand constraint placed by the Army. If low-quality contracts were actually constrained by the Army's demand for them, we would expect to see the low-quality contract goal functioning as a quota ($C_L = C_L^G$) in most cases. However, this is not observed in the data. Moreover, from Table 1.3, low-quality contracts are not a residual element in recruiting as the achievement of low-quality contracts is positively, not negatively, correlated with the achievement of high-quality contracts. Lastly, low-quality goals are often exceeded even when high-quality goals are met, and the Army has missed its total contract goal only once but its quality composition goal eight times during the sample period. This is further evidence that contract volume is more important than the quality composition ratio (60/40).

On the other hand, the numbers of high and low-quality accessions (contracted individuals leaving Delayed Entry Program and entering active duty) are constrained by the Army. This is evident in the precise nature by which the Army achieves its accessions goals each year (see Figure 1.10 and 1.11). The data illustrates the Delayed Entry Program is the buffer that reconciles the contract and accessions flows and allows the Army to contract as many low-quality soldiers as possible without violating the 60/40 quality composition rule in a given year.

1.6.3 Why are low-quality contract goals so often exceeded?

The analysis demonstrates that low-quality contract goals do not function as either quotas or effective ceilings and the DEP serves as a buffer between contracts and accessions in years where contracts exceed goals. However, the analysis does not demonstrate why low-quality goals are so often exceeded when the Army is centrally managing the recruiting process. While the data cannot answer this question, I hypothesize the answer is two-fold. First, based on the process by which accessions and contract goals are created, the Army and its recruiting force optimize related, but different, constrained maximization problems. This leads to potentially divergent outcomes. Second, uncertainty in the recruiting process, geographic and temporal dispersion of recruiting units, and a focus on volume over quality composition combine to incentivize recruiters to exceed low-quality contract goals when possible. This likely exacerbates the fact that the Army and its recruiting force have goals that are not entirely aligned.

As described in section 1.4 (Institutional Background), the Army strives to meet both quantitative (volume) and qualitative (quality composition) goals in the recruiting process. The Army first determines how many new soldiers will be required annually to maintain its congressionally authorized end-strength given attrition and reenlistment rates in the Army. This represents the Army's total accessions goal, A_T^G. Additionally, the Army strives to maintain congressionally mandated qualitative goals of no less than 60 percent new accessions with AFQT scores in the top half of the distribution and no less than 90 percent of new accessions possessing a high school degree. Thus, the Army's total accessions goal is a function of congressionally mandated end-strength goals, s, reenlistment rates, r, quality goals, q, and attrition rates, a

$$A_T^G = f(s, r, a, q) \qquad 1.2$$

At a national level and to a first order approximation, this overall annual accession goal for the Army is related to the overall annual contract goal by

$$C_T^G = A_T^G + \mathbb{E}[L] \qquad 1.3$$

where A is accessions, C, is contracts, and $\mathbb{E}[L]$, is the expected amount of contract attrition in the DEP (i.e., DEP loss).

At a sub-national level, the Army disaggregates the annual contract goal across the two dimensions of time and space. Across the dimension of time, the goal is distributed mostly uniformly with some consideration for the seasonal nature of recruiting. Across the spatial dimension, the overall contract goal is not distributed uniformly to recruiting stations across the country, but rather, characteristics of the qualified and eligible population and historic numbers of contracts from each geographic area are considered. Thus, the quantitative (total) and qualitative (mix of high and low-quality) contract goals for a given area i in period t are determined by

$$C_{i,t}{}_T^G = C_{i,t}{}_H^G + C_{i,t}{}_L^G = f(A_T^G, P_{i,t}, Q_{i,t}, \mathbb{E}[L_{i,t}], R_i) \qquad 1.4$$

where A_T^G is the Army's annual accessions goals, P is the past contract production, Q is the qualified and military available population (QMA), $\mathbb{E}[L]$ is the historic attrition rate of contract losses in the DEP, and R is recruiting resources (bonuses, number of recruiters, advertising, etc.). These high and low contract goals ($C_{i,t}{}_H^G$ and $C_{i,t}{}_L^G$) are then assigned to recruiting stations throughout the country. Thus, the Army as a whole has an annual accessions goal that is converted into monthly contract goals assigned to recruiting stations based on local demographics and historical propensity to enlist in the military.

Once goals are established, the Army and recruiting stations maximize related, but different objective functions. The Army, as an organization, seeks to maximize the number of new accessions subject to quantitative and qualitative constraints

$$A_T = max\, f(E, S, D, R) \text{ subject to} \qquad 1.5$$

$$A_T \geq A_T^G \qquad A_{CAT4} \leq 0.04A_T^G$$
$$A_H + A_L + A_{CAT4} \geq A_T^G \qquad R_{ad} \leq R_{FY\_ad}$$
$$A_H \geq 0.6A_T^G \qquad R_{\#Rec} \leq R_{FY\_\#Rec}$$
$$A_L \leq 0.4A_T^G \qquad R_{bonus} \leq R_{FY\_bonus}$$

where A_T is the total number of accession, A_T^G is the total annual accessions goal, E, S, D represent the economic, social, and demographic factors affecting recruiting, R represents recruiting resources (subscript 'FY' represents annual constraints) which also implicitly represent the cost of recruiting to the Army, L is low-quality individuals, H is high-quality individuals, and $CAT4$ is the number of new accessions who scored between the 10th and 30th percentile on the AFQT.[31]

Like the Army's aggregate contract goals, recruiting stations have both quantitative (${C_{i,t}}_T^G$) and qualitative (${C_{i,t}}_H^G$ and ${C_{i,t}}_H^G$) goals. Unlike the Army's aggregate goals, individual recruiting stations are not directly constrained by the 60 percent high-quality and 90 percent high school graduate composition requirements. Their assigned high and low-quality contract goals can skew toward either high or low contracts because they are informed by location-specific economic, demographic and social characteristics. Thus, recruiting stations attempt to maximize the total number of contracts ${C_{i.t}}_T$ in their recruiting area of responsibility, i, in a given period, t,

$$ {C_{i,t}}_T = max\, f(E, S, D, R) \text{ subject to} \qquad 1.6 $$

$$ {C_{i,t}}_H \geq {C_{i,t}}_H^G $$

$$ {C_{i,t}}_L \geq C_{i,tL}^G $$

$$ {C_{i,t}}_H + {C_{i,t}}_L \geq {C_{i,t}}_T^G $$

Given similar objective functions but with different constraints for the Army and

[31] The recruiting resources identified above (advertising dollars, number of recruiters, bonuses paid) represent the majority of the costs of recruiting to the Army. Recruiters are not only paid an annual salary, but during difficult recruiting periods, soldiers in the Army are offered bonuses to become recruiters and existing recruiters are offered additional cash rewards for continuing to stay on as a recruiter for an additional year.

for its recruiters, there is no reason to believe these will result in perfectly aligned incentives. The Army is focused on recruiting an accession cohort that supports its overall end-strength requirements and comprises no more than 40% low-quality accessions. The Army's nearly 1,000 recruiting stations, on the other hand, are focused on achieving their assigned high and low-quality contract goals but will prioritize total contract volume, given some minimum quality standard, over contract quality composition should recruiting conditions require it. In other words, recruiting stations will trade-off high for low-quality contracts to keep from missing their total contract goal, ${C_{i,t}}_{T}^{G}$.

In addition to misaligned goals between the Army and its recruiting units, there is also uncertainty in the recruiting process that drives recruiting stations to exceed low-quality contract goals. While recruiters prefer high-quality individuals to low-quality individuals, they face the "stochastic arrival" of volunteers (Cook and White, 1970). Individuals interested in military service do not queue at recruiting stations in order of AFQT score and high school graduation status. Rather, recruiters find willing individuals through a combination of active searching (job fairs, high school counselors, cold-calling, etc.) and passive processing (walk-ins to recruiting stations). In almost all cases, recruiting stations are unwilling to postpone enlisting a low-quality individual today in the hopes that she will find a high-quality individual tomorrow, regardless of contract goal progress. This has the potential to increase the acceptance of additional low-quality contracts because of the uncertain arrival of high-quality contracts. Due to the geographically disperse and intertemporal nature of recruiting, recruiters also know that while their recruiting station may not have been short low-quality contracts this quarter, another recruiting station in a different area may have been short. In the same manner, recruiters who may not have been short this quarter, know there is always the chance of being short in the next quarter (i.e., recruiter decisions have an intertemporal component). Thus, there always exists a perceived need to sign a low-quality, but otherwise qualified, individual to a contract.[32]

Due to this uncertainty and the dispersed nature of recruiting (across time and space), recruiting stations are likely to place a premium on total contract volume over the quality composition of annual recruiting cohorts. This is evident in the data; the Army has failed to achieve accessions goals only once since 2003 but has failed to meet quality composition standards in eight of the last fourteen years. If the Army prioritized quality composition of a cohort over the total contract volume, it is likely that fewer low-quality individuals would have been accepted in the years when high-quality contract goals were particularly difficult to achieve. Put simply, although recruiting stations are given specific goals for both high and low-quality contracts, and recruiters strive to meet these respective quality goals, *a* contract is better than *no* contract and "volume" takes priority over "quality", especially in difficult recruiting environments.

A third and final reason low quality goals are likely exceeded is the differential structure and alignment of the costs of recruiting between the Army and its recruiting stations. In general, there are significant fixed costs (recruiting station leases, lease and/or construction of Military Entrance Processing Stations, annual levels of advertising, etc.) and variable costs (recruiter salaries and incentives, recruit bonuses, etc.) which the Army as an institution bears. Conditional on these costs accruing to the institutional Army, individual recruiting stations (already resourced with recruiters, infrastructure, etc.) bear relatively little to no costs of recruiting an additional recruit beyond the paperwork and

[32] This is related to the results in Asch (1990). Asch's analysis of the Navy's Freeman plan in the mid '80s finds that Navy recruiters make intertemporal decisions regarding their effort in enlisting individuals based on contract goals and rewards structure. She finds that recruiters "deplete their inventory of potential recruits to win the reward. Once recruiters win their reward, they must divert their effort toward building their inventory rather than making enlistments.

time required to process an additional recruit. In the absence of a salient price signal, recruiting stations are susceptible to recruiting individuals beyond their assigned contract goals if presented with the opportunity. Related to this, enrolling additional recruits into the Delayed Entry program is nearly costless. Excluding the relatively small time and administrative marginal costs of processing additional individuals into the DEP, neither the Army nor recruiting stations bear any significant cost of placing additional individuals into the DEP. Once an individual signs an enlistment contract at one of the 65 MEPS, they return home to await military orders to report to their basic training class. This wait can last anywhere from a few weeks to one year, during which recruits are not on active duty and are not receiving pay or benefits.

Figure 1.22. Composition of Potential Recruit Population (levels for fiscal years 2001 to 2014

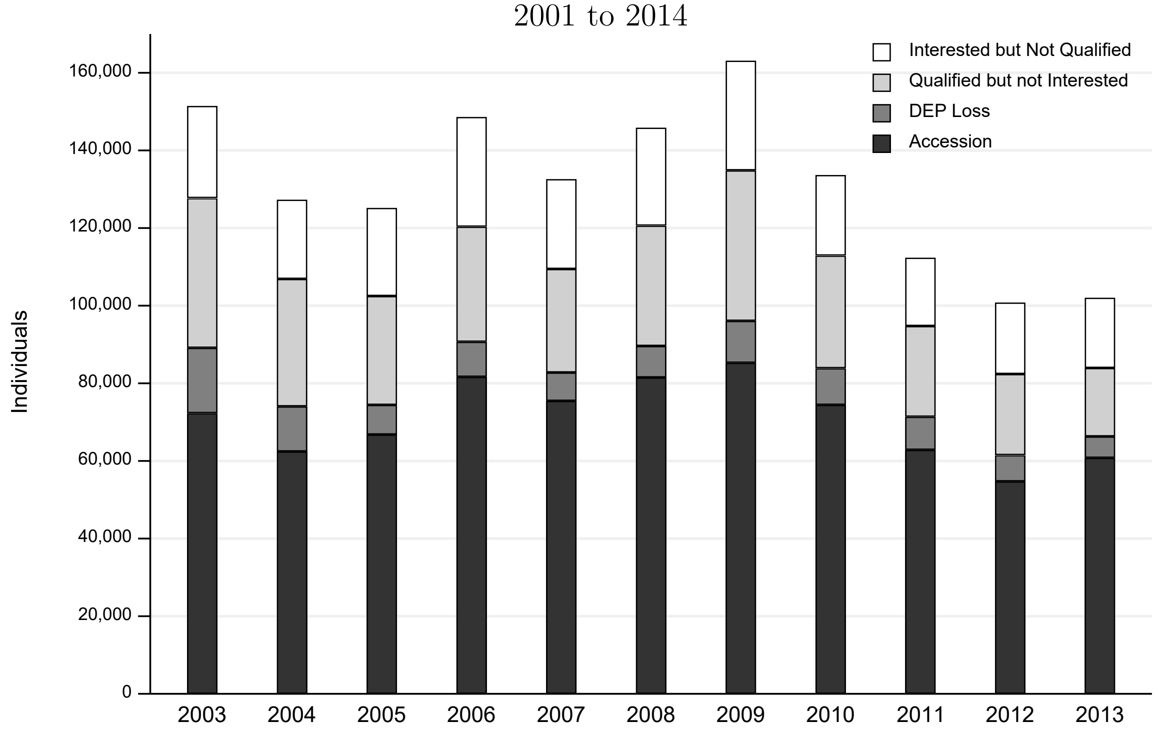
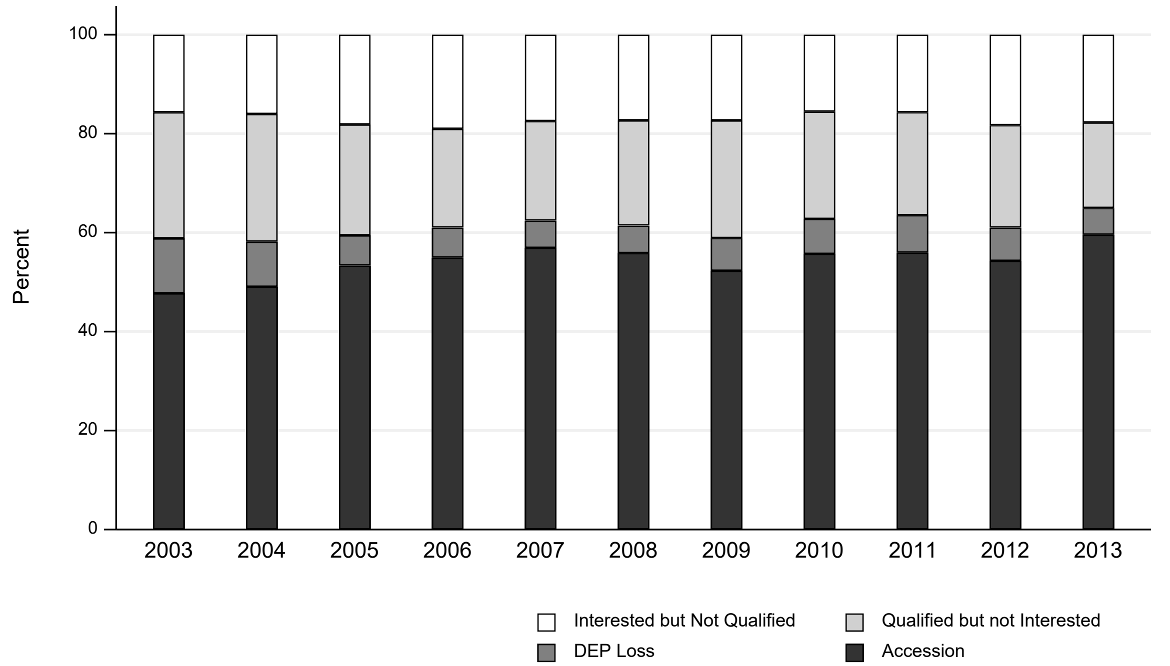


Figure 1.23. Composition of Potential Recruit Population (percent) for fiscal years 2001 to 2014



1.7 Discussion and Conclusion

In general, my findings suggest that the use of only high-quality contracts as the key outcome variable in research on the supply of individuals interested in military service is unnecessary and limits the researcher's ability to contribute a broader discussion about the sensitivity to economic and social conditions of an individual's decision to serve in the military. The common approach to solving the "identification problem" in the analysis of enlistment supply by splitting the contract population into high and low-quality and assuming that high-quality contracts are supply-constrained and low-quality contracts are demand-constrained is inadequate. This approach ignores roughly half of the contract population and results in an incomplete understanding of how labor market and social conditions impact the youth population's decision to enter military service.

Specifically, my analysis suggests that the number of observed high *and* low-quality contracts are determined by the youth population's willingness to enlist and not a demand constraint placed by the Army. If low-quality contracts were actually constrained by the Army's demand for them, we would expect to see the low-quality contract goal functioning as a quota, which we do not generally observe. Moreover, my analysis concludes that low quality contracts are also not a residual element in recruiting used to supplement, as necessary, any shortfalls in high quality contracts. This is apparent as the achievement of low-quality contracts is positively, not negatively, correlated with the achievement of high-quality contracts. In fact, low-quality goals are often exceeded even when high-quality goals are met. This set of conclusions supports future research that uses the entire recruit population and not just individuals deemed high quality.

In terms of understanding why low-quality goals are so often exceeded, data is less helpful. I conclude the Army and its recruiting force maximize related objective functions with different constraints. I believe this leads to potentially divergent outcomes. Uncertainty in the recruiting process, the geographic and temporal dispersion of recruiting units, and a focus on volume over quality combine to incentivize recruiters to exceed low-quality contract goals when possible.

It is also worth considering if contracts are the correct outcome to consider in any analysis of military enlistment. In addition to focusing on only the high-quality population, the majority of analysis in the literature uses signed enlistment contracts as the outcome of interest. This is done largely due to data availability and because recruiting goals assigned to recruiting stations are expressed in contracts and not in applicants or accessions.[33]

[33] The headquarters of the Army's recruiting command is the only organization with an accession goal. As described above, this goal is converted to a contract goal for distribution to their subordinate recruiting

On the one hand, signed enlistment contracts do represent an important outcome as approximately 85 percent of contracts enter active duty. On the other hand, signed enlistment contracts are an outcome of the applicant process and do not represent the population of the overall potential recruit supply. In addition, the use of contracts as the primary outcome when estimating the impact of economic and social conditions on military service is potentially confounded. Excluding qualified applicants processed at a MEPS station that do not sign a contract ignores a sizeable portion of the potential recruit population ('qualified but not interested' comprise roughly 15-25%; see Figure 1.23 above). Moreover, analysis using contracts as the outcome variable is confounded by the role of the Army in converting interested and qualified applicants into signed enlistment contracts.[34] In other words, estimates of supply elasticities using contracts as the outcome are measuring not only the impact of economic and social conditions on willingness to enlist, but also the ability of the Army to "translate" qualified and interested individuals into signed contracts. Holding economic and social conditions constant, if one were to improve the ability of the Army to convert interested and qualified applicants into contracts, estimates of supply elasticities for these populations would likely increase.

For purposes of future analysis, researchers should focus more broadly and consider the potential recruit population as comprised of those individuals that express enough interest in military service to meet with a recruiter and go to a MEPS to be screened for service. Given this, researchers could then examine a population that includes those individuals that express interest but are deemed unqualified (medical, physical, criminal),

organizations.

[34] This is also true to a lesser degree when considering the broader population of applicants. The Army itself has a role in creating and raising awareness of an "Army brand" through advertising while recruiters and the effort they expend also play a role in identifying and influencing individuals to consider military service. All this behavior potentially contributes to a propensity to enlist and, if the data is available, is important to include in the analysis.

those individuals that go to a MEPS but don't sign a contract, those individuals that sign an enlistment contract but fail to serve on active duty (DEP Loss), and those individuals that enter active duty. This broader focus will facilitate a more comprehensive understanding of the potential recruit population and potentially depict a more accurate representation of the forces influencing America's youth as they make decisions about how they will participate in the U.S. labor market.

Appendix

Figure A 1.1. High-quality Goal Adjustments (as fraction of total goals)

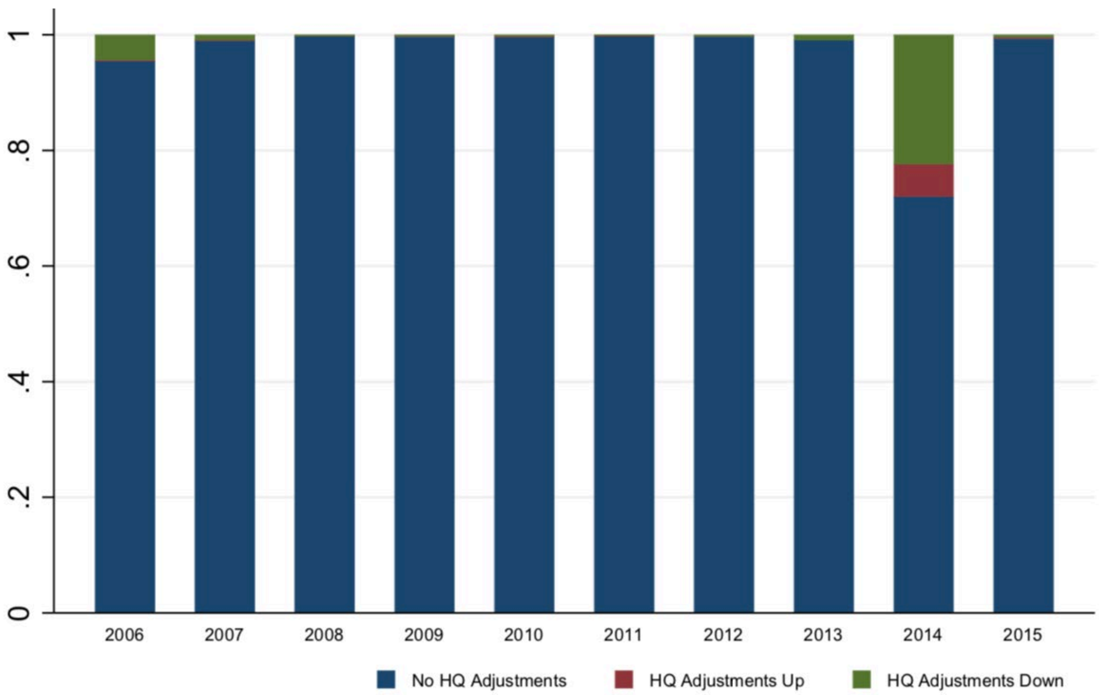


Figure A 1.2. Low-quality Goal Adjustments (as fraction of total goals)

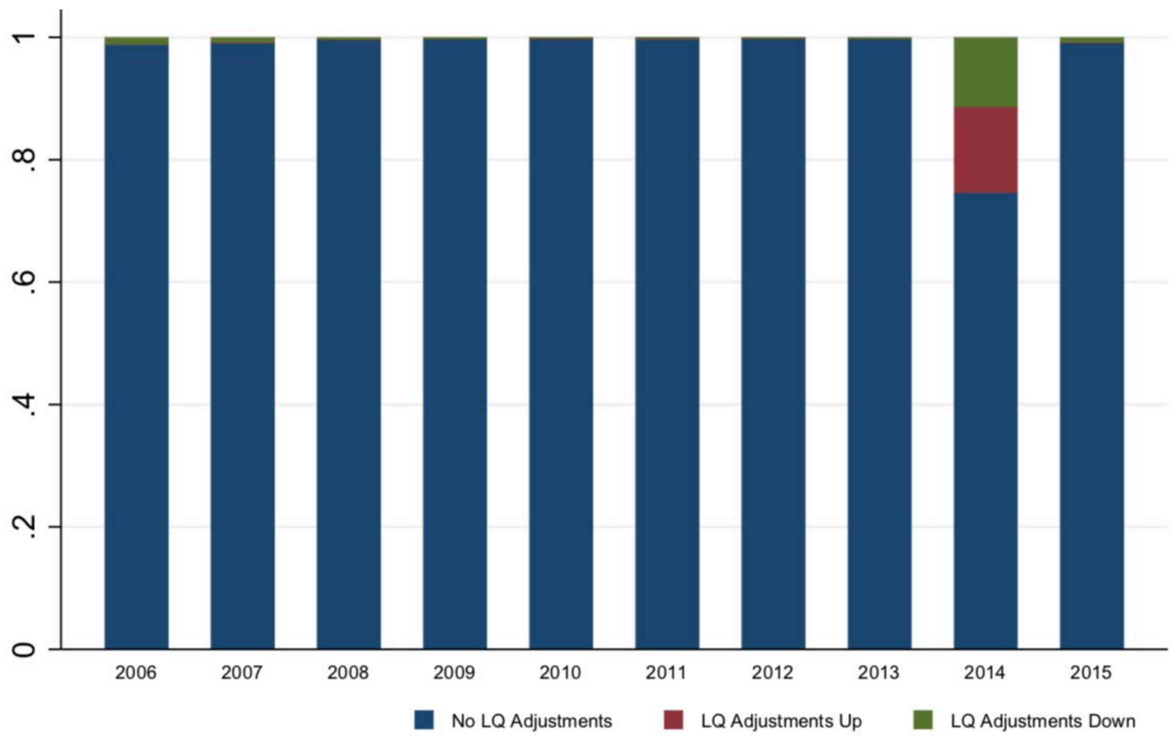


Figure A 1.3. Low-quality Goal Adjustments (as fraction of total goals)

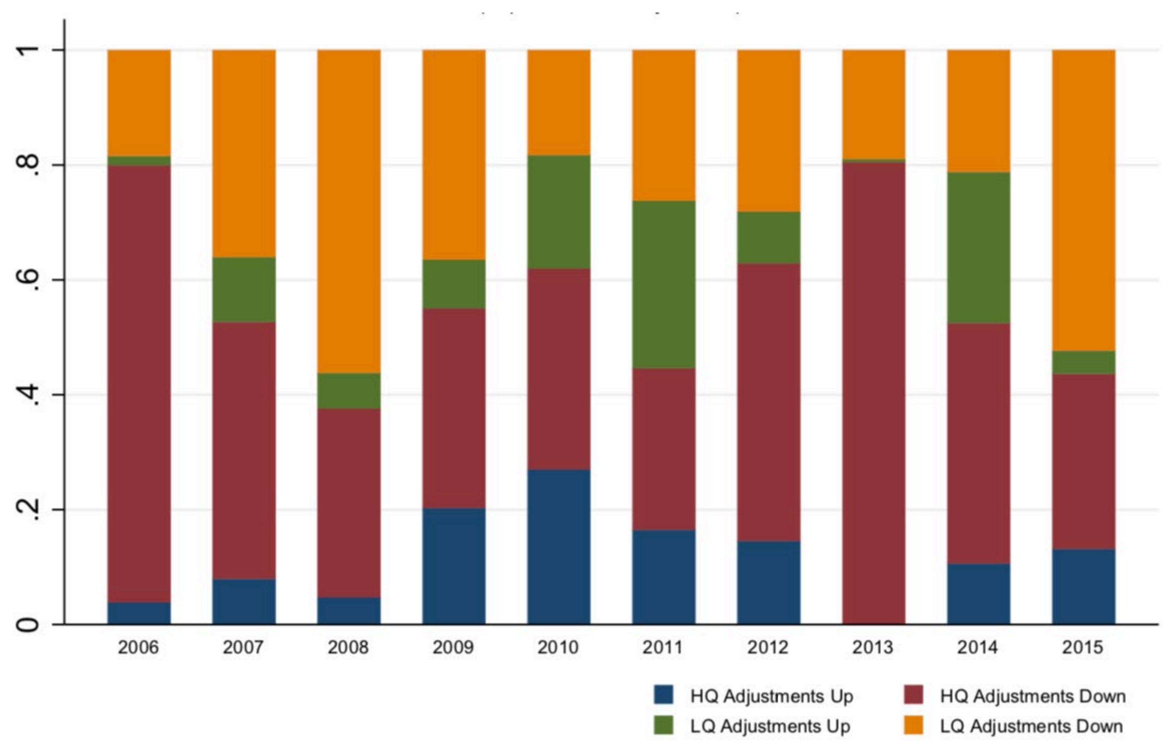


Figure A 1.4. Fraction of Recruiting Stations that experience changes in number of recruiters

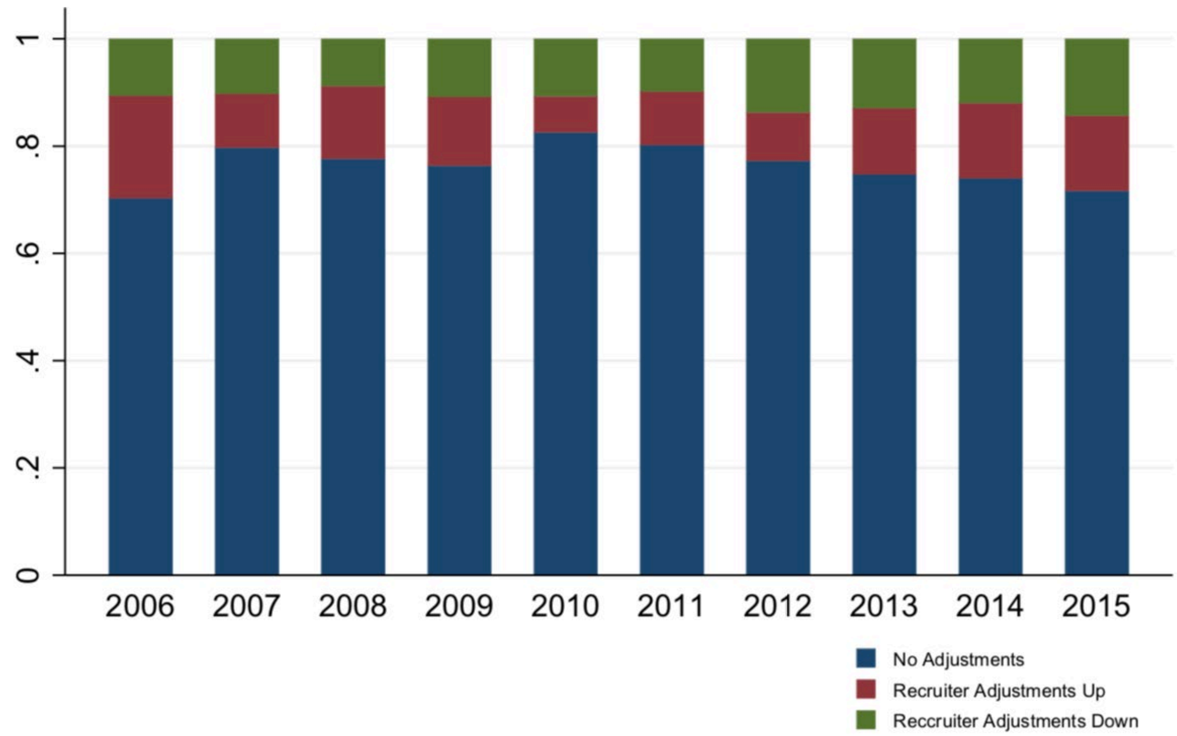


Figure A 1.5. Fraction of recruiter adjustments (as fraction of total adjustments)

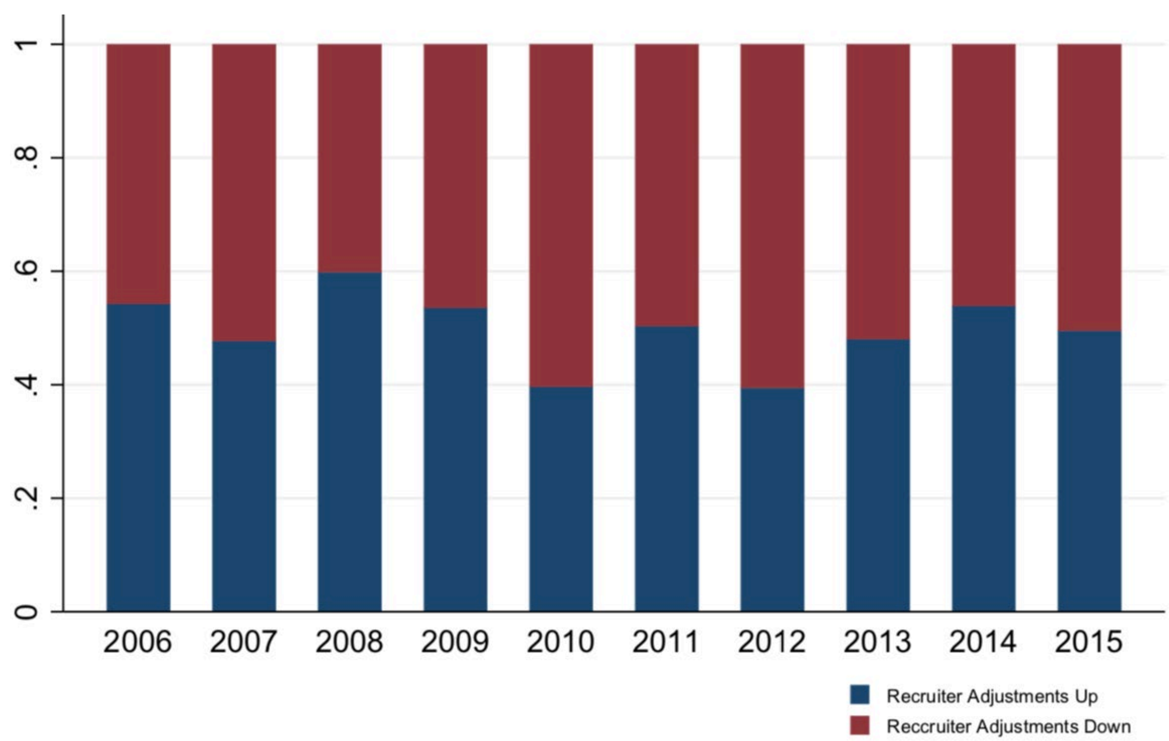


Figure A 1.6. Distribution of Recruiting Station Performance in Fiscal Quarters 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

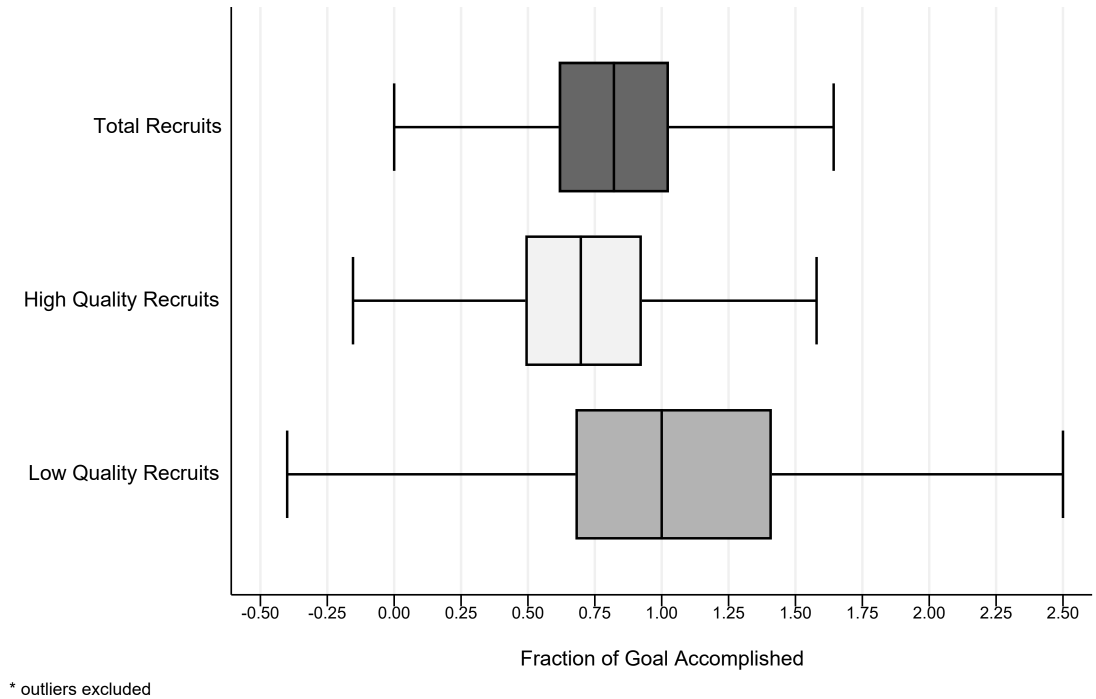


Figure A 1.7. Distribution of Recruiting Station Performance in Fiscal Years 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

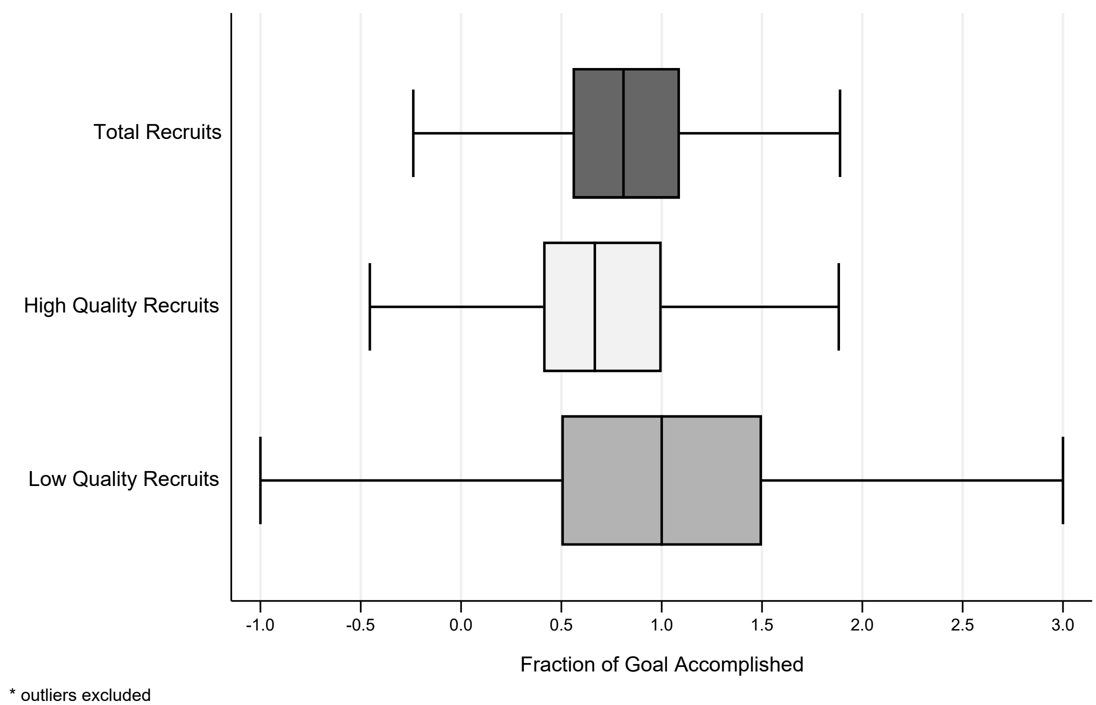


Figure A 1.8. Distribution of Recruiting Company Performance in Fiscal Quarters 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

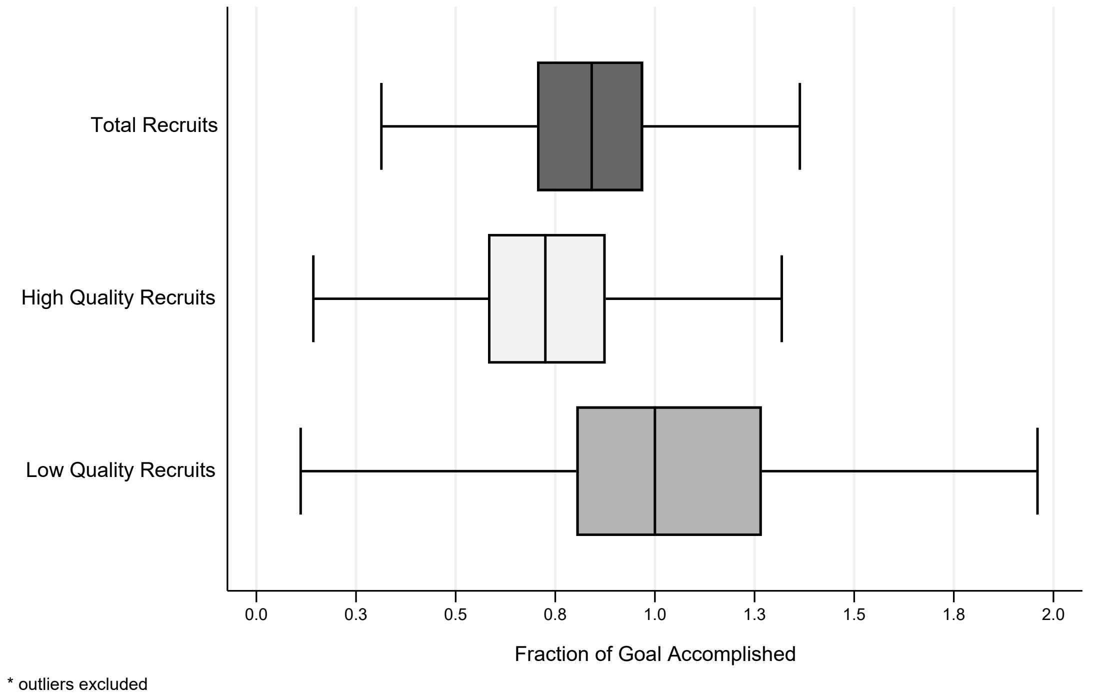


Figure A 1.9. Distribution of Recruiting Company Performance in Fiscal Years 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

