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THESIS

**CORRELATIONS BETWEEN LOCAL HEALTH
CONDITIONS AND MILITARY ACCESSIONS**

by

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**CORRELATIONS BETWEEN LOCAL HEALTH CONDITIONS
AND MILITARY ACCESSIONS**

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Submitted in partial fulfillment of the
requirements for the degree of

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ABSTRACT

This thesis studies the correlation between annual military accessions and local disease burden using county-level data from 2016 to 2019. One of the biggest challenges the military faces today is maintaining a healthy, professional, and strong military appropriately equipped—mentally, physically, and emotionally—to complete assigned missions and tasks. The worsening prevalence of obesity and other underlying diseases in the civilian population significantly affects the total number of successful military accessions each year, primarily due to the U.S. military force consisting of mostly young adults. To better understand how the variations in disease burdens affects military accessions, I measure local disease burdens using health conditions such as obesity, diabetes, mental health, and vision defects, and military accessions for all services at the county level. In my results, I find that the military mainly draws its accessions from unhealthier parts of the United States even after controlling for differences in income and education across counties. Therefore, my findings indicate that the military still draws many of its accessions from parts of the county with worse underlying disease burdens. These findings have important implications for future medical policy design and entry into the U.S. military.

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LIST OF ACRONYMS AND ABBREVIATIONS

AFQT	Armed Forces Qualification Test
ASVAB	Armed Services Vocational Aptitude Battery
BMI	Body Mass Index
CDC	Center for Disease Control and Prevention
DOD	Department of Defense
DoDMERB	Department of Defense Medical Examination Review Board
EPTS	Existed Prior to Service
F.Q.	Fully Qualified
MEPS	Military Entrance Processing Stations
NCHS	National Center for Health Statistics
NHANES	National Health and Nutrition Examination Survey
NRC	National Research Council
NSDUH	National Survey on Drug Use and Health
PQD	Permanent Medical Disqualification
SAMHSA	Substance Abuse and Mental Health Services Administration
SMWRA	Service Medical Waiver Review Authority
T2DM	Type 2 Diabetes Mellitus
TDQ	Temporary Medical Disqualification
USMEPCOM	U.S. Military Entrance Processing Command

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To my husband, thank you for always encouraging me to pursue my dreams and uplifting me throughout this thesis process. If it weren't for you, I might never have left my desk (or even the house, for that matter) over the last several months. I relied on my mother and sister more than they know, expelling my frustrations onto them about late nights and early mornings spent working and reworking my research—this meant the world to me.

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I. INTRODUCTION

In this thesis, I study the correlation between underlying health conditions and military accessions. More specifically, I look at the regional prevalence of some of the top medical disqualifiers for military accessions, such as obesity, diabetes, depression, and myopia (Washington et al., 2019), and their correlation with military accessions. I examine these conditions by combining county-level demographic and health data with military accession data and address the following research questions:

- Is there a correlation between prevalence of health conditions (such as obesity, diabetes, mental health and depression, and vision defects) and military accession rates at the county level?
- Is there a correlation between social and economic conditions and military accession rates at the county level?

For the purpose of this analysis, I define “accession” as the number of applicants who successfully passed the medical screening process and joined the U.S. military active-duty services (with or without a waiver). For the health condition measures, I pay particular attention to the U.S. youth population throughout my research because most military accessions consist of young adults recruited after completing their high school education and have earned their General Educational Diploma.

One of the biggest challenges the United States (U.S.) military faces today is its ability to maintain a healthy, professional, and strong military that is able (physically and mentally) to take on the demands of war (Yamane, 2007). Although the battlefield has changed dramatically over the last several decades, many of our military’s medical standards have mainly remained the same. A re-examination of medical disqualification standards in the application process for military enlistment might be in order, for the Department of Defense (DOD) as the prevalence of underlying health diseases such as obesity, mental health issues, depression, diabetes, and vision defects continue to increase among the U.S. population. Another obstacle for the DOD is getting applicants through the medical examination process—conducted at a Military Entrance Processing Station

(MEPS)—where it has become increasingly difficult to find fully qualified individuals able to serve. However, applicants can access with a medical waiver if they did not meet all the medical standards required during their first screening process.

The literature surrounding these underlying illnesses (i.e., obesity, diabetes, depression, and myopia) all suggest the prevalence to be increasing over the past several years, which is indicative of a worsening healthful nation (for example, Hedley et al., 2004; Li et al., 2016; Otto et al. 2006; Twenge et al., 2019). This rapidly increasing rate of underlying diseases in the U.S.—especially in the South, where a large part of the military draws its accessions—makes an already difficult task that much more challenging (Barker et al., 2011).

In my results, I find that the military mainly draws its accessions from unhealthier parts of the United States. For example, higher rates of obesity, diabetes, smoking, and lower rates of income are significantly correlated with military accessions per 10,000 people. Since these correlations remain significant even after controlling for economic conditions such as county-level income and education, this shows that the military is recruiting and accessing individuals from generally unhealthier parts of the United States. So, it is not just that the overall population is getting unhealthier, which may also be correct, but that the military is also drawing from parts of the county with worse underlying disease burdens.

II. INSTITUTIONAL BACKGROUND

In this chapter, I focus on identifying the top medical disqualifiers for all U.S. armed service branches looking at the last four years of Accession Medical Standards Analysis and Research Activity (AMSARA) reports (Boivin et al., 2016; Maby et al., 2017; Washington et al., 2018; Washington et al., 2019). Then I review current research on spatial variation among the identified leading medical disqualifiers to see how these disease rates compare across the United States and where the military is drawing their accessions.

Based on the latest AMSARA Annual Report (2019), about 72% of applicants for active, reserve, and the National Guard from 2013 to 2018 accessed into the military (Washington et al., 2019, p. 1). With almost 30% of applicants not applying for a waiver, this only further intensifies one of the significant difficulties the military faces in finding fully qualified individuals interested in joining the military (p. 3). Among active-duty applicants in 2018, 86% of disqualifications consisted of permanent medical disqualification (PQD) conditions that require a medical waiver for accession (p. 3). Among these PQD applicants, approximately 68% of active-duty applicants with a PQD waiver chose to apply (and were considered) for a medical waiver (p. 14). The success rate of those who applied for the medical waiver was 80% for active-duty applicants (p. 2).

Additionally, the 2019 AMSARA report categorizes someone as an Existed Prior to Service (EPTS) Discharge based on having been discharged within 180 days of service because of a preexisting medical condition (p. 8). The most common reasons for EPTS discharge, as outlined in the 2019 AMSARA annual report, were due to psychiatric and orthopedic conditions accounting for almost half of all discharges among all 2013–2018 enlisted accessions in the Army, Navy, Marine Corps, and Air Force (Washington et al., 2019, Table 36). Additionally, they reported that mood, anxiety, and adjustment disorders appeared in the top ten leading conditions among EPTS discharges for the Army, Navy, and Marine Corps (p. 45).

In the 2018 AMSARA annual report, the leading medical disqualifications of first-term enlisted active component applications from 2012–2016 compared to 2017 showed

that the most common PQD was for vision defects. The prevalence rate of vision defects increased slightly (from 2,012 to 2,958 per 100,000 applicants) in 2017 compared to the previous five years (Washington et al., 2018, p. 29). The same report states that the most frequent temporary medical D.Q. (TDQ) in 2017 were due to nutritional, endocrine, and metabolic disorders—a category including primarily weight-related disqualifications (i.e., obesity). The prevalence rate had decreased compared to the previous five-year period with 3,936 per 100,000 applicants instead of 4,865 per 100,000 applicants. Additionally, the second most common TDQ in 2017 was substance abuse. The substance abuse category consists mostly of those individuals who participate in cannabis and amphetamine use.

The 2017 AMSARA annual report states the top three medical conditions for PDQs in 2016 (listed in order) were nutritional, endocrine, and metabolic disorders (i.e., obesity and diabetes); vision defects—comprised mainly of refraction and accommodation; and substance-related disorders for all active-duty components (Maby et al., 2017, p. 8). Similarly, the National Research Council (NRC) stated the top five medical disqualifiers (accounting for over half of all medical disqualifications between 2003 and 2005) were body mass index (BMI), marijuana use, mental health issues, lower extremity injuries, and lung disease (*Assessing Fitness for Military Enlistment*, 2006, p. 109).

Studies on spatial variation for mental health and vision defects are limited; to some extent, this could be due to little understanding of these topics until recently, when technology has provided more ways to analyze the brain and negative impacts of technology on our vision. Most of my spatial variation research focuses on obesity and diabetes since these are underlying disease burdens commonly studied in the United States (Barker et al., 2011; Congdon, 2017; Li et al., 2016; Michimi & Wimberly, 2010; Mills et al., 2020; Myers et al., 2015; Shrestha et al., 2012).

What I have learned from these studies and the 2016 to 2019 AMSARA reports is that not only are the rates of underlying disease burdens increasing, but these rates are significantly different across various locations in the United States (Boivin et al., 2016; Maby et al., 2017; Washington et al., 2018; Washington et al., 2019). Most notably, the prevalence of obesity, diabetes, depression, and myopia—explored extensively throughout my thesis—are more often found in the U.S.'s southern region than any other part of the

country (Barker et al., 2011; Congdon, 2017; Michimi & Wimberly, 2010; Mills et al., 2020; Myers et al., 2015; Thomas et al., 2019).

Comparing AMSARA reports across all four years, I found that there to be an increasing prevalence of underlying health burdens on military accessions. Although I do not directly analyze whether differences in accession rates are due to the applicant's medical conditions or geographic differences in underlying health conditions, my thesis provides further insights into these topics.

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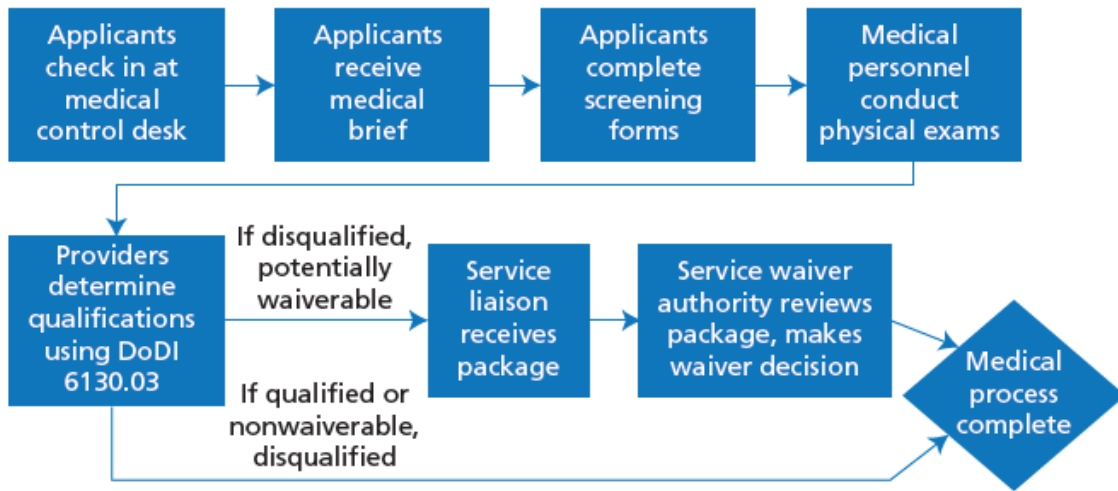
III. LITERATURE REVIEW

This chapter first outlines the U.S. Military Entrance Processing Command (USMEPCOM) medical screening process (refer to Figure 1) and several applicable DOD disqualifying conditions for enlisted military accessions relevant to my research. Each subsection explains the importance of a few of the more common underlying health diseases (i.e., obesity, mental health/depression, and eyesight) and the implications they pose for military accessions.

