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ANALYSIS OF UNIT VARIATION AND PEER INFLUENCE OF DESTRUCTIVE BEHAVIORS IN THE U.S. MILITARY

by

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We pursued three aims: 1) to study the relationship between unit composition and unit-level incidences of destructive behaviors, 2) to identify units at "high-risk" of destructive behaviors, and 3) to study how peers within a unit influence each other to engage in destructive behaviors. Among our key findings are: that the vast majority of units in each quarter have at least one member who engages in a destructive behavior; that we can empirically identify high-risk units that have particularly high incidences of multiple destructive behaviors; and that peers meaningfully influence each other's decisions to engage in destructive behaviors, especially among the younger and enlisted personnel.

These results can guide military policy-makers toward more informed choices about the optimal allocation of resources between individual- and unit-level interventions to reduce the prevalence of destructive behaviors, and our methodologies can serve as a basis for future research in this area.

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Analysis of unit variation and peer influence of destructive behaviors in the U.S. military*

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December 2019

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Abstract

As requested by OPNAV N17, we conduct an empirical investigation into unit-level variations and peer influences of destructive behaviors in the U.S. military, with a particular emphasis on the Navy and the Marine Corps. We assembled a comprehensive individual-level database that includes demographic, service, unit, and medical information on all active-duty service members from 2003 to 2015.

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These results can guide military policy-makers toward more informed choices about the optimal allocation of resources between individual- and unit-level interventions to reduce the prevalence of destructive behaviors, and our methodologies can serve as a basis for future research in this area.

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Executive Summary

Introduction

This report presents novel analysis on unit-level risk factors for destructive behaviors in the U.S. military, with a particular emphasis on the Navy and the Marines. Much is known about individual-level relationships between poor mental health and destructive behaviors, such as substance abuse, suicide attempts, and suicide completions (Shen et al., 2012, LeardMann et al., 2013, Cunha et al., 2015, Shen et al., 2016); however, very little is known about how these relationships vary by units - the groups in which individuals work and interact on a daily basis - and how individuals within units influence each other's decisions to engage, or to not engage, in destructive behaviors.

As requested by OPNAV N17, we pursued three specific aims: 1) to study the relationship between unit composition and unit-level incidences of destructive behaviors, 2) to identify units at "high-risk" of destructive behaviors, and 3) to study how peers within a unit influence each other to engage in destructive behaviors. Our work adds to the literature through the study of five disorders among U.S. military personnel: tobacco misuse, alcohol or drug misuse, depression, anxiety, and self-inflicted injury (a proxy for suicide attempts).

Study Population and Methodology

Our analysis covers every active-duty service member from all four services between 2003 and 2015, over 3,600,000 individuals serving in over 53,000 units. We linked over 10 administrative databases to capture each service member's demographic, service, deployment, and clinical diagnoses and to identify the units to which they were assigned or attached. Destructive behavior and mental health outcomes are identified via clinical diagnoses (ICD-9 codes) as recorded in individuals' TRICARE adminstrative files. We merged this clinical encounter data with the monthly-level personnel files of all service members.

A critical task for our project was to define units and peer groups for each service. To understand how peers might influence individual behavior, we ideally would like to identify units as the workplace in which service members have meaningful professional and organizational interactions with other members in the same unit. Empirically, there are several major challenges to such a grouping that we discuss in detail in the report. After consulting with various stakeholders and subject matter experts across all services, we define units and peer groups based primarily on the monthly attached unit identification codes (UIC), except for the Marine Corps, for which we use the monthly Major Command Codes (MCC) and Reporting Unit Codes (RUC) .

We use a combination of descriptive and multivariate regression analyses to address our three specific aims. To put our empirical methodology and results in context, our report first summarizes the literature on peer influences on individual behavior in both military and civilian settings. In short, there is a large body of evidence documenting that peers matter, and that policy interventions which take into account the structure of peer groups (i.e., units) can be more effective and efficient. Our work builds on this literature by providing the first comprehensive study of the risk factors for destructive behaviors in military units and how peers within units influence each other's destructive behavior.