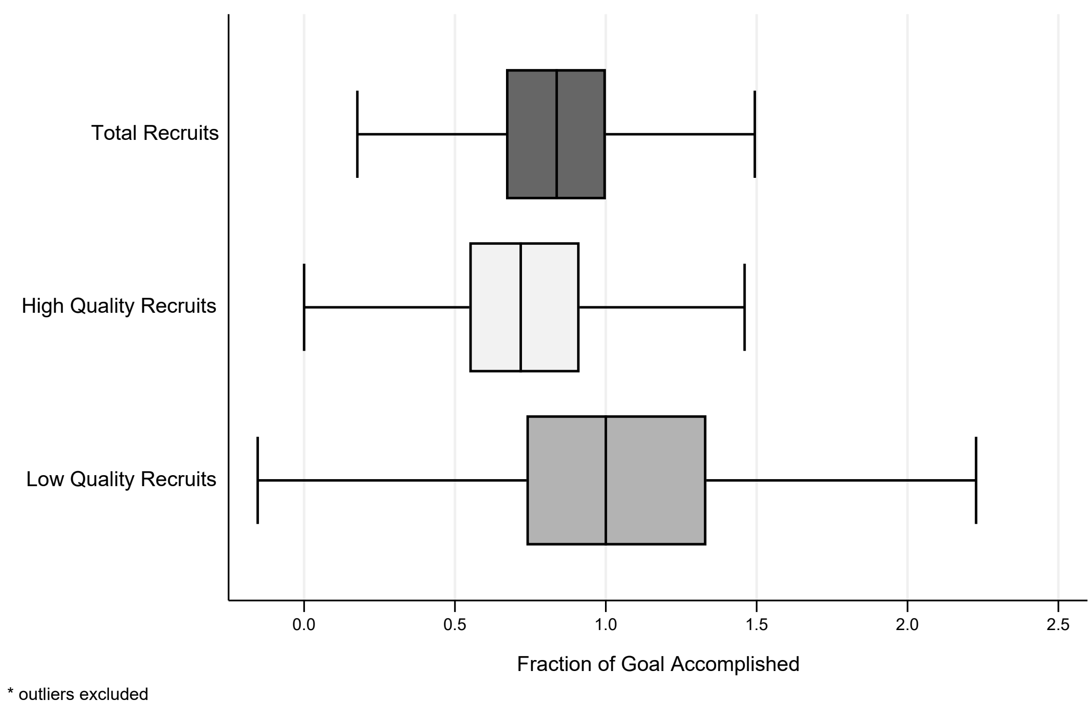


Figure A 1.10. Distribution of Recruiting Battalion Performance in Fiscal Quarters 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

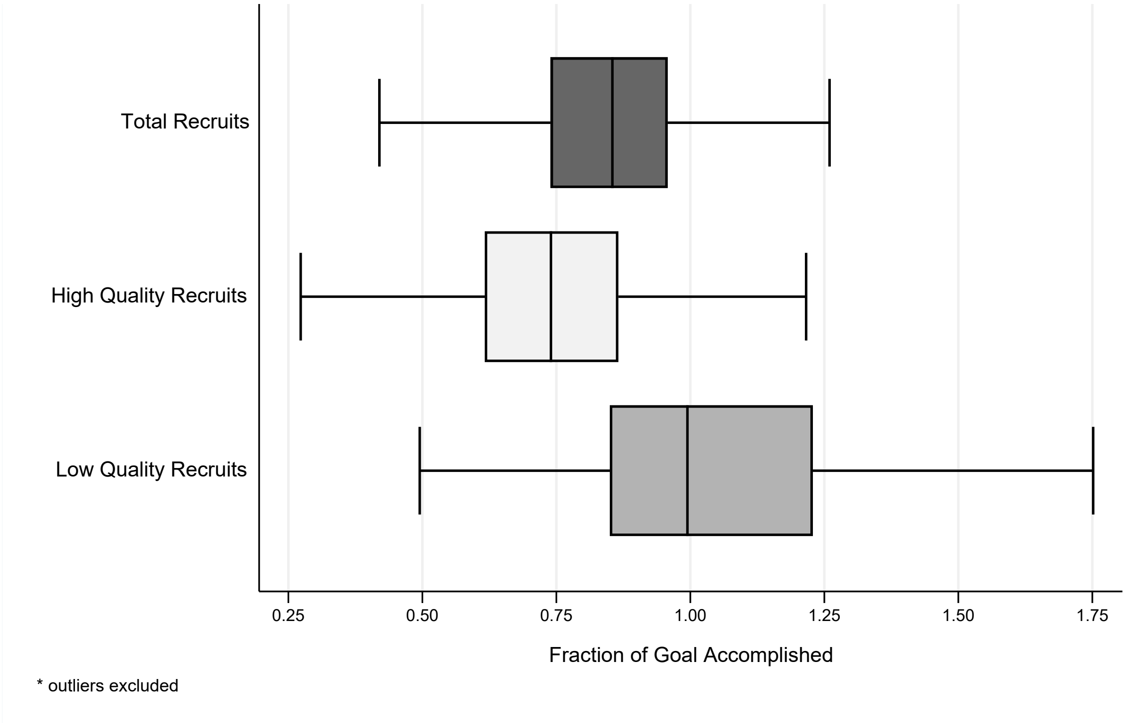


Figure A 1.11. Distribution of Recruiting Battalion Performance in Fiscal Years 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

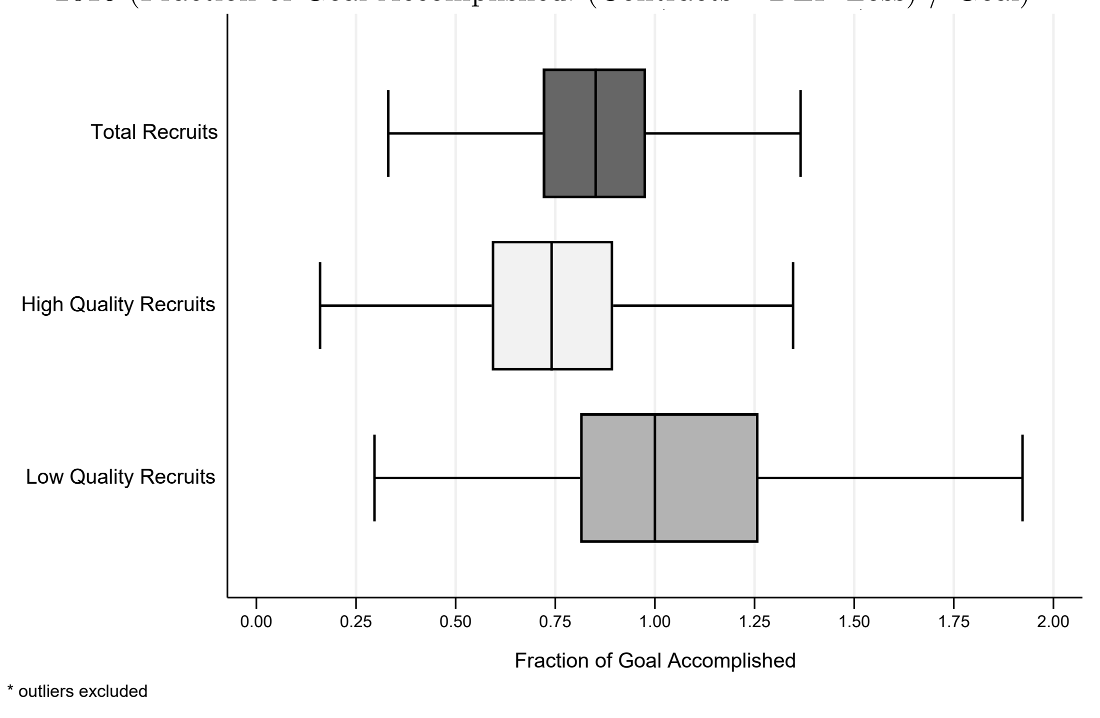


Figure A 1.12. Distribution of Recruiting Brigade Performance in Fiscal Quarters 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

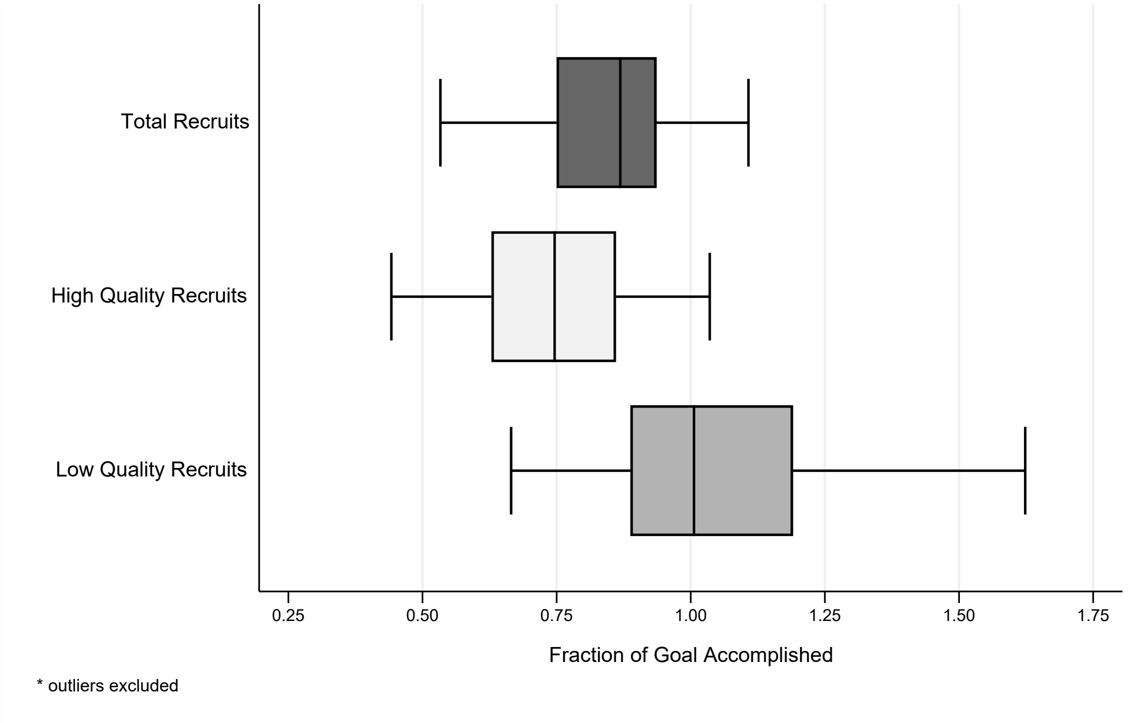


Figure A 1.13. Distribution of Recruiting Brigade Performance in Fiscal Years 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

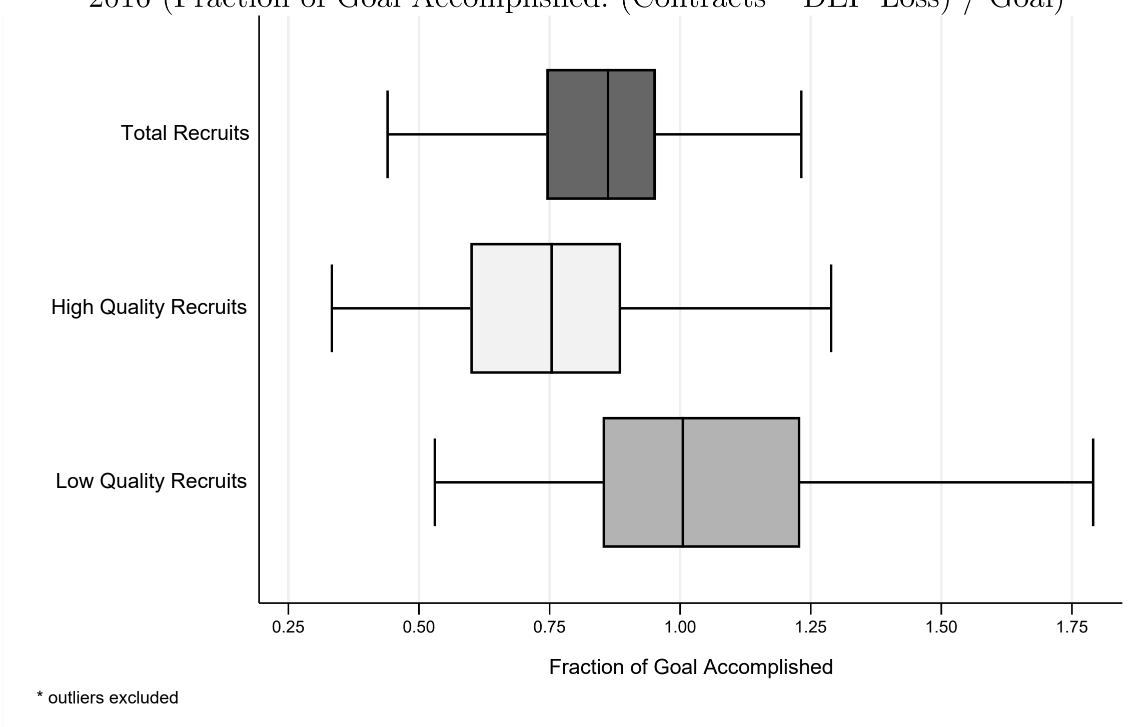


Figure A 1.14. Distribution of Army-wide Recruiting Performance in Fiscal Quarters 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)

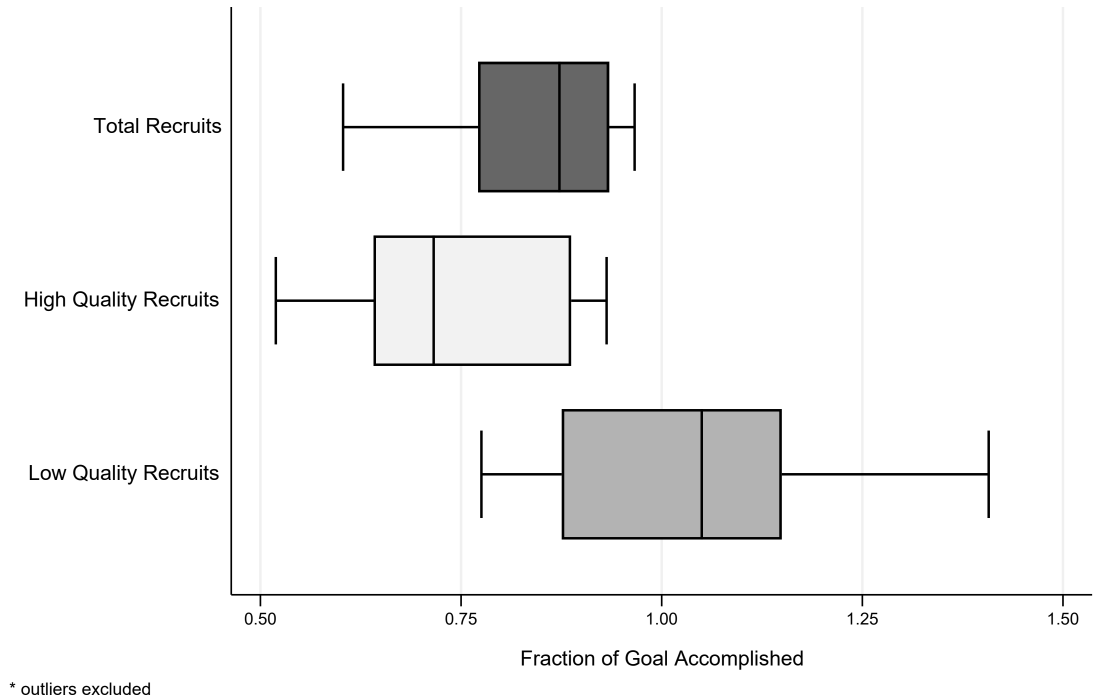
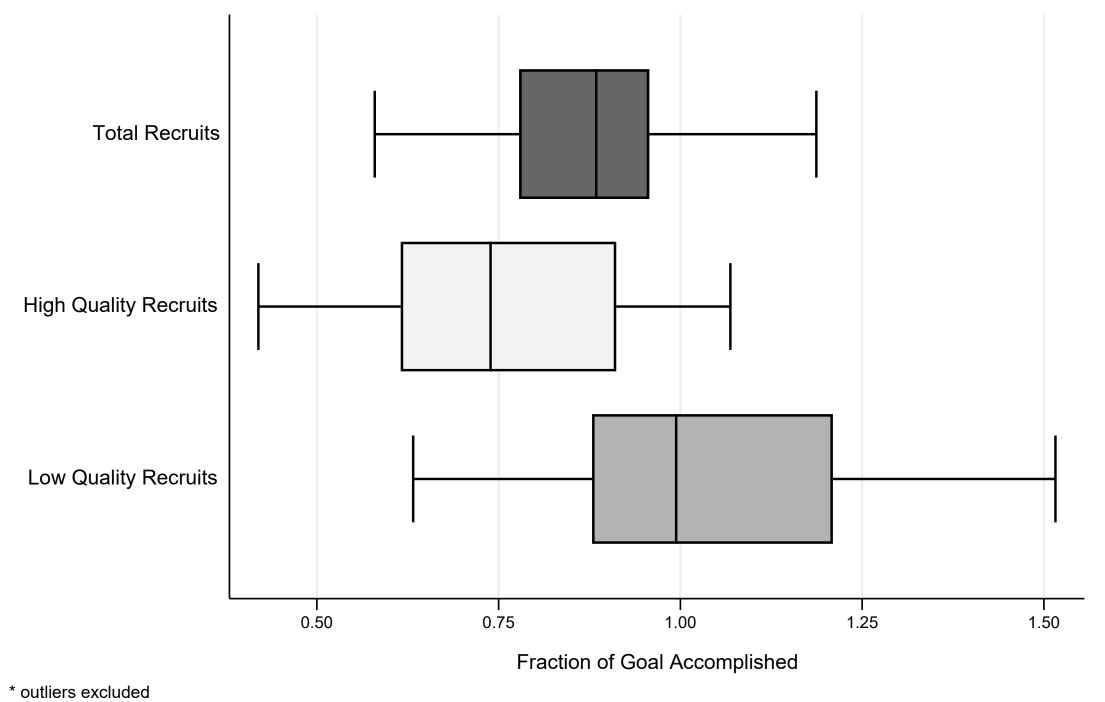


Figure A 1.15. Distribution of Army-wide Recruiting Performance in Fiscal Quarters 2003 to 2016 (Fraction of Goal Accomplished: (Contracts – DEP Loss) / Goal)



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CHAPTER 2

2.1 Background

Enlistment in the military continues to be an attractive alternative to the civilian labor market for recent high school graduates. Between 350,000 and 500,000 young people apply for employment in the armed forces annually and the Department of Defense (DOD) is the nation's largest employer of youth with 850,000 current active and reserve members under the age of 25.[35] Military service, while no longer as popular or widespread as it was during the middle of the 20th century, it is still viewed as a vehicle for socioeconomic mobility in the United States (Helmus et al 2018).[36]

Economic conditions are known to affect a wide variety of contemporaneous social, psychological, and physical outcomes.[37] They are also known to affect individual decision-making regarding human capital investments and labor market participation.[38] This paper

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[35] Representing approximately 2.5 percent of comparable civilian group. It is also the world's largest employer with over 3.2 million employees (just larger than China's Ministry of National Defense). See http://download.militaryonesource.mil/12038/MOS/Reports/2015-Demographics-Report.pdf, http://www.businessinsider.com/can-you-guess-the-top-employer-for-young-adults-2012-1, and https://www.weforum.org/agenda/2015/06/worlds-10-biggest-employers/?link=mktw

[36] In addition, see Kleykamp (2006) and Karsten (2001). Also, Angrist (1998) for discussion of the effect of military service on minority earnings.

[37] Such as, health (Ruhm 2000, Kerwin, Kofi, and DeCicca 2008), happiness (Clark and Oswald 1994), environmental stewardship (Meyer 2016), mental health (Gathergood 2013), crime (Raphael and Winter-Ebmer 2001), drug use (Arkes 2007, Hollingsworth et al. 2017), health insurance (Cawley et al. 2015), alcohol use (Dee 2001) and mortality (Stevens et al. 2015)

[38] For example, skill mismatch (Liu et al. 2016), college enrollment (Barr and Turner 2015), career success (Altonji et al. 2016), initial job (Brunner and Kuhn 2014), productivity (Lazear 2016), future employment (Raaum and Roed 2006), CEO careers (Shoar et al. 2011), and long-term unemployment (Ruhm 1991)

will examine the effect of local economic conditions on one aspect of this decision: enlistment into the military.

Young people seek employment in the military for many reasons, but the relative availability and attractiveness of civilian labor market alternatives is considered to be one of the primary factors in this decision.[39] In this paper, I examine the response of military applicants to changes in labor market conditions holding constant recruiting resources and other relevant demographic factors. Using U.S. Army recruiting and civilian labor market data from 2006 to 2014, I estimate the causal effect of economic conditions on enlistment for recruits in both low and high-quality categories.[40]

I find that a one percentage point increase in the contemporaneous employment-to-population ratio results in a rate increase of two low-quality individuals per 100,000 eligible population in the applicant pool, of which, one enters active duty. The rate of high-quality applicants increases by approximately one-third and the rate of high-quality accessions increasing by nearly two-thirds per 100,000. Conditional on being an applicant, poor labor market conditions do not appear to increase the fraction of individuals in the applicant pool that enter active duty. However, the fraction of those failing to sign a contract decreases while the fraction of those disqualified increases. The size of the causal estimates in my findings indicates that the neglect of the correlation between changes in labor supply and economic conditions in previous studies likely underestimated the effect of labor demand shocks on the enlistment response. Finally, I find that the impact of the employment-to-population ratio in the year leading up to the enlistment decision is

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[39] This correlation between economic conditions and enlistment in the military are well-documented (Warner, Simon, Payne 2001, Asch, Hosek, Warner 2007, Asch et al. 2010)

[40] High-quality recruits are defined as high school graduates scoring in the top half of the aptitude distribution. Specifically, high-quality recruits are high school seniors or graduates in Armed Forces Test Score Category (TSC) I-IIIA (AFQT ≥ 50). Low-quality recruits are high school graduates in TSC IIIB-IV (10 ≤ AFQT ≤ 50) or a high school dropout in any test score category above 31.

stronger than the effect of the contemporaneous employment-to-population ratio and indicates the enlistment decision incorporates labor market information from many months prior to the actual decision.

This paper contributes to the literature on the role of macroeconomic conditions on labor market outcomes and individual decision-making. It is the first paper to examine the intensive margin of enlistment to local labor market conditions (how the composition of the applicant pool changes), the first to estimate causal effects on enlistment, and is the first to consider both high and low-quality recruits across the four sub-groups of total applicants in the analysis (uninterested, unqualified, Delayed Entry Program losses, and accessions). Finally, this paper is also the first to include data from the period covering the majority of combat operations in Iraq and Afghanistan (2006-2014) and the Great Recession (2008-09).[41]

2.2 Literature Review

A narrowly-focused literature on economic conditions and military enlistment supply does not exist. Rather, estimates of the effect of labor market conditions on enlistment have appeared as part of broader research focused on the supply elasticities of an array of economic and social determinants of enlistment.[42] Generally, the literature focuses on high quality recruits and looks at subsets of that population (e.g., minorities in Asch, Heaton, Savych 2009 or older recruits in Rostker, Klerman, and Zander-Cotugno

[41] Combat operations in Afghanistan (Operation Enduring Freedom) started on October 7, 2001 and ended on December 31, 2014. Combat operations in Iraq (Operation Iraqi Freedom) started on March 20, 2003 and officially ended on December 18, 2011. The National Bureau of Economic Research (NBER) dates the Great Recession as beginning in December 2007 and ending in the 2nd quarter of 2009 but unemployment remained above 8 percent until September 2012. It wasn't until Sep 2015 that the unemployment rate returned to 5 percent.

[42] These studies are observational in nature except for an early paper examining the Army's enlistment bonus experiment in the early 1980s (Polich and Dertouzos 1986).

2014) or the effects of various incentives such as military pay (Hansen 2005, Asch et al. 2007, Asch et al. 2010), educational benefits (Warner, Simon, and Payne 2001, Simon, Negrusa, and Warner 2010), and cash bonuses (Polich and Dertouzos 1986, Asch et al. 2010). There is also a portion of the literature that examines the effect of recruiting resources such as advertising and recruiter incentives (Dertouzos 2003, Dertouzos and Garber 2006 and 2008).[43] Very few papers focus only on the effect of economic conditions on enlistment behavior but almost all the previous papers include a measure of labor market conditions, usually unemployment rates, as an independent control variable.[44]

The majority of these studies estimate supply elasticities using linear regression of quarter-by-state panel data.[45] The literature is generally focused on a broad range of determinants of enlistment and acknowledges the potential endogeneity between recruiting policy/resource decisions and enlistment. Therefore, the focus is generally on associations between variables and not causal interpretations. Still, there is a strong relationship in the data between the civilian unemployment rate and high-quality enlistment. Estimates of this elasticity range from 0.22 to 0.34 in the late '80s through early '90s (Warner 2001 and 2003) to 0.42 for the period from 1996 to 2005 (Warner and Simon 2007) to 0.11 during a period of historically low unemployment and high casualties in Iraq and Afghanistan (Asch et al. 2010; sample from 2005 to 2008).

Previous enlistment studies focus their analysis almost exclusively on high-quality

[43] There is an early strand of work on enlistment supply that dates to the late 1960s and the work of the President's Commission on an All-Volunteer Armed Force (Gates Commission). President Richard Nixon established the Gates Commission to examine the social and economic costs of ending military conscription. Early work by Altman and Fechter (1967), Fisher (1969), Altman (1969), Cook and White (1970), Gray (1970), and Cook (1971) examined the theoretical foundations of enlistment supply and attempted the first empirical estimates of enlistment and retention supply elasticities.

[44] Exceptions include Dale and Gilroy (1983). Arkes (2014) examines first term attrition and the unemployment rate.

[45] The most common method is ordinary least squares regression using two-way fixed effects although some earlier work uses simultaneous equations, switching regression models, or three-stage least squares.

individuals and use the number of signed high-quality enlistment contracts as the outcome of interest. This is done for both substantive and technical reasons. First, there is ample evidence that higher AFQT scores and a high school degree are good indicators of a young person's ability to successfully perform their assigned military job and complete their first term of enlistment.[46] Second, previous research in this area assumed the supply of low-quality individuals willing to enlist far exceeds the Army's demand. This assumption complicates quantitative analysis of supply decisions because observed low-quality enlistment contract totals are assumed to be constrained by the Army's demand and not evidence of supply behavior. On the other hand, high-quality individuals willing to sign an enlistment contract are assumed to be in short supply. This assumption led researchers to focus on high-quality individuals to isolate the pure supply effect and accurately estimate elasticities with respect to recruiting resources and economic and social factors.[47] See Crow (2019) for analysis that indicates the number of low-quality contracts is not constrained by the Army and that both high and low-quality individuals can be included in analytical studies of enlistment.

This focus on high-quality individuals and signed enlistment contracts is a limitation in the literature for several reasons. First, in most years, low-quality individuals typically comprise 40-60% of an annual recruiting cohort.[48] The analysis of only high-quality individuals leads to an incomplete understanding of the full youth population and

[46] Research indicates a positive relationship between AFQT scores and hands-on work performance (Wingard and Green, 1991), combat related tasks (Scribner, Smith, and Baldwin 1986; Orvis, Childress and Polich 1992), and effort and leadership metrics (Oppler at al. 2001). Early research also shows those with a high school diploma are less likely to attrite (Buddin 1988, Warner and Solon 1991).

[47] Since the advent of the All-Volunteer Force, the Army has never recruited a cohort of strictly high-quality recruits.

[48] The Department of Defense mandates that 60 percent of recruits are high-quality, i.e., high school graduates with AFQT ≥ 50. See Department of Defense Instruction 1145.01, Qualitative Distribution of Military Manpower, September 20, 2005, paragraph 4.1 at http://www.dtic.mil/whs/directives/corres/pdf/114501p.pdf.

the factors that influence them to serve. Second, signed enlistment contracts represent only one of four possible outcomes for individuals that visit a Military Entrance Processing Station (MEPS) to apply to serve in the military ("applicants"). The other outcomes that can be analyzed to provide relevant information regarding enlistment propensity are individuals that attend a MEPS appointment but fail to meet one or more enlistment criteria ("disqualified" - interested but not qualified), individuals that attend a MEPS appointment, are qualified, but choose not to enlist ("uninterested" - qualified but not interested), individuals that sign an enlistment contract but attrite from the Delayed Entry Program ("DEP loss"), and individuals that sign an enlistment contract and enter onto active duty ("accessions"). Each of these outcomes provides unique and relevant information about the enlistment response to local labor market conditions. See Figure 2.1 below for a graphical depiction of the recruiting process and each subpopulation.

2.3 Institutional Background on Recruiting

The Army uses both cognitive testing and education credentials to screen individuals. This ensures the military labor force meets congressionally mandated levels of human capital as measured by the Armed Forces Qualification Test (AFQT).[49] The result of this screening is the categorization into "high-quality" or "low-quality" groupings. High-quality individuals are high school seniors or graduates in the upper half of the aptitude distribution (AFQT greater than 50). Low-quality are high school graduates with an AFQT score between 10 and 50 or a high school dropout regardless of AFQT score.[50]

[49] The AFQT is a composite of four sub-tests (arithmetic reasoning, word knowledge, paragraph comprehension, and mathematics knowledge) of the more comprehensive Armed Services Vocational Aptitude Battery (ASVAB). The Armed Forces Qualification Test has been routinely used as a measure of ability since the introduction of the test in 1968.

[50] By Congressional mandate and Department of Defense Directive, at least 60 percent of recruits must score above the 50th percentile or higher on the AFQT and at least 90 percent of recruits must be high school

The Army determines its annual recruiting requirement based on its congressionally authorized end-strength, expected levels of reenlistment, and historical rates of attrition in the recruiting and basic training process. After the Army determines the number of new soldiers it will need to enter active duty in a given year ("accessions"), it uses historical rates of attrition in recruiting and basic training, along with local social, economic, and demographic data, to determine monthly contract goals in both high and low-quality categories. These contract goals represent the number of signed enlistment contracts required to meet the annual accessions goal. These contract goals are assigned to 1,000 recruiting centers across the United States where over 8,000 recruiters work to fill the Army with qualified recruits.[51]

Army recruiters will make over 16 million contacts (phone, email, in-person) with individuals as part of their effort to enlist 80,000 soldiers. Over 400,000 initial interviews will be conducted where young people interested in military service will meet with a recruiter to discuss potential military career options. The recruiter will provide information about military service and potential enlistment bonuses for specific military occupations. In addition, the recruiter will conduct a basic pre-screening of the candidate's education level, criminal history, marital and parental status, and medical and physical condition.[52]

All individuals who pass this initial screening will be given an appointment to the

graduates. In addition, no more than 4% of any cohort can possess an AFQT score less than 30. Applicants in Category IV without a high school degree and all applicants in Category V are ineligible for enlistment.

[51] A typical recruiting center has between 2 to 5 recruiters and will average 3 to 10 signed contracts per month.

[52] There is significant attrition in the military recruitment process. In 2015 alone, military recruiters contacted approximately 20 million individuals to obtain the nearly 280,000 recruits needed to sustain a military of 1.3 million personnel. 280,000 is roughly 4 percent of the non-college bound high school graduate population. In the case of the Army, to maintain congressionally mandated end-strength, the Army will enlist approximately100,000 men and women (contracts) annually. Due to attrition during the recruiting and basic training process, roughly 70,000 to 80,0000 (accessions) will ultimately serve on active duty.

nearest Military Entrance Processing Station (MEPS). Those that show for their appointments are known as applicants.[53] At the processing station, applicants will complete formal aptitude testing and physical examinations. The aptitude test is the Armed Services Vocational Aptitude Battery (ASVAB) which identifies cognitive aptitude in eight specific areas and is used to determine eligibility to enlist and appropriate occupations based on an individual's score. The physical examination is similar to a routine medical exam and includes drug and alcohol tests along with an assessment of physical fitness. Once screening is complete, applicants fall into one three outcomes: those that are disqualified due to medical, physical or conduct-related reasons (disqualified), those that are qualified but ultimately decide not to sign an enlistment contract (uninterested), and those that are qualified and still desire to serve in the Army. This last sub-group of applicants will meet with an enlistment guidance counselor to select a contract based on the results of their aptitude tests, medical qualifications, and their occupational preferences.[54]

The contract specifies the length of the enlistment term, a military occupational specialty, initial duty location, enlistment incentives, and a basic training report date. Upon signing the contract, individuals are entered into the Delayed Entry Program (DEP) for a period of one to twelve months.[55] Of the approximately 100,000 troops that sign an enlistment contract, roughly 15 percent will quit while in the Delayed Entry Program. When this occurs, the enlistee becomes a "DEP loss" and the requirement for that

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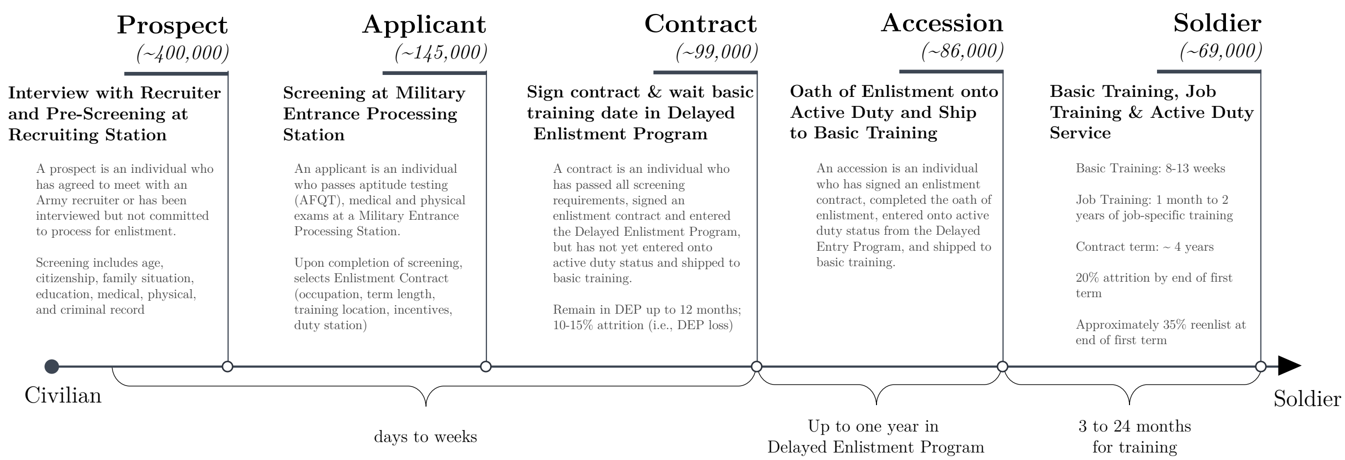
[53] There are 65 Military Entrance Processing Stations in the United States.

[54] I do not have data for individuals that applied for waivers (either denied or accepted).

[55] The DEP is used to smooth the flow accessions to training bases due to the uneven distribution of contract signings over the course of a single year (large surge in summer/fall months with dearth in winter/spring months). During their time in the DEP, the soldier will return home until they are to report back to the processing station, take the Oath of Enlistment, and "ship" to basic training. While in the Delayed Entry Program and before they swear the Oath of Enlistment onto active duty, individuals can break their enlistment contract without consequence. See Crow 2019.

contract is added back into their respective recruiting centers current contract goal.[56] Subsequently, about 85,000 soldiers will report to basic training (accessions) and roughly 69,000 will complete their first enlistment term. See Figure 2.1 for a graphical depiction of this process.

Figure 2.1. Recruiting Process



* Numbers in parentheses approximate quantity needed at each step to meet 86,000 soldier annual accessions goal
** Accession Goals = Contract Goals + Expected Delayed Entry Program (DEP) Loss

2.4 Data and Descriptive Statistics

The enlistment data for this project comes from two U.S. Army data sets and contains demographic, medical, aptitude, and enlistment contract information for approximately 1.14 million individuals that visited a Military Entrance Processing Station with the purpose of signing an enlistment contract between 2006 and 2014.[57] I condition the sample to include individuals that signed a contract only within the continental

[56] The contract goal is necessarily more than accession goal due to attrition during the recruiting and basic training process. In other words, contracts goals = accession goals + estimated Delayed Entry Program loss.
[57] The data include demographic characteristics such as age, gender, race, Armed Forces Qualification Test Score (AFQT), marital status, and enlistment contract details (occupation, contract length, bonus, educational benefits).

United States. I exclude the small fraction of individuals that enlist at recruiting stations in Hawaii, Alaska, overseas, and in U.S. territories such as Guam, Puerto Rico or the Virgin Islands.[58]

I configured the above data as a county*quarter panel and merged onto it a second file containing data on Army recruiters and recruiting goals, in addition to enlistment contracts signed by the other armed services (Air Force, Navy, Marine Corps). This second file was collected at the recruiting station*month level. To apportion this data to counties (rather than recruiting stations), I used the Census' intercensal estimates of county resident population and the fraction of zip codes each recruiting station was responsible for in each county to apportion the recruiters, recruiting goals, and DoD contract data to individual counties. Both Army data sets are taken from databases used to calculate service, pay, and promotion information for soldiers and to monitor, adjust, and reward recruiting performance. These datasets are used regularly by the Army and incentives exist for all parties (soldiers, recruiters, and military) to ensure their accuracy. Consequently, measurement error is assumed to be minimal.

The primary measure I use to represent local labor market conditions is the employment-to-population ratio which is derived from the U.S. Census Bureau's Quarterly Workforce Indicators (QWI).[59] I use the employment-to-population ratio rather than the unemployment rate for several reasons. First, it is less affected by seasonality and short-term fluctuations in labor markets.[60] Second, it is not affected by voluntary changes in

[58] Less than 2% of all recruits.
[59] The QWI data is part of the larger Longitudinal Employer-Household Dynamics data set. It uses data from the Quarterly Census of Employment and Wages (QCEW) and Unemployment Insurance (UI) data and excludes active duty military personnel. See https://lehd.ces.census.gov/data/ and https://www.bls.gov/cew/cewbultncur.htm.
[60] See https://www.pewresearch.org/fact-tank/2017/03/07/employment-vs-unemployment-different-stories-from-the-jobs-numbers/

labor force participation which means it more accurately reflects those that are no longer looking for work or that have left the labor force.[61] This is important because it accounts for individuals that leave the labor force to attend schooling, the primary alternative for those considering military service. The unemployment rate, especially since the beginning of the Great Recession, has also been found wanting as a gauge of labor market slack (e.g., Blanchflower and Levin, 2018). Finally, because of the way that unemployment and employment-to-population data is collected at the county level, the employment-to-population ratio is less likely to be measured with error (Currie and Schnell, 2018). One potential disadvantage to using the employment-to-population ratio is that employment numbers (numerator) are measured by the employer's location while the population (denominator) is measured by residence.

The two primary measures of local labor market conditions at the county level, the employment to population measure and the unemployment rate, both come from the Bureau of Labor Statistics. The employment numbers in the employment-to-population ratio come from the Quarterly Census of Employment and Wages and includes approximately 9.4 million covered establishments employing approximately 136.6 million individuals. This administrative data comes from the unemployment insurance accounting system in each state. Because it is a census, it does not include sampling error like a survey, but can include data entry mistakes and non-responses. The BLS has extensive data quality control procedures to guard against data entry mistakes and response rates typically exceed 95 percent.[62].