A. DISQUALIFYING CONDITIONS FOR MILITARY ACCESSION

The screening process to enlist in the military is an extensive process that consists of several steps, including thorough physical examinations that check for underlying health diseases such as obesity, diabetes, mental health issues (such as depression), and vision defects. USMEPCOM can administer over 300,000 medical exams for enlisted accessions per year at their 65 MEPS located across the United States (Lytell et al., 2019). Figure 1 walks through the enlistment medical application process from their first check-in at MEPS to completion. While this thesis focuses on enlisted military accessions, it is worth noting that the medical screening process is different based on the applicant's decision to apply to be an enlisted or officer servicemember.

Figure 1. The MEPS Enlisted Military Screening Process.
 Source: Lytell et al. (2019).



The applicant’s first step in completing the accession process is to complete all medical briefs and screening forms before receiving several physical exams by medical physicians. A few of these physical examinations include, but are not limited to, completing a sight and hearing test and checking urine and blood samples to check for any presence of drug abuse (Lytell et al., 2019).

As shown in Figure 1, the primary military instruction that outlines disqualifying accession conditions is DOD Instruction 6130.03: Medical Standards for Appointment, Enlistment, or Induction into the Military Services (Office of the Under Secretary of Defense for Personnel and Readiness [USD P&R], 2018). Of the many disqualifying conditions outlined in this instruction, the following are most relevant to my thesis:

1. Waist circumference exceeding 35 inches for women and 40 inches for men [indicative of obesity];
2. Fasting glucose levels greater than 100 mg/dL [indicative of diabetes];
3. History of myocardial infarction [otherwise known as a heart attack], cardiomyopathy [which is a form of heart disease that makes it harder for the heart to pump blood], cardiomegaly, hypertrophy (defined as the septal wall thickness of 15 mm or greater), or congestive heart failure;
4. Current near visual acuity of any degree that does not correct to 20/40 in the better eye, [otherwise known as farsightedness];

5. Current distant visual acuity of any degree that does not correct with glasses to at least 20/40 in each eye, [commonly referred to as nearsightedness or myopia];
6. Attention Deficit Disorders (ADD);
7. Learning disorders (e.g., dyslexia);
8. Depressive disorders;
9. Any history of substance-related and addictive disorders (except for caffeine and tobacco addictions); and
10. History of mental disorders that are reasonably expected to interfere with military performance. (USD P&R, 2018, pp. 11–44)

While this instruction provides an umbrella for general medical disqualifiers, accessing a fully qualified applicant becomes more challenging due to the additional requirements specific to each service branch. An example of this is the body fat accession standards for the Navy and Marine Corps. The Navy's body fat accession standards are that you cannot go above 23% body fat for males and 34% for females, while the Marine Corps accession standards are not to exceed 18% body fat for males and 26% for females.

If the applicant is fully qualified based on all the DOD Instruction 6130.03 criteria and all service-specific requirements, their medical screening process is complete. If not, this is where the applicant can request a medical waiver to be reviewed by the Service Medical Waiver Review Authority (SMWRA), who ultimately decides whether to grant or deny the waiver.

In the next few sub-sections, I provide a review of several of the most common underlying health diseases (i.e., obesity, diabetes, mental health/depression, and vision defects) that prevent enlisted military accessions found in the most recent AMSARA reports.

B. ASSOCIATED LITERATURE

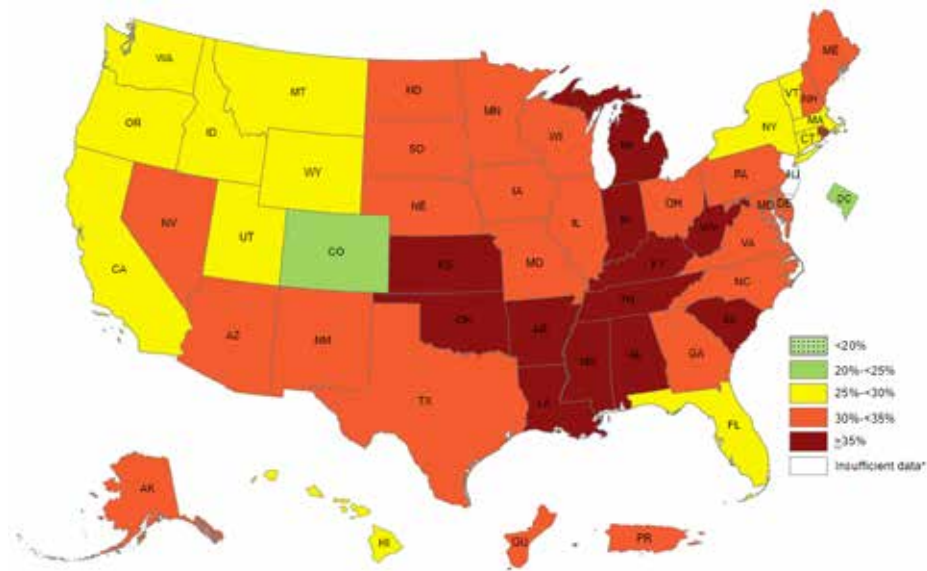
Regional differences in the prevalence of underlying diseases can provide a more in-depth understanding of whether the higher prevalence of disease burdens in military accessions is because the military is a subset of the overall U.S. population or if the military commonly recruits from unhealthier parts of the country.

A predominant theme to the literature on spatial disparities in the U.S. among underlying disease burdens is identifying the prevalence and any significant clusters of

these illnesses in the United States. Of the studies I examined, I found there are substantial spatial disparities among counties and regions regarding obesity, diabetes, mental health issues, vision defects, and associated risk factors (Congdon, 2017; Myers et al., 2015; Mills et al., 2020; Michimi & Wimberly, 2010).

Many studies estimate spatial disparities in obesity among U.S. counties (Congdon, 2017; Myers et al., 2015; Mills et al., 2020; Michimi & Wimberly, 2010). For example, Myers et al. (2015) found that in 2009 region-specific high obesity clusters accounted for 30% of counties in the South, but there were no high obesity clusters in counties in the West (p. 5). Similarly, Mills et al. (2020) found the highest level of extreme obesity (BMI ≥ 40) county-level prevalence in Southern states such as Arkansas, Alabama, and South Carolina, while counties in Western states like California, Colorado, and Massachusetts showed the lowest prevalence (p. 4). One of the reasons for geographic differences in obesity found in these studies can be explained by environmental measures such as food accessibility, living in an urban environment, and availability of resources to exercise (Congdon, 2017, pp. 6–7). Regarding food accessibility, consuming fresh fruits and vegetables is a huge factor in keeping obesity levels at bay. Michimi & Wimberly (2010) found that a large contributing factor to the higher obesity prevalence found in the South is that those living in non-metro areas (e.g., counties across the Mississippi Delta and large areas of the Great Plains) tend to consume fewer fruits and vegetables than those in West and Northeast counties (p. e3). Figure 2 displays the 2019 U.S. self-reported adult obesity prevalence map (CDC, 2020).

Figure 2. 2019 Self-Reported Adult Obesity Prevalence by U.S. State.
Source: CDC (2020).



The literature surrounding the exploration of obesity prevalence over the last several decades is extensive (for example, Hales et al., 2017; Hedley et al., 2004; Ogden et al., 2014; Yamane, 2007). Hedley et al. (2004) and Yamane (2007) found dramatic obesity rate increases in the U.S. among both children and adults with no signs of future improvement. In particular, Hedley et al. (2004) found that 65.1% of adults (aged 20 and older) were overweight (BMI=25-29.9), 30.4% were obese (BMI ≥ 30.0), and 4.9% were extremely obese (BMI ≥ 40.0) (p. 1160). Furthermore, 16% of children were identified as overweight, while 31% were at risk of being overweight (Hedley et al., 2004, p. 2850). Similarly, the proportion of obese individuals (18- to 29-year-olds, BMI ≥ 30.0) increased from 10 to 18% from 1995 to 2005 (Yamane, 2007, p. 1160); and from 1999–2000 through 2017–2018, the prevalence of obesity increased from 30.5% in 1999 to 42.2% in 2017 (Hales et al., 2020, p. 5). Therefore, the obesity prevalence rate increased by 11.7 percentage points, regardless of the Healthy People 2020 goal, which set a benchmark not to exceed a 30.5% obesity rate in America (Hales et al., 2020, p. 5).

These obesity findings pose a significant challenge for military recruiters since the number of children at risk of being overweight is double that of those already reported as

overweight. Hence, by the time these children reach recruitment age, they may already be medically disqualified. Furthermore, due to the escalating obesity rate for all individuals, if no substantial changes within DOD qualification policies occur, DOD recruiters will continue to struggle even more in finding fully qualified military accession applicants.

Contrasting studies on the obesity prevalence rate in the U.S. suggest that it could either hold or decrease over the next several decades as individuals expand their awareness of improving their overall health and wellbeing (Ogden et al., 2014). However, recent data more appropriately aligns with Hedley et al. (2004) and Yamane's (2007) findings since the Healthy People obesity target has more than doubled over the last decade from 15 to 30.6% in the United States (National Center for Health Statistics, 2012).