Findings and Recommendations

We have developed an empirical framework that allows military policy-makers to understand the variation in destructive behaviors at the unit level. Resources can be targeted at either the individual or the unit, and this framework and set of results covering the past decade give military policy makers vital information to make more informed choices about the optimal allocation of preventative resources. Here are the main take-away points from our analysis:

- Destructive behaviors are widespread across units, with about 80% of unit quarter observations having at least one member being diagnosed with one of the conditions we studied. However, incidence rates within units are relatively low. For these low incident units, a minimally invasive program that monitors the stress level of members along with basic resilience training might be sufficient to prevent escalation of destructive behaviors.

- Destructive behaviors are correlated within units. In particular, we have identified a small subset of military units - about 10% - that are at "high risk" of destructive behavior across multiple conditions. These multiple-high-risk units could benefit from additional interventions.

- The cross-unit variation in behaviors which is associated with common life stressors, such as divorce, demotion, or deployment, is similar across all services. These life stressors are systematically associated with higher rates of destructive behaviors at the unit level. A high percentage of members returning from Iraq or Afghanistan are associated with units being identified as high risks for substance use disorder, depression, and anxiety, and the magnitude is larger and more precisely estimated in the whole sample than in the Navy. We suggest that the Commander Risk Mitigation Dashboard incorporate and monitor these life stressors.

- High-risk units are not evenly distributed across geographic regions or platform types in the Navy. Within the Navy, units at risk of multiple destructive behaviors tend to be concentrated in the Northeast Census region, whereas there is higher concentration of high-risk units in the Midwest region for the U.S. military as a whole. Future research should study whether this variation is driven by the supply of mental health providers in each region and whether mental health resource capacity is adequate to meet the demand in regions that have higher prevalence of high-risk units.

- Within units, we found that peers impact each other's destructive behaviors in both positive and negative ways. Intervention policies - especially those that are targeted to the unit as a whole - should be designed with these potential peer influences in mind. One example is to inform individuals of the dangers of "following the crowd," while at the same time informing them of "learning from past experiences of your peers." More broadly, taking advantage of peer influence to change social norms on certain activities (such as tobacco use or pornography consumption) can potentially lead to positive changes in individual behaviors in the long run. Personnel planners may also consider using one's medical history in determining the assignment of individuals to units.

- There is a large degree of heterogeneity in peer influences across different subgroups. For example, younger and enlisted populations tend to be more readily influenced by peers. Any policies or intervention initiatives must recognize that a uniform policy across populations may not be effective.

- We found that peer influence tended to be weaker in the Navy and the Marine Corps, and stronger in the Army and Air Force. Policy interventions intended to leverage peers to influence individual behavior will likely vary in effectiveness across services.

- Future research could develop a machine learning algorithm that can predict which units are the most likely to be high risk *in the future*. Such an algorithm extends the analysis we performed by choosing the optimal functional form of relationship between covariates and outcomes. Such a line of research would directly support the Navy's current effort to use administrative databases to create a comprehensive picture of sailors' careers and health, and it could directly provide direct output to the Commander Risk Mitigation Dashboard which allows unit commanders to assess the health of their units.

- However, it is critical to recognize that the quality of any analysis hinges on the quality of the underlying data. One important lesson we learned from our research is that while some databases may be rich in information, they may be of limited use to the Navy if coverage is not complete. In particular, assessment data such as the Post Deployment Health Assessment are severely underutilized by the Navy, leaving them of little use when studying the population as a whole. The Periodic Health Assessment, which was not available to us, might be a viable alternative.

- Future research can apply the analytical framework we have developed to other behaviors that harm the mission of the Department of Defense (DoD), such as sexual assault and physical violence. If data were available from physical evaluation boards and pay records, our framework could also be applied to less severe but more widespread outcomes that affect unit readiness, such as missed training days, muscular and skeletal injury rates, and non-deployable rates. The leadership might also consider more focused analysis on Naval communities that might be high risk communities of these other outcomes (for example, muscular and skeletal injuries are very high in helicopter communities). The accumulation of insights learned from a study of all adverse outcomes - not just those in our current study - would allow for the identification of units that are "high risk" in a holistic set of destructive behaviors.