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[61] See https://www.epi.org/newsroom/useful_definitions/

[62] The QCEW also conducts two surveys, the Annual Refiling Survey (ARS) and the Multiple Worksite Report (MWR) to supplement and verify the data collected from each state's UI system. See https://www.bls.gov/cew/mwrforms.htm and https://www.bls.gov/responders/ars/forms/htm for more information. The population figures in the employment-to-population survey come from the U.S. Census Bureau's intercensal estimates of county populations. See https://www.census.gov/programs-

The unemployment rate at the county level is reported by the Local Area Unemployment Statistics (LAUS) program. The employment data used to calculate the labor force denominator in the unemployment rate is based primarily on the Current Employment Statistics (CES) and the QCEW but are adjusted using residency ratios to reflect place-of-residence estimates rather than place-of-work estimates (which is how the CES and QCEW are collected).

Unlike the QCEW, the unemployment data in the LAUS is derived from the monthly Current Population Survey (CPS) of approximately 60,000 households and counts of continued claims from state unemployment insurance systems. The method by which these estimates are created is known as the "Handbook method" which is an "effort to use available information to create unemployment estimates for an area that are comparable to what would be produced by a representative sample of households in that area." Because CPS data is not designed to be representative at the county-level of disaggregation, the LAUS uses CPS estimates at the state level, modeled as a sum of the true labor force data (signal) plus error (noise), and then apportions the unemployment numbers to a given area using pre-defined shares for each county. This method, while helpful to understand sub-state labor market conditions, is likely to introduce significant measurement error into the data and is less reliable than the administrative data upon which the employment data in the QCEW is based.

I create a Bartik-style shift-share instrument for local labor market conditions using QWI employment numbers provided at the two-digit North American Industry Classification System (NAICS) level. The conventional shift-share instrument measures national employment growth across industries weighted by local industry employment shares (see Equation 2.4). This instrument provides a measure of local labor demand

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surveys/popest/technical-documentation/methodology.html unrelated to changes in labor supply. It is used extensively in the literature as an instrument for local labor market conditions because it serves as an exogenous determinant of labor market demand in a given area.[63]

County-level demographic data comes from intercensal estimates maintained by the Census Bureau and includes population, gender, race, and ethnic status. Veteran population data comes from the Veteran's Administration's National Center for Veteran's Analysis and Statistics (NCVAS) annual county expenditure tables. Finally, poverty and household median income come from the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program.

The combined panel data represents nearly 110,000 county*quarters between fiscal years 2006 and 2014 and identifies the number and characteristics of total applicants, disqualified applicants, uninterested applicants, applicants who sign contracts, DEP losses, and accessions for each county*quarter.

Table 2.1 provides means of the outcome, explanatory variables, and recruiting resource variables. The outcome variable is the number of total applicants divided into each outcome for an applicant: applicants that meet all qualifying criteria but decide not to sign a contract (uninterested), applicants that are disqualified due to medical, physical or drug use (disqualified), applicants that meet a enlistment criteria and sign a contract (contracts), applicants that sign a contract but fail to enter active duty (DEP loss), and applicants that sign a contract and enter active duty by reporting to basic training (accessions).

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[63] See below in equation 3 in Section 2.5, Empirical Specification and Strategy. I am following Wozniak (2010) in the construction and use of this instrument. See also Katz and Murphy (1992), Blanchard and Katz (1992), Bound and Holzer (2000), Autor and Duggan (2003), and Goldsmith-Pinkham, Sorkin, Swift (2018).

On average, approximately 40 percent of applicants do not sign an enlistment contract (uninterested or unqualified) while approximately 55 percent serve on active duty. The remaining 5% are individuals that sign contracts but attrite from the Delayed Entry Program prior to entering active duty to attend basic training. In terms of recruiting organization and resources, there is a tremendous amount of variability due to the differing population densities across counties. For stations and recruiters per county, there are roughly 2.5 recruiting stations in each county with two recruiters assigned to each station. The average recruiting station is responsible for recruiting roughly six individuals with the contract goals for high-quality individuals approximately twice that for low-quality individuals.

Table 2.1. Summary Statistics for County*Quarters (Fiscal Years 2006 to 2014)

	Mean	SD	Min	Max
Outcome Variables				
(per 100,000 15 to 24-year old in cnty*qtr):				
Total Applicants	72.05	50.38	0.00	439..50
Not Qualified	12.63	14.42	0.00	156.98
Not Interested	15.69	15.90	0.00	149.95
Contracted	43.72	33.44	0.00	2206.50
Contracted but DEP Loss	4.53	7.09	0.00	87.96
Contracted and Accessed	39.19	30.88	0.00	286.64
Explanatory Variables (fraction unless noted):				
Employment to Population Ratio	0.58	0.12	0.00	0.82
Unemployment Rate	0.07	0.03	0.01	0.32
Veteran	0.09	0.03	0.02	0.44
Black	0.13	0.13	0.00	0.86
Hispanic	0.17	0.17	0.00	0.97
Poor	0.15	0.06	0.02	0.62
Civilian Earnings (in $1000s per quarter)	4.21	0.63	1.76	6.94
Median Household Income (in $1000s annually)	51.96	13.48	16.87	125.64
Recruiting Organization and Resources				
Recruiters per County	2.36	6.76	0	215
Recruiting Stations per County	0.56	0.27	1	38
Total Contract Goals (per quarter per county)	6.73	18.91	0	574
High-quality Contract Goals	4.45	12.38	0	383
Low-quality Contract Goals	2.28	6.89	0	323

Source: Office of Economic and Manpower Analysis, US Army Recruiting Command, Bureau of Labor and Statistics, and Census Bureau.

- All variables are weighted by county 15 to 24-year-old population.

- Notes: Individual Applicant for Army service data from 200510 to 201309 (FY 2006 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 109,166 county*quarter observations.

Table 2.2 compares the composition of the sub-groups of total applicants to the Army during this period. Except for the unqualified group, there is not significant variation across the sub-groups of applicants. The overall applicant pool consists of primarily male, white, high school graduates scoring in the middle of the AFQT distribution. As a group, individuals that express enough interest to go to a MEPS site but do not ultimately enlist ("uninterested") look similar to the total applicant pool. Those that are unqualified (failure of drug, medical, or physical exams or AFQT < 10) are more likely to be female and black and very few are a high school graduate with an AFQT score greater than 50. Individuals that sign a contract either become DEP losses or become an accession and attend basic training. As with not qualified individuals, DEP losses are more likely to be females and have lower AFQT scores than the total applicant pool. They are also more likely to have failed a medical exam or a drug test even though they were successful in obtaining a waiver. Finally, accessions are more likely to be male and high school graduates with a higher AFQT score than the total applicant pool.

Table 2.2. Composition of Applicants-Summary Statistics for County*Quarters

	Applicants	Not Interested	Not Qualified	DEP Loss	Accessions
Per 100,000 15 to 24-year old in cty*qtr	72.05 (50.38)	15.69 (15.90)	12.63 (14.42)	4.53 (7.09)	39.19 (30.88)
Composition (fraction):					
High-quality	0.49 (0.18)	0.56 (0.25)	0.16 (0.21)	0.54 (0.33)	0.56 (0.21)
Male	0.82 (0.12)	0.79 (0.19)	0.77 (0.21)	0.76 (0.27)	0.85 (0.13)
Black	0.19 (0.20)	0.17 (0.21)	0.27 (0.28)	0.19 (0.27)	0.18 (0.20)
High School Grad.	0.88 (0.13)	0.85 (0.20)	0.87 (0.20)	0.90 (0.20)	0.90 (0.14)
Medical Test Failure	0.11 (0.10)	0.00 (0.00)	0.28 (0.26)	0.17 (0.24)	0.10 (0.12)
Drug Test Failure	0.01 (0.03)	0.00 (0.00)	0.02 (0.08)	0.06 (0.15)	0.01 (0.03)
AFQT (avg)	53.22 (11.54)	52.98 (21.88)	25.75 (16.05)	43.03 (27.37)	56.11 (16.03)

Source: Office of Economic and Manpower Analysis and US Army Recruiting Command
- Standard Deviation in parentheses. All values are weighted by county 15 to 24-year-old population. Individual Applicant for Army service data from 200510 to 201309 (FY 2006 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 109,541 county*quarter observations.

I plotted both the raw distribution of each outcome and the normalized outcomes per 100,000 15 to 24-year-old population (box plots in Figures A 2.1 to Figure A 2.6 and histograms in Figures A 2.7 to Figure A 2.12) and found that the raw data is both non-normal and contains a high number of zero observations. Normalizing the data by the population reduced the skewness and made the distribution closer to normal (excluding the significant bunching at zero). Regarding total applicants and accessions, approximately 25 to 35 percent of the observations take a value of zero. The data for not interested, not qualified, contracts, and DEP loss exhibit similar distributional characteristics and contain and even higher number of zeros in the outcomes (60 to 80 percent). Given this and the discrete count nature of the observations, it is possible the data is better represented by a Poisson distribution than by a normal distribution. However, as seen in the standard deviations in parentheses in Table 2.2, the observed outcomes for applicants and their outcomes do violate a central criterion of the Poisson distribution; all the groups exhibit over-dispersion (unequal means and variances - $\mathbb{E}[Y_i] < \mathbb{V}[Y_i]$). This does not prevent estimation of an unbiased estimator but does have the potential to produce standard error estimates that exaggerate the precision of the parameter estimate.[64] I will explore this alternative distributional assumption further in Section 2.6.1 (Robustness Checks).

2.5 Empirical Specification and Strategy

I perform the first county-level analysis of the relationship between local labor market conditions and the supply of individuals interested in service in the U.S. Army. I use county*quarters as the unit of observation for analysis.[65] This approach allows me to capture the significant geographic variation across counties and balances the relative unimportance of month-to-month variation in the accomplishment of recruiting goals

[64] See Wooldridge (2010), Chapter 18.
[65] Previous studies on enlistment supply use state*quarter.

against the overall annual recruiting requirement.

I employ two estimation strategies in this paper. First, I conduct Ordinary Least Squares estimation using a comprehensive set of covariates to control for systematic differences in counties where interest in military service is high and counties where interest is lower (as measured by applicant behavior). I use OLS with the employment-to-population ratio as the key explanatory variable in the primary specification but include unemployment rates in my robustness checks in section 2.6.1. In each of these specifications, county fixed effects control for much of the cross-sectional variation (unobserved area heterogeneity potentially correlated with enlistment) and year by quarter effects control for seasonality and uniform national trends (mitigating unobserved aggregate trends in enlistment rates).

My main specification takes the form

$$Y_{it} = \alpha + \gamma E_{it} + \boldsymbol{\beta X}_{it} + \boldsymbol{\eta R}_{it} + \delta_i + \lambda_t + \mu_{it} + \varepsilon_{it} \qquad 2.1$$

where $\boldsymbol{i}$ and $\boldsymbol{t}$ index counties and quarters, respectively.

Y_{it} is the outcome variable representing interest in military service as measured by total applicants and its sub-outcomes per 100,000 15 to 24-year-old population as discussed in the previous section. E_{it} is the proxy for economic conditions; in this specification, it is the county-level employment-to-population ratio. The coefficient of interest, γ, measures the response of enlistment supply to the measure of local economic conditions. It is identified from within county changes in the enlistment rate (relative to other counties) coincident with within county changes in the employment-to-population ratio (relative to other counties).

$\boldsymbol{X}_{it}$ is a vector of demographic controls that holds constant gender, the percentage of the county that is veteran, black, median earnings for 15 to 24-year-olds, and percent poor. R_{it} is a vector of recruiting resource variables such as high and low-quality contract goals, the number of recruiters, and other military services' contracts as a fraction of the youth population.[66] δ_i is a county fixed effect which removes variation in enlistment rates caused by factors that vary across counties but are constant over time. These can include both local recruiting policies and procedures, differences in lifestyle, local school systems' ability to produce qualified applicants, or physical geography of the county. λ_t is a year by quarter fixed effect that eliminates the influence of common factors that cause seasonal and annual changes in enlistment across all counties (national recruiting policies such as bonuses, advertising, changes to recruiter incentives, demand for military forces, etc.). State-specific linear and quadratic trends are included in some specifications to account for heterogeneous trends in enlistment across states.

In the above specification, I assume local labor market conditions as measured by employment-to-population ratio (and later, unemployment rate) are conditionally exogenous to military enlistment in each county. In other words, the impact of employment-to-population ratios on enlistment is identified by variation in the timing and magnitude of enlistment within counties, conditional on demographic and recruiting controls, relative to plausibly exogenous within-county variation of employment-to-population ratios. If it is true that decreased employment opportunities in the civilian labor market encourage more young people to enlist in the military, then we can claim that local labor market conditions cause changes in military enlistment.

It is also possible local policies influencing enlistment rates, such as job training programs, are correlated with economic conditions. The inclusion of county-by-year fixed effects could help to mitigate this problem. It may also be the case that different areas

[66] While I can include the Air Force, Navy, and Marine Corps contracts, my data does not include the other military services' high and low-quality goals.

have different pre-existing enlistment rate trends for reasons other than economic conditions. The inclusion of area-specific time trends could address this problem. However, I cannot include area fixed effects, time fixed effects, area-by-time fixed effects and area-specific time trends without eliminating nearly all variation identifying variation in the model. For this reason, I chose to include county and annual fixed effects in addition to state-specific linear and quadratic time trends. I do not include county-by-year fixed effects in my specifications.

While it is very unlikely that enlistment rates somehow cause employment-to-population ratios to vary (simultaneity), it is possible there are unobservable characteristics (omitted variables) of the labor supply that influence both enlistment rates and labor market conditions.[67] These include unobserved social or cultural differences that make some populations more likely to join the military such as local attitudes to both military service and higher education. Chronic levels of unemployment could also lead to deterioration of local health conditions in such a way as to impact general levels of eligibility for enlistment in an area. If these characteristics are not mitigated by location, time fixed effects, and time trends, then OLS estimation will produce a biased estimate.

If enlistment in a county is a function of *both* local labor supply and demand, using employment-to-population ratios will likely confound the results. If interest in military service is affected by changes in the local labor supply, then part of the effect of unemployment on enlistment in the military could reflect this relationship. For example, unobserved migration could affect local labor supply as young men more likely to join the military could be more likely to move due to poor local labor conditions (this assumes they don't enlist elsewhere). Obtaining an unbiased estimate in this case requires the use

[67] In fact, enlistment rates could mechanically cause the unemployment rate to go down if an unemployed individual enlists in the military, but the effect would be very small.

the of labor demand shocks as an identifying source of variation.

To mitigate this potential endogeneity between enlistment and employment-to-population ratios due to omitted variables or correlation between enlistment and labor supply, I also estimate a two stage least squares model:

2SLS: $$Y_{it} = \alpha + \gamma E_{it} + \boldsymbol{\beta X}_{it} + \boldsymbol{\eta R}_{it} + \delta_i + \lambda_t + \mu_{it} + \varepsilon_{1,it} \qquad 2.2$$

First Stage: $$E_{it} = \alpha_2 + \delta_i + \lambda_t + \boldsymbol{\beta_2 X}_{it} + \boldsymbol{\eta}_2\boldsymbol{R}_{it} + \pi Z_{it} + \varepsilon_{2,it} \qquad 2.3$$

Reduced Form: $$Y_{it} = \alpha_3 + \delta_i + \lambda_t + \boldsymbol{\beta}_3\boldsymbol{X}_{it} + \boldsymbol{\eta}_3\boldsymbol{R}_{it} + \theta Z_{it} + \varepsilon_{3,it} \qquad 2.4$$

where $\boldsymbol{E}_{it}$ is the employment-to-population ratio and the instrument, Z_{it}, is a shift-share style instrument. Following Goldsmith and Pinkham (2018), the "shift-share is the inner product of industry-county-shares and the industry component of the growth rate". In my case, the instrument predicts *employment-to-population ratios* in a county if industries in the county expanded at the national rate of growth for each respective industry (excluding own-county growth rates).[68] By removing the employment growth in each county from the national growth rate calculation ($g_{jt}^{\sim i}$), the instrument does not contain local trends and is orthogonal to employment changes due to local labor supply shifts. Specifically, the expression for the instrument is given by

$$\mathrm{Z}_{it} = \sum_{j=1}^{J}\left(\frac{emp_{i,j,2006}}{emp_{i,2006}} \cdot \frac{\sum_{k\in\{counties\setminus i\}} emp_{j,k,t}}{\sum_{k\in\{counties\setminus i\}} emp_{j,k,2006}}\right) \cdot \frac{emp_{i,2006}}{pop_{i,2006}} = \sum_{j=1}^{J}\left(s_{i,j,2006} \cdot \ g_{jt}^{\sim i}\right) \cdot \frac{emp_{i,2006}}{pop_{i,2006}} \qquad 2.5$$

where i, t, and j index counties, quarter, and industries, respectively. It is constructed

[68] Specifically, when instrumenting for the employment-to-population ratio, I divide predicted employment by the working age population in period t in county i to obtain the predicted employment-to-population ratio. When instrumenting for unemployment rates, I use only predicted employment levels.

using Quarterly Workforce Indicator employment numbers for the working age population at the two-digit North American Industry Classification System (NAICS) level. This provides a measure of county-specific exposure to labor demand shocks which are likely correlated with local economic conditions (e.g., employment-to-population ratios) but is not a determinant of enlistment except through its effect on local labor market conditions. If national industry growth rates (absent own county growth rates) are not correlated with county-level labor supply shocks, the instrument will identify exogenous variation in county employment-to-population ratios (Autor and Duggan 2003).

Specifically, the identifying assumption for this specification is the initial industry composition in each county ($s_{i,j,2006}$) and the national industry growth rates ($g_{jt}^{\sim i}$) are exogenous to the changes in enlistment in each county. Thus, county-specific exposure to national employment shocks are an exogenous determinant of employment-to-population ratios but are not correlated with unobserved determinants of enlistment. This type of instrument has been used in the literature examining the effects of labor demand shifts and population adjustments on employment and earnings (Bound and Holzer 1996), economic conditions and crime (Raphael and Winter-Ebmer 2001), migration (Saks and Wozniak 2011), and is shown to be causally related to economic conditions (Davis, Loungani, and Malidhara 1997).

As noted above, the distributional form of the applicant data and the significant proportion of zeros in the outcome variables also suggests considering an alternative specification. Therefore, I also estimate a Poisson specification of the form

$$Y_{it} = \exp(\alpha + \gamma E_{it} + \boldsymbol{\beta} \boldsymbol{X}_{it} + \boldsymbol{\eta} \boldsymbol{R}_{it} + \delta_i + \lambda_t + \mu_{it} + \log p_{it} + \varepsilon_{1,it}) \qquad 2.6$$

where p_{it} represents the population of each county and is included to ensure outcomes are scaled correctly and consistent with the OLS specification.[69] The remaining explanatory variables are also consistent with the previous specifications (OLS and 2SLS) in equations 2.1 and 2.2. As discussed in the section above, the data for applicants and each sub-population is over-dispersed $\mathbb{E}[Y_i] < \mathbb{V}[Y_i]$. While the estimated coefficients of the maximum likelihood Poisson estimator are unbiased even if the assumption that the variance equals the mean is violated, the estimation of standard errors does depend on this assumption.[70] Given over-dispersion, estimation by conventional means results in overly precise estimates of standard errors. To correct for this, the variance-covariance matrix of the estimates is estimated using the Huber-White-Sandwich estimator which produces consistent standard errors in the model with over-dispersion. This method is less restrictive and does not require the mean equals the variance nor does it require homoscedasticity.[71]

2.6 Results

Initial analysis of the data shows that both the employment-to-population ratio and the unemployment rate are strongly related to the number of individuals expressing interest in enlisting in the military. Figures A 2.13 to A 2.22 are bin scatter plots of the overall applicant population and the four sub-outcomes of the enlistment process (per 100,000 15 to 24-year-old per county*quarter): individuals that are disqualified for medical, physical, or criminal reasons (disqualified), those that decide not to sign a

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[69] Technically, population is included as an exposure variable. For example, in a model where $\mathbb{E}[Enlistment\ |\boldsymbol{X}, Population] = \boldsymbol{X\beta} + \log population$, then $Enlistment = \exp(\boldsymbol{XB}) + population$

[70] See chapter 18 of Wooldridge (2010) or chapter 17 of Cameron and Trivedi (2010).

[71] Conditions for instrumental variables to be unbiased in Poisson regressions are identical to those required in a linear model but are implemented using non-linear Generalized Method of Moments. See Chapter 17 of Cameron and Trivedi (2010).

contract after visiting MEPS (uninterested), those that sign a contract but attrite from the Delayed Entry Program (DEP Loss), and individuals that sign a contract and serve on active duty (accession). For each category of individuals, conditional means of the data were plotted against the explanatory variables of interest with and without additional controls.[72] The results in column (2) of Table 2.3 are identical to and represented in the even-numbered binscatter plots in the appendix (Figure A 2.14, Figure A 2.16, etc.). These initial results reflect the relatively higher sensitivity to labor market conditions of those who enter active duty ('accessions') relative to those that become disqualified, uninterested, or DEP losses. This also partially reflects the greater impact of the employment-to-population ratio vis-a-vis the unemployment rate and accords with the more detailed findings below.

In Table 2.3, I present the main results from the estimation of equations 2.1 (OLS) and 2.2 (2SLS) for the effect of the contemporaneous employment-to-population rate on the rate of individuals per eligible population that visited a Military Entrance Processing Station with the intent of enlisting (total applicants) and the four sub-outcomes within this population.[73] All specifications include county and year by quarter effects, in addition to controls for civilian earnings, population and fraction veterans, blacks, and females. Columns (2) to (5) also include number of recruiters, high-quality goals, low-quality goals, and other DOD contracts per 100,000 15 to 24-year-olds. State-specific linear and

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[72] The first bin scatter plot for each population displays points representing the average number of applicants conditional on the average x-axis (unemployment or employment-to-population rates) value as represented by 20 equal-sized bins. The second bin scatter residualizes the x-variable and y-variables on the specified controls, adds the sample mean of each variable, then bins and plots. Controls in right panel of A13 to A24 are county fixed effects, time fixed effects, gender, race, veteran presence in counties, earnings, and recruiting resources. Average bonus amount is included as additional control for accessions and DEP loss.

[73] In the robustness section 2.6.1 Robustness Checks, I examine the effect of a one-year moving average on the same outcomes.

quadratic trends are included in columns (3) to (5), respectively.

Table 2.3. Effect of Current Employment-to-Population Rate on Military Enlistment (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (per 100,000 15 to 24-year old)					
Overall Outcome					
Total Applicants	0.0300	0.0272	-0.140**	0.0436	-2.534***
(mean: 72.05)	(0.0578)	(0.0576)	(0.0606)	(0.0613)	(0.205)
Sub-outcomes					
Total Disqualified	0.0211	0.0210	-0.0387*	-0.0408*	-0.778***
(mean: 12.63)	(0.0218)	(0.0218)	(0.0232)	(0.0236)	(0.0788)
Total Uninterested	0.0186	0.0191	0.0431*	0.0676***	-0.0884
(mean: 15.69)	(0.0238)	(0.0238)	(0.0252)	(0.0256)	(0.0850)
Total DEP Loss	-0.00365	-0.00353	-0.00214	-0.00222	0.0575
(mean: 4.53)	(0.0117)	(0.0117)	(0.0124)	(0.0127)	(0.0945)
Total Accessions	-0.0607	-0.0629	-0.206***	-0.0462	-1.732***
(mean: 39.19)	(0.0394)	(0.0393)	(0.0415)	(0.0420)	(0.141)
First-Stage (E/P)					31.12***
instrument					(0.364)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					9493.3
Observations	99311	99311	98554	98554	98538

- Preferred specification is in column (5). All regressions are weighted by mean of 15 to 24-year-old county population during sample period. Standard errors in parentheses are clustered at the county-level.
- All specifications include county and year by quarter effects, civilian earnings (in $1000), fraction veteran, black, and female as controls. Specifications for accessions and DEP loss also include bonus amounts in $1000. "USAREC Controls" include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts per 100,000 15 to 24-year-old. The total number of applicants is comprised of four sub-outcome groups: those individuals that are disqualified for medical, physical, or criminal reasons (disqualified), those that decide not to sign a contract after visiting MEPS (uninterested), those that sign a contract but attrite from the Delayed Entry Program (DEP Loss), and those that sign a contract and serve on active duty (accession). Panel Data at County*Fiscal Year Quarter level from 200510 to 201409 (FY 2006 to FY 2014); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In general, it appears that a decreasing employment-to-population ratio results in more individuals applying to the military which directly results in more individuals entering onto active duty (accessions). Specifically, for accessions, the coefficient of 0.0462 in column (4) implies that a one percentage point decrease in the county employment-to-population ratio is predicted to increase by 0.0462 the number of total accessions per 100,000 15 to 24-year-olds in a county*quarter. In this case, a one percentage point decrease in the employment-to-population ratio increases the total accessions in a county*quarter by 0.12 percent (mean of accessions is 39.19).

With respect to the instrumental variable specification in column (5), the direction of the effects is largely the same but increased by an order of magnitude. A one percentage point increase in the employment-to-population ratio increases applicants and accessions by 3.5 percent and 4.4 percent, respectively. Given that the shift-share instrument is a measure of local labor demand shocks, absent any endogenous labor supply effects, the increase in size from the OLS to 2SLS estimate makes sense. Many of the potential unobserved variables correlated with both enlistment and employment-to-population rates (physical and mental health, general levels of fitness, etc.) are procyclical (increase when employment-to-population ratios increase) and positively correlated with enlistment. In addition, other potentially unobserved factors like migration, are negatively correlated with labor market conditions and negatively correlated with enlistment. In both cases, the unobserved variables exert a positive bias on the negative OLS estimates. Mitigating these unobserved labor supply factors using the shift-share instrument to isolate labor demand variation results in smaller 2SLS estimates relative to OLS (larger in absolute value).[74]

[74] Given an omitted variable x_2, the effect on the OLS estimate, $\mathbb{E}[\beta_1]$, can be thought of as $\mathbb{E}[\beta_1] = \beta_1 + \beta_2 \cdot \frac{\mathbb{C}ov[x_1,x_2]}{\mathbb{V}[x_1]}$.

Another way to think about the relationship between the OLS and IV estimates is that OLS (assuming zero conditional mean assumption holds) estimates an average treatment affect (ATE) while 2SLS estimates the local average treatment effect (LATE). In my specification, the LATE is the effect of the employment-to-population ratio on enlistment for those individuals for which labor market conditions are more impactful to their labor market options than others. In other words, the shift-share instrument, representing local labor demand shocks, shifts the enlistment behavior of those relatively more sensitive to poor labor market conditions than the general youth population.[75]

Table 2.4 presents results for the same groups but disaggregated into those deemed high and low-quality by the Army.[76] These results make clearer the impact of the employment-to-population ratio on enlistment behavior: the overall increase in applicants and accessions reflected in Table 2.3 is comprised of an increase in both high quality and low quality applicants and accessions, however, the effect on high quality individuals is smaller. Given the coefficients in the table and their associated means, the rate of low-quality applicants and accessions both increase by roughly 6 percent for a one percentage point increase in the employment-to-population ratio, while high-quality applicants and accessions increase by approximately 1 and 3 percent, respectively.

Overall, this suggests two key findings: the presence of labor supply factors not accounted for in the OLS specification results biases the OLS estimates downward and the sensitivity of low-quality recruits to labor market conditions is roughly two to six times the sensitivity of high-quality recruits. This is consistent with the notion that low-quality

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[75] To put it yet another way, it is possible there are heterogeneous subpopulations and those induced to enlist by the employment-to-population ratio are relatively more sensitive to labor market conditions

[76] As a reminder, high-quality recruits are defined as high school graduates scoring in the top half of the aptitude distribution. Specifically, high-quality recruits are high school seniors or graduates in Armed Forces Test Score Category (TSC) I-IIIA (AFQT ≥ 50). Low-quality recruits are high school graduates in TSC IIIB-IV ($10 \leq$ AFQT ≤ 50) or a high school dropout in any test score category above 31.

individuals would be the most vulnerable in periods of difficult economic conditions and likely have the fewest civilian labor market options. However, this is inconsistent with the potential “crowding out” story where the ability of low-quality recruits to enlist during periods of economic contraction is negatively impacted by the number of high-quality individuals expressing interest in the military (Ellwood and Wise 1987).

Table 2.4. High and Low-Quality Individuals: Effect of Current Employment-to-Population Rate on Military Enlistment (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (per 100,000 15 to 24-year old)					
High-quality					
Applicants	-0.116***	-0.115***	-0.0338	0.0670*	-0.294**
(mean: 33.79)	(0.0348)	(0.0347)	(0.0368)	(0.0372)	(0.124)
Disqualified	-0.0169**	-0.0165**	-0.00553	-0.00519	-0.0410
(mean: 1.80)	(0.00748)	(0.00748)	(0.00798)	(0.00812)	(0.0270)
Uninterested	-0.00412	-0.00325	0.0268	0.0404**	0.0928
(mean: 8.53)	(0.0162)	(0.0162)	(0.0172)	(0.0174)	(0.0579)
DEP Loss	-0.00758	-0.00745	0.00334	0.00260	-0.118***
(mean: 2.42)	(0.00826)	(0.00826)	(0.00883)	(0.00898)	(0.0300)
Accessions	-0.145***	-0.144***	-0.124***	-0.0389	-0.608***
(mean: 21.05)	(0.0266)	(0.0266)	(0.0282)	(0.0286)	(0.0955)
Low-quality					
Applicants	0.147***	0.143***	-0.0963**	-0.0147	-2.187***
(mean: 38.26)	(0.0415)	(0.0414)	(0.0437)	(0.0444)	(0.149)
Disqualified	0.0380*	0.0375*	-0.0332	-0.0356	-0.737***
(mean: 10.83)	(0.0204)	(0.0203)	(0.0216)	(0.0220)	(0.0734)
Uninterested	0.0227	0.0224	0.0165	0.0273	-0.182***
(mean: 7.16)	(0.0157)	(0.0157)	(0.0167)	(0.0170)	(0.0564)
DEP Loss	0.00503	0.00504	-0.00355	-0.00301	-0.160***
(mean: 2.11)	(0.00815)	(0.00815)	(0.00871)	(0.00886)	(0.0296)
Accessions	0.0826***	0.0795***	-0.0743***	-0.00194	-1.088***
(mean: 18.14)	(0.0267)	(0.0266)	(0.0282)	(0.0286)	(0.0959)
First-Stage (E/P)					31.12***
instrument					(0.364)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quad. Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					9493.3
Observations	99311	98554	98554	98538	99311

- Notes same as in Table 2.3.

While Table 2.3 and Table 2.4 examine the changes in the levels of the rate of enlistments in the aggregate and across quality levels for county populations, Table 2.5 and Table 2.6 examine the impact of the employment-to-population ratio on the composition of the applicant pool. The results of the preferred specification in column (5) of Table 2.5 show that, conditional on showing an initial interest in the military by meeting with a recruiter and visiting a MEPS site (applicant), increasingly poor labor market conditions as measured by the employment-to-population ratio increases the number of individuals that begin the process of enlistment and are disqualified but decreases those that are uninterested at some point before signing a contract to serve on active duty. Overall, the relative number of accessions does not statistically change.

Table 2.6 disaggregates these changes in the composition of the applicant pool into high and low-quality individuals. Unlike what is reported in Table 2.4 for the rate of applicants per eligible population, the composition of the applicant pool (outcomes as a fraction of applicants) does not change a significant amount. Given a decreasing employment-to-population ratio of 1 percentage point, the fraction of high-quality accessions in the applicant pool increases by about 1 percent. Moreover, the increase in the fraction of individuals that begin the process of enlistment and are disqualified is split between high- and low-quality individuals (4.4 and 1.2 percent), while the decrease in the fraction of those that are uninterested is primarily due to the change in the fraction of low-quality individuals failing to sign a contract (2.3 percent).

Table 2.5. Effect of Current Employment-to-Population Rate on Applicant Outcomes (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
Total Disqualified	0.0254	0.0258	-0.0438	-0.0715**	-0.301***
(mean: 17.42)	(0.0265)	(0.0265)	(0.0282)	(0.0287)	(0.0961)
Total Uninterested	0.0866***	0.0885***	0.0932***	0.0905***	0.344***
(mean: 22.03)	(0.0283)	(0.0283)	(0.0301)	(0.0306)	(0.102)
Total DEP Loss	-0.0121	-0.0122	0.00860	-0.00536	-0.164**
(mean: 6.41)	(0.0178)	(0.0178)	(0.0190)	(0.0194)	(0.0650)
Total Accessions	-0.138***	-0.139***	-0.102***	-0.0593	-0.0968
(mean: 54.15)	(0.0351)	(0.0351)	(0.0374)	(0.0380)	(0.127)
First-Stage (E/P)					31.10***
instrument					(0.364)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					7318.9
Observations	78278	78278	77725	77725	77701

- Notes same as in Table 2.3.

Table 2.6. High and Low-Quality Individuals: Effect of Current Employment-to-Population Rate on Applicant Outcomes (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
High-quality					
Applicants	-0.0244	-0.0247	0.0327	0.0419	-0.0495
(mean: 49.12)	(0.0349)	(0.0349)	(0.0373)	(0.0379)	(0.127)
Disqualified	-0.0265**	-0.0266**	-0.0289**	-0.0304**	-0.121***
(mean: 2.72)	(0.0121)	(0.0121)	(0.0129)	(0.0132)	(0.0440)
Uninterested	0.0490**	0.0507**	0.0535**	0.0534**	0.119
(mean: 12.48)	(0.0223)	(0.0223)	(0.0237)	(0.0241)	(0.0806)
DEP Loss	0.00296	0.00271	0.0163	0.00730	-0.0994**
(mean: 3.52)	(0.0135)	(0.0135)	(0.0144)	(0.0147)	(0.0493)
Accessions	-0.0993***	-0.100***	-0.0647*	-0.0456	-0.260**
(mean: 30.05)	(0.0321)	(0.0321)	(0.0343)	(0.0349)	(0.117)
Low-quality					
Applicants	0.0311	0.0312	-0.0286	-0.0399	0.0426
(mean: 50.88)	(0.0350)	(0.0350)	(0.0373)	(0.0380)	(0.127)
Disqualified	0.0519**	0.0524**	-0.0148	-0.0410	-0.180**
(mean: 14.70)	(0.0244)	(0.0244)	(0.0260)	(0.0265)	(0.0886)
Uninterested	0.0375*	0.0377*	0.0398*	0.0372*	0.224***
(mean: 9.55)	(0.0200)	(0.0200)	(0.0213)	(0.0217)	(0.0727)
DEP Loss	-0.0115	-0.0114	-0.00437	-0.00941	-0.0582
(mean: 2.84)	(0.0121)	(0.0121)	(0.0129)	(0.0132)	(0.0441)
Accessions	-0.0366	-0.0374	-0.0382	-0.0165	0.142
(mean: 24.1)	(0.0299)	(0.0299)	(0.0319)	(0.0325)	(0.109)
First-Stage (E/P)					31.10***
instrument					(0.364)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					7303.4
Observations	78278	78278	77725	77725	77701

- Notes same as in Table 2.3.

2.6.1 Robustness Checks

In this section, I report the results from several robustness checks and alternative specifications. Specifically, I investigate the temporal aspect of labor market conditions and the enlistment decision, explore alternative measures of the general labor market conditions in an area, and check the sensitivity of the data to the distribution of the data generating process.

It is possible that contemporaneous measures of local labor market conditions are not the correct measure, but rather, economic conditions in the periods leading up to an individual's final decision to meet with a recruiter and go to Military Entrance Processing Station. To explore this, I created a one-year moving average (3 previous quarters and quarter of enlistment decision) of the unemployment rate to investigate this possibility. For those individual's enlisting out of high school, this captures the economic conditions present during their senior year of high school, a period when students are making decisions about post-high school plans for college, the labor market, or the military. For people already out of high school and in the labor force, using 12 months is also consistent with the idea that these individuals make the enlistment decision over a period of months and after experiencing the labor market first-hand. Table 2.7 presents the results of the OLS estimation of the one year moving average of the employment-to-population ratio on the rates of individuals that express interest in the enlisting. [77]

In general, the impact of the employment-to-population ratio in the year leading up to the enlistment decision is the same in direction as the contemporaneous rate but stronger. In this case, total applicants increase by 3.398 and total accessions increase by 4.24 for a one percentage point increase in employment-to-population rate. The

[77] Instruments for the one-year moving average unemployment rate and employment-to-population ratio are also created using a one-year moving average (3 previous quarters and quarter of enlistment decision).

contemporaneous employment-to-population rate increased each by 2.53 and 1.72, respectively. Table A 2.1 breaks the groups out by quality level. As with the contemporaneous rate, worsening economic conditions influence relatively more low-quality individuals to apply for military service resulting in relatively more low-quality accessions (with concomitant increases in low quality disqualified, not interested, and DEP losses, as well). Table A 2.2 and Table A 2.3 report the changes in the composition of the applicant pool. Unlike the effect of the contemporaneous rate, labor market conditions in the previous year increase the fraction of high-quality applicants and accessions while decreasing the relative fraction of low-quality applicants (see Table A 2.3).

Table 2.7. Effect of One-Year Moving Average Employment-to-Population Ratio on Military Enlistment (OLS and 2SLS)

Dependent Variable (per 100,000 15 to 24-year-old)	(1)	(2)	(3)	(4)	(5)
Overall Outcomes					
Total Applicants	0.115*	0.129**	0.0227	0.173**	-3.398***
(mean: 72.05)	(0.0624)	(0.0622)	(0.0670)	(0.0676)	(0.227)
Sub-outcomes					
Total Disqualified	0.0377	0.0414*	-0.0239	-0.0287	-0.905***
(mean: 12.63)	(0.0236)	(0.0236)	(0.0257)	(0.0260)	(0.0867)
Total Uninterested	0.0676***	0.0717***	0.119***	0.139***	0.0268
(mean: 15.69)	(0.0257)	(0.0257)	(0.0279)	(0.0282)	(0.0935)
Total DEP Loss	-0.0149	-0.0136	-0.00764	-0.0120	-0.425***
(mean: 4.53)	(0.0126)	(0.0126)	(0.0138)	(0.0140)	(0.0467)
Total Accessions	-0.0533	-0.0471	-0.158***	-0.0220	-2.621***
(mean: 39.19)	(0.0425)	(0.0425)	(0.0458)	(0.0463)	(0.156)
First-Stage (E/P)					35.22***
instrument					(0.41)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quad. Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					9559.6
Observations	99311	99311	98554	98554	98538

- One-year moving average includes 3 previous quarters and quarter of enlistment decision. All regressions are weighted by mean of 15 to 24-year-old county population during sample period. Standard errors in parentheses are clustered at the county-level.
- All specifications include county and year by quarter effects, civilian earnings (in $1000), fraction veteran, black, and female as controls. Specifications for accessions and DEP loss also include bonus amounts in $1000. "USAREC Controls" include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts per 100,000 15 to 24-year-old. The total number of applicants is comprised of four sub-outcome groups: those individuals that are disqualified for medical, physical, or criminal reasons (disqualified), those that decide not to sign a contract after visiting MEPS (uninterested), those that sign a contract but attrite from the Delayed Entry Program (DEP Loss), and those that sign a contract and serve on active duty (accession). Panel Data at County*Fiscal Year Quarter level from 200510 to 201409 (FY 2006 to FY 2014); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In addition to the employment-to-population ratio, I also investigate alternative measures of labor market conditions. Specifically, I explore contemporaneous and one year moving average unemployment rates. The results are presented in Table 2.8 in the main body of the text and Table A 2.4 to Table A 2.10 in the appendix.

Table 2.8 reports the results of the effect of the contemporaneous unemployment rate on each outcome in the enlistment process. As the economy slows down and the unemployment rate increases, there is an overall increase of 3.590 (5 percent) in the rate of applicants and 3.98 in the rate of accessions (10 percent). As for the break between high and low-quality groups, unlike the employment-to-population ratio, an increasing unemployment rate appears to decrease high-quality applicants and accessions but increase the rate of low-quality applicants and accessions. However, the effect is stronger for low quality than high quality (see column (5) in Table A 2.4).