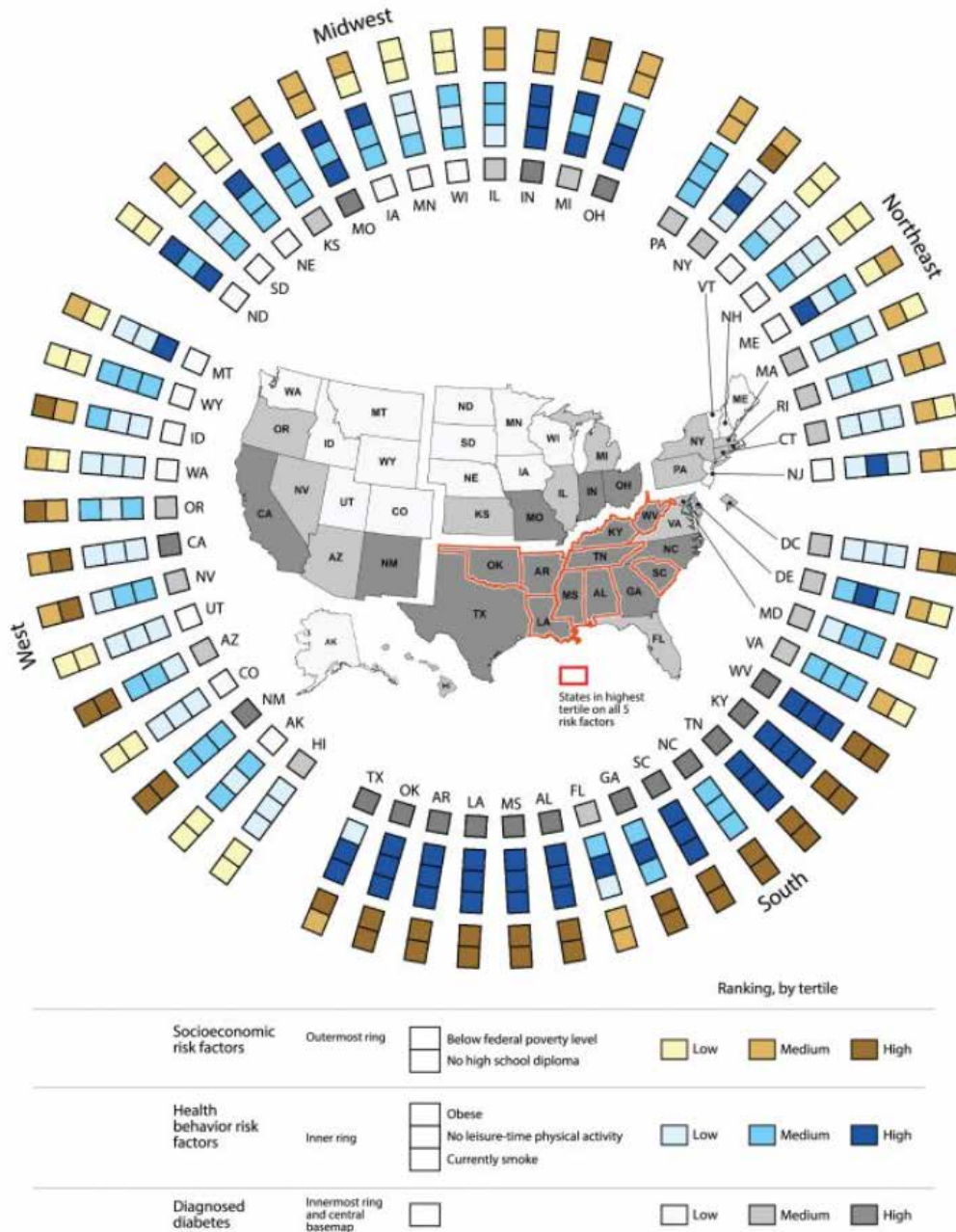
Not surprisingly, being overweight and obese is a significant risk factor for other underlying illnesses such as diabetes—another significant accession barrier identified in the past four years of AMSARA reports—and mental health issues like depression (Boyko et al., 2010). Diabetes mellitus is a disease that prevents the body from properly using the energy consumed from food (*Diabetes Mellitus*, 2018). There are two ways diabetes occurs: type 1, where the pancreas produces little to no insulin, and type 2, where the pancreas produces insulin but does not work correctly (*Diabetes Mellitus*, 2018). In almost all cases, those with type 1 or type 2 diabetes cannot enlist in the U.S. military (Almekinder, 2020). Although it is unlikely to get approved, applicants can submit a waiver to join and even deploy if their A1C is below 7 and under control (Almekinder, 2020; USD P&R, 2018).

While this seems heartening for those wanting to serve who have diabetes, it can also be a considerable obstacle that could negatively affect both the individual's well-being and military readiness (Boyko et al., 2010). A large part of military readiness is the ability for a service member to be deployable. In most cases, the environments associated with being deployed (e.g., Iraq, Afghanistan, out at sea for extended lengths of time) are not conducive for people with diabetes (Almekinder, 2020). For example, if a diabetic service member is on deployment, they will have limited medical support even though some diabetes medicines can cause incapacitation (Folaron et al., 2020, p. 487). Furthermore,

diabetes is a leading cause of kidney failure and death in the United States, thus justifiably being a major medical disqualifier for the military (López-DeFede, 2019).

Several studies have found the prevalence of diabetes to be an increasing problem, especially for those residing in the United States (Barker et al., 2011; Li et al., 2016; López-DeFede et al., 2019; Shrestha et al., 2012). To show how prevalent diabetes is in the U.S., I reproduced a ring map of the prevalence of diagnosed diabetes and other associated risk factors (e.g., living below the poverty level and obesity) for adults 25 years or older by state and region in Figure 3 from López-DeFede et al. (2019).

Figure 3. U.S. State Prevalence of Diagnosed Diabetes and Associated Risk Factors from 2014 to 2016 by Region. Source: Lòpez-DeFede et al. (2019).



Of the limited studies exploring spatial clustering in the U.S. for diabetes, Barker et al. (2011), Li et al. (2016), and Shrestha et al. (2012) found similar results showing distinct spatial clusters of diabetes in the United States, particularly for those living in the South. Barker et al. (2011) found there to be such a high prevalence of diabetes in the southern region of the U.S. that he recognized this area in his research as the “diabetes belt,” which consists of 644 Southeast counties observed as having an exceptionally high diabetes prevalence with 11% or higher (p. 435).

Previous studies focusing on the overall prevalence of diabetes in the U.S. suggest that although the rate is increasing, adolescents are not significantly affected by type 2 diabetes the same way adults are (Demmer et al., 2013; Sackett & Mavor, 2006). Demmer et al. (2013) examined over a decade worth of data published from 1999–2010 Continuous National Health and Nutrition Examination Survey (NHANES) to establish the first nationally representative estimates of the prevalence of diagnosed and undiagnosed type 2 diabetes mellitus (T2DM) among the U.S. youth population (aged 12–19) (p. 1108). Of 11,888 adolescents who reported having diabetes on their survey, a random subsample of 4,661 adolescents had to track their blood levels while fasting for comparison (p. 1106). Findings from their research showed that from the nationally representative sample of youths, the prevalence of T2DM was less than 1% (0.36 percent) overall and that 34% of T2DM appeared undiagnosed (p. 1112). Furthermore, the prevalence of all forms of diabetes had more than doubled since the 1990s, increasing from 0.41% to 0.84% (pp. 1108–12).

At first glance, this might provide some optimism for military recruits to potentially draw from this robust diabetes-free pool of young adults before they are at risk of developing type 2 diabetes. However, based on more recent information from the CDC public health data, almost 40% of people ages 16 to 24 do not meet the military’s medical qualification standards regardless of being non-diabetic (Sackett & Mavor, 2006, p. 3).

Pettitt et al. (2014) conducted a similar study to Demmer et al. (2013) to estimate the prevalence of diabetes in the U.S. youth population (aged < 20) in 2009 but found conflicting results (p. 402). According to Pettitt et al. (2014), diabetes is one of the leading chronic childhood diseases in the U.S., affecting more than 190,000 individuals under the

age of 20, overall and by diabetes type (p. 402). Of the 191,986 youths with diabetes, they found 166,984 have type 1 diabetes, and 20,262 have type 2 diabetes (p. 407). One of the strengths of Pettitt et al.'s study is the nearly 3.5 million SEARCH sites observing the U.S. population for sociodemographic factors (such as race/ethnicity, parental education, and income), thus accurately representing the U.S. youth who are at risk for diabetes (p. 407). One of the limitations of this study is that SEARCH relies on physicians to identify the subjects who have diabetes. Therefore, Pettitt et al. could not include case subjects found without diabetes in their prevalence estimates (p. 406).

Another limitation of Pettitt et al.'s (2014) study was that due to ineffectively conducting in-person visits in 2009, several diabetes risk factors such as obesity details and the presence of diabetes autoantibodies were not available to use in their research (p. 407). However, they were able to use previous SEARCH data that included provider assessments of diabetes types instead, which ended up being useful for their study (p. 407). In conclusion, more recent studies produced since Sackett & Mavor (2006) suggest that diabetes (both type 1 and type 2) is a rising issue in the U.S., especially considering its potential future impact on military accessions (Demmer et al., 2013; Pettitt et al., 2014).

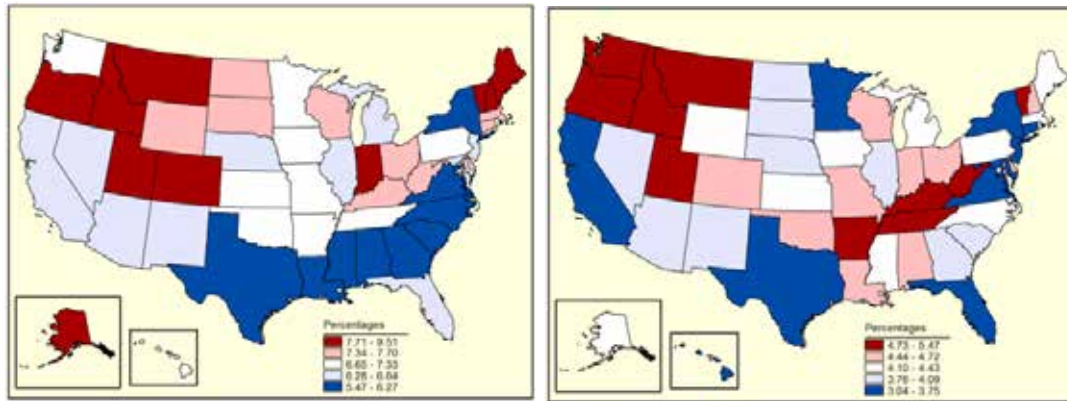
Mental health, more specifically depression, is another underlying disease identified in the AMSARA reports as a leading medical disqualifier for military accessions (Washington et al., 2019). The stigma surrounding mental health and depression is coming to an end due to societal shifts that have increased general acceptance for individuals that seek help. While this tends to be a difficult topic for servicemembers due to implicit norms within military culture, as the U.S. continues to normalize individuals seeking help regarding their mental health, this will eventually bleed over to the services. More service members are already reporting signs and symptoms of having depression and other related mental health disorders and seeking help through the military's behavioral health program.