1 Introduction

The overarching goal of this project was to provide innovative data analysis to support the operational needs of OPNAV N17Z on priority-area topics related to personnel readiness.

A wealth of recent empirical studies have improved our understanding of **individual-level** risk factors for destructive behaviors among both civilian and military populations (Tanielian et al., 2008, Ramchand and for Military Health Policy Research, 2011, Shen et al., 2012, 2010, LeardMann et al., 2013, Cunha et al., 2015, Shen et al., 2016). For example, a recent study on all active duty military members and veterans from 2002-12 showed that a wide range of mental health diagnoses, whether currently diagnosed or diagnosed in the past, were strong predictors of death by suicide, and that the risk of suicide remained elevated long after the occurrence of stressful events (Shen et al., 2016). Research has also shown that soldiers with the worst pre-military psychological health attribute scores had much higher odds of screening positive for depression and PTSD after returning home from combat deployment (Shen et al., 2017).

However, we still know very little about how **unit level** risk factors – factors that are separate from, yet comprised of, the individuals in units – may be associated with destructive behaviors. A recent study on Army units found that those whose members had a history of attempted suicide are associated with increased risk of future suicide attempts, even when members with a history rotate out (Ursano et al., 2017). And, several studies have supported the notion that suicidal behavior is contagious across individuals (Gould and Lake, 2013, Hoge et al., 2017). Units of individuals are an integral part of the organizational structure of the DoD, and military planners have long recognized that small units are an optimal place to allocate resources for prevention initiatives, to establish leadership expectations, and to enact change.

With this background in mind, the overarching theme and long term objective of our research effort is to gain deeper understanding of unit level variations, both cross and within, in adverse outcomes among military personnel, and to apply those findings to prevention policies in operational environments. As part of the project objective, this report first provides a comprehensive literature review of empirical research that studies the effects of peer influence on individual behaviors from both military and civilian settings. We then present our empirical analysis and findings on the following three research aims:

1. Determine whether there are systematic relationships between unit composition and unit-level incidences of the following behavioral and mental outcomes: tobacco misuse, alcohol or drug misuse, major depression, general anxiety, and suicide attempts.

2. For each outcome, identify "high-risk" units and investigate whether certain types of units consistently rank high across multiple destructive behavioral outcomes.

3. Investigate whether peers who have been diagnosed with destructive behaviors influence a service member's propensity to engage in destructive behaviors.

2 Background and Literature Review[1]

There is a wealth of literature that has analyzed individual risk factors of destructive behaviors. As our work focuses on unit-level factors and peer influences, we provide reviews of empirical research studying the workplace environment and the effects of peers on individual behaviors, in both military and civilian settings. We organized the literature by the outcomes examined (for example substance abuse, suicide, productivity, etc.). As a summary, previous literature, a majority of which focuses on adolescent populations, generally finds that peers can influence the take-up of some risky and positive behaviors. Our review also highlights the importance of timing when evaluating peer influences on individual behaviors and discusses the relevancy of the literature's findings to the DoD settings.

2.1 Substance Abuse

Most of the work on spillover (i..e., how one's behavior affect others) of substance use occurs among adolescents, at least partly because adolescents have easily defined sets of peers in their schools and classes. This outside intervention into who knows who is important, because individuals can choose their friends. Any analysis that does not account for differences in preferences may attribute differences in outcomes to "peer effects," when in reality, for instance, people who like to smoke choose to become friends with people who also like to smoke.

Among adolescents, there is consistent evidence that peers affect individuals' own substance use and abuse (Fletcher and Ross, 2018). A 10% increase in the proportion of classmates who smoke increased the likelihood of a teen smoking by 3%; the increase in smoking rates was 5% for every 10% increase in close friends who smoke (Ali and Dwyer, 2009, Fletcher, 2010). There were similar patterns for marijuana usage among teens (Ali et al., 2011a), and a 10% increase in the proportion of classmates who drink increased the likelihood of own

[1] This comprehensive literature review was submitted to the sponsor in January 2019 and is replicated here in order to have a self-contained technical report.

drinking by 4 percentage points (Ali and Dwyer, 2010). The participants in these studies were in their high school years, which is not far removed from the age of enlisted recruits in the DoD.