While I use the employment-to-population ratio as the primary measure of labor market conditions due to its more attractive properties (explained in Section 2.4), previous research has primarily focused on the number of high-quality contracts signed by individuals and uses the unemployment rate rather than the employment-to-population ratio. In terms of my sample, contracts signed are an aggregation of two sub-outcomes: high-quality DEP losses and accessions (see column (4) in Table A 2.4 in the appendix). The OLS estimates of those willing to sign high-quality contracts increases by 1.9 percent for a one percentage point increase in the unemployment rate. Previous estimates in the most recent literature, using the unemployment rate and OLS specifications for high-quality contracts find increases of about 1.6 percent for a one percentage point increase in the unemployment rate.[78]

[78] In terms of elasticity, the previous literature finds estimates of approximately 0.1, while my results imply

Table 2.8. Effect of Current Unemployment Rate on Military Enlistment (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (per 100,000 15 to 24-year old)					
Overall Outcome					
Total Applicants	1.771***	1.860***	1.127***	0.814***	3.590**
(mean: 72.05)	(0.104)	(0.103)	(0.109)	(0.124)	(1.711)
Sub-outcomes					
Total Disqualified	-0.0273	-0.0102	-0.0653	-0.00246	0.244
(mean: 12.63)	(0.0392)	(0.0392)	(0.0418)	(0.0479)	(0.658)
Total Uninterested	0.428***	0.446***	0.296***	0.324***	-0.279
(mean: 15.69)	(0.0428)	(0.0428)	(0.0455)	(0.0519)	(0.714)
Total DEP Loss	-0.0707***	-0.0649***	-0.104***	-0.0761***	-0.213
(mean: 4.53)	(0.0209)	(0.0209)	(0.0224)	(0.0257)	(0.351)
Total Accessions	1.360***	1.406***	0.933***	0.480***	3.976***
(mean: 39.19)	(0.0706)	(0.0705)	(0.0746)	(0.0852)	(1.185)
First-Stage (UE)					-2.48e-06***
instrument					(1.10e-07)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	No
State Quadratic Trend	No	No	No	Yes	No
2SLS	No	No	No	No	Yes
F (excluded instruments)					503.4
Observations	99311	99311	98554	98554	98538

- Notes same as in Table 2.3.

With respect to the contemporaneous and one-year moving average unemployment rate, the results are largely consistent in direction with the effects of the employment-to-population ratio. However, the effects are larger in magnitude. For the working-age population, a one percentage point increase in the unemployment rate is equal to an increase of 1.54 million individuals without a job. On the other hand, a one percentage

an elasticity of 0.14.

point decrease in employment-to-population ratio is equal to a change of about 1.97 million.[79] If these measures serve as a proxy actual labor market conditions, one would expect to see a relatively similar effect for a 1 percentage point change in unemployment (1.54 million jobs) and an approximately 3/4 percentage point change in the employment-to-population ratio (~ 1.54 million jobs). However, looking only at Table 2.8, a one percentage point increase in the unemployment rate increases the total applicant rate by 3.59 (5 percent of 72.06) and accessions by 3.98 (10 percent of 39.22). For the employment-to-population ratio, the analogous effects of an approximately 3/4 percentage point change are 2.8 percent and 3.4 percent, respectively. These effects are roughly 1/2 to 1/3 smaller than unemployment rate effects that are the result of similar labor market changes. This result can be interpreted in different ways. First, it is likely the differing precision with which county unemployment rates and employment-to-population ratios are measured results in different outcomes. Another interpretation is that the measures, if serving as signals for the actual labor market conditions, contain different information or are being interpreted differently by individuals making occupational choices.[80]

Table A 2.11 in the appendix reports the results of estimating equation 2.6 using a Poisson regression to account for the discrete nature of the data and the fraction of zero observations which drives the right-skewed shape of the distribution (Figures A 2.1 to Figure A 2.6).[81] The Poisson specification also includes the same demographic and recruiter controls, along with county fixed effects, year by quarter fixed effects, and state-

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[79] In 2010, the working age population was roughly 197 million while the labor force was roughly 154 million.

[80] In addition, the employment-to-population measure accounts for individuals leaving employment and returning to school and is less affected by seasonality and short-term labor market fluctuations.

[81] Approximately 25 to 35 percent of county*fiscal quarter observations are zero for total applicants and accessions and the fraction is as high as 80 percent for those that are disqualified or uninterested (Figures A 2.7 to Figure A 2.12)).

specific linear time trends, that are present in the previous OLS specifications. In general, the results in Table A 2.11 match the OLS results in Table 2.3 and Table 2.4 but are roughly 1.5 times as large in magnitude.[82] I attribute this magnitude difference to an inability to include a more flexible quadratic state trends which reduced the OLS estimates by one third to one half.

2.7 Discussion and Conclusion

2.7.1 Discussion

This paper examines the effect of local labor market conditions on military enlistment in several new dimensions. First, my results for high quality contracts using OLS specifications and the unemployment rate as the measure of labor market conditions (the focus of existing research) are largely consistent with previous literature.[83]

Using the results in Crow (2019) that indicate it is possible to identify the effect of labor market conditions on low quality contracts, I extend the research on labor market conditions and enlistment beyond high-quality contracts to all contracts, the differential effects on high vs. low-quality individuals, and more importantly, to the much broader population of military applicants. I also use the employment-to-population ratio as a more accurate measure of labor market conditions and provide the first plausibly causal estimates for the effect of local labor market conditions on enlistment.

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[82] The coefficients in Table A 2.11 are incident rate ratios (i.e., exponentiated coefficients). For example, a one unit (percentage point) decrease in the employment-to-population ratio, given other covariates are constant, results in a change in total applicants by a factor of 0.997. Put another way, the percent change in the incident rate of total applicants is an increase of 0.3 percent for every unit decrease in the employment-to-population ratio.

[83] The most recent sample periods in the literature range from the mid-1990s to 2008. These samples coincide with periods of decreasing end-strength, low unemployment, and relative economic stability.

Overall, my results suggest that the employment-to-population ratio is strongly related to the number of individuals expressing interest in enlisting in the military. Specifically, my findings show a decreasing employment-to-population ratio results in more individuals applying to the military which directly results in more individuals entering onto active duty (accessions). However, there is also a concomitant increase in the rate of those disqualified. This implies the individuals being influenced to apply for military service by worsening labor market conditions are relatively less qualified to serve on active duty.

When examining my results by applicant quality, the differential impact of the employment-to-population ratio on enlistment behavior becomes clearer: the overall increase in applicants and accessions is driven by increases in both high and low-quality individuals with low-quality responding at higher rates. These results suggest that the sensitivity of low-quality individuals to labor market conditions, previously uninvestigated, is larger than for high quality individuals. Specifically, decreases in the employment-to-population ratio increase the rate of low-quality applicants and accessions more than the rate of high-quality applicants and accessions by factors of six and two, respectively. This is consistent with the notion that low-quality individuals might be the most vulnerable in periods of increasing unemployment and likely have the fewest civilian labor market options. This, however, does not comport with a "crowding out" story where the ability of low-quality recruits to enlist during periods of economic contraction is impacted by the number of high-quality individuals expressing interest in the military (Ellwood and Wise 1987).[84]

[84] Ellwood and Wise examine "subgroups" of enlistees, not by quality markers per se, but by race, high school graduation status, and a categorization of "high scoring recruits"

The causal estimates in my findings, while similar in sign, are larger than the OLS estimates I report and that have been found in previous studies. This indicates that existing literature that neglected the correlation between changes in labor supply and economic conditions likely underestimated the effect of labor demand shocks on the enlistment response of both high and low-quality individuals.

Using the broader population of applicants and their outcomes, my research informs not only the extensive margin of enlistment to labor market conditions (above), but also the intensive margin of enlistment, as well. My findings suggest, conditional on showing an initial interest in the military by meeting with a recruiter and visiting a MEPS site (applicant), there is no impact of the employment-to-population ratio on the fraction of the applicant pool that accesses onto active duty because the rate of those individuals that are disqualified or DEP loss increases with decreases in the employment-to-population ratio. This is not true across both high quality and low-quality individuals. The fraction of high-quality accessions increases by about 1 percent while the fraction of low-quality accessions does not change. Moreover, the increase in the fraction of individuals that begin the process of enlistment and are disqualified is split between high and low-quality individuals while the decrease in those that are uninterested is primarily due to the fraction of low-quality individuals failing to sign a contract.

Finally, my paper is the first to consider the intertemporal component of the occupational choice to enlist in the military by considering the labor market conditions at a specific point in time (decision to enlist) and over the course of the year leading up to the decision to enlist. My findings suggest the impact of the labor market conditions in the year leading up to the enlistment decision is the same in direction as contemporaneous conditions but stronger. As with the contemporaneous employment-to-population ratio, worsening economic conditions influence relatively more low-quality individuals to apply for military service resulting in relatively more low-quality accessions, even as the rate of high-quality accessions increases by a smaller rate. The compositional effect on the intensive margin of enlistment is stronger for the one-year moving average employment-to-population ratio. Unlike the effect of the contemporaneous rate, labor market conditions in the previous year increase the fraction of high-quality applicants and accessions while decreasing the relative fraction of low-quality applicants.

2.7.2 Conclusion

My findings show that worsening economic conditions in an applicant's home county increase the number of applicants for military service and with this increase in applicants, the composition of the applicant pool shifts away from high quality toward low quality individuals. My findings also suggest that the decision to enter the military is perhaps informed more by long-standing (~ one year) economic conditions prior to the time of contract signing than during the immediate time of the enlistment decision. This not only informs the way the military recruits individuals, but also potentially contributes to economists' understanding of labor force transitions and the timing of these important decisions.

Appendix

Figure A 2.1. Distribution of Total Applicants per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

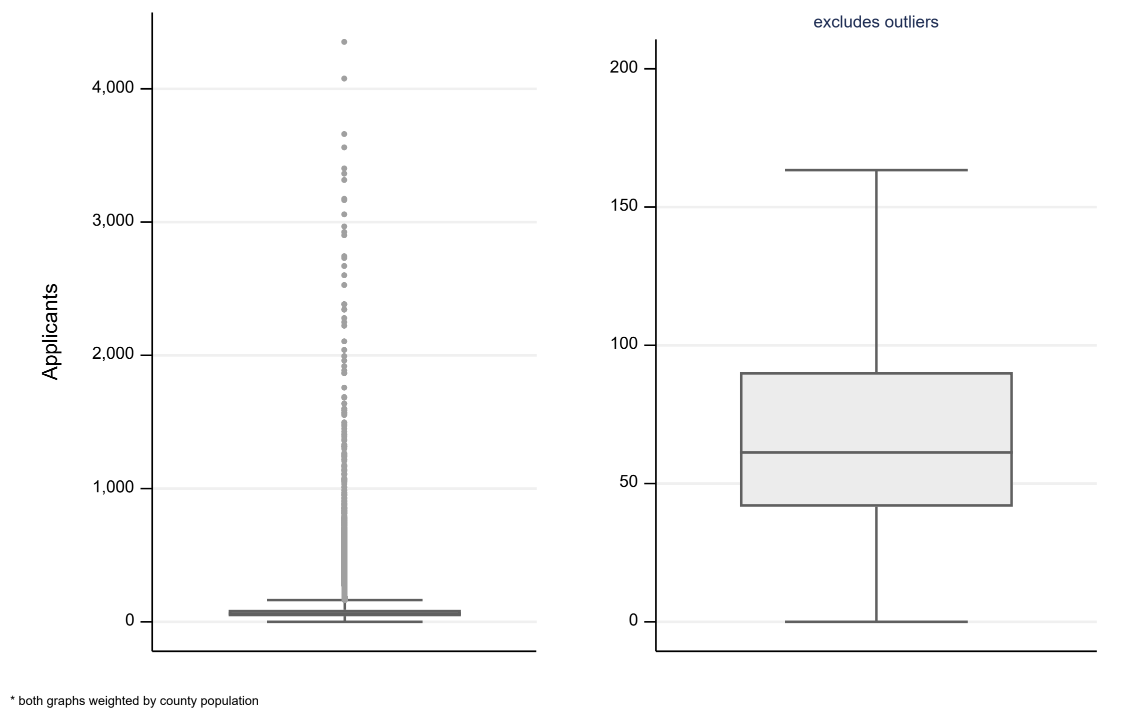


Figure A 2.2. Distribution of Disqualified Applicants per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

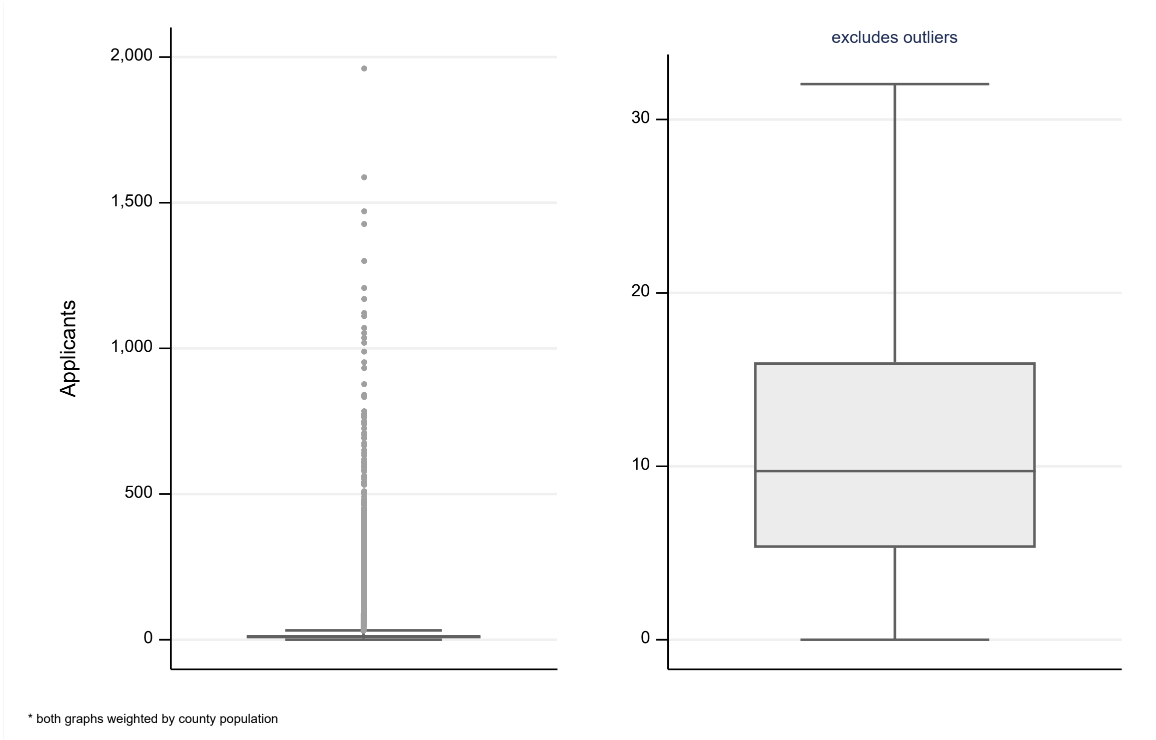


Figure A 2.3. Distribution of Qualified Applicants who failed to sign Contracts per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

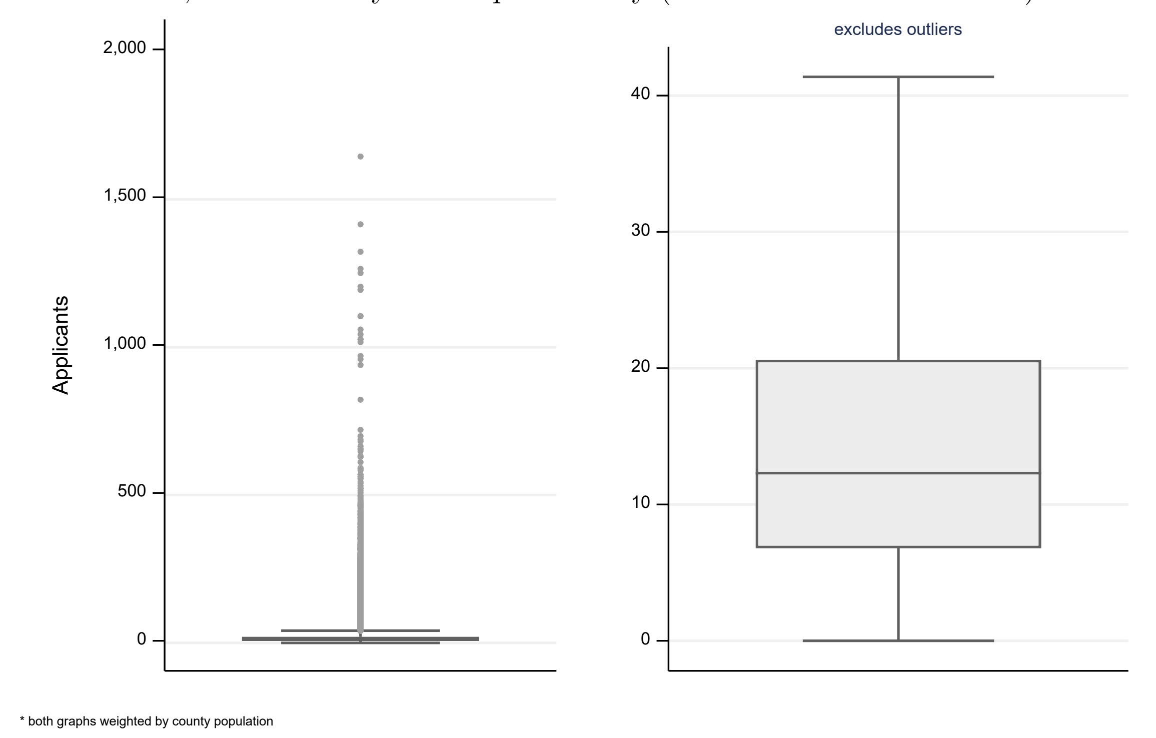


Figure A 2.4. Distribution of Qualified Applicants who signed Contracts per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

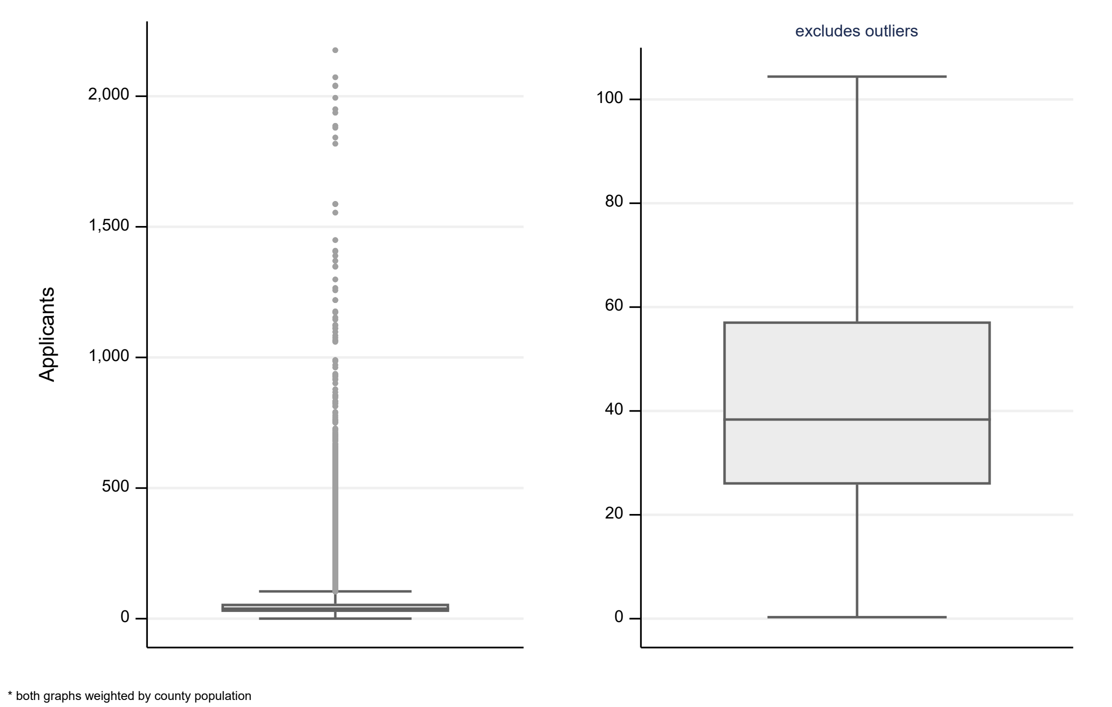


Figure A 2.5. Distribution of Qualified Applicants who signed Contracts and attrited from the Delayed Entry Program per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

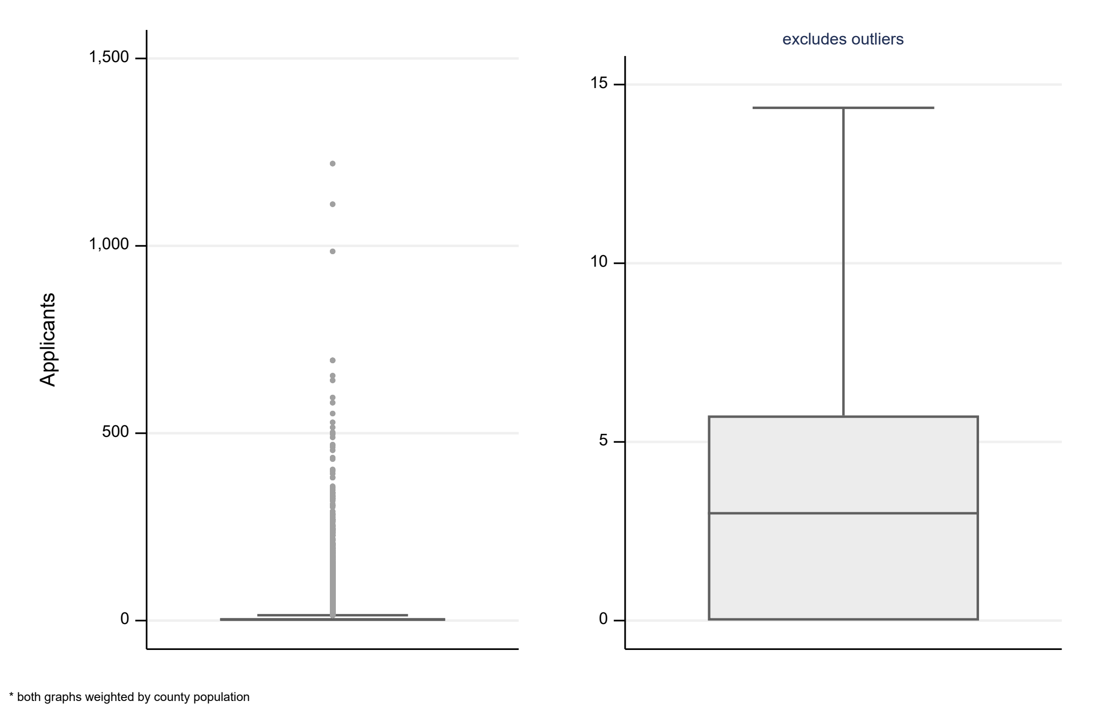


Figure A 2.6. Distribution of Qualified Applicants who signed Contracts and entered Active Duty per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

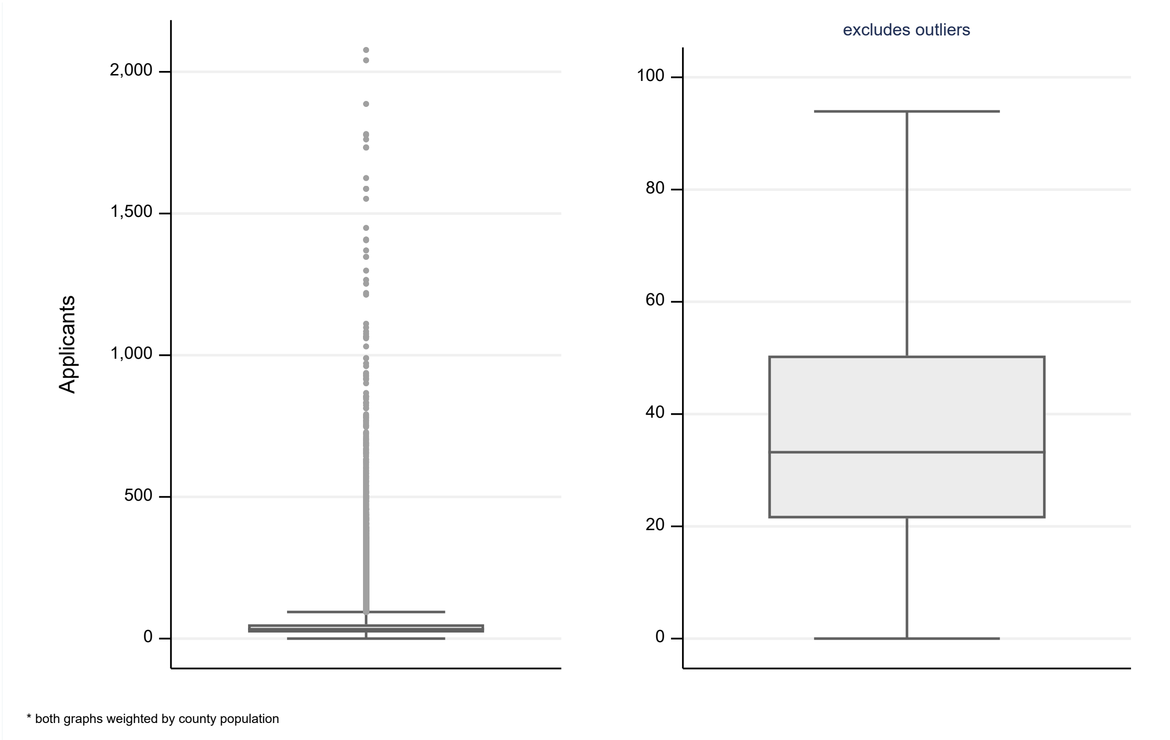


Figure A 2.7. Distribution of Total Applicants per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

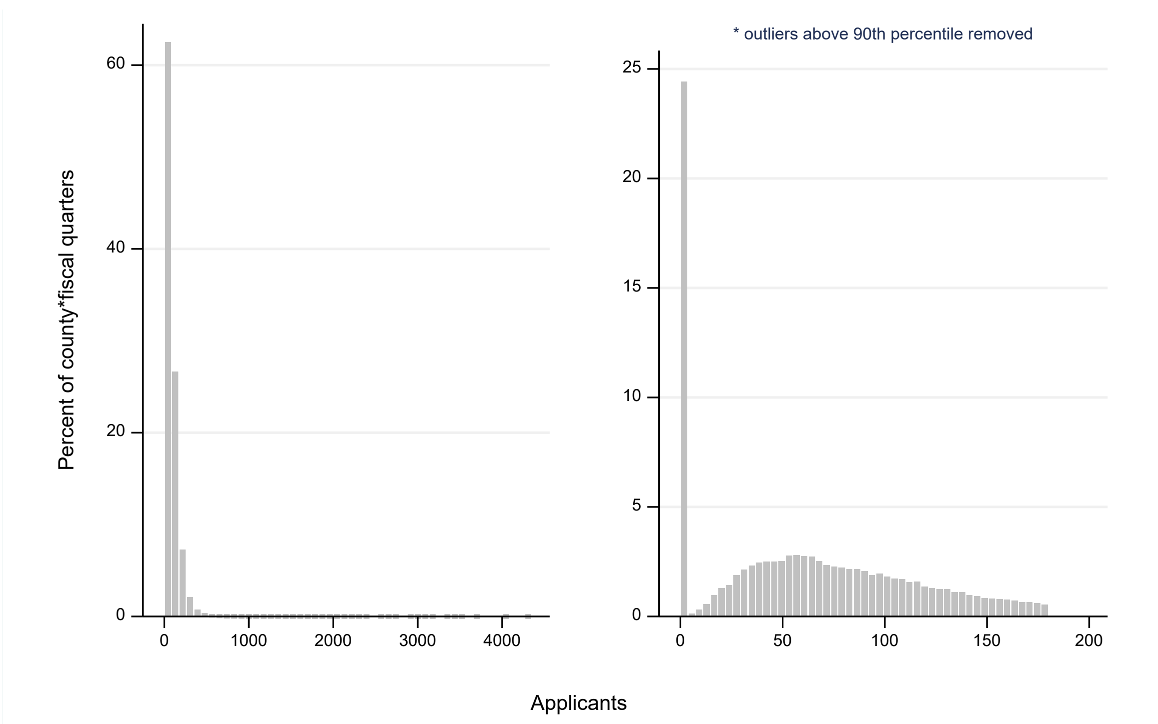


Figure A 2.8. Distribution of Disqualified Applicants per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

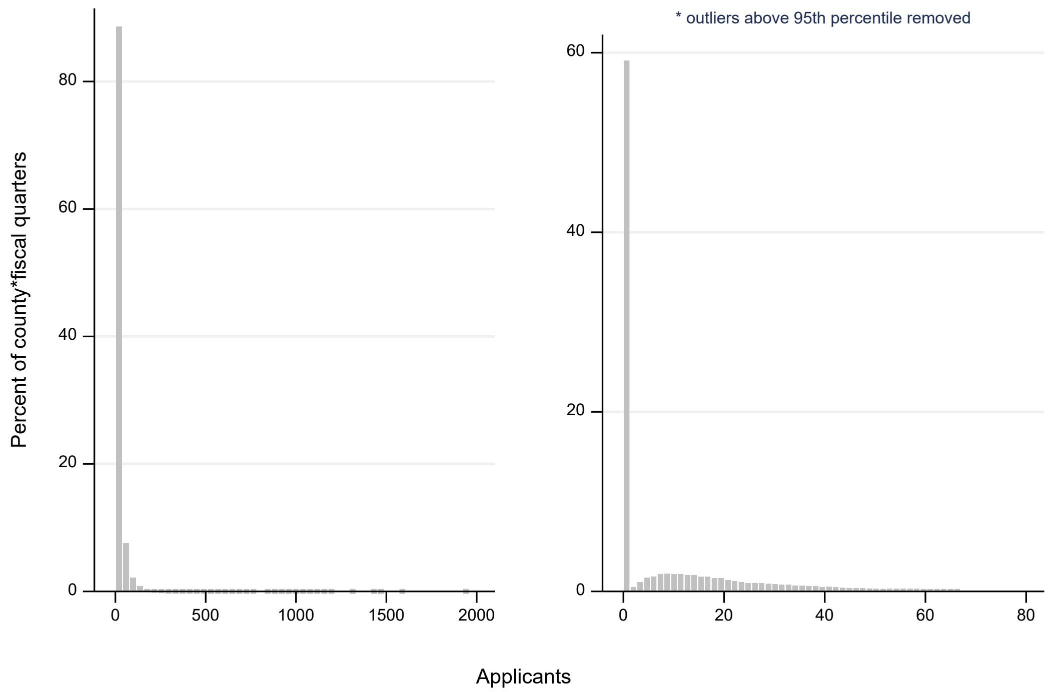


Figure A 2.9. Distribution of Qualified Applicants who failed to sign Contracts per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

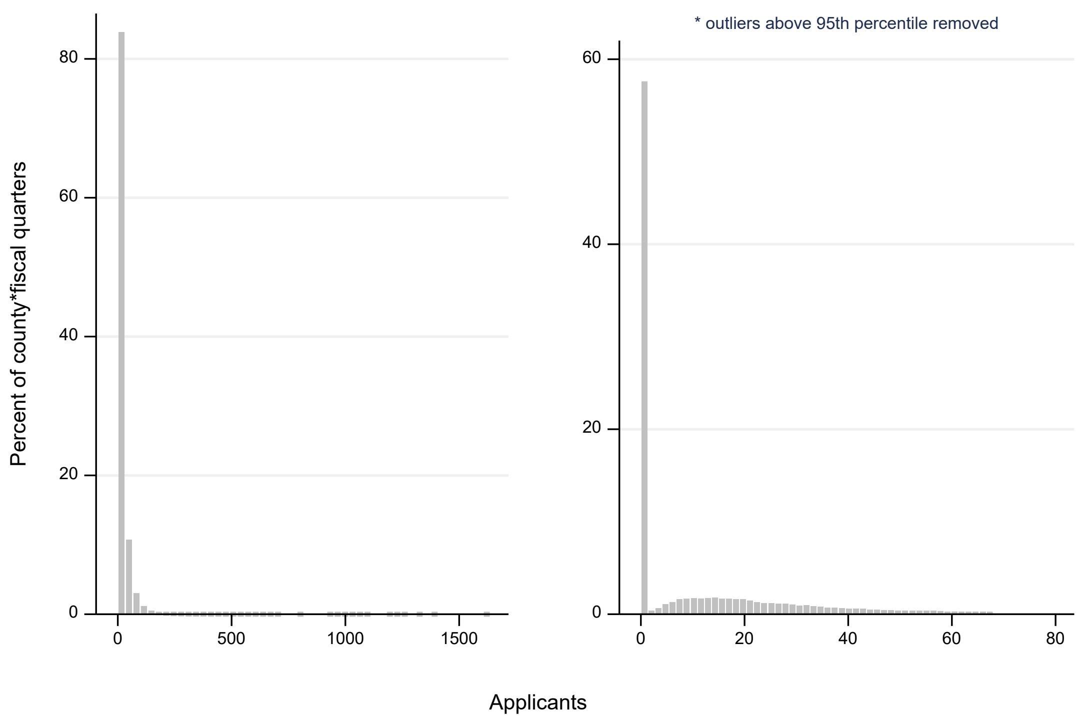


Figure A 2.10. Distribution of Qualified Applicants who signed Contracts per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

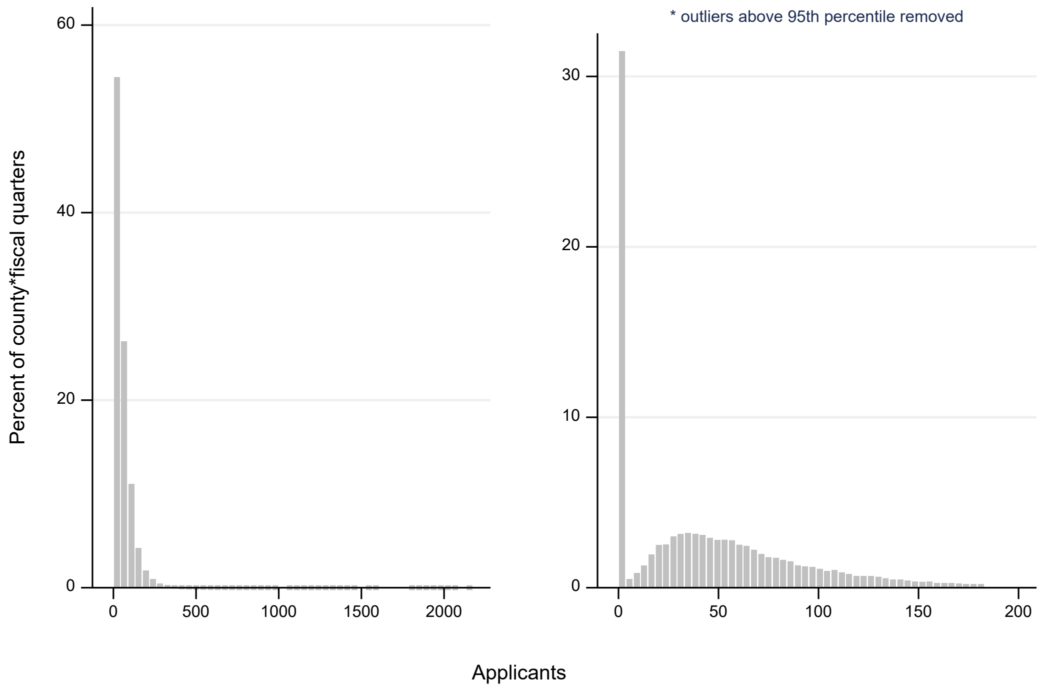


Figure A 2.11. Distribution of Qualified Applicants who signed Contracts and attrited from the Delayed Entry Program per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

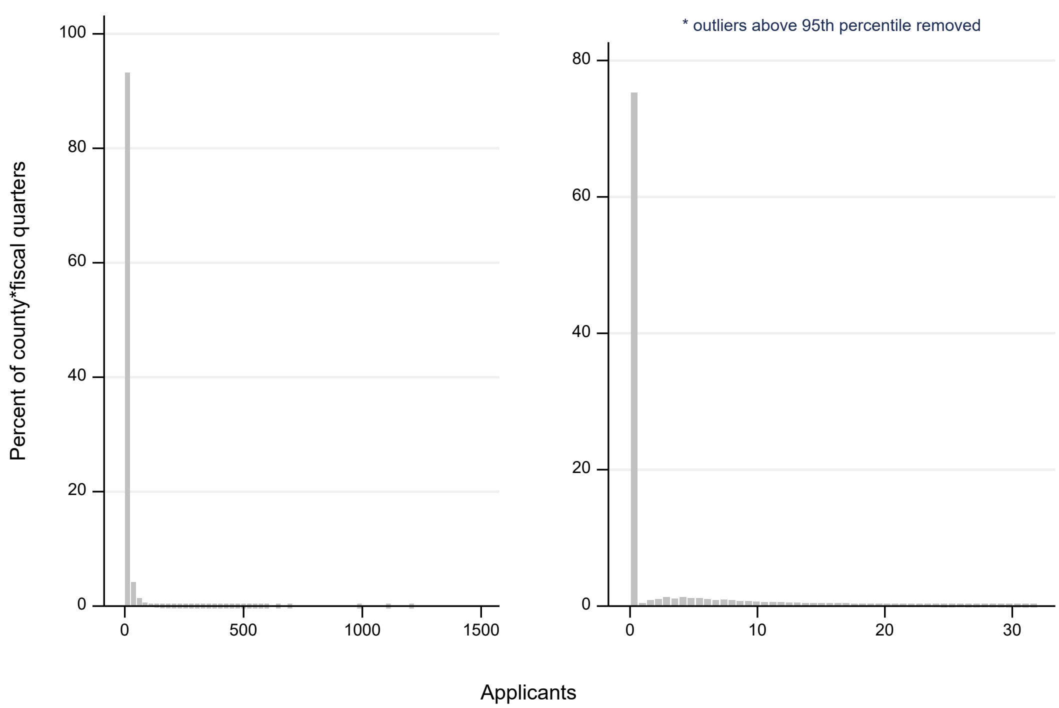


Figure A 2.12. Distribution of Qualified Applicants who signed Contracts and entered Active Duty per 100,000 15 to 24-year-old per County (Fiscal Years 2006 to 2014)