Interestingly, it does not appear that the prevalence of mental health and depression is increasing but that those suffering from mental health and other behavioral issues are encouraged to seek help in dealing with their problems more. It appears that the increase in the prevalence of mental health and depression diagnosis stems from an increase in reporting and not a rise in the diseases themselves. *Mental Health: A Report of the Surgeon*

General (1999) found that almost 21% of children and adolescents (aged 9 to 17) had mental or addictive disorders associated with impairment (p. 123). More specifically, a breakdown and the percentages for the prevalence of children and adolescents suffering from mental health disorders provided by this report are anxiety disorders (13 percent); mood disorders (6.2 percent); disruptive disorders (10.3 percent); substance use disorders (2 percent); and “any disorder”—such as panic disorders, schizophrenia, or anorexia—(20.9 percent) (U.S. Department of Health and Human Services, 1999, p. 124).

Furthermore, they found that the mental disorders found in young adults did not carry over to adulthood, implying that some children can essentially “grow out of” their disease through the natural development process (U.S. Department of Health and Human Services, 1999, p. 48). If this finding holds, this could have potentially positive implications for the DOD and military accessions. There is a possibility that medically disqualified young adults (due to a mental health issue) could be evaluated later into adulthood and be fully qualified. By looking at the Substance Abuse and Mental Health Services Administration’s (SAMHSA), national health prevalence estimates maps of serious mental illness found in U.S. adults in Figure 4 this theory holds (*National Survey on Drug Use and Health [NSDUH]*, 2018, pp. 53–4). These maps show that the highest annual average percentages of mental illness from 2016–2017 are over half that for older adults than younger adults (NSDUH, 2018, pp. 53–4).

Figure 4. Annual Averages of Serious Mental Illness (2016-2017) for Adults Ages 18 to 25 (left) and Adults Ages 26 and Older (right). Source: NSDUH (2018).



Sackett and Mavor (2006) also reviewed *Mental Health: A Report of the Surgeon General* (1999) and concluded that almost 21% of adolescents with a mental or addictive disorder means nearly 4 million children in the U.S. suffer from a significant mental health disorder (p.136). They also predicted that roughly 10 to 15% of older young adults would have at least one psychiatric diagnosis, with a significant proportion of those experiencing two or more psychiatric conditions (p. 137). Adolescents having these types of psychiatric diagnoses will be problematic as they make up most of the military's accessions (U.S. Department of Health and Human Services, 1999, p. 137).

According to Ireland et al. (2012), service members diagnosed with a preexisting mental health condition during their accession process tend to leave the military early and are significantly less likely (77 percent) to deploy (p. 1149). However, an exciting finding from Ireland's study is that even if an individual shows signs of a non-severe mental disorder within their first few months of service, they are likely to be retained if the service member proves to be stable with the treatment (p. 1149). A significant drawback to this is that if those symptoms are present during the applicant's medical examination, they would not have qualified for accession (p. 1149). One of the reasons why Ireland et al. felt the military kept these servicemembers was the decline in military enlistment surrounding 2006 due to conflicts with Iraq and Afghanistan and increased costs associated with

recruiting, providing medical screenings basic training requirements (p. 1149). These costs were estimated to be approximately \$33,000 per enlistee in 2005 which, have only increased since then (p. 1149).

Cultural trends, rising from the mid-2000s that contribute to increases in mood disorders and suicidal behaviors (i.e., social media applications and other forms of electronic communication) might have a more considerable impact on adolescents, creating somewhat of a cohort effect (Twenge et al., 2019, p. 185). Twenge et al. (2019) analyzed mood disorder indicators and suicide-related outcomes finding that suicide has become an increasing problem over the last ten years (p. 185). However, they also suggest that while this may hold true for individuals under 26, little evidence supports these findings for older adults (2019, p. 185). Further results from their study showed that from 2005 to 2017, rates of major depressive episodes occurring in the last year increased by 52 percent—from 8.7% to 13.2 percent—among adolescents (aged 12 to 17) (N = 611,880) (p. 185). Their report shows that from 2009 to 2017, a similar increasing trend occurred, with the rates of major depression increasing from 8.1% to 13.2% for young adults (aged 18 to 25) (p. 185). Their findings from 2008 to 2017 also showed similar results: a 71% increase in severe psychological distress for young adults ages 18 to 25 with sporadic increases among older adults (p. 185).

Twenge et al. (2019) also found that the consistent increase in mood disorders and other suicide-related outcomes was mostly due to the individual's generation. Furthermore, Millennials—those born in the early 1980s—and innovation Generation persons (iGen'ers)—those born in the late 1990s—were both found to have a steady rise in mood disorders and other suicide-related outcomes than people born before 1980 (Twenge et al., 2019, p. 188). The recent growth in mood disorders for adolescents might be due to the increased use of technology for communication, education, and entertainment in the United States (p. 198).

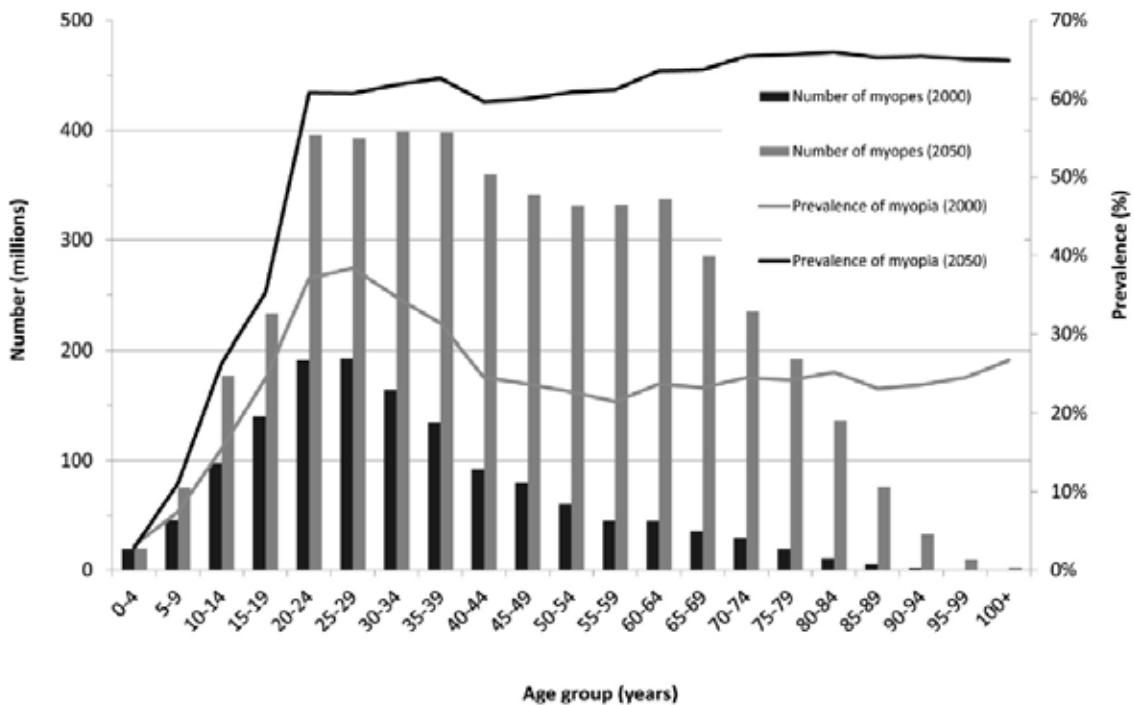
Lin et al. (2016) shared the same train of thought as Twenge et al. in their study on the association between social media use and depression among U.S. young adults (p. 328). One of their main findings is that people who spend more time physically engaging with others are less likely to develop depression and tend to have a higher sense of self-worth

than those who use technology to engage with others (Lin et al., 2016 p. 328). Typically, Millennials and iGen'ers use technology as their primary means of communication with others since it has been around for most, if not all, of their life. Therefore, like Twenge et al. and Lin et al. suggest, these generations are the most likely to see increases in mental health and depression disorders, thus negatively affecting the military accession process.

I was only able to find a few studies related to spatial variations across the U.S. for mental health-related illnesses that mostly focus on depression (Clarke, 2020; Thomas et al., 2019; Weinberger et al., 2018). In 2019, the National Center for Health Statistics (NCHS) found that, on average, 4.7% of all U.S. adults aged 18 and older regularly suffered from having feelings of depression (Clarke, 2020). Weinberger et al. (2018) also found that the U.S. diabetes prevalence significantly increased from 2005 to 2015 despite controlling for factors like demographics (Weinberger et al., 2018). One study in particular (Thomas et al., 2019) centered its research around women in the military, finding that respondents from the South region of the U.S. were more likely to be diagnosed with depression. These results are of no surprise since my previous research found the South to have a higher prevalence of obesity and diabetes, indicating that the South might be a generally unhealthier part of the United States overall.

The last underlying disease burden presented by the AMSARA reports that my literature review focuses on is the increasing hardship for military recruiters in accessing fully qualified individuals due to vision defects such as myopia (nearsightedness) (Washington et al., 2019). More individuals show weakened eyesight and do not meet the necessary vision requirements during the medical examination to access as the rate of vision defects across the U.S. continues to rise each year. Holden et al. (2016) recognize this increasing trend and demonstrate the global prevalence of myopia and what those trends would look like projecting out to the year 2050 from 2000 (Figure 5; Holden et al., 2016, p. 1040).

Figure 5. Projected Distribution Estimate of Myopic People by Age Group from 2000 and 2050. Source: Holden et al. (2016).



Myopia deficiencies are a noticeable concern for the DOD since their goal is to access and retain healthy individuals, especially when myopia-related vision defects account for almost 10% of approved waivers that grant military accession (Washington et al., 2019). Otto et al. (2006) conducted a study that determined how recruits that accessed with a medical waiver due to myopia compared to recruits that accessed without having any medical disqualifiers before entry. Their analysis found that servicemembers requiring a medical waiver due to myopia or other visual defects were just as likely to be retained as those who did not require a medical waiver prior to entering their service branch (p. 1140).

One of the main concerns affecting the DOD raised in their study is the treatment costs associated with myopia. The entire medical screening process is already costly; therefore, additional costs related to screening individuals for vision defects might not be necessary for most military positions, such as those who conduct their work in an office setting. However, Otto et al. point out that glasses, contacts, and laser eye surgery can

easily correct most myopia defects (2006, p. 1137). Furthermore, the military provides service members with annual eye examinations and glasses at no extra cost since their TRICARE benefits cover those expenses. Therefore, Otto et al. views the current vision requirements as too strict and suggests that the DOD consider revising their medical disqualification standards to save on treatment costs and allow more individuals with minor vision defects, such as mild to moderate myopia, to access without a waiver (p. 1141).

In contrast to Otto et al.'s study, Buckingham et al. (2003) emphasize just how critical it is to have excellent vision in the military, with force readiness being a top priority (p. 198). Their study found that of 4,825 active-duty members examined over four months in 1997, over 70% of them were not mission-ready in terms of being eye health ready, mostly due to lapsed eye examinations (p. 198). Additionally, over half of the service members who were issued glasses were found not to be mission-ready due to mismanaging their annual vision requirements (p.198). Furthermore, Buckingham et al. emphasize the vital importance of having an up-to-date visual readiness program to ensure the military has healthy individuals who are always mission-ready (2003, p. 194).

While Otto et al. (2006) and Buckingham et al. (2003) agree on the importance vision has for optimum mission readiness, a limitation to both studies is considering what applicant's daily job requirements will be once they access. Visual acuity is vital for sailors who work on the bridge of warships and fly airplanes as their primary job; however, those who work in an office setting (like Information Professionals and Cryptologic Technicians) do not require the same visual acuity. Another limitation is that each branch approves all medical waivers on a case-by-case basis, limiting all military accessions (Otto et al., 2006, p. 1138).

Holden et al. (2016) addressed regional differences among vision deficiencies, particularly myopia on a global scale. This study concluded that between the years 2000 and 2050, we can expect to see considerable worldwide increases in the prevalence of myopia (Holden et al., 2016). Metha and Wen (2019) find similar results to those found in Holden et al.'s study and go on to suggest that this could be due to people spending less time engaging in outdoor activities and more time participating in near work activities (e.g., watching TV, playing video games, and working on the computer). However, an ongoing

effort is being made to continue to provide individuals with treatment options that either slow or stop the progression of myopia disorders (Metha & Wen, 2019).

C. SUMMARY

In this chapter, I review underlying health diseases such as obesity, diabetes, mental health, depression, and vision defects because of the increasing prevalence of these diseases, which were primary barriers for military accessions provided by the most recent AMSARA reports.

My findings suggest that while obesity seemed to be the primary concern, mental health is undoubtedly a significant problem for the DOD. I found it interesting that people do not seem to have become more unstable among those with mental health disorders, but individuals are becoming more comfortable seeking help. While it is remarkable that more people seek help in combating their mental illnesses, ironically, as mental health treatment is becoming more accepted in society, it is problematic for the military if the mental health standards to join the military remain the same.

Another concerning trend is that the high prevalence of obesity among U.S. adults in 2017–2018 was 42.4%, with no significant differences among men and women or between age groups (Hales, 2020), especially for individuals living in southern states (Barker et al., 2011; Congdon, 2017; Michimi & Wimberly, 2010; Mills et al., 2020; Myers et al., 2015; Thomas et al., 2019). With findings like these, where almost half of the U.S. population is obese, it is easy to see how underlying diseases such as obesity, mental health, etc., can negatively affect the potential for increased military accessions based on current medical disqualifying factors.

Additionally, as the rate of obesity continues to increase each year, whether the criteria for obesity-related medical disqualifiers need to be updated calls for further discussion. Over time, the rising obesity prevalence rates will pose an even more significant threat for the DOD to keep accessing fully qualified individuals. They will either have to increase the already demanding operational tempo due to having fewer accessions or loosen the standards regarding individuals being overweight and obese.

There are similar concerning trends regarding other common medical disqualifiers for military accessions, such as diabetes and depression. Although diabetes in the U.S. is generally increasing, it is significantly less prevalent in the youth population (Demmer et al., 2013; Pettitt et al., 2014). Since most military accessions consist of individuals from the youth population, the DOD should not be overly concerned with diabetes and its effects on successfully recruiting healthy individuals. However, I did not find similar results surrounding mental health and depression. These findings lead me to believe that the medical screening standards surrounding diabetes can and should remain the same without significantly impacting military accessions.

One of the main concerns amongst my findings was that inconsistencies exist in the recruiting processes, which can be very concerning for anyone who is thinking of joining the military, especially related to myopia (Otto et al., 2006) and depression (Ireland et al., 2012). Having inconsistent standards in the medical screening process in any capacity poses just as significant of a threat in other areas such as obesity, mental health, and depression as it does for visual defects. Moreover, this proves to be a limitation for every study that I have analyzed since having any variation in medical disqualification standards is a significant concern for accessing healthy, capable, and qualified individuals. Until there are consistent standards across all military branches at all medical screening locations, accession rates suffer.

Regarding visual defects, I found differing opinions on how the DOD should move forward (for example, Buckingham et al., 2003 and Otto et al., 2006) with evidence supporting both the vital importance for individuals to have perfect vision and that not all servicemembers need such strict visual standards. One of the more prevalent limitations to these studies is not considering each service member's specific job type and associated requirements. For instance, those who have more visually demanding jobs, such as those serving on the bridge of a warship or who assist a pilot while flying, should be required to get a waiver for visual defects. However, those who spend most of their time in a setting where visual acuity is not critical, like an analyst or general technician, could have loosened visual requirements to have an easier time accessing otherwise qualified individuals.

Thus, my thesis estimates the impact of underlying health burdens such as obesity, diabetes, mental health, and vision defects on military accessions using regression analysis. Moreover, knowing the geographic variation in obesity rates can also improve recruitment efforts. Therefore, my thesis provides empirical evidence on the relationship between the prevalence of underlying disease burdens related to my research (i.e., obesity, diabetes, depression, and myopia) and military accession.

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IV. DATA AND METHODOLOGY

This chapter describes the data used for my thesis, including the sample population and the regression analysis variables. Additionally, I provide detailed information regarding each variable that I used to run my regressions for each table presented in my thesis's results – Chapter V.

A. DATA

I first used existing 2016 to 2019 DMDC MEPCOM Accession data at the county-level to measure the number of people in each county enlisting in the military every year. Next, I studied the diseases that most negatively affected military accessions. Using the AMSARA reports, I identified obesity, diabetes, mental health and depression, and visual defects as among the most common illnesses preventing military accessions. Since each state has several MEPS locations, I wanted to further analyze my data by obtaining health data and my DMDC accession data at the county level. Therefore, I found County Health Rankings National Data provided by the University of Wisconsin Population Health Institute: School of Medicine and Public Health, providing me with the necessary independent variables to carry out my evaluation.

My study's main outcome is military accessions per capita measured at the county level from 2016 to 2019. I multiply accessions by 10,000, so the coefficients are simpler to interpret. To organize my independent variables, I separated them into six categories: 1) health, 2) mental health, 3) demographics, 4) race, 5) education, and 6) income.

My health category consists of the variables that capture the percentage of the population who suffer from issues related to obesity and diabetes. The seven specific variables that I used related to an individual's health were the percentage of the entire U.S. population who: 1) are obese, 2) have poor physical health, 3) have limited access to exercise, 4) have frequent physical distress, 5) are inactive, 6) have food insecurity, and 7) have diabetes.

I also included the percentage of the U.S. adult population who smoke and life expectancy in my health category because these variables prove to be good indicators of a

county's overall health status. Unfortunately, I could only obtain the life expectancy data for 2019 from my county health dataset and consequently is a limitation in my study.

For the mental health category, I used three variables from the county health data that best represent individuals who suffer from mental health illnesses and depression. These three variables, constructed by the 2020 County Health Rankings, consist of the percentage of the county population with poor mental health, mental distress, and poor sleep. Data collected for the poor mental health days variable consist of the average number of mentally unhealthy days self-reported by individuals based on how they felt their mental status was over the past 30 days. Frequent mental distress data consists of the percentage of adults who reported having at least 14 poor mental health days in a month. Furthermore, those categorized to suffer from insufficient sleep were the percentage of adults who said that they experience less than 7 hours of sleep a night on average.

The demographics category consists of two variables that capture the youth population and older adults. I particularly paid attention to the youth population during my study since recruiters generally spend their time and energy focused on attracting high school graduates for military accession. Therefore, the two demographics categories that I used were the percentages of the county population under 18 and over 65.

To capture racial differences across counties, I used the percentage of the population who are Black, White, Hispanic, and other. The other group consists of any other race identified (e.g., Asian, Alaskan Natives, Pacific Islander, etc.) in the county health rankings data. I also chose to add the share of women in a county and a variable that captures those who live in a rural area. The percentage of the population living in a rural area was the variable I used to account for rural counties.

For my education category, I chose two variables: high school graduates and those with some college experience. High school graduates are the percentage of ninth-graders who graduate for their first time after completing four years of high school education. Adults (aged 25 to 44) with at least some post-secondary education make up the variable "some college rate" (*Explore Health Rankings / Rankings Data & Documentation*, n.d.).

My income category comprises median household income and the unemployment rate. Note that the unemployment rate is the percentage of the population older than 16 years old and unemployed but looking for a job. These variables are important health factors for me to capture since living well-below the median income level could negatively affect an individual's general health and wellbeing (*Explore Health Rankings | Rankings Data & Documentation*, n.d.). Moreover, past studies find a correlation between unemployment rates and military accessions; for example, Henderson (2015) found in his research that state and county unemployment rates have a statistically significant effect on Navy recruiting that may be applicable for all service branches.

The DMDC accession data I collected for 2016 through 2019 covered all 3,129 counties in the United States. From this data, I found 25,770 people for the median population and 102,635 people for the average population, increasing just over 2% from 2016 to 2019 (average of 101,547 people in 2016 to 103,666.2 people in 2019).

B. METHODS

In this study, I quantitatively analyzed the effects of local health conditions such as obesity, diabetes, and mental health (e.g., depression) on military accessions at the county level. I estimate the following regression model to assess if any correlation exists between underlying disease burdens and military accessions in county c , in state s , and year.

$$y_{cst} = \beta_0 + \beta_1(Health)_{cst} + \beta_2(Mental\ Health) + \beta_3(Demographics) + \beta_4(Race) + \beta_5(Education) + \beta_6(Income) + \tau_t + \gamma_s + \varepsilon_{cst}$$

The independent variables captured in the different categories are as explained above. To control for common factors that affect all counties in the same manner over time, I include year fixed effects (τ_t) in all my models. In the second set of models (Table 3), I include state fixed effects, which exploit variation across counties within the same state. In the third set of models (Table 4), I run regressions including county fixed effects to exploit the variation within counties over time. I also chose to run population-weighted regressions (in Tables 2 through 4) to generate estimates that more accurately represent the

U.S. population by allowing larger states like California to carry more weight than smaller states like Rhode Island.

The next chapter of my thesis shows the summary statistics for counties with above and below median accessions per 10,000 people, and the control variables, and describes the regression results.

V. RESULTS

A. SUMMARY STATISTICS

Table 1 shows the summary statistics for my key independent variables and the outcome variable military accessions per 10,000 people at the county level. For instance, the average percentage of obese adults across all U.S. counties is 31.38% (ranging from 11% in Eagle County, Colorado, to almost 50% in Jefferson County in Mississippi State). This table also displays the average for each independent variable by median accessions per 10,000 people. For example, my results reveal that counties with below-median accessions have a higher percentage of Hispanics compared to counties with above-median accessions per 10,000 people.