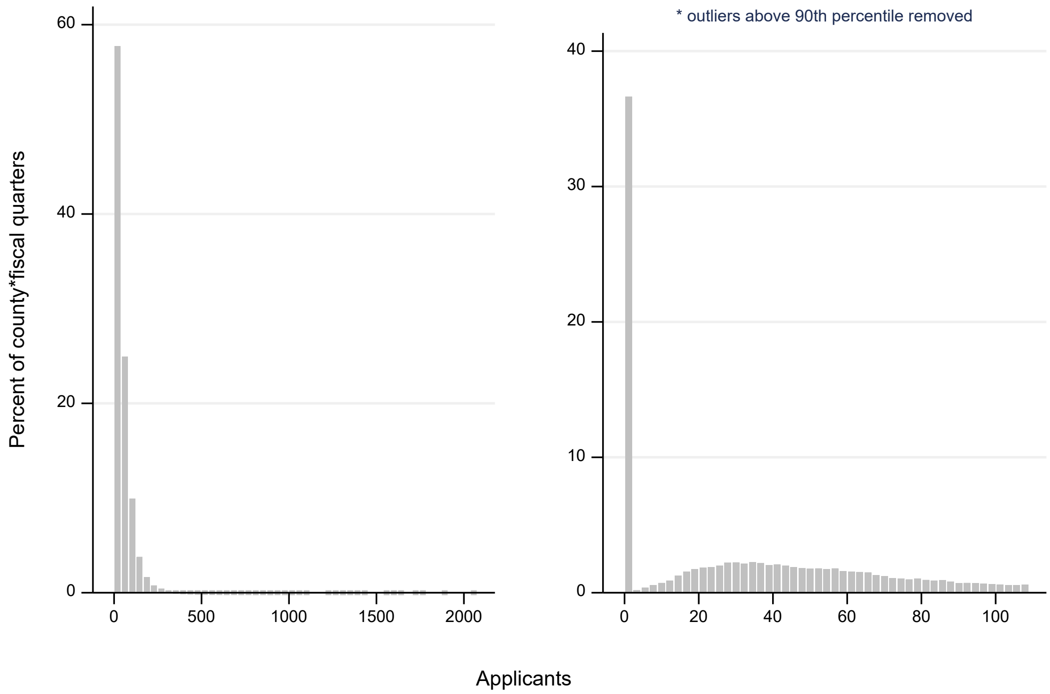
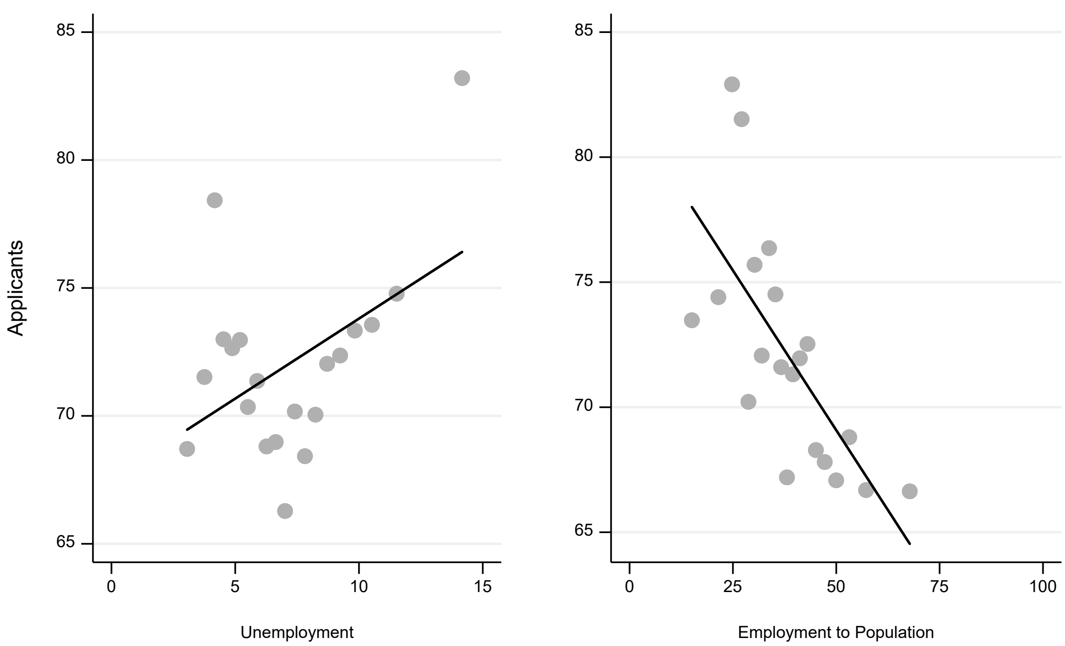
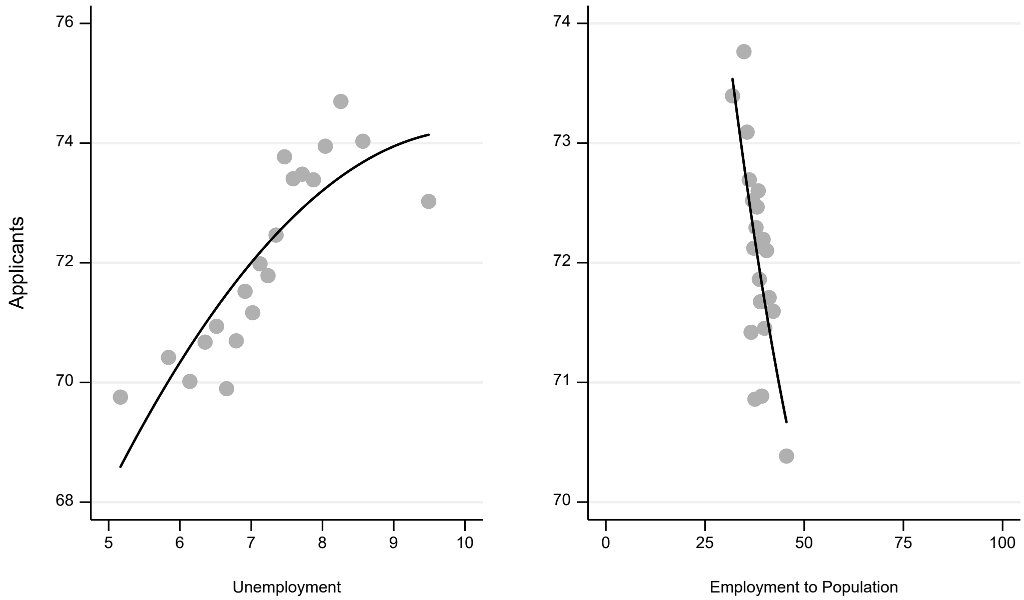


Figure A 2.13. Bin Scatter of Applicants per 100,000 vs. Labor Market Conditions (conditional on labor market conditions only - Fiscal Years 2006 to 2014)



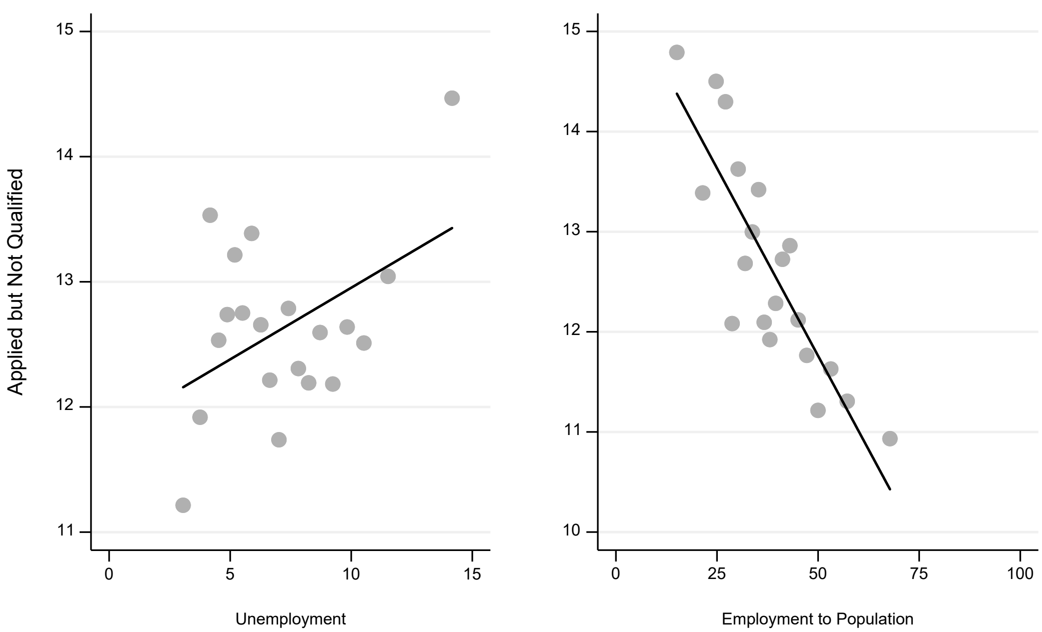
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value in each bin. Solid line represent best linear fit estimated by OLS

Figure A 2.14. Bin Scatter of Applicants per 100,000 vs. Labor Market Conditions (conditional on labor market conditions and additional controls – Fiscal Years 2006 to 2014)



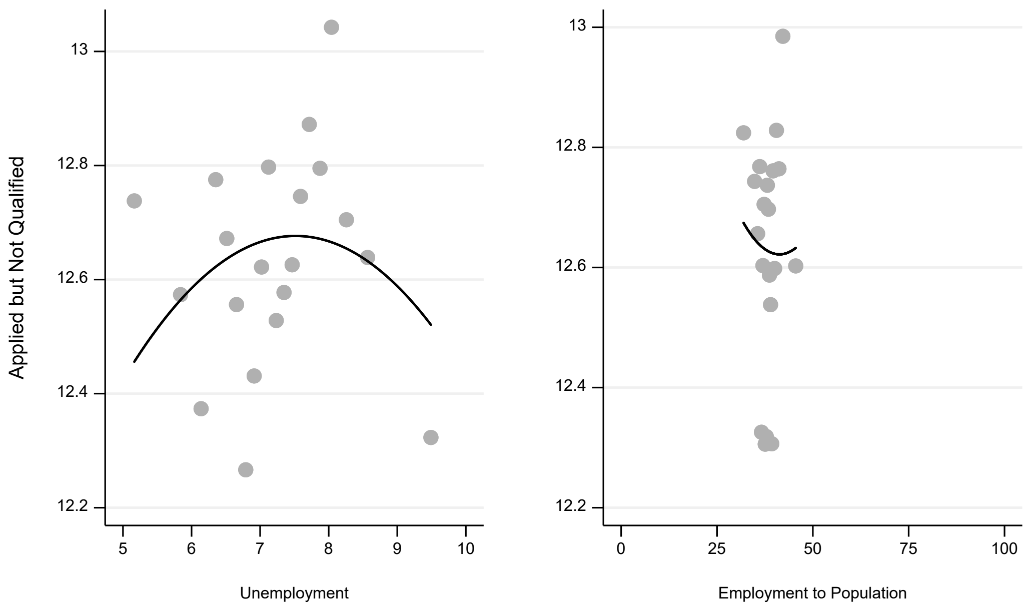
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value, county FE, time FE, gender, race, veteran presence, local earning, and recruiting resources
Solid line represent best quadratic fit estimated by OLS.

Figure A 2.15. Bin Scatter of Disqualified Applicants per 100,000 vs. Labor Market Conditions (conditional on labor market conditions only - Fiscal Years 2006 to 2014)



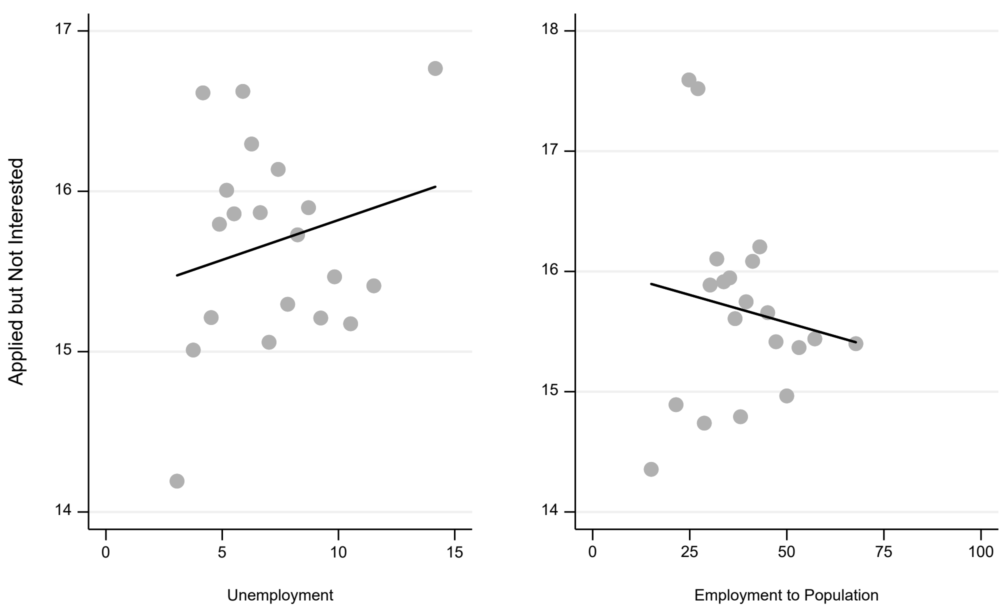
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value in each bin. Solid line represent best linear fit estimated by OLS

Figure A 2.16. Bin Scatter of Disqualified Applicants per 100,000 vs. Labor Market Conditions (conditional on labor market conditions and additional controls – Fiscal Years 2006 to 2014)



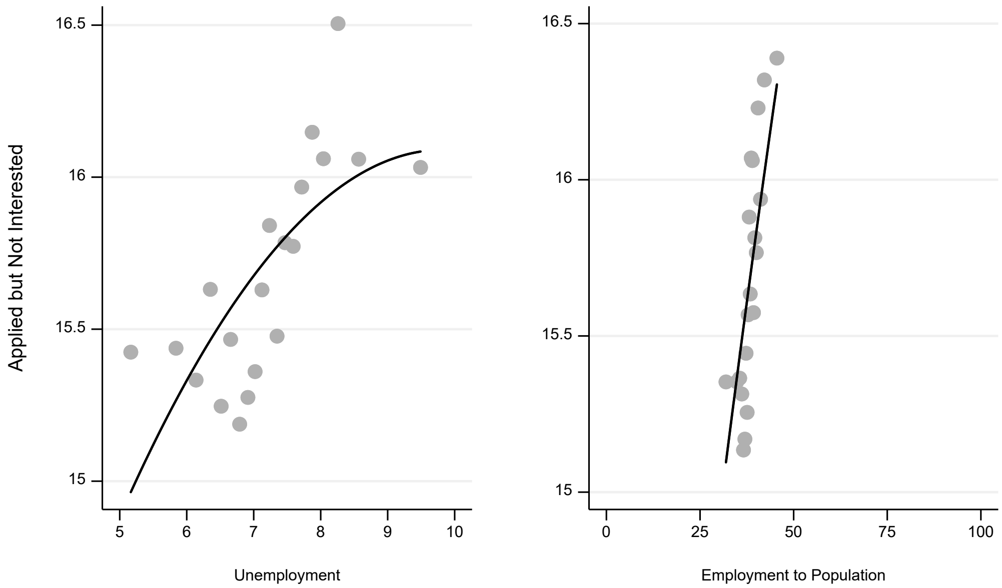
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value, county FE, time FE, gender, race, veteran presence, local earning, and recruiting resources
Solid line represent best quadratic fit estimated by OLS.

Figure A 2.17. Bin Scatter of Qualified Applicants who failed to sign Contracts per 100,000 vs. Labor Market Conditions (conditional on labor market conditions only - Fiscal Years 2006 to 2014)



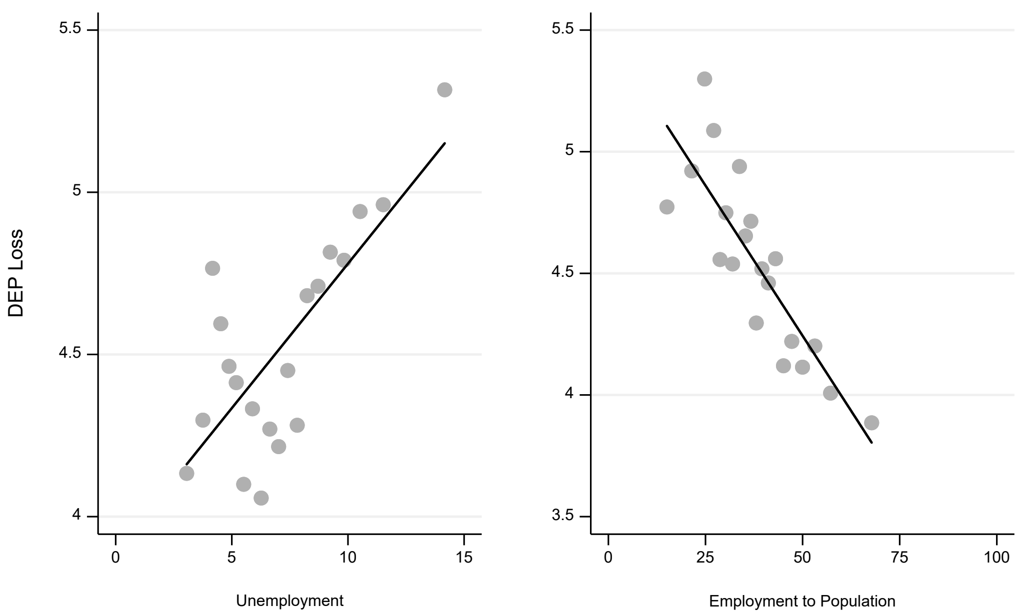
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value in each bin. Solid line represent best linear fit estimated by OLS

Figure A 2.18. Figure A18. Bin Scatter of Qualified Applicants who failed to sign Contracts per 100,000 vs. Labor Market Conditions (conditional on labor market conditions and additional Controls – Fiscal Years 2006 to 2014)



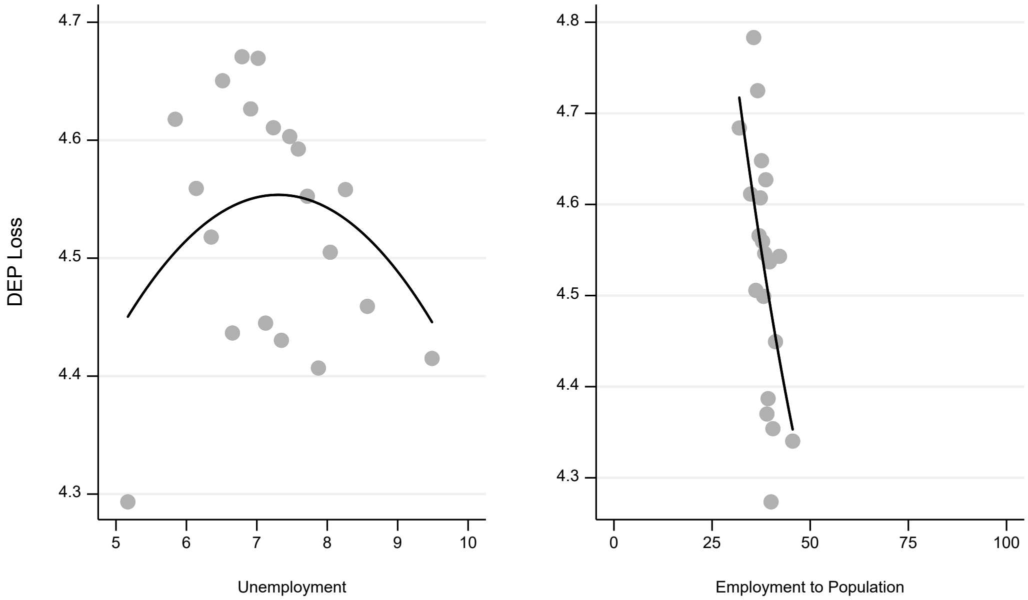
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value, county FE, time FE, gender, race, veteran presence, local earning, and recruiting resources
Solid line represent best quadratic fit estimated by OLS.

Figure A 2.19. Bin Scatter of Qualified Applicants who signed Contracts and attrited from the Delayed Entry Program per 100,000 vs. Labor Market Conditions (conditional on labor market conditions only– Fiscal Years 2006 to 2014)



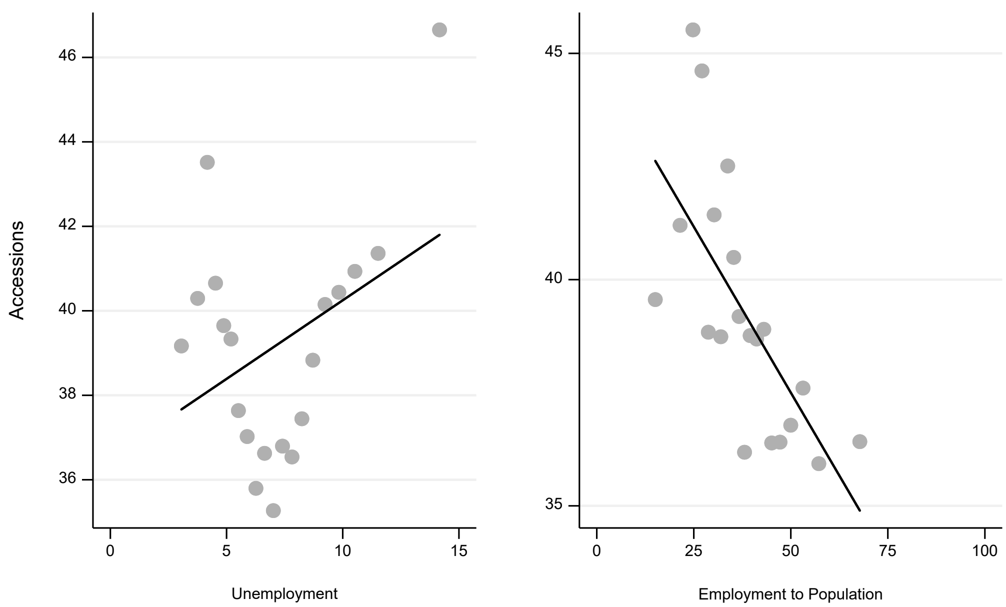
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value in each bin. Solid line represent best linear fit estimated by OLS

Figure A 2.20. Bin Scatter of Qualified Applicants who signed Contracts and attrited from the Delayed Entry Program per 100,000 vs. Labor Market Conditions (conditional on labor market conditions and additional controls– Fiscal Years 2006 to 2014)



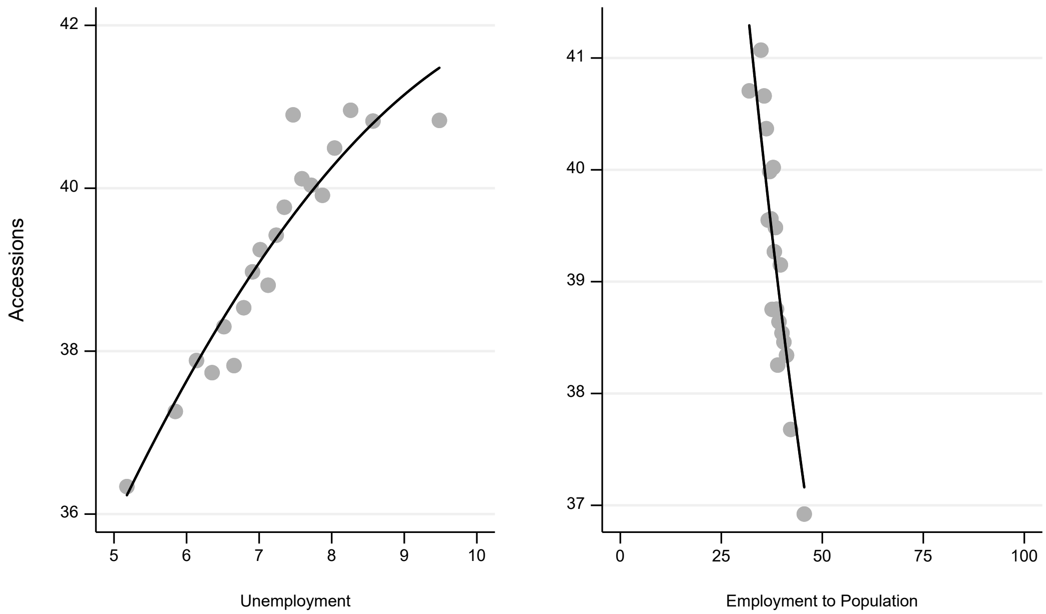
Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value, county FE, time FE, gender, race, veteran presence, local earning, and recruiting resources
Solid line represent best quadratic fit estimated by OLS.

Figure A 2.21. Bin Scatter of Qualified Applicants who signed Contracts and entered Active Duty per 100,000 vs. Labor Market Conditions (conditional on labor market conditions only– Fiscal Years 2006 to 2014)



Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value in each bin. Solid line represent best linear fit estimated by OLS

Figure A 2.22. Bin Scatter of Qualified Applicants who signed Contracts and entered Active Duty per 100,000 vs. Labor Market Conditions (conditional on labor market conditions and additional controls– Fiscal Years 2006 to 2014)



Binned scatter plots of applicants weighted by population of 15 to 24 year old in county (20 equal-sized bins)
Points represent average number of applicants conditional on average x-axis value, county FE, time FE, gender, race, veteran presence, local earning, and recruiting resources
Solid line represent best quadratic fit estimated by OLS.

Table A 2.1. High and Low-Quality Individuals: Effect of One-Year Moving Average Employment-to-Population Rate on Military Enlistment (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (per 100,000 15 to 24-year old)					
High-quality					
Applicants	-0.119***	-0.111***	0.0295	0.115***	-0.554***
(mean: 33.79)	(0.0375)	(0.0375)	(0.0406)	(0.0411)	(0.136)
Disqualified	-0.0157*	-0.0146*	0.000424	0.00140	-0.0479
(mean: 1.80)	(0.00807)	(0.00807)	(0.00882)	(0.00896)	(0.0297)
Uninterested	0.00730	0.0102	0.0537***	0.0645***	0.133**
(mean: 8.53)	(0.0175)	(0.0175)	(0.0190)	(0.0192)	(0.0637)
DEP Loss	-0.0148*	-0.0141	0.00104	-0.00207	-0.189***
(mean: 2.42)	(0.00892)	(0.00892)	(0.00976)	(0.00991)	(0.0331)
Accessions	-0.178***	-0.172***	-0.124***	-0.0505	-1.009***
(mean: 21.05)	(0.0287)	(0.0287)	(0.0312)	(0.0316)	(0.106)
Low-quality					
Applicants	0.234***	0.239***	0.00319	0.0659	-2.763***
(mean: 38.26)	(0.0448)	(0.0447)	(0.0483)	(0.0489)	(0.165)
Disqualified	0.0534**	0.0559**	-0.0244	-0.0301	-0.857***
(mean: 10.83)	(0.0220)	(0.0220)	(0.0239)	(0.0243)	(0.0808)
Uninterested	0.0602***	0.0615***	0.0656***	0.0747***	-0.107*
(mean: 7.16)	(0.0170)	(0.0170)	(0.0184)	(0.0187)	(0.0620)
DEP Loss	0.00119	0.00181	-0.00643	-0.00777	-0.224***
(mean: 2.11)	(0.00880)	(0.00880)	(0.00963)	(0.00978)	(0.0327)
Accessions	0.121***	0.122***	-0.0286	0.0321	-1.552***
(mean: 18.14)	(0.0288)	(0.0288)	(0.0311)	(0.0316)	(0.106)
First-Stage (E/P)					35.22***
instrument					(0.41)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					9559.6
First-Stage (E/P)					35.22***

- One-year moving average includes 3 previous quarters and quarter of enlistment decision.
- All regressions are weighted by mean of 15 to 24-year-old county population during sample period. Standard errors in parentheses are clustered at the county-level.
- All specifications include county and year by quarter effects, civilian earnings (in $1000), fraction veteran, black, and female as controls. Specifications for accessions and DEP loss also include bonus amounts in $1000.
- "USAREC Controls" include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts per 100,000 15 to 24-year-old.
- The total number of applicants is comprised of four sub-outcome groups: those individuals that are disqualified for medical, physical, or criminal reasons (disqualified), those that decide not to sign a contract after visiting MEPS (uninterested), those that sign a contract but attrite from the Delayed Entry Program (DEP Loss), and those that sign a contract and serve on active duty (accession). Panel Data at County*Fiscal Year Quarter level from 200510 to 201409 (FY 2006 to FY 2014);
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 2.2. Effect of One-Year Moving Average Employment-to-Population Rate on Applicant Outcomes (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
Total Disqualified	0.0579**	0.0596**	-0.0381	-0.0627**	-0.213**
(mean: 17.42)	(0.0286)	(0.0286)	(0.0312)	(0.0317)	(0.106)
Total Uninterested	0.0916***	0.0941***	0.0954***	0.0896***	0.487***
(mean: 22.03)	(0.0305)	(0.0305)	(0.0332)	(0.0337)	(0.113)
Total DEP Loss	-0.0169	-0.0169	0.00571	-0.0105	-0.265***
(mean: 6.41)	(0.0192)	(0.0192)	(0.0210)	(0.0214)	(0.0720)
Total Accessions	-0.185***	-0.188***	-0.127***	-0.0830**	-0.331**
(mean: 54.15)	(0.0378)	(0.0378)	(0.0413)	(0.0419)	(0.141)
First-Stage (E/P)					35.22***
instrument					(0.41)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					7291.3

- Notes same as Table A 2.1

Table A 2.3. Fraction High and Low-Quality Individuals: Effect of One-Year Moving Average Employment-to-Population Rate on Applicant Outcomes

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
High-quality					
Applicants	-0.0917**	-0.0934**	-0.0222	-0.0134	-0.368***
(mean: 49.12)	(0.0377)	(0.0377)	(0.0412)	(0.0418)	(0.140)
Disqualified	-0.0207	-0.0207	-0.0231	-0.0236	-0.156***
(mean: 2.72)	(0.0131)	(0.0131)	(0.0143)	(0.0145)	(0.0486)
Uninterested	0.0247	0.0269	0.0228	0.0187	0.00361
(mean: 12.48)	(0.0240)	(0.0240)	(0.0262)	(0.0266)	(0.0890)
DEP Loss	-0.00256	-0.00288	0.0139	0.00351	-0.167***
(mean: 3.52)	(0.0146)	(0.0146)	(0.0159)	(0.0162)	(0.0546)
Accessions	-0.161***	-0.163***	-0.118***	-0.0969**	-0.504***
(mean: 30.05)	(0.0346)	(0.0346)	(0.0378)	(0.0384)	(0.129)
Low-quality					
Applicants	0.0996***	0.101***	0.0261	0.0147	0.372***
(mean: 50.88)	(0.0377)	(0.0378)	(0.0412)	(0.0419)	(0.140)
Disqualified	0.0786***	0.0803***	-0.0150	-0.0391	-0.0568
(mean: 14.70)	(0.0263)	(0.0263)	(0.0288)	(0.0292)	(0.0978)
Uninterested	0.0668***	0.0671***	0.0727***	0.0710***	0.482***
(mean: 9.55)	(0.0216)	(0.0216)	(0.0235)	(0.0239)	(0.0803)
DEP Loss	-0.0112	-0.0108	-0.00515	-0.0111	-0.0900*
(mean: 2.84)	(0.0130)	(0.0130)	(0.0143)	(0.0145)	(0.0489)
Accessions	-0.0210	-0.0221	-0.0101	0.00997	0.156
(mean: 24.1)	(0.0322)	(0.0323)	(0.0353)	(0.0358)	(0.120)
First-Stage (E/P)					35.22***
instrument					(0.41)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					7291.0

- Notes same as Table A 2.1

Table A 2.4. High and Low-Quality Individuals: Effect of Current Unemployment Rate on Military Enlistment (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (per 100,000 15 to 24-year old)					
High-quality					
Applicants	1.261^{***}	1.291^{***}	0.877^{***}	0.784^{***}	-6.420^{***}
(mean: 33.79)	(0.0623)	(0.0622)	(0.0661)	(0.0755)	(1.085)
Disqualified	0.0701^{***}	0.0713^{***}	0.0541^{***}	0.0628^{***}	-0.690^{***}
(mean: 1.80)	(0.0134)	(0.0134)	(0.0144)	(0.0165)	(0.229)
Uninterested	0.230^{***}	0.237^{***}	0.154^{***}	0.163^{***}	-1.796^{***}
(mean: 8.53)	(0.0290)	(0.0291)	(0.0309)	(0.0354)	(0.494)
DEP Loss	-0.0125	-0.0104	-0.0276^{*}	0.00154	-0.570^{**}
(mean: 2.42)	(0.0148)	(0.0148)	(0.0159)	(0.0182)	(0.250)
Accessions	0.876^{***}	0.894^{***}	0.622^{***}	0.453^{***}	-3.551^{***}
(mean: 21.05)	(0.0477)	(0.0477)	(0.0508)	(0.0581)	(0.821)
Low-quality					
Applicants	0.517^{***}	0.576^{***}	0.258^{***}	0.0519	9.706^{***}
(mean: 38.26)	(0.0745)	(0.0744)	(0.0787)	(0.0900)	(1.309)
Disqualified	-0.0973^{***}	-0.0815^{**}	-0.119^{***}	-0.0652	0.934
(mean: 10.83)	(0.0365)	(0.0365)	(0.0390)	(0.0446)	(0.615)
Uninterested	0.198^{***}	0.209^{***}	0.143^{***}	0.162^{***}	1.522^{***}
(mean: 7.16)	(0.0282)	(0.0282)	(0.0301)	(0.0344)	(0.477)
DEP Loss	-0.0570^{***}	-0.0534^{***}	-0.0755^{***}	-0.0750^{***}	0.373
(mean: 2.11)	(0.0146)	(0.0146)	(0.0157)	(0.0180)	(0.247)
Accessions	0.488^{***}	0.516^{***}	0.317^{***}	0.0434	7.187^{***}
(mean: 18.14)	(0.0479)	(0.0478)	(0.0507)	(0.0581)	(0.862)
First-Stage (UE)					$-2.52e{-}06^{***}$
instrument					(1.12e-07)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					507.7

- Notes same as Table A 2.1

Table A 2.5. Effect of Current Unemployment Rate on Applicant Outcomes (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
Total Disqualified	-0.245***	-0.242***	-0.141***	0.0101	-2.778***
(mean: 17.42)	(0.0473)	(0.0474)	(0.0506)	(0.0580)	(0.814)
Total Uninterested	0.0610	0.0628	0.0520	0.0895	-5.202***
(mean: 22.03)	(0.0506)	(0.0506)	(0.0539)	(0.0618)	(0.895)
Total DEP Loss	-0.309***	-0.308***	-0.244***	-0.223***	0.745
(mean: 6.41)	(0.0318)	(0.0319)	(0.0341)	(0.0391)	(0.540)
Total Accessions	0.437***	0.430***	0.286***	0.0621	7.544***
(mean: 54.15)	(0.0627)	(0.0627)	(0.0670)	(0.0768)	(1.133)
First-Stage (UE)					-2.50e-06***
instrument					(1.11e-07)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	No
State Quadratic Trend	No	No	No	Yes	No
2SLS	No	No	No	No	Yes
F (excluded instrument)					392.8

- Notes same as Table A 2.1

Table A 2.6. High and Low-Quality Individuals: Effect of Unemployment Rate on Applicant Outcomes (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
High-quality					
Applicants	-0.00265	-0.00631	-0.0251	-0.122	-4.588***
(mean: 49.12)	(0.0624)	(0.0625)	(0.0667)	(0.0767)	(1.083)
Disqualified	0.00416	0.00544	0.0379	0.0210	-0.775**
(mean: 2.72)	(0.0217)	(0.0217)	(0.0231)	(0.0266)	(0.370)
Uninterested	-0.0337	-0.0338	-0.0131	-0.0437	-3.621***
(mean: 12.48)	(0.0398)	(0.0398)	(0.0425)	(0.0487)	(0.697)
DEP Loss	-0.174***	-0.174***	-0.138***	-0.120***	0.303
(mean: 3.52)	(0.0241)	(0.0242)	(0.0258)	(0.0296)	(0.408)
Accessions	0.0886	0.0830	0.0123	-0.0881	-0.943
(mean: 30.05)	(0.0574)	(0.0575)	(0.0614)	(0.0704)	(0.980)
Low-quality					
Applicants	0.00964	0.0134	0.0232	0.135*	4.628***
(mean: 50.88)	(0.0626)	(0.0626)	(0.0669)	(0.0768)	(1.085)
Disqualified	-0.249***	-0.247***	-0.178***	-0.0107	-2.001***
(mean: 14.70)	(0.0436)	(0.0437)	(0.0466)	(0.0535)	(0.746)
Uninterested	0.0947***	0.0966***	0.0653*	0.133***	-1.576**
(mean: 9.55)	(0.0358)	(0.0358)	(0.0382)	(0.0439)	(0.612)
DEP Loss	-0.134***	-0.133***	-0.107***	-0.102***	0.587
(mean: 2.84)	(0.0216)	(0.0216)	(0.0231)	(0.0266)	(0.367)
Accessions	0.349***	0.348***	0.270***	0.160**	8.345***
(mean: 24.1)	(0.0534)	(0.0535)	(0.0572)	(0.0656)	(1.002)
First-Stage (UE)					31.10***
instrument					(0.364)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	No
State Quadratic Trend	No	No	No	Yes	No
2SLS	No	No	No	No	Yes
F (excl. instrument)					7303.4

- Notes same as Table A 2.1

Table A 2.7. Effect of One-Year Moving Average Unemployment Rate on Military Enlistment (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (per 100,000 15 to 24-year old)					
Overall Outcome					
Total Applicants	1.626***	1.724***	0.644***	0.116	5.990***
(mean: 72.05)	(0.111)	(0.111)	(0.123)	(0.142)	(1.270)
Sub-outcomes					
Total Disqualified	-0.106**	-0.0901**	-0.201***	-0.164***	0.839*
(mean: 12.63)	(0.0421)	(0.0421)	(0.0472)	(0.0547)	(0.486)
Total Uninterested	0.360***	0.378***	0.187***	0.170***	0.646
(mean: 15.69)	(0.0460)	(0.0460)	(0.0513)	(0.0593)	(0.526)
Total DEP Loss	-0.0487**	-0.0423*	-0.111***	-0.0797***	0.133
(mean: 4.53)	(0.0225)	(0.0225)	(0.0253)	(0.0293)	(0.258)
Total Accessions	1.333***	1.387***	0.685***	0.0772	4.236***
(mean: 39.19)	(0.0760)	(0.0758)	(0.0842)	(0.0973)	(0.875)
First-Stage (UE)					-3.72e-06***
instrument					(1.22e-07)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					1242.4

- One-year moving average includes 3 previous quarters and quarter of enlistment decision.
- All regressions are weighted by mean of 15 to 24-year-old county population during sample period. Standard errors in parentheses are clustered at the county-level.
- All specifications include county and year by quarter effects, civilian earnings (in $1000), fraction veteran, black, and female as controls. Specifications for accessions and DEP loss also include bonus amounts in $1000.
- "USAREC Controls" include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts per 100,000 15 to 24-year-old.
- The total number of applicants is comprised of four sub-outcome groups: those individuals that are disqualified for medical, physical, or criminal reasons (disqualified), those that decide not to sign a contract after visiting MEPS (uninterested), those that sign a contract but attrite from the Delayed Entry Program (DEP Loss), and those that sign a contract and serve on active duty (accession). Panel Data at County*Fiscal Year Quarter level from 200510 to 201409 (FY 2006 to FY 2014);

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 2.8. High and Low-Quality Individuals: Effect of One-Year Moving Average Unemployment Rate on Military Enlistment (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (per 100,000 15 to 24-year old)					
High-quality					
Applicants	1.389***	1.420***	0.903***	0.776***	-2.995***
(mean: 33.79)	(0.0670)	(0.0669)	(0.0746)	(0.0862)	(0.772)
Disqualified	0.0605***	0.0609***	0.0373**	0.0419**	-0.395**
(mean: 1.80)	(0.0144)	(0.0144)	(0.0162)	(0.0188)	(0.167)
Uninterested	0.255***	0.262***	0.170***	0.179***	-1.118***
(mean: 8.53)	(0.0312)	(0.0313)	(0.0349)	(0.0404)	(0.360)
DEP Loss	0.00339	0.00517	-0.0235	0.0117	-0.176
(mean: 2.42)	(0.0159)	(0.0159)	(0.0179)	(0.0208)	(0.183)
Accessions	0.964***	0.984***	0.627***	0.414***	-1.803***
(mean: 21.05)	(0.0513)	(0.0513)	(0.0573)	(0.0664)	(0.595)
Low-quality					
Applicants	0.244***	0.310***	-0.248***	-0.630***	8.735***
(mean: 38.26)	(0.0802)	(0.0800)	(0.0888)	(0.103)	(0.950)
Disqualified	-0.166***	-0.151***	-0.238***	-0.206***	1.235***
(mean: 10.83)	(0.0393)	(0.0393)	(0.0440)	(0.0510)	(0.454)
Uninterested	0.104***	0.116***	0.0175	-0.00910	1.767***
(mean: 7.16)	(0.0303)	(0.0303)	(0.0339)	(0.0393)	(0.352)
DEP Loss	-0.0499***	-0.0455***	-0.0855***	-0.0865***	0.318*
(mean: 2.11)	(0.0157)	(0.0157)	(0.0177)	(0.0205)	(0.181)
Accessions	0.371***	0.406***	0.0661	-0.316***	5.759***
(mean: 18.14)	(0.0515)	(0.0514)	(0.0572)	(0.0663)	(0.616)
First-Stage (UE)					-3.72e-06***
instrument					(1.22e-07)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					1215.3

- Notes same as Table A 2.7

Table A 2.9. Effect of One-Year Moving Average Unemployment Rate on Applicant Outcomes (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
Total Disqualified	-0.338***	-0.335***	-0.198***	-0.0485	-1.649***
(mean: 17.42)	(0.0508)	(0.0509)	(0.0569)	(0.0662)	(0.595)
Total Uninterested	0.0643	0.0655	0.0856	0.139**	-4.191***
(mean: 22.03)	(0.0543)	(0.0544)	(0.0607)	(0.0705)	(0.646)
Total DEP Loss	-0.310***	-0.310***	-0.236***	-0.209***	0.747*
(mean: 6.41)	(0.0342)	(0.0342)	(0.0383)	(0.0446)	(0.398)
Total Accessions	0.516***	0.511***	0.285***	0.0314	5.211***
(mean: 54.15)	(0.0673)	(0.0673)	(0.0754)	(0.0876)	(0.807)
First-Stage (UE)					-3.72e-06***
instrument					(1.22e-07)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					930.4

- Notes same as Table A 2.7

Table A 2.10. High and Low-Quality Individuals: Effect of One-Year Moving Average Unemployment Rate on Applicant Outcomes (OLS and 2SLS)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable (as fraction of Total Applicants)					
High-quality					
Applicants	0.110	0.105	0.0822	0.00108	-3.552***
(mean: 49.12)	(0.0670)	(0.0671)	(0.0751)	(0.0874)	(0.791)
Disqualified	-0.0257	-0.0250	0.00928	-0.0149	-0.554**
(mean: 2.72)	(0.0233)	(0.0233)	(0.0261)	(0.0303)	(0.272)
Uninterested	0.0139	0.0133	0.0641	0.0602	-2.908***
(mean: 12.48)	(0.0427)	(0.0428)	(0.0478)	(0.0555)	(0.506)
DEP Loss	-0.180***	-0.181***	-0.143***	-0.124***	0.375
(mean: 3.52)	(0.0259)	(0.0259)	(0.0290)	(0.0338)	(0.301)
Accessions	0.168***	0.163***	0.0511	-0.0675	-1.223*
(mean: 30.05)	(0.0616)	(0.0617)	(0.0691)	(0.0804)	(0.725)
Low-quality					
Applicants	-0.102	-0.0967	-0.0827	0.0187	3.505***
(mean: 50.88)	(0.0672)	(0.0672)	(0.0753)	(0.0876)	(0.792)
Disqualified	-0.312***	-0.310***	-0.207***	-0.0334	-1.094**
(mean: 14.70)	(0.0468)	(0.0469)	(0.0525)	(0.0610)	(0.547)
Uninterested	0.0505	0.0522	0.0217	0.0792	-1.279***
(mean: 9.55)	(0.0384)	(0.0384)	(0.0430)	(0.0500)	(0.450)
DEP Loss	-0.127***	-0.126***	-0.0926***	-0.0814***	0.472*
(mean: 2.84)	(0.0231)	(0.0232)	(0.0260)	(0.0303)	(0.270)
Accessions	0.347***	0.348***	0.229***	0.110	6.242***
(mean: 24.1)	(0.0574)	(0.0574)	(0.0644)	(0.0749)	(0.704)
First-Stage (UE)					-3.72e-06***
instrument					(1.22e-07)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					930.4

- Notes same as Table A 2.7

Table A 2.11. Effect of Current Employment-to-Population Ratio on Military Enlistment (Poisson)

Dependent Variable	(1)	(2)	(3)
Overall			
Total Applicants	0.995***	0.995***	0.997***
(mean: 72.05)	(0.000000198)	(0.000000195)	(0.000000197)
Sub-outcomes			
Total Disqualified	0.997***	0.997***	0.996***
(mean: 12.63)	(0.000000374)	(0.000000369)	(0.000000399)
Total Uninterested	1.000***	1.000***	1.002***
(mean: 15.69)	(0.000000306)	(0.000000305)	(0.000000314)
Total DEP Loss	0.994***	0.994***	0.998***
(mean: 4.53)	(0.000000435)	(0.000000434)	(0.000000479)
Total Accessions	0.992***	0.991***	0.995***
(mean: 39.19)	(0.000000248)	(0.000000246)	(0.000000253)
USAREC Controls	No	Yes	Yes
State Linear Trend	No	No	Yes

Coefficients are incident rate ratios (i.e., exponentiated coefficients) of the Poisson regression. All regressions are weighted by county populations and include 15 to 24-year-old population as exposure variable to account for differences in county size/importance. Standard errors are in parentheses and are heteroskedastic robust. All specifications include county and year by quarter effects, civilian earnings (in $1000), fraction veteran, black, and female as controls. Specifications for accessions and DEP loss also include bonus amounts in $1000. - "USAREC Controls" include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts per 100,000 15 to 24-year-old. Note: Panel Data for Applicant at County*FYQ level from 200510 to 201409 (FY 2006 to FY 2014); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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CHAPTER 3

3.1 Background

The abuse of opioid analgesics (opioids) in the United States is a public health emergency.[85] Since 1999, the amount of prescription opioids sold in the U.S. has quadrupled while the amount of pain reported by Americans remains unchanged. This rise in opioid supply has led to a similar four-fold increase in the number of deaths from prescription drug abuse.[86] In 2013, prescription drug abuse resulted in more than 50 percent of all overdose deaths in the United States.[87] Young adults are the biggest abusers of prescription opioids with over 12 percent of the 18 to 25-year old population using prescription drugs non-medically in 2014.[88]

At the same time, nearly 70 percent of America's youth are unfit for military service and for nearly half of these unqualified young people, the disqualifying factor is drug abuse.[89] This problem extends to those serving on active duty. While illicit drug use

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[85] https://www.npr.org/2017/10/26/560276721/trump-declares-opioid-crisis-a-public-health-emergency

[86] See Center for Disease Control Wide-ranging Online Data for Epidemiologic Research (CDC WONDER)

[87] See https://www.cdc.gov/drugoverdose/epidemic/index.html. While heroin (illegal opioids) and prescription opioids are both a problem, the non-medical use of prescription pain relievers (abuse of legal opioids) is the larger problem. In 2011, there were 11.1 million past year users of non-medical prescription pain relievers opposed to 620,000 past year heroin users. See the Center for Behavioral Health Statistics and Quality Data Review, August 2013 at https://archive.samhsa.gov/data/2k13/DataReview/DR006/nonmedical-pain-reliever-use-2013.pdf.