The following regression models (Tables 2 through 5) represent how the relationship between my independent variables and my outcome variable changed after controlling for things such as demographics, income and unemployment, health, and mental health, with the application of fixed effects for the year, state, and county.

Table 1. Summary Statistics for Variables

	Overall Sample		Counties with above-median accessions per 10,000 people		Counties with below-median accessions per 10,000 people	
	Mean	Standard Dev	Mean	Standard Dev	Mean	Standard Dev
Outcomes						
Accessions (per 10,000 people)	10.17	6.49	14.37	6.70	6.30	1.85
Independent Variables						
Health						
Percentage of the Population who are Obese	31.38	4.55	32.32	4.07	30.52	4.93
Percentage of the Population with Poor Physical Health	3.89	0.73	3.98	0.68	3.90	0.73

	Overall Sample		Counties with above-median accessions per 10,000 people		Counties with below-median accessions per 10,000 people	
	Mean	Standard Dev	Mean	Standard Dev	Mean	Standard Dev
Percentage of the Population with Limited Access to Exercise	61.15	23.81	62.08	21.40	64.69	23.60
Percentage of the Population with Frequent Physical Distress	11.84	2.38	12.11	2.22	11.84	2.39
Percentage of the Population who are Inactive	26.46	5.28	26.79	5.02	25.97	5.73
Percentage of the Population with Food Insecurity	14.39	4.15	14.69	4.22	14.43	3.97
Percent Diabetes	11.35	2.48	11.71	2.47	11.04	2.50
Percentage of the Adult Population who Smoke	18.01	3.67	18.35	3.32	17.89	3.86
Life Expectancy Age (2019 Only)*	77.44	3.00	77.28	2.73	78.86	4.30
Mental Health						
Percentage of the Population with Poor Mental Health	3.83	0.61	3.94	0.58	3.84	0.58
Percentage of the Population with Mental Distress	11.83	1.98	12.16	1.85	11.80	1.92
Percentage of the Population with Poor Sleep	33.04	4.13	33.69	4.03	33.25	3.90
Demographics						
Percent of the Population over 65	18.19	4.56	17.79	4.09	17.66	4.54
Percent of the Population under 18	22.39	3.45	22.65	2.99	22.29	3.56
Race						
Percent Black	8.95	14.29	11.00	15.70	8.28	13.06
Percent White	76.70	20.01	75.89	19.51	76.01	20.32
Percent Hispanic	9.24	13.62	8.52	12.45	10.60	15.17
Percent Other	5.11	8.68	4.59	6.69	5.11	8.33
Percent Rural	58.59	31.48	55.39	28.66	52.42	31.35
Percent Female	49.91	2.27	50.09	2.07	50.00	2.15

	Overall Sample		Counties with above-median accessions per 10,000 people		Counties with below-median accessions per 10,000 people	
	Mean	Standard Dev	Mean	Standard Dev	Mean	Standard Dev
Education						
HS Rate	86.29	8.35	86.97	7.57	85.55	8.97
Some College Rate	56.97	11.65	56.50	10.66	56.78	12.17
Income						
Median Household Income	49,081.27	12802.85	49,035.34	12119.19	49,720.21	14145.24
Unemployment Rate	5.42	2.06	5.32	1.87	5.72	2.09
No. of Observations	11,000		5724		5276	

*The number of observations Life Expectancy Age is 3,073 because I have only 2019 data.

Based on the results provided in Table 1, counties with above-median accessions per 10,000 people have a larger percentage of individuals with obesity than counties where the accessions per 10,000 people are below the median. White individuals across all U.S. counties account for 76.7% of the population while Black individuals account for 8.95%, Hispanics 9.24%, and every other race 5.11%. The average household income from 2016 to 2019 is \$49,081 and is lower (\$49,035) for the counties with above-median accessions per 10,000 people compared to counties with below-median accessions per 10,000 people (\$49,720). Therefore, median income in counties with above-median accessions per 10,000 people is \$700 less than median income in counties with below-median accessions per 10,000 people.

I estimated four models to study the relationship between my outcome variable (accessions per 10,000 people) and various county characteristics. The first regression model (1) I ran in Table 2 controls for demographics (including race) and education levels for each county. For the second regression model (2), I controlled for everything in the first model, as well as median household income and unemployment rate. It is also important to note that I include indicators for each quartile of the median income distribution with quartile 1 being the omitted group. In regression model three (3), I added the health control

variables to the previously mentioned controls and added mental health control variables to regression model four (4). Since this data was collected across the years 2016 to 2019, I included year fixed effects to each of these regression models in Table 2. Year fixed effects helped me control for national shocks that affect accession per 10,000 people in the same way across counties each year. Furthermore, I separated income into four quartiles for all my regressions—listed as Income Categories 1 through 4—to distinguish between counties with lower and higher incomes.

Table 2. Year Fixed Effects Regression Table

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
<i>Variables</i>				
Percent of the Population Age 65 and Older	0.0856* (0.0440)	0.0947** (0.0414)	0.1235*** (0.0435)	0.1501*** (0.0487)
Percent of the Population Less than Age 18	0.4705*** (0.0537)	0.4968*** (0.0546)	0.3900*** (0.0539)	0.4200*** (0.0621)
Percentage of the Population who are African Americans	0.0457*** (0.0139)	0.0445*** (0.0132)	0.0284 (0.0173)	0.0172 (0.0176)
Percentage of the Population who are Hispanics	-0.0283** (0.0138)	-0.0260* (0.0135)	0.0331** (0.0165)	0.0388** (0.0157)
Percentage of Population other than Black, White, or Hispanic	-0.0512* (0.0310)	-0.0225 (0.0294)	-0.0161 (0.0301)	-0.0255 (0.0240)
Percentage of the Population in a Rural Area	0.0231*** (0.0061)	0.0201*** (0.0058)	0.0014 (0.0057)	0.0057 (0.0058)
Percentage of the Population who are Female	-0.5132*** (0.1071)	-0.5762*** (0.1078)	-0.6029*** (0.1095)	-0.6276*** (0.1177)
High School Graduates	-0.0024 (0.0167)	0.0293* (0.0176)	0.0086 (0.0159)	0.0085 (0.0152)

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
Variables				
Percentage of Adults Ages 25 to 44 with Some College Education	-0.0162 (0.0193)	0.0295 (0.0231)	0.1039*** (0.0262)	0.1154*** (0.0267)
Income Category 2 ⁺		0.1187 (0.3299)	0.7422** (0.3297)	0.6956** (0.3369)
Income Category 3 ⁺⁺		-0.9092** (0.4136)	0.2392 (0.3864)	0.1674 (0.4109)
Income Category 4 ⁺⁺⁺		-2.2408*** (0.4981)	-0.4429 (0.5849)	-0.5046 (0.5954)
Percentage of People Ages 16+ who are Unemployed and Looking for Work		-0.0194 (0.0844)	-0.1630* (0.0834)	-0.1985** (0.0857)
Percentage of Adults that Report BMI >=30			0.1690*** (0.0400)	0.1759*** (0.0404)
Average Number of Reported Physically Unhealthy Days per Month			3.0903*** (1.0390)	3.1269*** (1.0124)
Percentage of the Population with Access to Places for Physical Activity			-0.0429*** (0.0079)	-0.0442*** (0.0079)
Percent of People Affected by Frequent Physical Distress			-0.8846** (0.3770)	-1.0227** (0.4012)
Percentage of Adults that Report No Leisure-time Physical Activity			-0.0225 (0.0296)	-0.0472 (0.0315)
Percent of Food Insecure People			0.0883* (0.0465)	0.1182** (0.0486)
Percent of People with Diabetes			0.2229*** (0.0682)	0.1822** (0.0707)
Percentage of Adults that Smoke			0.0742 (0.0681)	0.0647 (0.0683)

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
Variables				
Average Number of Reported Mentally Unhealthy Days per Month				-0.1399 (0.8897)
Percent of People Affected by Mental Distress				0.1572 (0.3874)
Percent of People Suffering from Insufficient Sleep				0.1065* (0.0546)
Year==2017	0.1810*** (0.0505)	0.2387** (0.0993)	-0.0346 (0.1286)	-0.1159 (0.1254)
Year==2018	0.3020*** (0.0615)	0.4091*** (0.1228)	-0.0079 (0.1893)	-0.0902 (0.2000)
Year==2019	7.4343*** (0.1562)	7.5289*** (0.2141)	6.8645*** (0.2908)	6.7569*** (0.3026)
Observations	11,000	11,000	10,953	10,953
R-squared	0.506	0.525	0.556	0.558

Demographic Controls	Yes	Yes	Yes	Yes
Income and Unemployment	No	Yes	Yes	Yes
Health	No	No	Yes	Yes
Mental Health	No	No	No	Yes
Fixed Effects	Year	Year	Year	Year

Robust standard errors clustered at the county level in parentheses

Income Category 1 is the first quartile (lowest 25% of median household income)

+ Second quartile (25.1% - 50% median household income)

++ Third quartile (51% - 75% median household income)

+++ Fourth quartile (highest 25% of median household income)

*** p<0.01, ** p<0.05, * p<0.1

The percentage of the population less than 18 years old in row 2 of Table 2 shows a reasonably large and statistically significant correlation with accessions per 10,000 people in every regression model. I would expect to see this result because most accessions are recruited during their last couple of years in high school while students are trying to

decide how they want to enter the workforce upon earning their GED. Furthermore, in row 7 of Table 2, I find a statistically significant negative effect for females on accessions per 10,000 people. These findings show that a 1 percentage point increase in the percentage of females decreases the number of accessions by 0.63 per 10,000 people. This result is not surprising due to the military being a predominately male-dominated environment. As I added more controls for health and mental health and fixed effects for the year, the coefficients on the Income Category 2 (second quartile) for income increased in magnitude and statistical significance. My preferred regression model (4), including all controls and year fixed effects, shows that the number of people accessed per 10,000 in counties with Income Category 2 increases by 0.70 persons compared to counties in Category 1 (the first quartile).

More importantly, are the results that show a significant correlation between the percentage of the population suffering from underlying health issues (i.e., obesity, physically unhealthy days reported per month, diabetes, and insufficient sleep) on accessions per 10,000 people across all regression models. For example, a 1 percentage point increase in the percentage of obese adults increases the number of accessions by 0.17 per 10,000 people. For diabetes, my results show that a 1 percentage point increase in the percentage of people with diabetes increases the number of accessions by 0.18 per 10,000 people. Furthermore, a 1 percentage point increase in the percentage of people who suffer from insufficient sleep increases the number of accessions by 0.11 per 10,000 people. These results are surprising since obesity, diabetes, and mental health issues (which can stem from inadequate sleep) are among the top medical disqualifiers for military accession. Yet, they suggest accessions are drawn from counties with poor underlying health conditions.

Table 3 is the same as Table 2, including the same controls (i.e., demographics, income and unemployment, health, and mental health) and year fixed effects. The main difference is these models also include state fixed effects. Including state fixed effects allows me to control for time-invariant state characteristics and exploits variation across counties within the same state over time.

Table 3. Year and State Fixed Effects Regression Table

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
<i>Variables</i>				
Percent of the Population Age 65 and Older	-0.0441 (0.0438)	-0.0289 (0.0445)	-0.0262 (0.0433)	0.0079 (0.0454)
Percent of the Population Less than Age 18	0.4254*** (0.0627)	0.4814*** (0.0701)	0.3347*** (0.0688)	0.3457*** (0.0676)
Percentage of the Population who are African Americans	0.0030 (0.0133)	-0.0090 (0.0134)	-0.0188 (0.0180)	-0.0448** (0.0175)
Percentage of the Population who are Hispanics	-0.0648*** (0.0194)	-0.0707*** (0.0185)	-0.0217 (0.0187)	-0.0271 (0.0188)
Percentage of Population other than Black, White, or Hispanic	-0.1400*** (0.0265)	-0.1163*** (0.0271)	-0.1072*** (0.0222)	-0.1159*** (0.0219)
Percentage of the Population in a Rural Area	0.0157*** (0.0055)	0.0114** (0.0052)	-0.0004 (0.0052)	0.0033 (0.0052)
Percentage of the Population who are Female	-0.3759*** (0.1139)	-0.4679*** (0.1180)	-0.5035*** (0.1202)	-0.4931*** (0.1200)
High School Graduates	-0.0195 (0.0186)	0.0068 (0.0184)	0.0099 (0.0180)	0.0088 (0.0178)
Percentage of Adults Ages 25 to 44 with Some College Education	-0.0004 (0.0224)	0.0512* (0.0270)	0.1480*** (0.0278)	0.1501*** (0.0271)
Income Category 2 ⁺		0.0087 (0.2998)	0.6046** (0.2724)	0.5308** (0.2632)
Income Category 3 ⁺⁺		-0.7602* (0.3908)	0.3145 (0.3489)	0.1368 (0.3536)
Income Category 4 ⁺⁺⁺		-2.0679*** (0.5225)	-0.4404 (0.5466)	-0.5138 (0.5417)
Percentage of People Ages 16+ who are Unemployed and Looking for Work		0.1654**	-0.0447	-0.0525

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
<i>Variables</i>				
		(0.0680)	(0.0632)	(0.0643)
Percentage of Adults that Report BMI >=30			0.2301***	0.2234***
			(0.0315)	(0.0310)
Average Number of Reported Physically Unhealthy Days per Month			2.6988***	1.7460**
			(0.8361)	(0.8301)
Percentage of the Population with Access to Places for Physical Activity			-0.0173***	-0.0191***
			(0.0062)	(0.0061)
Percent of People Affected by Frequent Physical Distress			-0.5520*	-0.3211
			(0.3180)	(0.3704)
Percentage of Adults that Report No Leisure-time Physical Activity			0.0741**	0.0279
			(0.0324)	(0.0325)
Percent of Food Insecure People			0.0088	0.0254
			(0.1003)	(0.0954)
Percent of People with Diabetes			0.2467***	0.1913***
			(0.0603)	(0.0599)
Percentage of Adults that Smoke			0.0618	0.0210
			(0.0765)	(0.0753)
Average Number of Reported Mentally Unhealthy Days per Month				0.8152
				(0.7654)
Percent of People Affected by Mental Distress				-0.2313
				(0.3438)
Percent of People Suffering from Insufficient Sleep				0.2305***
				(0.0456)
Year==2017	0.2583***	0.4693***	0.0958	0.0499
	(0.0522)	(0.0914)	(0.1222)	(0.1134)
Year==2018	0.4293***	0.7571***	0.0532	0.0286
	(0.0593)	(0.1146)	(0.1780)	(0.1928)

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
Variables				
Year==2019	7.6714*** (0.1558)	8.0872*** (0.1978)	7.0346*** (0.2574)	6.9919*** (0.2716)
Observations	11,000	11,000	10,953	10,953
R-squared	0.580	0.594	0.628	0.634

Demographic Controls	Yes	Yes	Yes	Yes
Income and Unemployment	No	Yes	Yes	Yes
Health	No	No	Yes	Yes
Mental Health	No	No	No	Yes
Fixed Effects	Year, State	Year, State	Year, State	Year, State

Robust standard errors clustered at the county level in parentheses

Income Category 1 is the first quartile (lowest 25% of median household income)

+ Second quartile (25.1% - 50% median household income)

++ Third quartile (51% - 75% median household income)

+++ Fourth quartile (highest 25% of median household income)

*** p<0.01, ** p<0.05, * p<0.1

The results from regression (4) in Table 3 show a significant positive effect on the percentage of the population who are less than 18 on accessions per 10,000 people. These results are similar to those found in Table 2; however, comparing counties within states instead of counties across states, the coefficient has slightly decreased from 0.42 to 0.35 persons accessed per 10,000 people. Regression (2) indicates that the number of people accessed per 10,000 in 2017 and 2018 increased by 0.47 and 0.76 persons, respectively, compared to 2016. Furthermore, the results from regression (4) show that compared to 2016, the number of people accessed per 10,000 in 2019 increased by almost seven people.

Regression (4) results in Table 3 for obesity, physically unhealthy days reported per month, diabetes, and insufficient sleep show statistically significant positive effects on accessions per 10,000 people, similar to the findings in Table 2. Therefore, even comparing counties within states, the positive relationship between counties with poor underlying health and accessions per 10,000 people still exists. For instance, a 1 percentage point

increase in the percentage of obese adults increases the number of accessions by 0.22 per 10,000 people. Additionally, a 1 percentage point increase in the percentage of individuals who experienced 14 days or more of physically unhealthy days increases accessions per 10,000 people by 0.18. Lastly, a 1 percentage point increase in the percentage of people suffering from insufficient sleep increases accessions per 10,000 by 0.23.

Table 4 examines the effects of health, mental health, demographics, race, education, and income on accessions per 10,000 people as in Table 2. However, in Table 4, I applied both year and county fixed effects to my regression models. This is even a tighter comparison that exploits only variation within counties over time.

Table 4. Year and County Fixed Effects Regression Table

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
<i>Variables</i>				
Percent of the Population Age 65 and Older	-0.1140 (0.0791)	-0.0991 (0.0793)	-0.0808 (0.0759)	-0.0668 (0.0801)
Percent of the Population Less than Age 18	0.3429*** (0.0997)	0.3992*** (0.1136)	0.3475*** (0.1119)	0.3697*** (0.1182)
Percentage of the Population who are African Americans	0.0742*** (0.0265)	0.0590** (0.0230)	0.0426* (0.0246)	0.0437* (0.0251)
Percentage of the Population who are Hispanics	-0.0390** (0.0154)	-0.0397*** (0.0130)	-0.0116 (0.0183)	-0.0066 (0.0193)
Percentage of Population other than Black, White, or Hispanic	-0.1192*** (0.0378)	-0.0973*** (0.0369)	-0.0910*** (0.0332)	-0.0915*** (0.0348)
Percentage of the Population in a Rural Area	0.0190** (0.0090)	0.0167* (0.0088)	0.0021 (0.0086)	0.0029 (0.0086)
Percentage of the Population who are Female	-0.2487	-0.3038*	-0.3974**	-0.4423**

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
<i>Variables</i>				
	(0.1577)	(0.1636)	(0.1671)	(0.1758)
High School Graduates	0.0136	0.0256	0.0128	0.0166
	(0.0170)	(0.0178)	(0.0177)	(0.0174)
Percentage of Adults Ages 25 to 44 with Some College Education	-0.0270	0.0075	0.0734*	0.0785*
	(0.0258)	(0.0349)	(0.0430)	(0.0443)
Income Category 2 ⁺		0.0646	0.3628	0.3881
		(0.3553)	(0.3395)	(0.3439)
Income Category 3 ⁺⁺		-0.6460	-0.0768	-0.0759
		(0.5147)	(0.4898)	(0.4984)
Income Category 4 ⁺⁺⁺		-1.6124**	-0.7001	-0.6658
		(0.7253)	(0.6321)	(0.6383)
Percentage of People Ages 16+ who are Unemployed and Looking for Work		0.1476	0.0121	-0.0016
		(0.1001)	(0.0922)	(0.0906)
Percentage of Adults that Report BMI >=30			0.0738**	0.0734**
			(0.0351)	(0.0355)
Average Number of Reported Physically Unhealthy Days per Month			1.6307**	1.7785**
			(0.7787)	(0.7356)
Percentage of the Population with Access to Places for Physical Activity			-0.0293***	-0.0287***
			(0.0066)	(0.0064)
Percent of People Affected by Frequent Physical Distress			-0.3683	-0.5879**
			(0.2570)	(0.2837)
Percentage of Adults that Report No Leisure-time Physical Activity			0.0217	0.0218
			(0.0410)	(0.0409)
Percent of Food Insecure People			0.0352	0.0313
			(0.0589)	(0.0611)
Percent of People with Diabetes			0.2152***	0.1992***
			(0.0648)	(0.0636)

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
Variables				
Percentage of Adults that Smoke			0.0127 (0.0503)	-0.0012 (0.0507)
Average Number of Reported Mentally Unhealthy Days per Month				-0.1764 (0.7143)
Percent of People Affected by Mental Distress				0.3503 (0.2855)
Percent of People Suffering from Insufficient Sleep				0.0137 (0.0372)
Year==2017	0.2315*** (0.0616)	0.4345*** (0.1330)	0.2510* (0.1461)	0.1415 (0.1490)
Year==2018	0.4233*** (0.0896)	0.7294*** (0.1858)	0.3793** (0.1794)	0.1856 (0.1996)
Year==2019	7.6055*** (0.1966)	8.0166*** (0.3115)	7.5141*** (0.3065)	7.2987*** (0.3259)
Observations	11,000	11,000	10,953	10,953
R-squared	0.793	0.797	0.803	0.804

Demographic Controls	Yes	Yes	Yes	Yes
Income and Unemployment	No	Yes	Yes	Yes
Health	No	No	Yes	Yes
Mental Health	No	No	No	Yes
Fixed Effects	Year, County	Year, County	Year, County	Year, County

Robust standard errors clustered at the county level in parentheses

Income Category 1 is the first quartile (lowest 25% of median household income)

+ Second quartile (25.1% - 50% median household income)

++ Third quartile (51% - 75% median household income)

+++ Fourth quartile (highest 25% of median household income)

*** p<0.01, ** p<0.05, * p<0.1

The most remarkable finding in Table 4 is that comparing within counties, the positive relationship between underlying health diseases and accessions per 10,000 people still holds. So even after controlling for county fixed effects, not only is there an increasing trend in underlying health disease burdens over time, but the military is also drawing accessions from places that are unhealthier. More specifically, in regression (4) for rows 14, 15, 16, and 20 regarding obesity, the coefficients on the average number of reported physically unhealthy days per month, having access to places for physical activity, and diabetes are all statistically significant. Therefore, my results show (regression (4), in Table 4) that for a 1 percentage point increase in the percentage of the population with access to places to conduct physical activity (e.g., a gym or other fitness-related facility) decreases the number of accessions by 0.03 per 10,000 people. Meaning, counties with more active individuals that can join a gym (or another training facility) have fewer military accessions. The regression (4) results show that a one percentage point increase in the percentage of adults with a BMI greater than or equal to 30 is associated with 0.073 more accessions per 10,000 people. Furthermore, my results show that a 1 percentage point increase in the % of diabetics increases accessions per 10,000 people by 0.20 with all controls and the application of year and county fixed effects.