[88] See results from 2014 National Survey on Drug Use and Health (https://www.samhsa.gov/data/sites/default/files/NSDUH-MHDetTabs2014/NSDUH-MHDetTabs2014.htm)

[89] From DoD analysis of 2016 National Survey on Drug Use and Health. 8 percent of 12 to 17-year-olds and 23 percent of 18 to 25-year-olds reported using illicit drugs in past month. Marijuana, prescription opioids, and cocaine were top three drugs abused. The remaining reasons for ineligibility are a combination of

among this population is far below the civilian rate, the abuse of prescription drugs is higher. According to the 2008 Department of Defense Survey of Health-Related Behaviors, 11 percent of service members reported misusing prescription drugs. This is an increase from 2 percent in 2002 and 4 percent in 2005. Moreover, most reported abuse is with prescription opioid pain medications (Jeffrey et al. 2013). Similar to the supply of opioids prescribed by civilian doctors, the "number of opioid prescriptions written by military physicians quadrupled between 2001 and 2009--to almost 3.8 million".[90]

The current economic literature on opioid use centers around economic conditions and opioids (Currie, Jin, and Schnell 2018, Ruhm 2018) physician behavior and opioid supply (Laird 2016, Currie and Schnell 2017), welfare considerations of reducing opioid use (Kilby 2015), opioids and crime (Dav, Deza, and Horn 2018) and the relationship between abuse and drug overdoses (Ruhm 2017). There is also some investigation into the relationship between economic conditions (Carpenter, McClellan, Rees 2017) and labor force participation (Krueger 2017, Aliprantis and Schweitzer 2018, Harrris et al 2018) as they relate to opioid abuse.

While there are many studies relating the effects of military service to health outcomes (Bedard and Descheses 2006, Dobkin and Shabani 2009) or combat exposure to substance use (Jacobson et al. 2008, Angrist, Chen, and Frandsen 2010, Cesar, Chesney, Sabia 2016), there has been no exploration of substance abuse, specifically opioids, and its effect on military enlistment supply or active duty outcomes.[91]

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criminal misconduct, medical and physical limitations, limited aptitude, obesity, and mental health issues. See https://www.samhsa.gov/data/sites/default/files/NSDUH-FFR1-2016/NSDUH-FFR1-2016.htm#illicit and https://www.army.mil/article/195623/despite_challenges_army_wont_lower_enlistment_standards.

[90] Message from the Director, National Institute on Drug Abuse (NIDA), November 2012 (https://www.drugabuse.gov/about-nida/directors-page/messages-director/2012/11/addressing-drug-abuse-in-armed-forces)

[91] Bachman et al. 1999, Bachman et al. 2000 are two exceptions. In addition, Peters 2009 does look at the effects drinking in the military but from a perspective of social capital and alcohol.

Using a unique dataset that combines military applicants, active duty soldiers, and opioid consumption, I estimate the effect of opioid use on applicants for military service, on the composition of the applicant pool, and on active duty outcomes such as attrition in the first enlistment term. I use plausibly exogenous variation in Prescription Drug Monitoring Program (PDMP) implementation dates to instrument for access to opioids. Although one might expect to find opioid use reduces interest in military service or the ability to qualify for application, I find suggestive evidence to support the opposite conclusion. Although in many cases the significance of my results vary or become non-significant in the presence of flexible state-specific trends or instrumenting, the magnitude and direction of the effects are largely stable and consistent with theory. Specifically, my results indicate opioid use in a county increases the rate of individuals that apply for military service and this increase in the applicant pool results in a higher rate of accessions. This increase is attributed to a decrease in the rate of applicants that fail to sign a contract. In other words, it does not appear opioid use negatively impacts military service through direct detrimental effects of abuse in young users, rather, it appears opioid use in a county indirectly effects military enlistment by lowering the opportunity cost of military service (in a manner similar to poor labor market conditions) or through exposure to the negative externalities of opioid abuse; both mechanisms result in an increased rate of enlistments.

Conditional on applying for military service and being an applicant, increased opioid use reduces the fraction of high-quality applicants in the applicant pool. This reduction in the fraction of high-quality applicants is accompanied by a concurrent increase in the fraction of low-quality applicants. Within the high-quality applicant pool, the fraction of accessions increases because of decreases in the fraction of high-quality DEP losses and those that are disqualified. The larger fraction of low-quality applicants results in a relatively larger increase in low-quality accessions because these additional low-quality applicants are disqualified or become uninterested in military service at lower rates and thus more low-quality individuals enter active duty.

With respect to active duty soldiers, the results suggest there is little effect of increased opioid use in the county from which they enter the military. However, the rate of individual attrition during the first enlistment term does appear to decrease while completion of the first term and reenlistment for a second term appears to increase. This decrease in attrition may be attributed to a combination of self-selection out of the military applicant pool by already marginally qualified individuals, effective screening of those additional low-quality applicants, or increasing opportunity costs of leaving the Army for those active duty soldiers enlisting from counties negatively afflicted by the opioid epidemic.

The primary contribution of this paper is to examine the role of the opioid crisis in the context of the military's shrinking pool of qualified potential recruits.[92] Furthermore, this paper provides the first analysis of the effect of opioids on active duty outcomes. Finally, this paper also provides ancillary evidence as to the role of opioids in the reduction in labor force participation by examining another avenue by which young people choose to provide labor (military service).

3.2 Institutional Background

3.2.1 Military Drug Testing

Prior to 2017 and during the period my sample is drawn from, the Army used two different drug tests to screen soldiers.[93] Applicants to military service were tested for

[92] https://www.wsj.com/articles/recruits-ineligibility-tests-the-military-1403909945

[93] In February 2017, the DoD changed policy to require all applicants for military service to take the same

marijuana, cocaine, amphetamines, and methamphetamine at a Military Entrance Processing Station prior to signing an enlistment contract and entering active duty. Opioids were not included in this test until 2017 and later. Upon receipt of a positive test, new applicants to military service must wait 45 days to re-apply after a first positive test for marijuana, two years after a second positive test, and are permanently disqualified from military service after a third positive test. For cocaine and methamphetamines, applicants that test positive must wait 12 months after their first test and are permanently disqualified after a second positive test.

Active duty soldiers are screened for marijuana, cocaine, heroin, and methamphetamines at least once each year through randomized drug urinalysis. In addition, collected samples are "pulse-tested" (approximately 40 percent of specimens screened) for opiates (codeine, morphine, hydrocodone, hydromorphone), and opioids (oxycodone, oxymorphone). The consequences of positive test results for active duty members are dictated by the Uniformed Code of Military Justice (UCMJ) and range from non-judicial punishment (extra duty, forfeiture of pay, restrictions on leave, reduction in rank) to judicial punishments (courts-martial that can result in imprisonment or discharge from service) depending on the circumstances and context.

3.2.2 Prescription Drug Monitoring Programs

PDMPs are statewide electronic data systems that collect, analyze, and make available prescription data on controlled substances dispensed by non-hospital pharmacies and practitioners.[94] The purpose of PDMPs is to prevent doctor shopping, the

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26-drug panel that was used for active duty members since the early 1990s. See Department of Defense Instruction (DoDI) 1010.1 Military Personnel Drug Abuse Testing Program and DoDI 1010.16, Technical Procedures for the Military Personnel Drug Abuse Testing Program (MPDATP).

[94] See the Substance Abuse and Mental Health Services Administration's Center for the Application of

inappropriate use of multiple pharmacies by abusers, and the diversion of controlled substances for non-medical use. Currently, 49 states and the District of Columbia have operational PDMPs. Missouri is the only state without a PMDP, however, in 2017, St. Louis County established a PDMP and has expanded it to over 59 towns and counties since it began.[95]

The first PMDP was established in California in 1939 (see Table 3.1). By the early 1980s, nine states had established analog PDMPs with a focus on enforcing existing drug laws and collecting prescription information on Schedule II controlled substances only.[96] Seven more states established PDMPs in the 1990s with the ability to transmit data electronically and expanded coverage beyond Schedule II drugs to include drugs included in Schedules III through V.

Since 2000, 33 states and the District of Columbia have implemented a PDMP and many have expanded the nature and use of their programs. The majority of PDMPs now provide electronic access for dispensers and prescribers (pharmacists and doctors) with some expanding access to entities such as law enforcement, courts, and substance abuse prevention organizations.

PDMPs generally vary along three primary dimensions: types of drugs monitored,

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Prevention Technologies (SAMHSA CAPT) at
https://www.samhsa.gov/capt/sites/default/files/resources/pdmp-overview.pdf

[95] The St. Louis County program now covers roughly half of the population of Missouri. See https://news.stlpublicradio.org/post/minus-state-action-st-louis-county-drug-monitoring-program-expands#stream/

[96] Schedule I substances have no accepted medical use (e.g., heroin, marijuana, ecstasy, etc.) and have a high potential for abuse. Schedule II substances do have acceptable medical uses but have a high potential for abuse and include nearly all opioids. Schedule III (Tylenol with codeine) and Schedule IV (Xanax, Valium, etc.) controlled substances have lower potentials for abuse but may lead to moderate or low dependence. Schedule V substances have low potential for abuse (Robitussin AC, etc.). See Controlled Substance Schedule published by the U.S. Drug Enforcement Administration at https://www.deadiversion.usdoj.gov/schedules/#define.

mandatory enrollments, and criteria for and frequency of reporting to the state-wide database. Currently, 35 states require collection of data on Schedules II through V while only 16 states collect Schedules II through IV. All states allow access to both prescribers and dispensers, but only 28 states mandate dispenser use while 26 states mandate prescriber querying of the database prior to prescribing drugs subject to their respective PDMP laws. Some states require pharmacists to consult the PDMP prior to dispensing opioids while others make it optional. The required frequency of reporting of prescription and dispensed drugs varies from real-time data entry to once-per-month.[97]

[97] Prescription Drug Monitoring Program Training and Technical Assistance Center. PDMP enrollment of prescribers and dispensers. pdmpassist.org/pdf/Mandatory_Enrollment_20180417a.pdf. Updated April 20, 2018. Accessed July 26, 2018 and https://www.pharmacytimes.com/contributor/marilyn-bulloch-pharmd-bcps/2018/07/the-evolution-of-the-pdmp

Table 3.1. Prescription Drug Monitoring Programs

State	Enacted	Operational	User Access	Electronic Data Reception	Mandatory Prescriber Use	Mandatory Dispenser Use
Alabama	5/13/05	1/1/06	6/28/07	1/1/06		
Alaska	9/7/08	8/1/11	1/1/12	8/1/11		
Arizona	9/19/07	10/1/08	12/1/08	10/1/08		
Arkansas	3/11/11	3/1/13	5/16/13	3/1/13		
California	1/1/39	1/1/39		1/1/07		
Colorado	6/3/05	7/1/07	2/4/08	7/1/07		
Connecticut	6/6/06	7/1/08		7/1/08	10/1/15	
Delaware	7/15/10	3/1/12	8/21/12	3/1/12		
D.C.	2/22/14					
Florida	6/18/09	9/1/11	10/17/11	9/1/11		
Georgia	5/13/11	7/1/13	7/1/13	7/1/13		
Hawaii	1/1/43	1/1/43		1/1/92		
Idaho	1/1/67	1/1/67	6/1/99	1/1/04		
Illinois	1/1/61	1/1/68		1/1/00		
Indiana	1/1/97	1/1/98		1/1/98	7/1/14	
Iowa	5/31/06	1/1/09	3/19/09	1/1/09		
Kansas	7/1/08	2/1/11	4/1/11	2/1/11		
Kentucky	7/15/98	1/1/99	7/1/99	1/1/99	7/20/12	7/20/12
Louisiana	7/1/06	11/1/08	1/1/09	11/1/08	8/1/14	
Maine	6/23/03	7/1/04	1/1/05	7/1/04		
Maryland	5/10/11	8/20/13	12/20/13	8/20/13		
Massachusetts	1/1/92	1/1/94		1/1/94	7/1/14	
Michigan	1/1/88	1/1/89		1/1/03		
Minnesota	7/1/07	1/4/10	4/15/10	1/4/10		
Mississippi	1/1/05	1/1/05	12/1/05	1/1/08		
Missouri						
Montana	7/1/11	3/12/12	11/1/12	3/12/12		
Nebraska	4/14/11	4/14/11	4/14/11	4/14/11		
Nevada	6/29/95	1/1/97	7/1/97	1/1/97	10/1/15	
N. Hampshire	6/12/12	9/2/14	10/16/14	9/2/14	1/21/16	
New Jersey	1/4/08	9/1/11	1/5/12	9/1/11	11/1/15	11/1/15

State	Enacted	Operational	User Access	Electronic Data Reception	Mandatory Prescriber Use	Mandatory Dispenser Use
New Mexico	7/15/04	1/1/05	8/1/05	1/1/05	9/28/12	9/28/12
New York	1/1/72	4/1/73	2/1/10	1/1/99	8/27/13	
North Carolina	8/13/05	7/1/07	10/1/07	7/1/07		
North Dakota	12/1/05	9/1/07	9/1/07	9/1/07		10/1/14
Ohio	5/18/05	7/1/06	10/2/06	7/1/06	12/31/15	
Oklahoma	5/15/90	1/1/91		1/1/91	11/1/15	
Oregon	7/23/09	6/1/11	9/1/11	6/1/11		
Pennsylvania	1/1/72	1/1/73			6/30/15	
Rhode Island	1/1/78	1/1/79		1/1/06	6/28/16	
South Carolina	6/14/06	2/1/08	9/1/08	2/1/08		
South Dakota	3/29/10	12/5/11	3/1/12	12/5/11		
Tennessee	1/1/03	12/1/06	1/1/07	12/1/06	4/1/13	
Texas	9/1/81	1/1/82	1/1/82	1/1/01		
Utah	1/1/95	1/1/96	1/1/97	1/1/96		
Vermont	5/31/06	1/1/09	4/1/09	1/1/09	5/20/15	
Virginia	4/5/02	9/1/03	6/1/06	9/1/03	7/1/15	
Washington	7/22/07	10/7/11	1/4/12	10/7/11		
West Virginia	7/1/95	7/1/95		9/1/02	6/8/12	6/8/12
Wisconsin	5/18/10	4/1/13	6/1/13	4/1/13		
Wyoming	3/7/03	7/1/04	10/1/04	7/1/04		

-Note: California, Hawaii, Idaho, Illinois, Indiana, Kentucky, Massachusetts, Michigan, Nevada, New York, Oklahoma, Pennsylvania, Rhode Island, Tennessee, Texas, Utah, and West Virginia are removed from the active duty sample due to PDMPs occurring prior to the beginning of the Army sample (2003).
- In addition to above states, Alabama, Maine, Mississippi, New Mexico, Ohio, Tennessee, Virginia, and Wyoming are removed from the applicant sample for the same reason (PDMP enactment prior to 2006).
- Source: The Prescription Drug Abuse Policy System (PDAPS) at http://pdaps.org/. PDAPS is maintained by a for-profit organization, Legal Science, LLC, but works in conjunction with Temple University's Center for Health Law, Policy, and Practice. The data maintained by PDAPS is a continuation of work done by the Health Law Research Program of the Robert Wood Johnson Foundation.

3.3 Data and Descriptive Statistics

3.3.1 Opioid Data

The opioid data comes from the U.S. Drug Enforcement Administration's Automation of Reports and Consolidated Orders System (ARCOS).[98] ARCOS generates a Retail Drug Summary report of the manufacture and distribution of all Schedule II-IV controlled substances in the United States. The report contains quarterly data on the number of milligrams of each controlled substance distributed to each three-digit zip code in the United States (retail pharmacies, hospitals, etc.).[99] This data includes all opioids distributed to pharmacies, hospitals, practitioners, teaching institutions, and narcotic treatment programs. While the ARCOS data is collected at the three-digit zip code level, I aggregate it to the county-level to merge with the enlistment, active duty, and economic data.[100]

In Figure 3.1 and Figure 3.2, in addition to Table 3.2, I present data for all states and data for the post-2002 PDMP states. The comparability between the two samples is important because I use the smaller population in my analysis for active duty outcomes. I do this to align my active duty Army data (2003 forward) with the PDMP implementation dates (17 states implement PDMPs prior to my Army sample dates).[101]

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[98] Opioids are defined here as opioid prescriptions, including codeine, fentanyl, hydrocodone, hydromorphone, methadone, morphine, oxycodone, and meperidine.
[99] https://www.deadiversion.usdoj.gov/arcos/retail_drug_summary/index.html
[100] To do this, I first generated total three-digit zip code population using Census zip code population data. Then, I determined the number of people from each three-digit zip code living in each county which allowed me to generate the percent of each three-digit zip code population living in each county and the percent of each county that a specific three-digit zip code contributes. After multiplying the percent of each three-digit zip code living in each county by the number of opioid grams in each three-digit zip code, I determined the number of grams from the three-digit zip in each county. Finally collapsing by county creates the total grams distributed in each county.
[101] As stated in the note to Table 3.1, I further reduce the sample to post-2005 PDMP states for my applicant sample. The post-2005 sample is comparable in covariate balance to the post-2002 sample and the overall sample. I do not include those tables but they are available upon request.

Figure 3.1 illustrates the rise in opioids from 2003 to roughly 2010 with oxycodone accounting for approximately 35 percent of all opioids distributed in the United States during this time. Figure 3.2 graphs opioid use in the post-2002 PDMP states and shows the trends in opioid distribution to be parallel to the trends in the overall population of states. Table 3.2 reflects the predominance of oxycodone, methadone, hydrocodone, and fentanyl compared to other opioids and it also shows the relatively similar consumption levels of opioids between all states and those that implemented PDMPs after 2002. While there are some compositional differences, the total level of MME per capita is roughly similar between all states and the subset of post-2002 PDMP states.

Figure 3.1. Opioid Use in Morphine Milligram Equivalents per person (FY 2003 to FY 2016-all states)

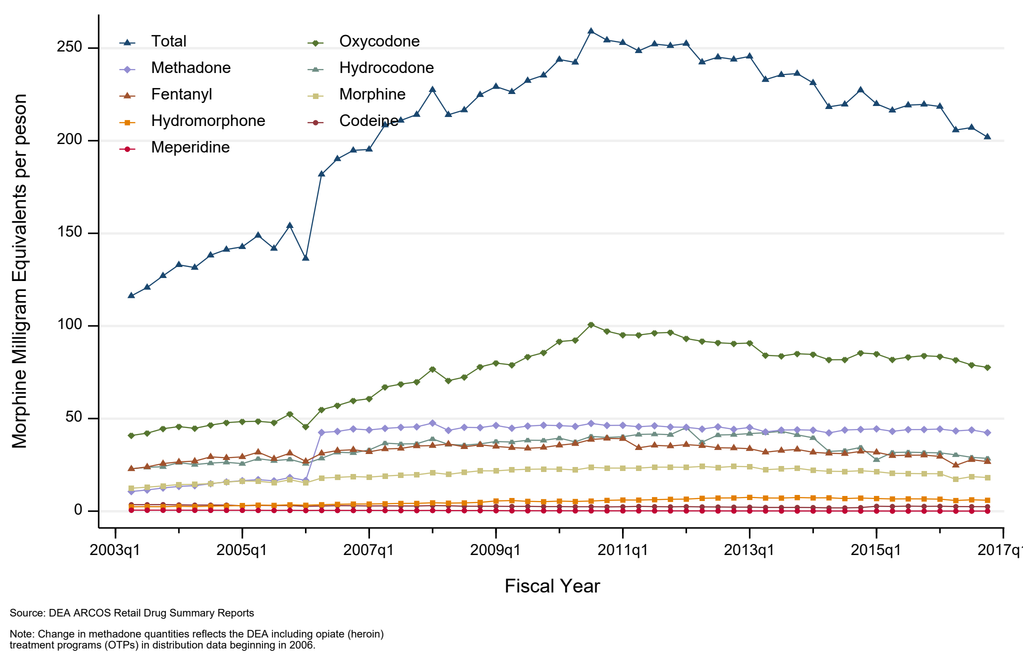

Figure 3.2. Opioid Use in Morphine Milligram Equivalents per person (FY 2003 to FY 2016-Post 2002 PDMP States)

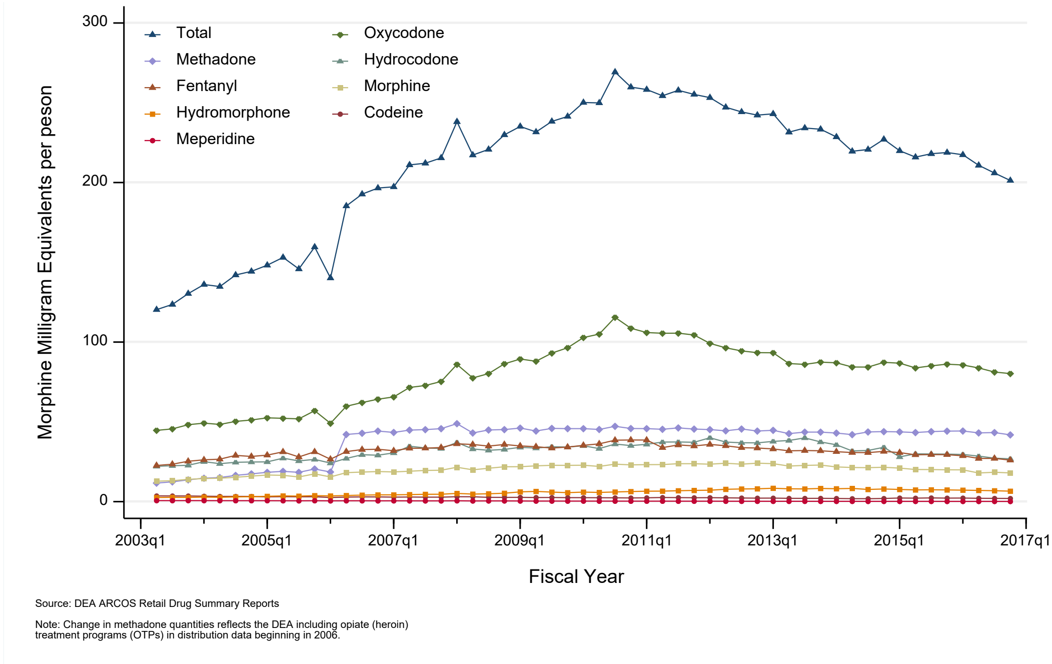

Table 3.2. Summary Statistics for Morphine Milligram Equivalents per person per quarter (FY 2003 to 2016)

	All States	Post-2002 PDMP States
	mean	mean
Meperidine	0.29	0.31
Codeine	2.68	2.46
Hydromorphone	5.26	5.72
Morphine	20.09	20.10
Fentanyl	32.15	31.83
Hydrocodone	34.29	31.64
Methadone	38.52	38.66
Oxycodone	74.79	80.00
Total Opioids	208.07	210.66

Source: Drug Enforcement Administration Automated Reports and Consolidated Ordering System (ARCOS) Retail Drug Summary Reports

- Notes: There are 448 drug*quarter observations. All variables are weighted by county adult populations. MME conversion calculated using Centers for Medicare and Medicaid Services Opioid Oral Morphine Milligram Equivalent (MME) Conversion Factors, dated August 2017. Document found at: https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Opioid-Morphine-EQ-Conversion-Factors-Aug-2017.pdf

For the analysis in this paper, I use oxycodone consumption as the measure of opioid use in the sample. I do this for several reasons. First, as stated above, oxycodone accounts for roughly 35 percent of all opioids in my sample. Oxycodone also has the highest variance of use in the sample; its use increased five-fold from 1999 to 2011 while the next nearest (hydrocodone) increased by only a factor of 2 (Jones 2013). In terms of likelihood of abuse, oxycodone has been rated as most similar to heroin among all other opioids in neuropsychological experiments (Comer 2008). This is further corroborated by findings in the 2016 National Survey on Drug Use and Health (NSDUH) conducted by the Substance Abuse and Mental Health Services Administration (SAMHSA).[102] Also, Paulozzi (2006) finds oxycodone involvement in drug abuse deaths to be larger than any other opioids (until rise of fentanyl post-2012).[103]

3.3.2 Army Enlistment Data (Applicants and Active Duty)

The military data in my sample is comprised of both applicant data collected for individuals that visited a Military Entrance Processing Station (MEPS) and active duty soldier data from the U.S. Army's personnel database. The applicant data represents roughly 1.129 million individuals who visited a MEPS with the purpose of signing an enlistment contract between 2006 and 2014. The data include several demographic characteristics such as age, gender, race, Armed Forces Qualification Test Score (AFQT), marital status, recruiting resources and enlistment contract details (occupation, contract length, bonus, educational benefits).[104] The results of medical and drug tests are also

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[102] https://www.samhsa.gov/data/sites/default/files/NSDUH-DetTabs-2016/NSDUH-DetTabs-2016.pdf

[103] See Section 3.4 for discussion of use of oxycodone as measure of opioids as it relates to PDMP effectiveness in controlling access to opioids.

[104] Recruiter resources (recruiters and recruiting goals, in addition to enlistment contracts signed by the Air Force, Navy, Marine Corps) are collected at the recruiting station*month level. To apportion this data to counties (rather than recruiting stations), I used the Census' intercensal estimates of county resident

included in the sample. I condition the sample to include individuals that signed a contract only within the continental United States. I exclude the small fraction of individuals that enlist at recruiting stations in Hawaii, Alaska, overseas, and in U.S. territories such as Guam, Puerto Rico or the Virgin Islands.[105]

The active duty data contains roughly 667,000 individuals that served in the U.S. Army during the period 2003 to 2014. To be included in this sample, individuals must have enlisted after 2002 and had the *opportunity* to complete their first term by November 2017. Given most enlistment terms are 3 to 4 years, this implies the last enlistment contract dates in the data are in 2013 and 2014. In addition to the same demographic data as the applicants, this data includes performance data such as the time between promotions and length of career. It also includes enlistment term outcomes such as successful completion of enlistment term, reenlistment, and roughly 30 different codes identifying reasons for separation from the military prior to the enlistment contract terms.

County labor market and demographic data come from the BLS and the Census Bureau.[106] Veteran population data comes from the Veteran's Administration's National Center for Veteran's Analysis and Statistics (NCVAS) annual county expenditure tables. Finally, poverty and household median income come from the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program.

The Army applicant panel represents over 1.129 million applicants to the U.S. Army applying in 110,000 county*quarters between fiscal years 2006 and 2014 and

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population and the fraction of zip codes each recruiting station was responsible for in each county to apportion the recruiters, recruiting goals, and DoD contract data to individual counties.

[105] Less than 2% of all recruits.

[106] Specifically, the economic data comes from the Local Area Unemployment Statistics (LAUS) and the U.S. Census Bureau's Quarterly Workforce Indicators (QWI). County-level demographic data comes from intercensal estimates maintained by the Census Bureau and includes population, gender, race, and ethnic status.

identifies the number and characteristics of total applicants, disqualified applicants, uninterested applicants, applicants who sign contracts, Delayed Entry Program (DEP) losses, and accessions for each county*quarter. The active duty panel represents over 667,000 soldiers enlisting in 92,000 county*quarters from 2003 to 2014.[107] The soldiers in this panel have all had the opportunity to complete their first enlistment term and some have served as many as 16 years.[108] Both Army data sets are taken from transactional databases used to calculate service, pay, and promotion information for soldiers. These datasets are used regularly by the Army and incentives exist to ensure their accuracy. Consequently, measurement error is assumed to be minimal.

Table 3.3 provides means of the applicant data and the control variables used in specifications focused on applicants. It is split by all states and post-2006 PDMP states. The outcome variables for applicants is the number of total applicants divided into the five outcomes possible for an applicant: applicants that meet all qualifying criteria but decide not to sign a contract (uninterested), applicants that are disqualified due to low aptitude, medical, physical or drug use (disqualified), applicants that meet enlistment criteria and sign a contract (contracts), applicants that sign a contract but fail to enter active duty (DEP loss), and applicants that sign a contract and enter active duty by reporting to basic training (accessions).[109] On average, approximately 40 percent of applicants do not sign an enlistment contract (uninterested or unqualified) while approximately 55 percent serve on active duty. The remaining 5% are individuals that sign

[107] Post-2006 PDMP sample for applicants includes 449,000 applicants applying in 47,000 quarters and post-2002 PDMP sample for active duty includes 344,000 soldiers serving from 53,000 county*quarters.
[108] Soldiers in this dataset could have enlisted as early as 2002 and could still be on active duty as of November 2017 (last period in data set).
[109] I cannot see individuals that are prevented from enlisting due to failing a national background check (i.e., possess a criminal record). An initial local background check is conducted prior to the applicant's appointment at a MEPS. A formal FBI national background check is conducted at MEPS, but results are not returned until after the soldier has enlisted and is placed in the Delayed Entry Program.

contracts but attrite from the Delayed Entry Program prior to entering active duty to attend basic training. Within both the outcome and the control variables, the two samples (all states and post-2006 PDMP states) are similar. The notable exceptions in the smaller subset of states is a larger average number of applicants, an increase of three percentage points in fraction black and decrease of six percentage points in fraction Hispanic.[110]

[110] The post-2006 PDMP sample removes 25 states, including large population states such as California, Texas, and New York.

Table 3.3. Summary Statistics for County*Quarters (FY 2006 to 2014)

	All States	Post 2006 PDMP States
	mean	mean
Outcome Variables		
(per 100,000 15 to 24-year-old in cnty*qtr):		
Total Applicants	72.18	78.86
Not Qualified	12.61	13.78
Not Interested	15.76	17.18
Contracted	43.81	47.90
Contracted but DEP Loss	4.53	4.74
Contracted and Accessed	39.28	43.16
Control Variables		
(fraction at county level unless noted):		
Unemployment Rate	0.07	0.07
Employment to Population Ratio	0.38	0.40
Veteran	0.09	0.10
Black	0.13	0.16
Hispanic	0.17	0.11
Poor	0.15	0.15
Civilian Earnings (in $1000s)	4.22	4.14
Median Household Income (in $1000s)	52.19	51.42

Source: Office of Economic and Manpower Analysis and US Army Recruiting Command

- All values are weighted by county 15 to 24-year-old population.

- Notes: Individual Applicant for Army service data from 200510 to 201309 (FY 2006 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 109,541 county*quarter observations for the total sample and 47,904 observations in the post-2006 sample. Additional graphs that examine all states vs. post-2006 PDMP states in terms of MME per person, active duty soldier population, and the composition of the applicant pool also do not report significant differences between the two samples and are available from the author upon request.

Table 3.4 is a breakdown of the composition of the applicant pool across education, race, gender, medical/substance problems, and AFQT scores. Apart from the average number of applicants per county*quarter being smaller, the composition of the applicant population within these dimensions across the two samples is consistently within 1-2 percentage points for all but the AFQT (within 3 points). See Table A 3.1 in the appendix for the comparable data for all states.

Table 3.4. Composition of Applicants-Summary Statistics for County*Quarters (FY 2006 to 2014-post 2006 PDMP Implementation)

	Applicants	Not Interested	Not Qualified	DEP Loss	Accessions
Per 100,000 15 to 24 year-old in cnty*qtr	78.86	17.18	13.78	4.74	43.16
	(56.36)	(19.16)	(17.67)	(8.56)	(36.16)
Composition (fraction):					
High-quality	0.49	0.56	0.17	0.55	0.55
	(0.20)	(0.27)	(0.23)	(0.35)	(0.22)
Male	0.81	0.79	0.76	0.75	0.85
	(0.14)	(0.22)	(0.24)	(0.30)	(0.15)
Black	0.22	0.19	0.31	0.22	0.21
	(0.23)	(0.24)	(0.31)	(0.31)	(0.24)
High School Graduate	0.88	0.84	0.87	0.90	0.89
	(0.14)	(0.22)	(0.21)	(0.22)	(0.15)
Medical Test Failure	0.11	0.00	0.30	0.17	0.10
	(0.11)	(0.00)	(0.28)	(0.27)	(0.13)
Drug Test Failure	0.01	0.00	0.02	0.06	0.01
	(0.04)	(0.00)	(0.09)	(0.17)	(0.03)
AFQT	52.89	50.79	25.34	39.58	55.07
	(13.32)	(24.26)	(17.36)	(29.17)	(18.09)

Source: Office of Economic and Manpower Analysis and US Army Recruiting Command

- Standard Deviation in parentheses
- All values are weighted by county 15 to 24-year-old population.
- Notes: Individual Applicant for Army service data from 200510 to 201309 (FY 2006 to FY 2014). There are 47,904 county*quarter observations for the post-2006 sample. Contracts – DEP Loss = Accessions.

Finally, Table 3.5 provides means of the soldier data used in analysis focused on active duty outcomes. It compares the composition of both active duty soldier samples (all states and post-2002 PDMP states). The active duty soldier populations are similar in AFQT, gender, race, and education composition to the pool of applicants that ultimately accessed onto active duty (accessions). The data also contains active duty outcomes such as career length, rank, and reasons for separation.

Table 3.5. Composition of Active Duty Soldiers-Summary Statistics for County*Quarters (FY 2006 to 2014)

	All States mean	Post-2002 PDMP States mean
Demographics		
Age at Contract Date	21.59	21.59
Female	0.16	0.16
Black	0.18	0.23
Hispanic	0.13	0.09
Married	0.16	0.16
Family (spouse or children)	0.33	0.34
Soldier Quality		
High-quality (AFQT > 50 & High School Graduate)	0.54	0.52
Low-quality (AFQT < 50 or High School Dropout)	0.43	0.45
Armed Forces Qualification Test percentile	59.23	58.84
AFQT Categories (% of subpopulation):		
TSC I: > 99 AFQT > 93	0.06	0.06
TSC II: 92 > AFQT > 65	0.33	0.32
TSC IIIA: 64 > AFQT > 50	0.25	0.25
TSC IIIB: 49 > AFQT > 31	0.34	0.36
TSC IV & V: 1 > AFQT > 30	0.02	0.02
Education (% of subpopulation):		
High School Graduate	0.74	0.75
GED	0.12	0.13

Some College	0.06	0.06
Bachelor's Degree	0.04	0.05
Associate's Degree	0.02	0.02
Graduate Degree	0.00	0.00
High School Dropout	0.00	0.00
Military Career		
Length of Enlistment Contract (years)	3.73	3.72
Career Length (years)	4.31	4.08
Enlisted Rank Achieved:		
Private	0.08	0.07
Private 2	0.08	0.08
Private First Class	0.11	0.11
Specialist	0.44	0.46
Sergeant	0.20	0.20
Staff Sergeant	0.07	0.06
Sergeant First Class	0.01	0.01
Master Sergeant	0.00	0.00
Sergeant Major	0.00	0.00
Months to E4 Promotion	12.78	12.90
Months to E5 Promotion	27.02	27.31
Body Mass Index	25.21	25.27
Substance Abuse and Medical Problems at MEPS:		
Medical Problems	0.09	0.09
Drug Test Failure	0.01	0.01
Marijuana Test Failure	0.01	0.01
Cocaine Test Failure	0.00	0.00
Alcohol Test Failure	0.00	0.00
Completed Terms of Service	0.23	0.21
Voluntary Completion	0.21	0.20
Involuntary Completion	0.02	0.02
Reenlist	0.37	0.38
Separated Early	0.39	0.41
Voluntary Separation	0.03	0.03
Involuntary Separation	0.36	0.37

Reasons for Separation (Grouped by type*)		
Entry Problems	0.09	0.08
Disability Problems	0.06	0.06
Physical Standards	0.07	0.06
Substance Abuse	0.03	0.04
Hardship	0.03	0.03
AWOL	0.03	0.02
Retention	0.01	0.02
Unsatisfactory Performance	0.01	0.01
School	0.01	0.01
Legal	0.00	0.00

Source: Office of Economic and Manpower Analysis
- Notes: Individual Applicant for Army service data from 200210 to 201409 (FY 2003 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 92,111 county*quarter observations for the full sample and 55,300 for the partial sample.
- All values are weighted by county 15 to 24-year-old population.
* See Table A 3.2 in the appendix for greater detail on separation reasons

3.4 Empirical Specification and Identification Strategy

I employ two identification strategies in this paper. First, I conduct Ordinary Least Squares (OLS) estimation using a comprehensive set of covariates to control for systematic differences in counties where enlistment rates are high and counties where enlistment rates are low. Krueger (2017) finds that "conditional on individuals' disability status, self-reported health, and demographic characteristics, pain medication is more widely used in counties where healthcare professionals prescribe more opioid medication". In other words, conditional on social and medical characteristics, cross-county differences in opioid prescription rates are exogenously determined by medical practices and norms within each county.[111] The specific identifying assumption in the OLS specification is county

[111] This assumption is also supported by the CDC's own analysis. "Prescribing rates for opioids vary widely across different states. In 2012, health care providers in the highest-prescribing state wrote almost 3 times as many opioid prescriptions per person as those in the lowest prescribing state. Health issues that cause

differences in opioid prescription rates, conditional on economic, social, and demographic control variables, are the exogenous result of differences in medical practices and norms in each county.

Specifically, I conduct panel regression analysis and the main specification takes the following form:

$$Y_{it} = \alpha_1 + \delta_i + \lambda_t + \gamma \ln OP_{it} + \boldsymbol{\beta X}_{it} + \boldsymbol{\eta R}_{it} + \varepsilon_{it} \qquad 3.1$$

where i and t index counties and quarters, respectively.

Y_{it} is the variable of interest per capita, OP_{it} is the measure of opioid use (milligrams of morphine equivalent per capita). The coefficient of interest is γ and measures the response of the variable of interest to opioid use in the county. Because this is a panel regression analysis with area and time fixed effects, the coefficient of interest is identified by within-recruiting station area changes in enlistments varying with within county variation in opioid use.

For military applicants, the variables of interest are the rate of applicants per eligible population to military service and the four outcomes of application to the military (not qualified, not interested, DEP loss, and accessions). For active duty soldiers, I investigate the rate of first enlistment term outcomes (attrition, completion, or reenlistment) and the specific reasons for attrition during the first term.

$\boldsymbol{X}_{it}$ is a vector of social, economic, and demographic controls and $\boldsymbol{R}_{it}$ is a vector of recruiting control variables such as contract goals, number of recruiters, and other military services' contracts.[112] δ_i is a county fixed effect, λ_t is a fiscal year by quarter fixed effect,

people pain do not vary much from place to place, and do not explain this variability in prescribing.". See "State-to-State Variability" at https://www.cdc.gov/drugoverdose/data/prescribing.html

[112] Social and demographic controls include median income, ratio of veterans, county unemployment rates,

and ε_{it} is the error term. The year by quarter fixed effect holds constant those determinants of the variables of interest that vary across time (seasonally and annually) but are fixed nationally (e.g., national recruiting policies, national opioid policies, enlistment bonuses, troop surge into Iraq, etc.). The county fixed effect controls for potential confounding factors that vary across counties but are fixed over time (e.g., lifestyle differences, religiosity, local propensity for military service, etc.). State*year linear and quadratic time trends are included to control for state-specific exogenous changes in enlistment which cannot be explained by included independent variables.

While it is unlikely that enlistment or military service somehow cause opioid use rates to vary, if there remain omitted variables that influence both enlistment rates and opioid use, (unobserved levels of health/fitness/medical conditions in the area, criminal activity, or local levels of social and economic optimism about the future), then estimates resulting from the OLS specification will be biased.

Because of this remaining likelihood of endogeneity, I also conduct two-stage least squares regression analysis. This analysis accounts for and mitigates possible correlation between unobserved determinants of military enlistment or service and opioid abuse. I use the introduction of Prescription Drug Monitoring Programs as an instrument for access to opioids. Prescription Drug Monitoring Programs are state level databases designed to limit abuse of opioid prescriptions by both patients (doctor-shopping) and physicians/pharmacies (pill-mills). The state-level variation in the timing of the PDMPs allows identification of the causal effects of opioid abuse on military enlistment rates. During my sample period of 2003 to 2016, 34 states adopted PDMPs. Seventeen states

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percent black, and percent female. All recruiting resources are as a fraction of the county's 15-24-year-old population.

adopted PDMPs prior to 2003 and are removed from the sample.[113]

PMDPs are a valid instrument if they are correlated with opioid use, not correlated with unobserved factors affecting enlistment, and the only means by which the introduction of a PDMP affects enlistment or military service is through the availability of opioids for non-medical use.[114] If these conditions hold, then PDMPs will isolate the exogenous variation in opioid use and its effect on military enlistment and active duty outcomes.

The two-stage least squares specification is

2SLS: $Y_{it} = \alpha_1 + \delta_i + \lambda_t + \gamma OP_{it} + \boldsymbol{\beta}_1 \boldsymbol{X}_{it} + \boldsymbol{\eta}_1 \boldsymbol{R}_{it} + \varepsilon_{1,it}$ 3.2

First Stage: $OP_{it} = \alpha_2 + \delta_i + \lambda_t + \beta_2 X_{it} + \eta_2 R_{it} + \boldsymbol{\Pi} \cdot \boldsymbol{Z}_{it} + \varepsilon_{2,it}$ 3.3

Reduced Form: $Y_{it} = \alpha_3 + \delta_i + \lambda_t + \beta_3 X_{it} + \eta_3 R_{it} + \boldsymbol{\Pi} \cdot \boldsymbol{Z}_{it} + \varepsilon_{3,it}$ 3.4

where $\boldsymbol{\Pi} \cdot \boldsymbol{Z}_{it} = \sum_{\tau=1}^{T} \pi_\tau D_{\tau,ist}$ is a vector of instruments for opioid use comprised of lags of time, τ, elapsed since implementation of PDMP in that state.[115] For each instrument, I use 12 quarters (3 years) of lags.[116] $D_{\tau,ist}$ is an indicator equal to one if the PDMP is in effect in county $\boldsymbol{i}$ in the quarter $\boldsymbol{t}$.[117] Standard errors, clustered at the state level, are reported.

There are three publicly available sources of data regarding the history and

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[113] California, Hawaii, Idaho, Illinois, Indiana, Kentucky, Massachusetts, Michigan, Nevada, New York, Oklahoma, Pennsylvania, Rhode Island, Tennessee, Texas, Utah, and West Virginia are removed from the sample due to PDMP implementation prior to the beginning of the Army sample.

[114] If omitted factors causing inconsistent OLS estimates are correlated with both enlistment and the introduction of PDMPs, then IV estimates will also be inconsistent.

[115] Instrumental variable construction and specification is modeled on Kilby 2015.

[116] 12 quarters of lags are chosen based on results of event study. See Figure 3.3 and Figure 3.4 below.

[117] To address potential endogeneity concerns with the employment-to-population ratio, I use a shift-share instrument representing local labor demand shocks to instrument for the employment-to-population ratio that is included in the vector of economic and demographic controls.

implementation dates of PDMPs.[118] These three sources of data tend to serve as the primary reference for most academic research on PDMP's and their effect on opioid use (see below): The National Alliance for Model State Drug Laws (NAMSDL), the Prescription Drug Abuse Policy System (PDAPS), and the Prescription Drug Monitoring Program Training and Technical Assistance Center (PDMP TTAC). NAMSDL and PDMP TTAC are both non-profit operations funded by grants from the Department of Justice, and in the case of TTAC, works in conjunction with Brandeis University. PDAPS is a for-profit organization that works in conjunction with Temple University's Center for Health Law, Policy, and Practice and the Robert Wood Johnson Foundation.

I use the PDAPs data source for two reasons. First, while all three appear as primary sources of PDMP data in various academic papers, the NAMSDL site information is not as comprehensive or updated as regularly (specifically regarding dates) as the other two sources. Furthermore, while the dates on the TTAC and PDAPs sites appear to be similar, the TTAC website provides dates only in years (missing months) and so lacks the quarterly variation of the rest of my drug and enlistment data.

There is a robust literature focused on PDMPs and their effect on various opioid use/abuse measures and the results are somewhat mixed. It appears the varied nature of the results are due to differences in research designs, method/source for dating PDMP laws, sample period, and data sources for both measures of opioids and the respective outcome (prescriptions, bulk distribution, overdoses, poisoning, etc.)

Early papers (Simeon and Holland 2006, Reisman 2009, Paulozzi 2011) find that PDMPs reduce prescription oxycodone distribution (~35 percent of opioids in my sample). Many of these same papers also find that other opioid drugs (e.g., hydrocodone) are not

[118] See Horwitz et. al (2018) for a discussion of the sources and quality of data on PDMP legislative and implementation dates.

affected by PDMPs. A more recent paper by Kilby (2015) finds the same effect on oxycodone using both DEA ARCOS and proprietary data from a health analytics corporation. In addition, Bao et al. (2016) find that PDMPs are associated with a significant reduction in opioid prescribing. Other papers in the literature find effects of PDMPs on other opioid-related outcomes such as drug overdoses and/or poisoning from drug ingestion (Patrick et al., 2016; Reifler et al., 2012; Simoni-Wastila and Qian, 2012). Recent papers focus on prescriber and dispenser mandates added to already existing PDMPs and find it is the mandates that reduce opioid use measures (Buchmueller and Carey, 2017; Meinhofer, 2017). Finally, Mallat (2017) focuses on PDMPs without mandates and finds significant effects among oxycodone prescriptions. The papers closest in research design (cross-state variation in PDMP implementation dates), data sources (PDAPS and ARCOS), and methodology to my efforts are Kilby (2015) and Mallat (2017) do find effects of PDMPs on quantities of oxycodone opioids in a geographic location. If there is any agreement at all in the literature on PDMPs and opioids, it's that oxycodone consumption appears to be reduced by the introduction of PDMPs which were largely targeted at oxycodone (Meinhofer 2017). For this reason, and the reasons laid out above in Section 3.3.1 (Opioid Data), my analysis will use oxycodone as the measure for opioid consumption.

In addition to reviewing the literature described above, I conducted an event-study analysis to determine the effect of PDMPs on opioid use and its suitability as an instrument. I use the specification:

$$Y_{it} = \alpha_t + \delta_i + \mu_{it} + \sum_{\tau=-6}^{6} \sigma_\tau D_{\tau,st} + \boldsymbol{\beta X_{it}} + \varepsilon_{it} \qquad 3.5$$

where Y_{it} is opioid usage measured by morphine milligram equivalents per capita and $D_{\tau,st}$ are dummy variables for each quarter before and after the PDMP date. I use twelve quarters before and after and normalize τ to 0 in the year of the PDMP date. Each specification is weighted by county population and includes median income, employment-to-population ratio, fraction veterans, black, female, and the percent living below poverty line as controls. County and year by quarter fixed effects in addition to state*year linear time trends are included, as well.

I conduct this event-study to determine which of the four possible PDMP implementation dates to use as an instrument for opioid use (see Table 3.1). They are the date of enactment (legislative date), the date the PDMP went into operational effect, the date on which users of the PDMP could access the data, and the date on which electronic data was first reported to the PDMP. There are two additional dates that could serve as potential instruments (mandatory prescriber use and mandatory dispenser use), however, their use would further reduce the sample size since there are currently only 18 states that require mandatory prescriber use and 5 states that require dispenser use. In addition, nearly all the mandatory dispenser and prescriber use dates are outside the sample window.

Figure 3.3 and Figure 3.4 are the results of the event-study analysis examining the effect of each PDMP date on the level of oxycodone in a county (for the active duty and the applicant sample, respectively). While there does seem to be a small decline in oxycodone use in the 12 to 18 months leading up to the operational effect of the law, this can be explained by lags between legislative approval of the law and its implementation (which average roughly 6-9 months in difference). These anticipatory effects are somewhat evident in the data in Figure 3.3 and Figure 3.4 but I do not asses them as differential pre-trends or PDMP endogeneity to other conditions. It is clear the enactment date and date individuals could access the PDMP are not as strong of an instrument as the "effect" date. The date the PDMP received data electronically ("electr") is similar to the "effect" date because in all but one state (Mississippi) the date the PDMP went into effect and the date it could receive data electronically are the same date. Based on the literature discussed above and the results of the event studies, I use the dates in column (2) of Table 3.1, the PDMP operational effectiveness date, as the preferred instrumental variable for opioid use in my specification.[119]

[119] The event-studies depicting the reduced form (effect of PMDPs on Applicants, Accessions, and active duty outcomes) are in the appendix in Figure A 3.1 to Figure A 3.5.

Figure 3.3 Effect of PDMP Introduction on Oxycodone (ARCOS data)-Active Duty Sample (FY 2003 to 2014)

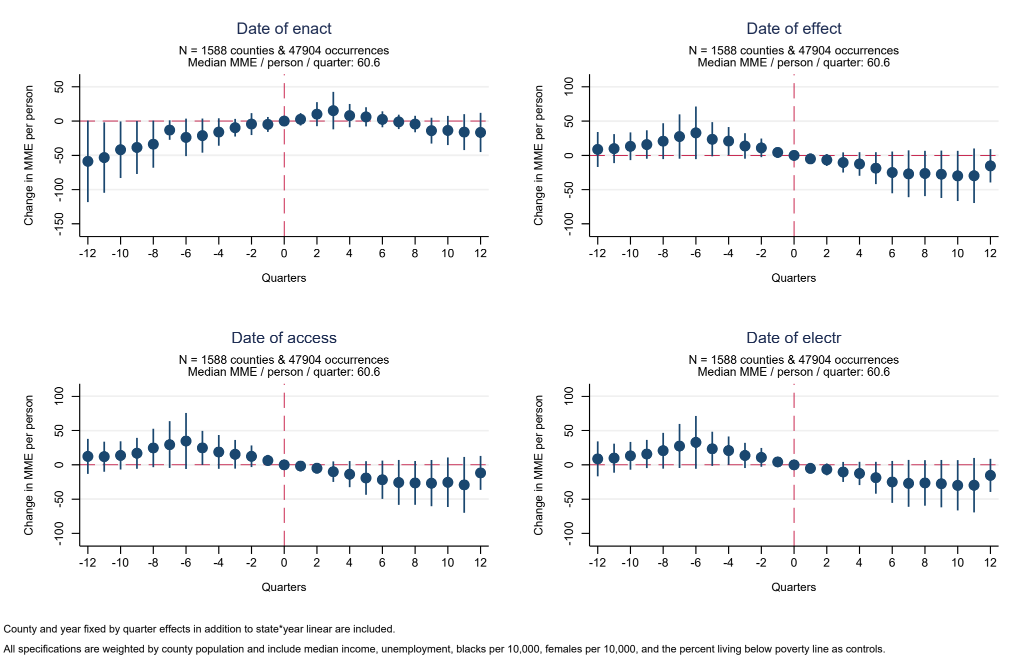
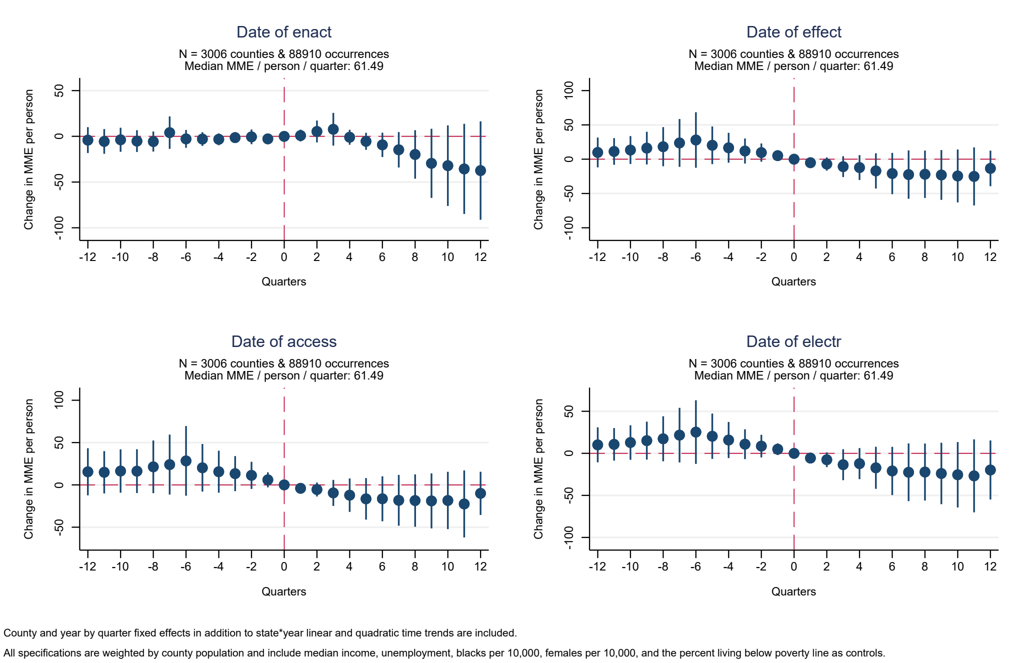


Figure 3.4 Effect of PDMP Introduction on Oxycodone (ARCOS data)-Applicant Sample (FY 2006 to 2014)



Finally, I conducted additional analysis to ensure that PDMP laws are not endogenous to other variables in the environment. For example, to ensure PDMPs were not implemented in response problems other than opioid diversion and abuse (that could potentially effect recruiting, e.g., economic issues, etc.), I conducted falsification tests for both the employment-to-population rate and the unemployment rate. I estimated OLS specifications with the dependent variable a dummy that indicates the PDMP is in effect and the key independent variable a measure of local labor market conditions. As with all models in this analysis, I included appropriate demographic and social controls as well. The null results of these falsification tests support the conclusion that PDMP laws were not passed in response to local economic conditions.[120]

3.5 Results

3.5.1 Applicants

In Table 3.6, I present the main results from the estimation for equations 3.1 and 3.2 for the effect of morphine milligram equivalents (MME) per capita on the rate of military enlistment from each county. The key explanatory variable is the natural log of MME per capita and the dependent variables are the different outcomes of individuals that visit a MEPS with the intent of enlisting. All specifications include county and year by quarter effects in addition to demographic, economic, and recruiting resource controls per population. Columns (1) to (4) are the results of the OLS specification and column (5) is the 2SLS specification using the date the PDMP went into operation as the instrumental variable for the MME per capita and a shift-share instrument representing local labor demand shocks as the instrument for the employment-to-population ratio. Both OLS and 2SLS results are limited to the post-2006 PDMP states. In general, the

[120] Results are available from author by request.

results suggest the rate of applicants per eligible population (extensive margin) is increased and the rate of those that are DEP losses is increased by an increase in opioid use (Column (5)). However, there is no effect on the rate of those that are not interested or not qualified.

The OLS estimates are stable with the addition of recruiting controls and linear state-specific time trends. In most cases, the use of the PDMP effect date as an instrument increases the size of the coefficient and maintains the sign. However, when flexible (quadratic) state-specific trends or instruments are included in the analysis, the significance of the results diminishes and in many cases disappears. The sensitivity of the results to the inclusion of flexible trends is likely attributed to the correlation between increases in opioid use in a county with unidentified trends in state levels of military enlistment. This results in an inability to determine the causal effect of opioids and the effect of these unidentified trends. In regards to the effect of the instrument on the significance of the results, this is not due to a lack of first stage significance, but rather, a weak relationship between the military outcomes I investigate and PDMPs as demonstrated in the reduced form estimation (see Figure A 3.1to Figure A 3.5 in the appendix).

Specifically, for the rate of applicants, the coefficient of 9.349 in column (5) in Table 3.6 implies that a one percent increase in the MME per capita in a county is predicted to increase by 0.0935 the rate of applicants in that county*quarter. Given the mean rate of applicants in a county*quarter was 77.46, this indicates a 1.2 percent increase in applicants for a ten percent increase in MME per capita. With respect to the outcomes for the applicants, those that are disqualified and those that sign a contract but fail to access onto active duty (DEP loss) are not affected. The effect on accessions of a ten percent increase in MME per capita is an increase of approximately 3.3 percent.

Table 3.6. Effect of Opioid Usage on Composition of Army Enlistment (OLS and 2SLS) - Dependent Variable (per 100,000 15 to 24-year old)

	(1)	(2)	(3)	(4)	(5)
ln (MME per capita)					
Overall Outcome					
Total Applicants	6.566***	6.282***	6.311***	3.150	9.349
(mean: 77.46)	(1.923)	(1.801)	(1.500)	(2.998)	(14.09)
Sub-Outcomes					
Total Disqualified	0.0181	0.00269	-0.132	0.198	0.400
(mean: 13.25)	(0.446)	(0.436)	(0.346)	(0.557)	(4.435)
Total Uninterested	1.747***	1.656**	1.481***	0.271	-6.515
(mean: 16.77)	(0.615)	(0.613)	(0.490)	(0.526)	(10.09)
Total DEP Loss	0.0853	0.0869	0.163	0.443	2.723
(mean: 4.69)	(0.220)	(0.209)	(0.203)	(0.285)	(2.712)
Total Accessions	4.486***	4.329***	4.532***	2.035	14.29
(mean: 42.75)	(1.115)	(1.035)	(0.979)	(2.278)	(11.34)
Recruiting Controls	No	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes	Yes
Year by quarter effects	Yes	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS (PDMP Effective Date)	No	No	No	No	Yes
F (excluded instruments)					53
Observations	47147	47147	47147	47147	47000

- All dependent variables per 100,000 15 to 24-year old and regressions are weighted by county populations. Standard errors are in parentheses and clustered at state-level. All specifications include civilian earnings, unemployment, fraction poor, veteran, black, and female as controls. Recruiting controls include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts. All specifications include only states with PDMP implementation after 2006-excludes NY, TX, OK, PA, TN, WV, HI, UT, NV, ID, MI, KY, IL, RI, CA, IN, MA, AL, ME, MS, NW, OH, VA, WY. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel Data at County*FYQ level from 200510 to 201509 (FY 2006 to FY 2015).
- The instrument for the MME per capita is the PDMP effective date and the instrument for the employment-to-population ratio is a shift-share instrument representing labor demand shocks.
- The total number of applicants experience four outcomes: those individuals that are disqualified for medical, physical, or criminal reasons, those that decide not to sign a contract after visiting MEPS, those that sign a contract but attrite from the Delayed Entry Program (DEP Loss), and those that sign a contract and serve on active duty (accession). Panel Data at County*FYQ level from 200510 to 201509 (FY 2006 to FY 2015).

To explore these results more fully, I transformed the outcome variable(s) to be fractions of the applicant pool (i.e., accessions (AC), DEP loss (DL), not qualified (NQ), not interested (NI) all as fractions of applicants in that county*quarter rather than as fraction of county eligible population). These variables represent the intensive margin of enlistment and help to explain how opioid use might adjust the composition of the applicant pool.

These results are in Table 3.7. Increased opioids appear to reduce the fraction of applicants that are deemed not qualified or uninterested by roughly the same amount (1.1 percent decrease for 10 percent increase in MME per person). The overall fraction of accessions appears to increase by 1.3 percent for this same ten percent increase in MME person. Table 3.8 reports the results of the changes to the applicant pool broken out by high and low-quality (i.e., the fraction of applicants that become NI, NQ, DL, and AC by high and low-quality). The results reflect a substitution of high-quality for low-quality in applicants. In particular, for a ten percent increase in opioids per capita, the fraction of the applicant pool that is high quality is reduced by 0.5 percent which drives a similar increase (0.43 percent) in the fraction of low-quality applicants. The decrease in the fraction of high-quality applicants is offset by decreases in those high quality that are disqualified and DEP losses, resulting in an overall increase in the fraction of high-quality accessions (0.8 percent for ten percent increase). Regarding the low-quality portion of the applicant pool, the fraction of the applicant pool comprised of low-quality accessions increases by 1.8 percent for a ten percent increase in MME per person. This is due to relatively large decreases in the fraction of low-quality individuals that are disqualified or uninterested. Overall, the results in Table 3.6 to Table 3.8 indicate that increased opioid consumption in a county increases the size of the applicant pool while at the same time changing the composition of the applicants such that it results in relatively more low quality applicants and accessions.

Table 3.7. Effect of Opioid Usage on Composition of Army Enlistment (OLS and 2SLS) - Dependent Variable (as fraction of Total Applicants)

	(1)	(2)	(3)	(4)	(5)
ln (MME per capita)					
Total Disqualified	-1.210	-1.179	-1.429**	-1.254	-1.835
(mean: 16.93)	(0.743)	(0.742)	(0.664)	(1.256)	(3.997)
Total Uninterested	-0.470	-0.501	-0.922	-2.101*	-2.511
(mean: 21.83)	(0.813)	(0.802)	(0.836)	(1.031)	(4.133)
Total DEP Loss	-0.174	-0.157	-0.0682	0.436	-1.773
(mean: 6.30)	(0.251)	(0.250)	(0.263)	(0.296)	(1.540)
Total Accessions	1.644	1.640	2.191*	2.735*	7.164
(mean: 54.80)	(1.113)	(1.089)	(1.072)	(1.563)	(6.873)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					53.66
Observations	34446	34446	34446	34446	34378

- All dependent variables are fraction of total applicant pool and regressions are weighted by county populations. Standard errors are in parentheses and clustered at state-level. All specifications include civilian earnings, unemployment, fraction poor, veteran, black, and female as controls. Recruiting controls include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts. All specifications include only states with PDMP implementation after 2002-excludes NY, TX, OK, PA, TN, WV, HI, UT, NV, ID, MI, KY, IL, RI, CA, IN, MA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel Data at County*FYQ level from 200510 to 201509 (FY 2006 to FY 2015).

Table 3.8. Effect of Opioid Usage on Composition of Army Enlistment (OLS and 2SLS) - Dependent Variable (as fraction of Total Applicants)

	(1)	(2)	(3)	(4)	(5)
ln (MME per capita)					
High-quality					
Applicants	0.660*	0.678*	1.170***	0.300	-2.427
(mean: 49.57)	(0.382)	(0.383)	(0.274)	(0.623)	(6.126)
Disqualified	-0.446*	-0.443*	-0.238	-0.298	-1.330
(mean: 2.85)	(0.223)	(0.231)	(0.142)	(0.239)	(1.686)
Uninterested	0.177	0.171	0.0238	-0.939	0.112
(mean: 12.40)	(0.558)	(0.557)	(0.614)	(0.712)	(3.539)
DEP Loss	-0.0188	0.000623	0.0771	0.333*	-2.127
(mean: 3.54)	(0.169)	(0.170)	(0.166)	(0.175)	(1.769)
Accessions	0.736	0.754	1.045**	0.983	2.461
(mean: 30.77)	(0.494)	(0.495)	(0.465)	(0.708)	(5.814)
Low-quality					
Applicants	-0.574	-0.596	-1.167***	-0.220	2.203
(mean: 50.09)	(0.402)	(0.403)	(0.232)	(0.545)	(6.243)
Disqualified	-0.763	-0.736	-1.191**	-0.956	-0.506
(mean: 14.08)	(0.595)	(0.587)	(0.554)	(1.090)	(3.597)
Uninterested	-0.646	-0.672*	-0.945***	-1.161***	-2.623
(mean: 9.42)	(0.386)	(0.387)	(0.281)	(0.379)	(3.324)
DEP Loss	-0.137	-0.139	-0.138	0.119	0.494
(mean: 2.72)	(0.130)	(0.132)	(0.134)	(0.162)	(1.861)
Accessions	0.971	0.945	1.135	1.810*	4.388
(mean: 23.87)	(0.790)	(0.765)	(0.734)	(0.980)	(3.657)
USAREC Controls	No	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS	No	No	No	No	Yes
F (excluded instruments)					53.66
Observations	34446	34446	34446	34446	34378

- Notes same as in Table 3.7

3.5.2 Active Duty

I focus on the first enlistment term for active duty outcomes. Specifically, I investigate attrition prior to the first enlistment term being complete, completion of the first enlistment term, and reenlistment for a second term. With respect to attrition, I examine the separate reasons for separating from the service prior to the end of the first enlistment term.

Active duty outcomes for first term soldiers are reported in Table 3.9 and Table A 3.13. Restricting the sample to the outcome of first term enlistments only, the data suggests increased opioid consumption in a county reduces attrition by 0.0162 (1 percent for a 10 percent increase in opioids per person). The rate of individuals completing their first term and separating from the military or on the rate of individuals choosing to reenlist for a second term appear to increase by approximately 3.4 and 2.1 percent, respectively. Table A 3.13 (appendix) reports the separate reasons why an individual is involuntary separated from military service. The reduction in involuntary separations is driven almost entirely by a large reduction in the rate of individuals going AWOL or deserting (~9 percent for a 10 percent increase in opioids per capita), those separated for economic or family hardship, or for those with unsatisfactory entry performance in first 180 days.[121] In addition, Table 3.10 reports results of transforming the dependent variables into fractions of all involuntary separations to investigate how the composition of the pool of those involuntarily separated might change in response to increased opioid use.

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[121] See Uniformed Code of Military Justice, Articles 87 (Missing Movement), 86 (Absent Without Leave), 85 (Desertion). Of the three, desertion is the most severe. In general, someone is considered AWOL if they are absent for roughly one month or less and intend to return to military control. Someone is considered a deserter if they are absent for more than one month or have no intent to return to military control. Missing movement is a lesser offense concerned with not being present for a deployment. See https://jsc.defense.gov/military-law/current-publications-and-updates/ and http://www.loc.gov/rr/frd/Military_Law/military-legal-resources-home.html

Table 3.9. Effect of Opioid use per capita on active duty Enlistment Term Completion (OLS and 2SLS) - Dependent Variable (per 100,000 15 to 24-year old)

	(1)	(2)	(3)	(4)
Dep. Var. ln(MME per capita)				
Overall				
Attrition before first term end	1.867***	1.514***	1.907***	-1.621
(mean: 15.79)	(0.476)	(0.396)	(0.441)	(5.100)
Completed first term	1.215***	0.984***	0.977***	2.882
(mean: 8.37)	(0.233)	(0.226)	(0.325)	(3.770)
Reenlist for second term	2.311***	1.784***	1.827***	3.185
(mean: 15.19)	(0.364)	(0.416)	(0.480)	(4.069)
Subgroup				
Voluntary Attrition	0.178***	0.154**	0.193**	-0.304
(mean: 1.35)	(0.0603)	(0.0678)	(0.0878)	(0.762)
Involuntary Attrition	1.689***	1.360***	1.714***	-1.317
(mean: 14.45)	(0.488)	(0.400)	(0.454)	(4.840)
Voluntary Completion	1.166***	0.957***	0.945***	1.985
(mean: 7.75)	(0.201)	(0.211)	(0.279)	(3.288)
Involuntary Completion	0.0489	0.0264	0.0318	0.898
(mean: 0.161)	(0.0505)	(0.0429)	(0.0739)	(0.762)
State Linear Trend	No	Yes	Yes	Yes
State Quadratic Trend	No	No	Yes	Yes
2SLS (PDMP Effective Date)	No	No	No	Yes
F (excluded instruments)				20.29
Observations	53236	53236	53236	51510

- All regressions weighted by county populations. Standard errors are in parentheses and clustered at county-level for OLS specifications and state-level for the IV specification. All specifications include county and year fixed effects. Unemployment rate, median household income, population 15 to 24-year old, fraction veteran, black, female, and poor are controls. All specifications include only states with PDMP implementation after 2002-excludes NY, TX, OK, PA, TN, WV, HI, UT, NV, ID, MI, KY, IL, RI, CA, IN, MA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10. Effect of Opioid use per capita on reasons for separation from active duty (OLS and 2SLS) - Dependent variable is fraction of all involuntary separations

	(1)	(2)	(3)	(4)
Dependent Variable (in order of frequency)				
Entry Performance/Conditions	-0.0531	0.0398	-1.199	-21.01
(mean: 23.85)	(0.975)	(0.970)	(0.963)	(12.87)
Disability during service	-0.115	-0.0192	0.232	-0.0405
(mean: 17.35)	(0.600)	(0.574)	(0.745)	(6.704)
Physical conditions	0.745	0.394	0.909	7.784
(mean: 16.71)	(0.731)	(0.736)	(0.834)	(9.151)
Substance Abuse	-0.00149	-0.0526	-0.290	5.873
(mean: 9.64)	(0.461)	(0.426)	(0.648)	(7.748)
Misconduct	-0.490	-0.760*	-0.557	11.98
(mean: 11.79)	(0.399)	(0.391)	(0.393)	(9.165)
Economic or Family Hardship	-0.605	-0.305	0.0707	-10.47
(mean: 9.50)	(0.501)	(0.480)	(0.542)	(7.584)
Unauthorized Absence	-0.494	-0.463	-0.0550	2.609
(mean: 7.37)	(0.365)	(0.371)	(0.582)	(4.042)
Selected for removal to downsizing	0.244	0.230	0.364	6.656
(mean: 3.64)	(0.403)	(0.375)	(0.445)	(5.803)
Legal Jeopardy (courts-martial, etc.)	0.127	0.0348	-0.185	-6.545
(mean: 1.35)	(0.189)	(0.184)	(0.239)	(5.041)
State Linear Trend	No	Yes	Yes	Yes
State Quadratic Trend	No	No	Yes	Yes
2SLS (PDMP Effective Date)	No	No	No	Yes
F (excluded instruments)				23.86
Observations	37489	37489	37489	36696

- All dependent variables are fraction of total involuntary separations and regressions are weighted by county populations. Standard errors are in parentheses and clustered at county-level for OLS specifications and state-level for the IV specification. All specifications include civilian earnings, unemployment, fraction poor, veteran, black, and female as controls. Recruiting controls include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts. All specifications include only states with PDMP implementation after 2002-excludes NY, TX, OK, PA, TN, WV, HI, UT, NV, ID, MI, KY, IL, RI, CA, IN, MA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel Data at County*FYQ level from 200510 to 201509 (FY 2006 to FY 2015).

3.5.3 Robustness Checks

In the preferred specification above, I chose to log-transform the key independent variable, MME per capita. Log transformations facilitate interpretations of relative changes (multiplicative) whereas linear transformations may make it easier to interpret absolute, or additive, changes. However, by using the natural log of MME per capita rather than simply MME per capita, I am implying that a 100 percent change in MME per capita at a very low levels has the same effect as the doubling of MME starting at very high levels of MME per capita.[122] Using only MME per capita as the dependent variable would allow equal percent changes at higher levels of MME to effect enlistment greater than at low starting levels of MME.

To investigate this, I reproduced the analysis in Table 3.6 using MME per capita as the key dependent variable and report the results in Table 3.11. The pattern of significance does not change, however, the estimates for a 10 percent increase in MME per capita are roughly 35 percent of the magnitude of the estimates from the specification using the natural log of MME per capita. Specifically, for a ten percent increase in MME per capita (6.9 MME), the increase in applicants (0.30 or 0.37 percent) is smaller than the results of the specification using the natural log of MME (1.2 percent)[123]. The same relationship exists for accessions, as well.[124]

[122] For example, $\ln(20) - \ln(10) = \ln(200) - \ln(100) = \ln(2)$, whereas $20\text{-}10 \neq 200\text{-}100$

[123] The increase in those leaving the DEP after signing a contract and prior to accessing (0.0089 or 4.5 percent) is also smaller than the results of the specification using the natural log of MME (6 percent).

[124] For a 10 percent increase in MME (6.9 MME per capita), accessions increase by $0.0675*6.9 = 0.466$ which is roughly 1 percent. Using log (MME per capita), the increase in accessions was approximately 3.5 percent.

Table 3.11. Effect of Opioid Usage on Composition of Army Enlistment (OLS and 2SLS) - Dependent Variable (per 100,000 15 to 24-year old)

	(1)	(2)	(3)	(4)	(5)
MME per capita					
Overall Outcome					
Total Applicants	0.0201**	0.0203**	0.0159***	-0.00475	0.0432
(mean: 77.46)	(0.00745)	(0.00764)	(0.00539)	(0.00469)	(0.0703)
Sub-Outcomes					
Total Disqualified	-0.00500**	-0.00482**	-0.00578***	-0.00565*	0.00201
(mean: 13.25)	(0.00222)	(0.00229)	(0.00196)	(0.00280)	(0.0223)
Total Uninterested	0.00658*	0.00644*	0.00619**	-0.000174	-0.0322
(mean: 16.77)	(0.00333)	(0.00343)	(0.00276)	(0.00320)	(0.0520)
Total DEP Loss	0.000230	0.000273	0.000393	0.00165***	0.0143
(mean: 4.74)	(0.000594)	(0.000591)	(0.000525)	(0.000591)	(0.0147)
Total Accessions	0.0184***	0.0187***	0.0151***	0.000339	0.0675
(mean: 43.16)	(0.00445)	(0.00438)	(0.00400)	(0.00267)	(0.0577)
Recruiting Controls	No	Yes	Yes	Yes	Yes
County Effects	Yes	Yes	Yes	Yes	Yes
Year by quarter effects	Yes	Yes	Yes	Yes	Yes
State Linear Trend	No	No	Yes	Yes	Yes
State Quadratic Trend	No	No	No	Yes	Yes
2SLS (PDMP Eff. Date)	No	No	No	No	Yes
F (excluded instruments)					7.884
Observations	47147	47147	47147	47147	47000

- All dependent variables per 100,000 15 to 24-year old and regressions are weighted by county populations. Standard errors are in parentheses and clustered at county-level for OLS specifications and state-level for the IV specification. All specifications include civilian earnings, unemployment, fraction poor, veteran, black, and female as controls. Recruiting controls include number of recruiters, high-quality goals, low-quality goals, and other DoD contracts. All specifications include only states with PDMP implementation after 2002-excludes NY, TX, OK, PA, TN, WV, HI, UT, NV, ID, MI, KY, IL, RI, CA, IN, MA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Panel Data at County*FYQ level from 200510 to 201509 (FY 2006 to FY 2015).
- Mean value of MME per capita is 241. 10^{th} percentile is 120.72, 25^{th} percentile is 156.68, 75^{th} percentile is 289.05, and 90^{th} percentile is 368.27.
- The total number of applicants are comprised of four sub-groups: those individuals that are disqualified for medical, physical, or criminal reasons, those that decide not to sign a contract after visiting MEPS, those that sign a contract but attrite from the Delayed Entry Program (DEP Loss), and those that sign a contract and serve on active duty (accession). Panel Data at County*FYQ level from 200510 to 201509 (FY 2006 to FY 2015).

Finally, I also considered an alternative measure of opioid use. Rather than using aggregate MME per capita in a county*quarter, I developed a measure related to the number of users and their consumption of opioids in a county*quarter to try to understand the impact of an additional user/abuser in a geographic area. Using data from the Center for Disease Control (CDC) on prescriptions per capita by county for 2006 to 2014 and merging it with aggregate opioid data collected from the DEA ARCOS system (total morphine milligram equivalents in each county), I created a measure of MME per prescription per day to understand the amount of opioids being used by an individual user at the county level.

When used as the key measure of opioid consumption, on either enlistment or active duty outcomes, the OLS results are not significant, the first stage significance of the specification using PDMP as an instrument goes away, and I find no significant 2SLS results. This is true for both the applicant pool and the active duty first term soldiers. Given that the first stage is not significant (PDMPs do not limit the doses per prescription), I interpret this loss of the first stage as preliminary evidence that while PMDPs don't appear to limit the doses per prescription, they do have an effect on overall opioid consumption by limiting the number of prescriptions written per person.[125]

3.6 Discussion and Conclusion

The opioid epidemic has wreaked havoc on the health and well-being of communities across the United States. The highly addictive nature of opioids often results in non-medical use by both those properly prescribed and those accessing the drugs illegally

[125] In results not included in this paper, I find that a 10% increase in prescriptions per 100,000 people (~0.001593 * 1966.25) decreases the rate of applicants per capita by approximately 3.9 percent. In addition, the first stage results (effect of post-PDMP quarter dummies on the prescription rate) is significant and negative. Results are available upon request from the author.

through family or friends.[126] Because opioids tend to proliferate through family members and households, the mechanisms by which this epidemic impact military service are likely varied and may be both direct and indirect.

Individuals that use opioids themselves are at increased risk of being screened by the military during the application process (drug testing) or are relatively weaker candidates (medically or physically) and will be disqualified for related reasons. It is also possible that individuals using opioids illegally aren't screened by drug testing but, due to the highly addictive nature of opioids, decide they cannot leave home because it is the source of their access to the drug. Moreover, individuals that are not opioid users are still negatively impacted by family or close friends' use as it may require them to forego opportunities in the military because they feel a responsibility to remain at home to provide for addicted relatives or care for those individuals that aren't necessarily addicted but are incapacitated to such a degree by other health conditions correlated with opioid usage.

On the other hand, it is possible high levels opioid use in a county, and the associated negative externalities described above, serve to motivate individuals to leave that county in search of social or economic opportunity. Military service may be one avenue by which individuals in opioid-afflicted counties choose to escape their less lucky family and friends' fates. While somewhat counterintuitive, this is the scenario my results appear to support.