Table 5 is the same as Table 2 with the inclusion of year and state fixed effects without the weighted average for the entire population. By previously using the weighted average in Tables 2 through 4, I more accurately represented the population. For example, Texas accounts for a larger population than a state with a smaller population like Vermont. However, after running the same regressions as in Table 3 and comparing the results with those in Table 5, I did not find a significant difference between the two sets of results. Meaning, while I accurately represented the weighted average for each state's population density in Tables 2 through 4, the results are similar to those in Table 5, where the weighted average to the population is not applied.

Table 5. Year and State Fixed Effects Regression Table – No Average Weighted Population

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
Percent of the Population Age 65 and Older	-0.0603*	-0.0727**	-0.0876***	-0.0661*
	(0.0354)	(0.0366)	(0.0337)	(0.0353)
Percent of the Population Less than Age 18	0.1913***	0.2240***	0.1501***	0.1527***
	(0.0473)	(0.0478)	(0.0491)	(0.0490)
Percentage of the Population who are African Americans	0.0406***	0.0371**	0.0575**	0.0398
	(0.0126)	(0.0144)	(0.0267)	(0.0246)
Percentage of the Population who are Hispanics	-0.0449***	-0.0484***	-0.0299	-0.0362**
	(0.0109)	(0.0115)	(0.0183)	(0.0181)
Percentage of Population other than Black, White, or Hispanic	-0.0632***	-0.0648***	-0.0515***	-0.0542***
	(0.0122)	(0.0136)	(0.0137)	(0.0135)
Percentage of the Population in a Rural Area	0.0003	-0.0007	-0.0007	0.0006
	(0.0038)	(0.0040)	(0.0044)	(0.0045)
Percentage of the Population who are Female	-0.0682	-0.1056	-0.0511	-0.0342
	(0.0978)	(0.0960)	(0.0939)	(0.0966)
High School Graduates	0.0188*	0.0284**	0.0303***	0.0306***
	(0.0113)	(0.0112)	(0.0111)	(0.0113)
Percentage of Adults Ages 25 to 44 with Some College Education	0.0196*	0.0427***	0.0577***	0.0580***
	(0.0114)	(0.0133)	(0.0150)	(0.0148)

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
Income Category 2 ⁺		0.3135* (0.1688)	0.2198 (0.1804)	0.2185 (0.1779)
Income Category 3 ⁺⁺		-0.4182* (0.2222)	-0.5357* (0.2886)	-0.5455* (0.2811)
Income Category 4 ⁺⁺⁺		-1.6790*** (0.3556)	-1.7827*** (0.4963)	-1.8419*** (0.4890)
Percentage of People Ages 16+ who are Unemployed and Looking for Work		0.0793 (0.0758)	0.1470*** (0.0551)	0.1355** (0.0564)
Percentage of Adults that Report BMI >=30			0.1029*** (0.0356)	0.0931** (0.0377)
Average Number of Reported Physically Unhealthy Days per Month			3.5122*** (0.6352)	2.9480*** (0.6366)
Percentage of the Population with Access to Places for Physical Activity			-0.0003 (0.0042)	-0.0004 (0.0042)
Percent of People Affected by Frequent Physical Distress			-1.2568*** (0.2542)	-1.0786*** (0.2560)
Percentage of Adults that Report No Leisure-time Physical Activity			-0.0101 (0.0320)	-0.0224 (0.0342)
Percent of Food Insecure People			-0.1252 (0.1018)	-0.1210 (0.1069)

	(1)	(2)	(3)	(4)
	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People	Accessions per 10,000 People
Percent of People with Diabetes			0.0632 (0.0533)	0.0422 (0.0532)
Percentage of Adults that Smoke			0.1864*** (0.0511)	0.1601*** (0.0492)
Average Number of Reported Mentally Unhealthy Days per Month				-0.0328 (0.5037)
Percent of People Affected by Mental Distress				-0.1076 (0.2396)
Percent of People Suffering from Insufficient Sleep				0.1826*** (0.0560)
Year==2017	0.1671** (0.0686)	0.2426** (0.1081)	0.2419* (0.1383)	0.2643 (0.1760)
Year==2018	0.4412*** (0.0811)	0.5637*** (0.1369)	0.6383*** (0.1859)	0.6921** (0.2798)
Year==2019	8.1020*** (0.1261)	8.2879*** (0.2136)	8.2677*** (0.2717)	8.3074*** (0.3685)
Observations	11,000	11,000	10,953	10,953
R-squared	0.356	0.361	0.368	0.370

Demographic Controls	Yes	Yes	Yes	Yes
Income and Unemployment	No	Yes	Yes	Yes
Health	No	No	Yes	Yes
Mental Health	No	No	No	Yes
Fixed Effects	Year, State+	Year, State+	Year, State+	Year, State+

Robust standard errors clustered at the county level in parentheses

Income Category 1 is the first quartile (lowest 25% of median household income)

+ Second quartile (25.1% - 50% median household income)

++ Third quartile (51% - 75% median household income)

+++ Fourth quartile (highest 25% of median household income)

*** p<0.01, ** p<0.05, * p<0.1

+ Year and state fixed effects without average weighted population

The main difference between regression (4) in Table 3 and Table 5 is that statistical significance is present for the percentage of adults that smoke on accessions per 10,000 people in Table 5. These results suggest that a 1 percentage point increase in the percentage of adult smokers increases accessions per 10,000 people by 0.16. Therefore, this result could be due to adult smoking picking up the correlation between counties with strong ties to military culture and their association with tobacco use. For example, states with a higher smoking population, like Virginia – which has the highest overall adult smoking percentage at 26.8% – tend to have a more robust military presence.

B. KEY FINDINGS

One of the primary key findings of this study is that the results show the military is enlisting people from unhealthy parts of the country, for example, in the southern regions of the U.S., where underlying disease burdens are more prevalent. When looking at obesity rates and accessions across counties, this was particularly interesting. Even after comparing data within counties, I still found the relationship between the percentage of the population with underlying health diseases (i.e., obesity, diabetes, and physical distress) and accessions to be positively correlated. Consequently, it is not just that the population is getting unhealthier, but the military is also drawing from parts of the country that have worse underlying disease burdens. However, recruiters should be looking to access healthy individuals with lower obesity rates, not higher.

VI. CONCLUSION AND RECOMMENDATIONS

I found several correlations between accessions and underlying health diseases, accessions and income, and accessions and year using DMDC military accession data for enlisted personnel and Health Rankings National Data at the county-level for years 2016 through 2019. My study's key results suggest that the accessions per capita are higher in counties with poor underlying health and younger populations.

The key results of this study suggest that:

1. The DOD should consider updating disqualifying conditions as patterns of increasing or decreasing underlying health burdens change. I recommend this because obesity, mental health, and other underlying health burdens continue to rise in the U.S. each year. For instance, minor medical disqualifications for the applicant could be waived during their first medical examination if they will be primarily working at a desk job and not in the field. As long as the applicant can complete their assigned tasks and positively contribute to accomplishing the mission entrusted to their command, being obese or having mental disorders like ADD might not be problematic. Additionally, like Otto et al. (2016) suggests, I think the DOD should relax the vision defects standards to allow applicants with minor myopia issues to more easily access. Therefore, minor discrepancies in medical disqualifications can be automatically waived depending on job type and allow otherwise qualified individuals to access.

2. Each military branch could change its medical disqualification requirements to be more attuned to each specific job type. For example, the obesity and optical disqualifiers could be loosened for those working primarily in administrative roles where physical demands are not necessarily needed to complete their primary duty. Those that do have physically demanding jobs (such as a Navy SEAL or Marine who can easily be forward deployed to work in the field) would use the original disqualifying standards. Since all military members must complete a physical fitness test upon checking into their gaining command, each member could be reviewed based on the original disqualifications or the revised disqualification.

3. Recruiters should focus their recruiting efforts on counties with overall healthier individuals for more medically qualified accessions. Based on my findings, instead of attracting individuals from counties that are more prevalent to have people with underlying disease burdens like obesity, they can focus on recruiting in counties with more fit and healthier individuals. For instance, the average number of accessions per capita in Macon, Alabama, is above the U.S. median (6.49%) at 6.72%, with 47.8% of individuals have a BMI greater than or equal to 30. However, suppose recruiters focused on healthier counties in the U.S. and invested more time and resources in those areas. In that case, they could increase the probability of accessing healthier individuals into the military, thus improving overall force readiness.

4. Conduct a follow-on study to compare the impacts of underlying health burdens on military accessions before and after the COVID-19 pandemic. My study results will be even more interesting once the data is published for 2020 and 2021 to compare the correlation with underlying disease burdens to military accessions during the COVID-19 pandemic. For instance, I suspect that due to individuals having to shelter in place and quarantine for almost all of 2020, there will be an even further increasing trend among underlying health diseases such as mental health, depression, and obesity. Based on my conclusion that military accessions are drawn mainly from counties with unhealthier individuals, those who access once the pandemic has ended are even more likely to be people with underlying illnesses. Therefore, conducting a follow-on study to compare the impacts of COVID-19 on underlying health burdens and how this affects future military accessions would be beneficial to the DOD and USMEPCOM.

5. Obtain life expectancy data for 2016 through 2018 to add to the established 2019 life expectancy data for consistency across all years in this study. Except for life expectancy, I had data across all four years for each of my independent variables. Therefore, if the life expectancy variables were updated in the County Health Rankings Data for the years before 2019, it would improve my regression analysis findings.

The implications of these findings suggest that DOD recruiting organizations such as USMEPCOM can use this relevant county-level information to support their future military accession goals. Furthermore, each of the MEPS locations can use these results as

a guide to strengthen or loosen medical disqualification standards in certain counties based on the most prevalent underlying disease burdened areas. The NRC may also be interested in these findings to achieve one of their primary goals in accessing the most qualified and healthy individuals who will excel in today's technology-driven environment.

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