Though the significance of the results vary when flexible state-specific trends or

[126] See Substance Abuse and Mental Health Services Administration, Results from the 2013 National Survey on Drug Use and Health: Summary of National Findings, NSDUH Series H-48, HHS Publication No. (SMA) 14-4863. Rockville, MD: Substance Abuse and Mental Health Services Administration, 2014.
16. Also, Centers for Disease Control and Prevention. Policy impact: prescription painkiller overdoses. 2011. Available at: http://www.cdc.gov/HomeandRecreationalSafety/pdf/PolicyImpact-PrescriptionPainkillerOD.pdf

instruments are included, the magnitude and direction of the effects are largely stable and consistent with account described above. The analysis suggests that increases in opioid use are associated with an increase in the rate of applicants to military service and an increase in accessions. Both outcomes are counterintuitive and have parallels in the motivating effect of unemployment on enlistment. In this case, opioid use in their county serves as another dimension by which the opportunity cost of military service can be measured. In this case, high levels of opioid use in a county reduces the opportunity costs to an individual of joining military service in a manner similar to the depressive effects of high unemployment, etc.

The findings in this paper also indicate that increased opioid consumption in a county not only increases the rate of applicants to the Army, but at the same time, changes the composition of the remaining applicant pool such that it results in relatively more low-quality accessions because they are likely the most vulnerable to the negative externalities present in areas most-afflicted by the opioid crisis.

Regarding individuals already serving on active duty, the results of this paper are less conclusive but are consistent with this story. Increased opioid use does appear to reduce attrition of individuals serving their first enlistment term and increase both the rate of individuals completing their term and the rate of individuals choosing to reenlist for a second term. This is consistent with the idea that individuals enlisting from counties consuming high levels of opioids perceive separation from the military as having a relatively higher opportunity cost. This could be due to concern about their own history with opioid use, an increased propensity for use by family members or friends in their home of record, or the likely low level of valuable labor market options in the location from which they enlisted into the military.

While the results of this paper are not conclusive, they do inform yet another dimension of the effects of the opioid epidemic in the U.S. and provide the military with some evidence that opioids exacerbate the military's already difficult task of manning the force with qualified recruits.

Appendix

Table A 3.1. Summary Statistics for Morphine Milligram Equivalents (FY 2003 to 2016-all states)

	mean	sd	min	max
Meperidine	68,892,569	35,734,208	20,553,682	131,280,873
Codeine	656,474,791	86,758,881	471,954,532	826,753,715
Hydromorphone	1,310,125,630	437,843,992	555,370,038	1,905,310,315
Morphine	4,972,501,185	917,534,236	2,846,322,848	6,102,235,608
Fentanyl	7,931,815,823	1,007,229,157	5,237,439,828	9,767,309,756
Hydrocodone	8,477,995,966	1,632,580,293	5,258,569,385	11,360,635,008
Methadone	9,576,935,828	3,181,001,924	2,438,576,580	11,697,102,599
Oxycodone	18,565,290,030	4,820,006,695	9,390,237,874	24,874,954,621
Total Opioids	51,560,031,822	11,247,935,730	26,678,180,185	63,968,230,885

Source: Drug Enforcement Administration Automated Reports and Consolidated Ordering System (ARCOS) Retail Drug Summary Reports

- Notes: There are 448 drug*quarter observations. All variables are weighted by county adult populations. MME conversion calculated using Centers for Medicare and Medicaid Services Opioid Oral Morphine Milligram Equivalent (MME) Conversion Factors, dated August 2017. Document found at https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Opioid-Morphine-EQ-Conversion-Factors-Aug-2017.pdf

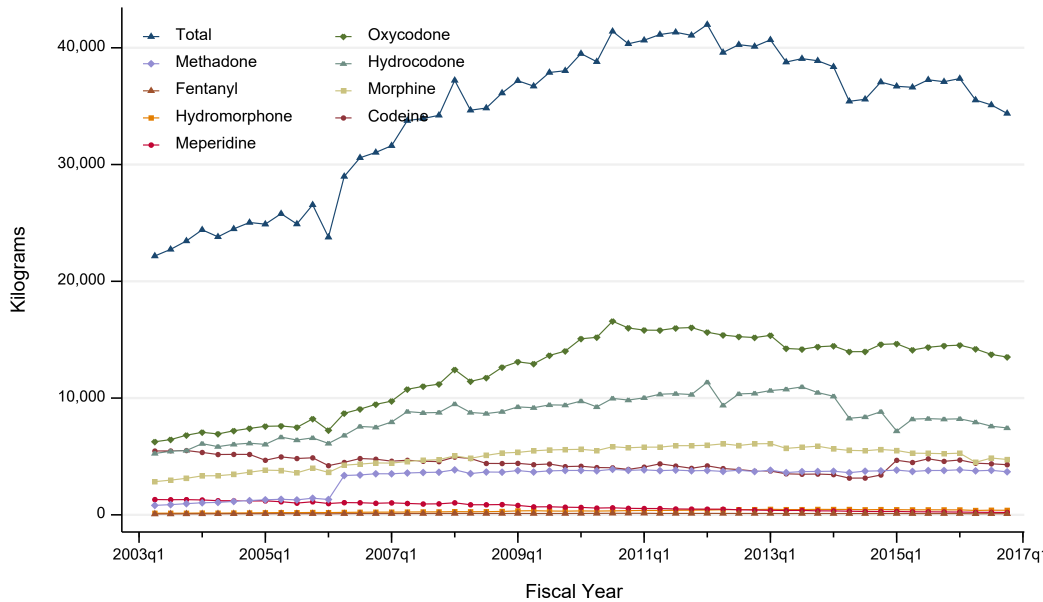
Table A 3.2. Summary Statistics for Morphine Milligram Equivalents (FY 2003 to 2016-post 2002 PDMP States)

	mean	sd	min	max
Meperidine	44,435,682	22,875,465	13,364,671	83,787,288
Codeine	359,221,600	52,603,819	263,504,399	471,365,837
Hydromorphone	851,341,152	299,501,253	338,174,638	1,261,722,892
Morphine	2,964,058,467	536,502,885	1,742,725,996	3,628,251,791
Fentanyl	4,673,627,095	620,678,667	3,084,927,059	5,756,942,610
Hydrocodone	4,619,324,917	841,946,955	3,004,314,236	6,063,603,619
Methadone	5,738,429,310	1,804,810,487	1,579,079,867	7,065,918,091
Oxycodone	11,855,106,732	3,098,529,615	6,068,069,108	17,051,497,191
Total Opioids	31,088,709,369	6,718,537,089	16,372,444,028	39,760,332,074

Source: Drug Enforcement Administration Automated Reports and Consolidated Ordering System (ARCOS) Retail Drug Summary Reports

- Notes: There are 448 drug*quarter observations. MME conversion calculated using Centers for Medicare and Medicaid Services Opioid Oral Morphine Milligram Equivalent (MME) Conversion Factors, dated August 2017. Document found at https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Opioid-Morphine-EQ-Conversion-Factors-Aug-2017.pdf

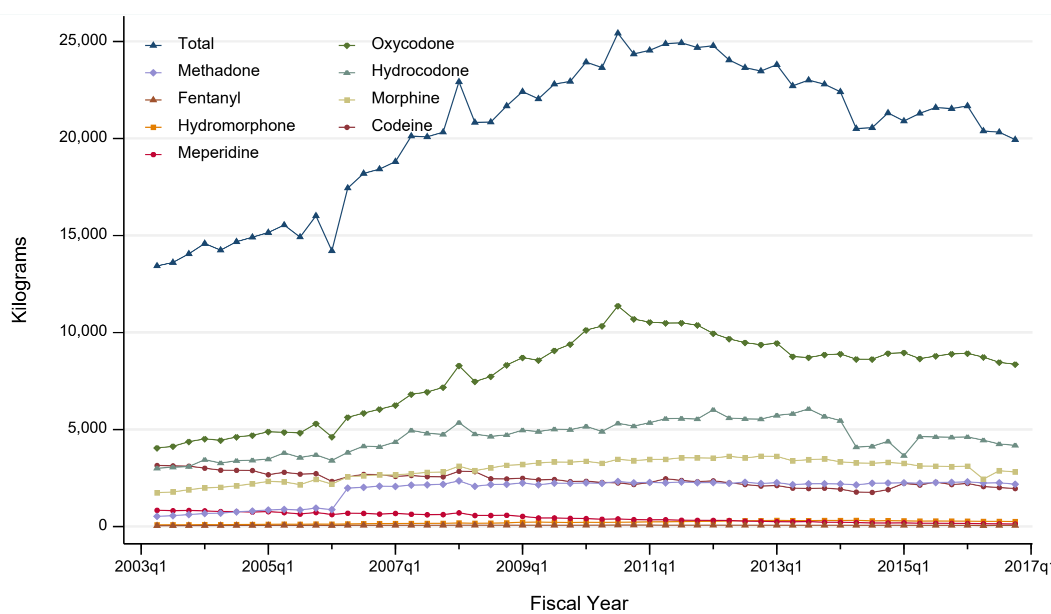
Table A 3.3. Opioids in Kilograms (FY 2003 to FY 2016-all states)



Source: DEA ARCOS Retail Drug Summary Reports

Note: Change in methadone quantities reflects the DEA including opiate (heroin) treatment programs (OTPs) in distribution data beginning in 2006.

Table A 3.4. Opioids in Kilograms (FY 2003 to FY 2016-post 2002 PDMP states)



Source: DEA ARCOS Retail Drug Summary Reports

Note: Change in methadone quantities reflects the DEA including opiate (heroin) treatment programs (OTPs) in distribution data beginning in 2006.

Table A 3.5. Summary Statistics for Morphine Milligram Equivalents per person (FY 2003 to 2016)

	mean	sd	min	max
Meperidine	0.29	0.16	0.08	0.57
Codeine	2.68	0.43	1.84	3.60
Hydromorphone	5.26	1.61	2.42	7.50
Morphine	20.09	3.26	12.40	24.18
Fentanyl	32.15	3.75	22.82	39.29
Hydrocodone	34.29	6.03	22.92	45.15
Methadone	38.52	12.32	10.63	47.58
Oxycodone	74.79	17.68	40.92	100.74
Total Opioids	208.07	40.96	116.26	259.07

Source: Drug Enforcement Administration Automated Reports and Consolidated Ordering System (ARCOS) Retail Drug Summary Reports

- Notes: There are 448 drug*quarter observations. MKE conversion calculated using Centers for Medicare and Medicaid Services Opioid Oral Morphine Milligram Equivalent (MME) Conversion Factors, dated August 2017. Document found at https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Opioid-Morphine-EQ-Conversion-Factors-Aug-2017.pdf

Table A 3.6. Summary Statistics for Morphine Milligram Equivalents per person (FY 2003 to 2014-post 2002 PDMP States)

	mean	sd	min	max
Meperidine	0.31	0.17	0.09	0.62
Codeine	2.46	0.46	1.72	3.46
Hydromorphone	5.72	1.84	2.48	8.30
Morphine	20.10	3.13	12.79	24.08
Fentanyl	31.83	3.72	22.65	38.64
Hydrocodone	31.64	4.97	22.05	39.94
Methadone	38.66	11.60	11.59	48.83
Oxycodone	80.00	19.14	44.54	115.41
Total Opioids	210.66	40.87	120.19	269.10

Source: Drug Enforcement Administration Automated Reports and Consolidated Ordering System (ARCOS) Retail Drug Summary Reports

- Notes: There are 448 drug*quarter observations. MKE conversion calculated using Centers for Medicare and Medicaid Services Opioid Oral Morphine Milligram Equivalent (MME) Conversion Factors, dated August 2017. Document found at https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Opioid-Morphine-EQ-Conversion-Factors-Aug-2017.pdf

Table A 3.7. Summary Statistics for County*Quarters (FY 2006 to 2014-All States)

	mean	sd	min	max
Outcome Variables (number per county-quarter):				
Total Applicants	91.61	142.58	0.00	808.00
Not Qualified	16.95	27.72	0.00	179.00
Not Interested	20.32	31.96	0.00	271.00
Contracted	57.11	89.07	1.00	485.00
Contracted but DEP Loss	5.60	9.75	0.00	76.00
Contracted and Accessed	48.74	78.72	0.00	432.00
Explanatory Variables (fraction unless noted):				
Unemployment Rate	0.07	0.03	0.01	0.32
Employment to Population Ratio	0.39	0.13	0.00	2.18
Veteran	0.09	0.03	0.02	0.44
Black	0.13	0.13	0.00	0.86
Hispanic	0.16	0.16	0.00	0.97
Poor	0.15	0.05	0.02	0.62
Civilian Earnings (in $1000s)	4.23	0.63	1.76	6.94
Median Household Income (in $1000s)	52.54	13.87	16.87	125.64

Source: Office of Economic and Manpower Analysis and US Army Recruiting Command

- All explanatory variables are weighted by county adult populations

- Notes: Individual Applicant for Army service data from 200510 to 201309 (FY 2006 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 109,541 county*quarter observations.

Table A 3.8. Table Summary Statistics for County*Quarters (FY 2006 to 2014-Post 2006 PDMP Implementation States)

	mean	sd	min	max
Outcome Variables (number per county-quarter):				
Total Applicants	52.74	81.25	0.00	675.00
Not Qualified	9.11	13.76	0.00	128.00
Not Interested	12.17	20.31	0.00	191.00
Contracted	33.52	51.72	1.00	420.00
Contracted but DEP Loss	3.06	5.34	0.00	60.00
Contracted and Accessed	28.39	45.85	0.00	391.00
Explanatory Variables (fraction unless noted):				
Unemployment Rate	0.07	0.03	0.01	0.30
Employment to Population Ratio	0.41	0.13	0.00	2.18
Veteran	0.10	0.03	0.03	0.43
Black	0.15	0.15	0.00	0.86
Hispanic	0.11	0.12	0.00	0.90
Poor	0.14	0.05	0.02	0.62
Civilian Earnings (in $1000s)	4.16	0.61	1.76	6.94
Median Household Income (in $1000s)	51.80	14.30	16.87	125.64

Source: Office of Economic and Manpower Analysis and US Army Recruiting Command

- All explanatory variables are weighted by county adult populations.

- Notes: Individual Applicant for Army service data from 200510 to 201309 (FY 2006 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 109,541 county*quarter observations.

Table A 3.9. Composition of Applicants-Summary Statistics for County*Quarters (FY 2006 to 2014-All States)

	Applicants	Not Interested	Not Qualified	DEP Loss	Accessions
Number per cnty*qtr.	91.61	20.32	16.95	5.60	48.74
	(142.58)	(31.96)	(27.72)	(9.75)	(78.72)
Composition (fraction):					
High-quality	0.49	0.56	0.16	0.55	0.56
	(0.18)	(0.25)	(0.21)	(0.33)	(0.21)
Male	0.82	0.80	0.77	0.76	0.85
	(0.12)	(0.19)	(0.21)	(0.28)	(0.13)
Black	0.19	0.17	0.27	0.19	0.18
	(0.19)	(0.21)	(0.28)	(0.27)	(0.20)
High School Graduate	0.88	0.85	0.87	0.90	0.90
	(0.14)	(0.20)	(0.20)	(0.20)	(0.14)
Medical Test Failure	0.11	0.00	0.28	0.17	0.10
	(0.11)	(0.00)	(0.26)	(0.24)	(0.12)
Drug Test Failure	0.01	0.00	0.02	0.06	0.01
	(0.03)	(0.00)	(0.08)	(0.15)	(0.03)
AFQT	53.03	52.56	25.58	42.61	55.78
	(11.89)	(22.26)	(16.14)	(27.56)	(16.50)

Source: Office of Economic and Manpower Analysis and US Army Recruiting Command

- Standard Deviation in parentheses

- All values are weighted by county 15 to 24-year-old population.

- Notes: Individual Applicant for Army service data from 200510 to 201309 (FY 2006 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 109,541 county*quarter observations.

Table A 3.10. Composition of Active Duty Soldiers-Summary Statistics for County*Quarters (FY 2006 to 2014)

	mean	sd	min	max
Demographics				
Age at Contract Date	21.59	1.63	17.00	42.00
Female	0.16	0.14	0.00	1.00
Black	0.18	0.21	0.00	1.00
Hispanic	0.13	0.17	0.00	1.00
Married	0.15	0.15	0.00	1.00
Family (spouse or children)	0.33	0.33	0.00	7.00
Soldier Quality				
High-quality (AFQT > 50 & High School Graduate)	0.54	0.22	0.00	1.00
Low-quality (AFQT < 50 or High School Dropout)	0.43	0.21	0.00	1.00
Armed Forces Qualification Test percentile	59.18	8.30	10.00	99.00
AFQT Categories (% of subpopulation):				
TSC I: > 99 AFQT > 93	0.06	0.09	0.00	1.00
TSC II: 93 > AFQT > 65	0.33	0.19	0.00	1.00
TSC IIIA: 65 > AFQT > 50	0.26	0.17	0.00	1.00
TSC IIIB: 50 > AFQT > 31	0.34	0.20	0.00	1.00
TSC IV & V: 1 > AFQT > 30	0.02	0.06	0.00	1.00
Education (% of subpopulation):				
High School Graduate	0.74	0.20	0.00	1.00
GED	0.12	0.17	0.00	1.00
Some College	0.06	0.09	0.00	1.00
Bachelor's Degree	0.04	0.08	0.00	1.00
Associate's Degree	0.02	0.05	0.00	1.00
Graduate Degree	0.00	0.02	0.00	1.00
High School Dropout	0.00	0.03	0.00	1.00
Military Career				
Length of Enlistment Contract (years)	3.72	0.40	2.00	6.00
Career Length (years)	4.28	1.38	0.07	14.89
Sergeant Major	0.00	0.00	0.00	0.14
Enlisted Rank Achieved:				

Private	0.08	0.11	0.00	1.00
Private 2	0.08	0.11	0.00	1.00
Private First Class	0.11	0.12	0.00	1.00
Specialist	0.44	0.20	0.00	1.00
Sergeant	0.20	0.16	0.00	1.00
Staff Sergeant	0.07	0.10	0.00	1.00
Sergeant First Class	0.01	0.05	0.00	1.00
Master Sergeant	0.00	0.01	0.00	1.00
Months to E4 Promotion	12.78	3.02	0.00	101.84
Months to E5 Promotion	26.96	8.19	0.89	152.72
Did not complete initial enlistment term	0.36	0.19	0.00	1.00
Bar to Reenlist	0.02	0.06	0.00	1.00
Body Mass Index	25.20	1.48	14.50	45.83
Substance Abuse and Medical Problems at MEPS:				
Medical Problems	0.09	0.12	0.00	1.00
Drug Test Failure	0.01	0.04	0.00	1.00
Marijuana Test Failure	0.01	0.04	0.00	1.00
Cocaine Test Failure	0.00	0.01	0.00	1.00
Alcohol Test Failure	0.00	0.00	0.00	1.00
Reasons for Separation:				
Completed Terms of Service	0.30	0.19	0.00	1.00
Reenlists	0.19	0.18	0.00	1.00
Medical Physical Procedure	0.04	0.08	0.00	1.00
Entry Performance	0.04	0.09	0.00	1.00
Misconduct (Drug-related)	0.04	0.08	0.00	1.00
Disability	0.03	0.07	0.00	1.00
Serious Misconduct	0.04	0.07	0.00	1.00
Temporary Disabled	0.03	0.06	0.00	1.00
Non-Disability Condition	0.04	0.08	0.00	1.00
Parenthood	0.03	0.06	0.00	1.00
Pattern of Misconduct	0.02	0.06	0.00	1.00
Separation in lieu of Courts-Martial	0.02	0.06	0.00	1.00
Permanently Disabled	0.03	0.06	0.00	1.00
Disabled (combat)	0.01	0.04	0.00	1.00
Disabled (non-combat)	0.01	0.04	0.00	1.00
Physical Standards	0.01	0.05	0.00	1.00
Personality Disorder	0.01	0.03	0.00	1.00

Weight	0.01	0.04	0.00	1.00
Economic Hardship	0.01	0.04	0.00	1.00
Unsatisfactory Performance	0.01	0.04	0.00	1.00
Courts-Martial	0.00	0.03	0.00	1.00
Deserter	0.00	0.02	0.00	1.00

Source: Office of Economic and Manpower Analysis

- Notes: Individual Applicant for Army service data from 200210 to 201409 (FY 2003 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 92,111 county*quarter observations.

Table A 3.11. Summary Statistics for Active Duty Soldiers (FY 2003 to 2014-post 2002 PDMP counties)

	mean	sd	min	max
Demographics				
Age at Contract Date	21.51	1.70	17.00	42.00
Female	0.17	0.16	0.00	1.00
Black	0.21	0.24	0.00	1.00
Hispanic	0.08	0.14	0.00	1.00
Married	0.15	0.15	0.00	1.00
Family (spouse or children)	0.33	0.36	0.00	7.00
Soldier Quality				
High-quality (AFQT > 50 & High School Graduate)	0.54	0.23	0.00	1.00
Low-quality (AFQT < 50 or High School Dropout)	0.43	0.23	0.00	1.00
Armed Forces Qualification Test percentile	59.35	9.00	17.00	99.00
TSC I: > 99 AFQT > 93	0.06	0.10	0.00	1.00
TSC II: 93 > AFQT > 65	0.33	0.21	0.00	1.00
TSC IIIA: 65 > AFQT > 50	0.26	0.19	0.00	1.00
TSC IIIB: 50 > AFQT > 31	0.34	0.22	0.00	1.00
TSC IV & V: 1 > AFQT > 30	0.02	0.07	0.00	1.00
Education (% of subpopulation):				
High School Graduate	0.74	0.21	0.00	1.00
GED	0.13	0.18	0.00	1.00
Some College	0.06	0.10	0.00	1.00
Bachelor's Degree	0.04	0.08	0.00	1.00
Associate's Degree	0.02	0.06	0.00	1.00
Graduate Degree	0.00	0.02	0.00	1.00
High School Dropout	0.00	0.03	0.00	1.00
Military Career				
Length of Enlistment Contract (years)	3.75	0.43	2.00	6.00
Career Length (years)	4.31	1.47	0.07	14.89
Sergeant Major	0.00	0.00	0.00	0.00
Enlisted Rank Achieved:				
Private	0.07	0.12	0.00	1.00

Private 2	0.08	0.12	0.00	1.00
Private First Class	0.11	0.13	0.00	1.00
Specialist	0.44	0.22	0.00	1.00
Sergeant	0.20	0.17	0.00	1.00
Staff Sergeant	0.07	0.11	0.00	1.00
Sergeant First Class	0.01	0.05	0.00	1.00
Master Sergeant	0.00	0.01	0.00	1.00
Months to E4 Promotion	12.91	3.30	0.00	99.80
Months to E5 Promotion	27.06	8.90	0.89	129.74
Did not complete initial enlistment term	0.37	0.21	0.00	1.00
Bar to Reenlist	0.02	0.06	0.00	1.00
Body Mass Index	25.13	1.59	14.50	45.83
Substance Abuse and Medical Problems at MEPS:				
Medical Problems	0.09	0.13	0.00	1.00
Drug Test Failure	0.01	0.04	0.00	1.00
Marijuana Test Failure	0.01	0.04	0.00	1.00
Cocaine Test Failure	0.00	0.01	0.00	1.00
Alcohol Test Failure	0.00	0.00	0.00	1.00
Reasons for Separation:				
Completed Terms of Service	0.28	0.20	0.00	1.00
Reenlists	0.19	0.19	0.00	1.00
Medical Physical Procedure	0.04	0.09	0.00	1.00
Entry Performance	0.04	0.09	0.00	1.00
Misconduct (Drug-related)	0.04	0.08	0.00	1.00
Disability	0.04	0.08	0.00	1.00
Serious Misconduct	0.04	0.08	0.00	1.00
Temporary Disabled	0.03	0.07	0.00	1.00
Non-Disability Condition	0.04	0.09	0.00	1.00
Parenthood	0.03	0.07	0.00	1.00
Pattern of Misconduct	0.02	0.07	0.00	1.00
Separation in lieu of Courts-Martial	0.02	0.06	0.00	1.00
Permanently Disabled	0.03	0.07	0.00	1.00
Disabled (combat)	0.01	0.04	0.00	1.00
Disabled (non-combat)	0.01	0.04	0.00	1.00
Physical Standards	0.01	0.05	0.00	1.00
Personality Disorder	0.01	0.03	0.00	1.00
Weight	0.01	0.05	0.00	1.00

Economic Hardship	0.01	0.04	0.00	1.00
Unsatisfactory Performance	0.01	0.05	0.00	1.00
Courts-Martial	0.00	0.03	0.00	1.00
Deserter	0.00	0.03	0.00	1.00

Source: Office of Economic and Manpower Analysis

- Notes: Individual Applicant for Army service data from 200210 to 201409 (FY 2003 to FY 2014). Only states with PDMP Implementation after 2000. Excludes NY, TX, OK, PA, TN, WV, HI, UT, NV, ID, MI, KY, IL, RI, CA, IN, MA and overseas recruiting stations. There are 55,351 county*quarter observations.

Table A 3.12. Individual reasons for Separation (broken out from grouped types in Table 3.5)

	All States	Post-2002 PDMP States
	mean	mean
Medical Physical Procurement Standards	0.04	0.04
Entry Level Performance and Conduct	0.05	0.05
Misconduct (Drugs)	0.04	0.03
Disability	0.03	0.03
Misconduct (serious)	0.04	0.02
Disability (temporary)	0.03	0.01
Non-Disability Conditions	0.04	0.04
Parent	0.03	0.02
Pattern of Misconduct	0.02	0.02
In Lieu of Courts-Martial	0.02	0.00
Disability (permanent)	0.03	0.02
Disability (combat)	0.01	0.01
Disability (non-combat)	0.01	0.01
Physical Standards	0.01	0.01
Personality Disorder	0.01	0.01
Weight	0.01	0.01
Economic	0.01	0.01
Unsatisfactory Performance	0.01	0.01
Courts-Martial	0.00	0.00
Deserter	0.00	0.03
Misconduct Problems	0.06	0.04
AWOL	0.00	0.00
Disability (prior to service)	0.00	0.00
Reduction in Force	0.01	0.01
Non-Retention	0.01	0.00
Misconduct (civil conviction)	0.00	0.00
Misconduct (other)	0.00	0.00
Drug Rehabilitation Failure	0.00	0.00
Alcohol Rehabilitation Failure	0.00	0.00
Officer	0.01	0.01
Attend Civilian School	0.01	0.01

Source: Office of Economic and Manpower Analysis
- Notes: Individual Applicant for Army service data from 200210 to 201409 (FY 2003 to FY 2014). Excludes applicants from Hawaii, Alaska, and overseas recruiting stations. There are 92,111 county*quarter observations for the full sample and 55,300 for the partial sample.

Figure A 3.1 Effect of PDMP on Applicants to Army (Reduced Form)

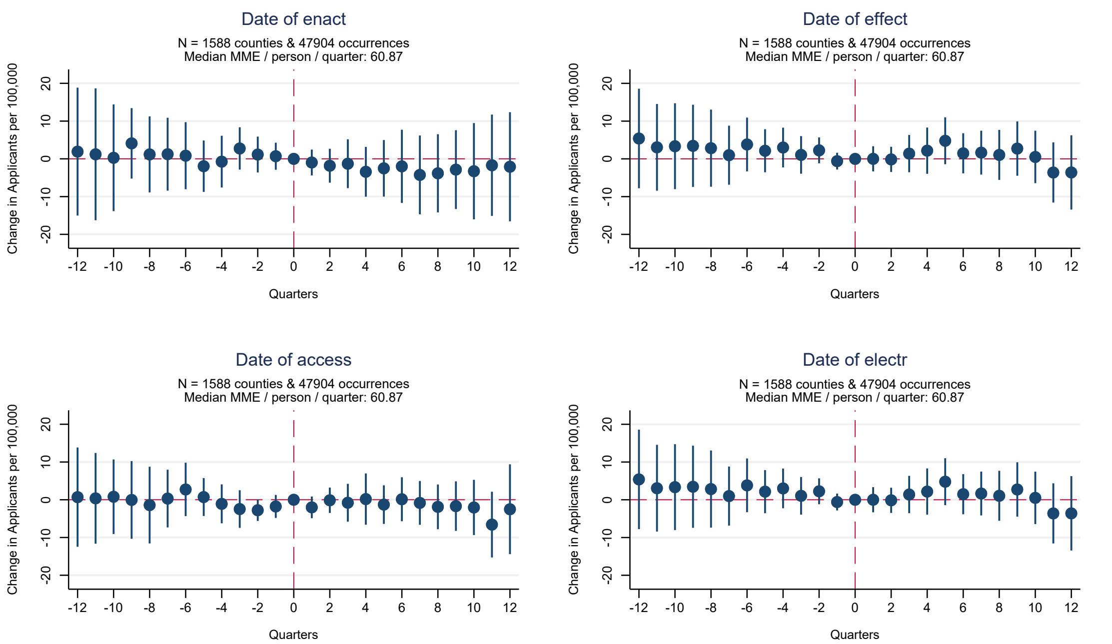


Figure A 3.2 Effect of PMDP on Accessions to Army (Reduced Form)

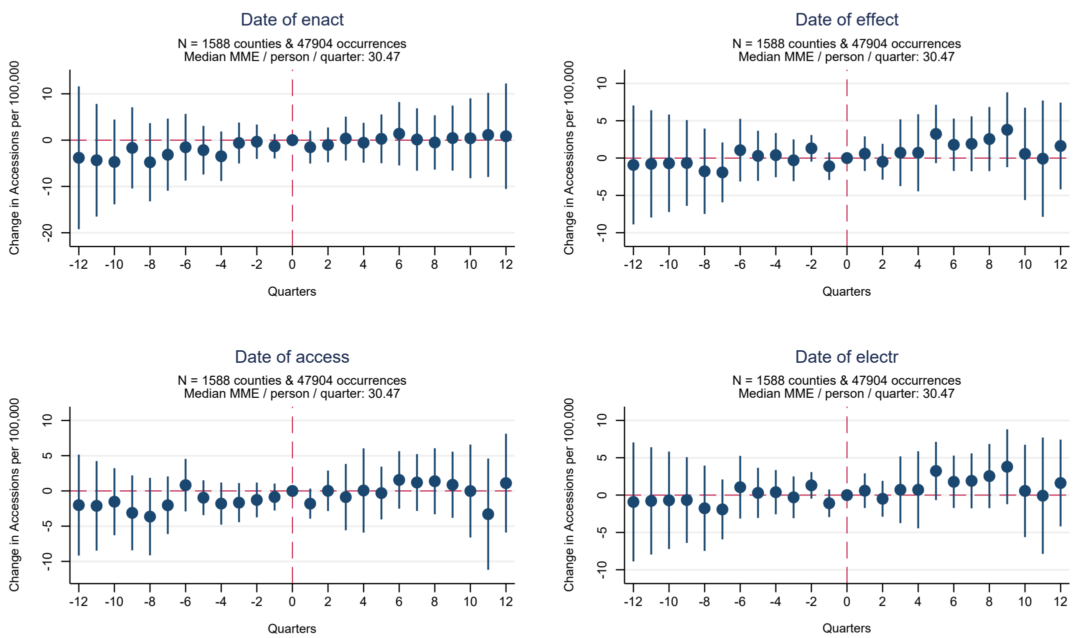


Figure A 3.3 Effect of PDMP on First-Term Separations (Reduced Form)

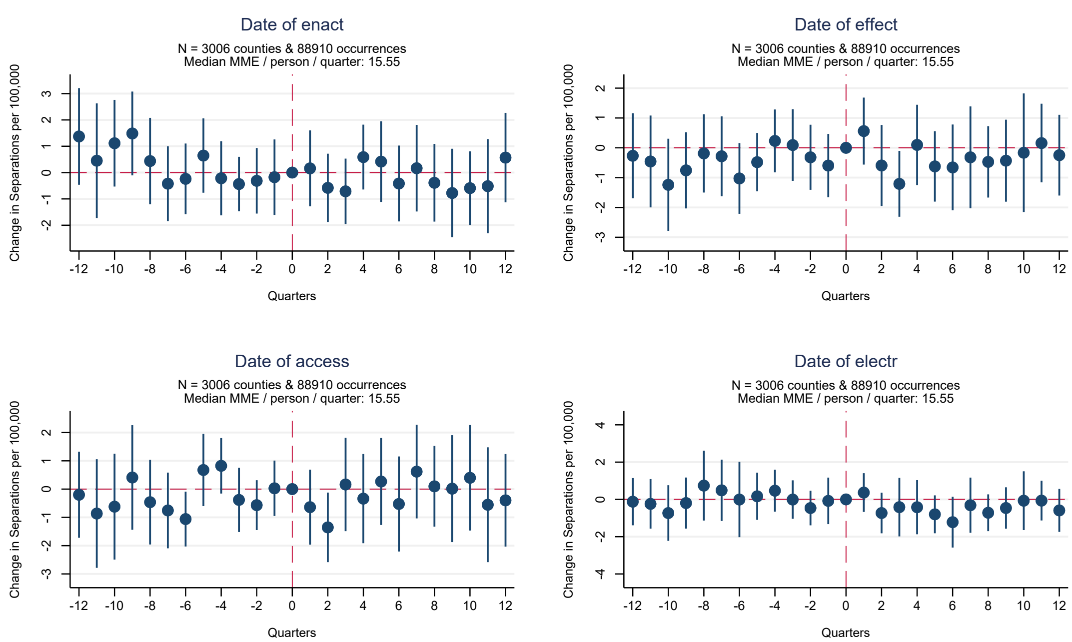


Figure A 3.4 Effect of PDMP on First-Term Completions (Reduced Form)

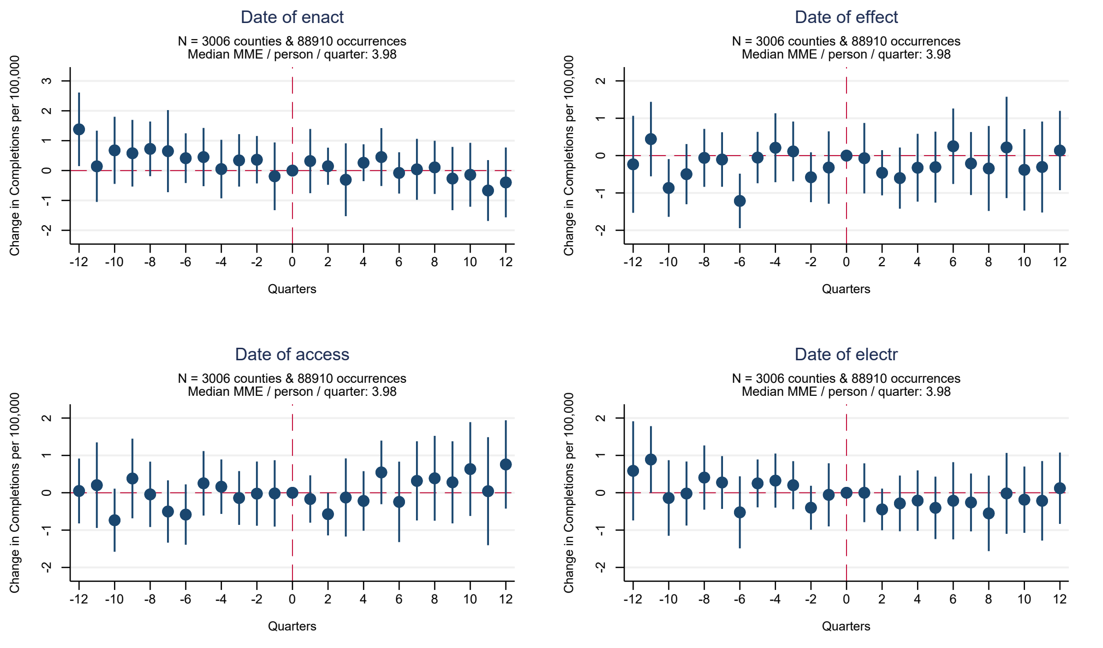


Figure A 3.5 Effect of PDMP on First-Term Reenlistments (Reduced Form)

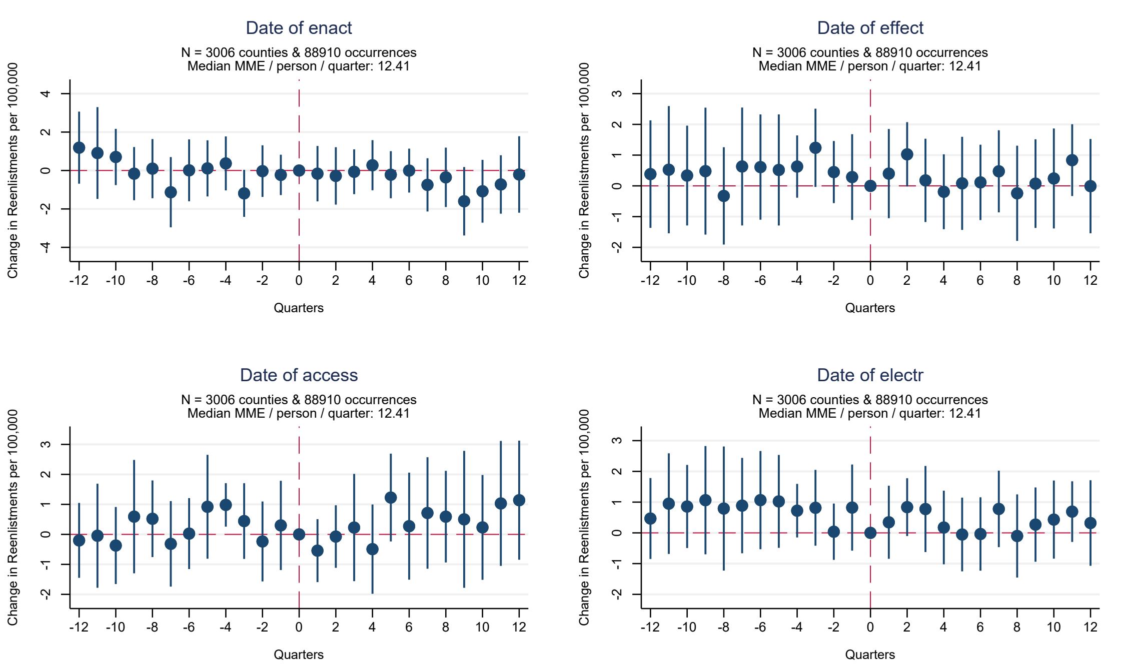


Table A 3.13 Effect of Opioid use per capita on reasons for separation from active duty (OLS and 2SLS) - Dependent Variable (per 100,000 15 to 24-year old)

	(1)	(2)	(3)	(4)
Dependent Variable (in order of frequency)				
Entry Performance	0.558***	0.493***	0.540***	-1.501
(mean: 3.43)	(0.133)	(0.123)	(0.110)	(1.779)
Disability during service	0.284***	0.214***	0.258**	0.220
(mean: 2.46)	(0.0926)	(0.0624)	(0.101)	(1.259)
Physical conditions	0.373**	0.282*	0.394**	0.693
(mean: 2.40)	(0.162)	(0.139)	(0.147)	(1.565)
Substance Abuse	0.201*	0.137	0.131	-0.388
(mean: 1.42)	(0.107)	(0.0833)	(0.121)	(0.925)
Misconduct	0.101	0.0428	0.109*	0.662
(mean: 1.74)	(0.0616)	(0.0500)	(0.0568)	(0.988)
Economic or Family Hardship	0.0931	0.107*	0.143**	-1.340
(mean: 1.30)	(0.0580)	(0.0564)	(0.0686)	(1.219)
Unauthorized Absence	-0.0615	-0.0450	0.0186	-0.951
(mean: 1.07)	(0.0653)	(0.0610)	(0.0791)	(1.394)
Selected for removal to downsizing	0.0883**	0.0912**	0.0818	0.810
(mean: 0.50)	(0.0420)	(0.0405)	(0.0483)	(0.723)
Legal Jeopardy (courts-martial, etc.)	0.00716	-0.00402	-0.0168	-0.0532
(mean: .18)	(0.0157)	(0.0162)	(0.0170)	(0.184)
State Linear Trend	No	Yes	Yes	Yes
State Quadratic Trend	No	No	Yes	Yes
2SLS (PDMP Effective Date)	No	No	No	Yes
F (excluded instruments)				20.29
Observations	53236	53236	53236	51510

- All regressions weighted by county populations. Standard errors are in parentheses and clustered at county-level for OLS specifications and state-level for the IV specification. All specifications include county and year fixed effects. Unemployment rate, median household income, population 15 to 24-year old, fraction veteran, black, female, and poor are controls. All specifications include only states with PDMP implementation after 2002-excludes NY, TX, OK, PA, TN, WV, HI, UT, NV, ID, MI, KY, IL, RI, CA, IN, MA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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