Looking at a slightly older age, being randomly assigned to a college roommate who binge drinks was associated with an increase in own binge-drinking rates (Eisenberg et al., 2014). This substance use had real consequences for students: males randomly assigned to a college roommate who drank in high school had a 0.25 point lower GPA than males assigned to a non-drinking roommate (Kremer and Levy, 2008). There was no such peer effect among women for drinking and college GPA (Kremer and Levy, 2008). Similarly, being assigned a roommate who smokes increased smoking for men, but actually decreased it for women. There was no relationship between roommate drug use and own illicit drug use (Eisenberg et al., 2014).

Once a person has started smoking, peers may have a limited influence on quitting behavior. Among pregnant women who smoked, a peer counseling program decreased daily cigarettes (by 9.1 daily cigarettes), relative to a control condition with typical care (which reduced daily cigarettes by 4.5); however, quit rates were the same in both conditions (at 21-24% across conditions) (Malchodi et al., 2003). Even spouses may not be enough: as the authors of one study of smoking cessation among spouses note, "Love conquers all but nicotine" (Palali and Van Ours, 2017). Another study does find small effects of spouses on substance use. When a spouse was randomly assigned to one smoking cessation program, there was a seven percentage-point decrease in smoking among their (smoking) spouses (Fletcher and Marksteiner, 2017). There is less evidence of peer effects among friends on quitting behavior. While peers influence the decision to start smoking, quitting depends on more than just peer influence, but on professional help. Peers may also affect one's decision to stop drinking. Randomly assigning therapy to one spouse decreased heavy drinking in the (drinker) spouse by 14 percentage points; drinking treatments involving chemical interventions (i.e., acamposate or naltrexone) did not affect spouses (Fletcher and Marksteiner, 2017).

2.2 Suicide

Most research on the peer effects of suicide has focused on the adolescent context, though there is a general consensus that other people's suicidal behavior can influence own suicidal thoughts and actions. Prominent celebrities died by suicide is robustly associated with an increase in suicide rates in the following days (Gould, 2001, Stack, 2002), suggesting some sort of spillover effect in suicide. However, suicide rates increase following any sort of unexpected event, even if it is a positive event – for example, the return of US hostages held in Iran, or the first artificial heart transplant in humans, or Reagan's "Tear down this wall" speech (Hoffman and Bearman, 2015). Thus, Hoffman and Bearman hypothesize that the driver of suicidal spillover is more about disruption to social order and expectations than about imitation per se. In the military context, then, a peer suicide may be associated with higher suicide rates, but other unexpected or disruptive events may have a similar effect.

The adolescent peer effects literature may also offer insights into the DoD context. Looking at randomly assigned college roommates, there was no relationship between being assigned a college roommate with prior suicidal ideation and own suicidal ideation; similar patterns held for non-suicidal self-injury (Eisenberg et al., 2014). Timing may play an important role in peer effects: a friend's suicide increased own suicidal thoughts and attempts during the first year after the loss, but six years later concurrent behaviors were the most influential factor for suicidality (Feigelman and Gorman, 2008). Thus, more recent suicidal behavior may have more relevance in spillover than past behavior. The spillover of friend or acquaintance suicide attempts has been found to be larger than more distant peer effects (Crepeau-Hobson and Leech, 2014).

Among adolescents, girls tend to be affected by their same-grade female peers' experience with familial suicidal behavior, but not by similar experiences of their male peers (Fletcher, 2017). To the extent that suicidal behavior or ideation is transmitted to peers in the DoD, there may be complicated and possibly gender-specific pathways that mediate the effects.

2.3 Other Risky Behavior

Peers may influence other risky behavior as well. Among adolescents, unsafe sex is one potential risky behavior. A 10% increase in the proportion of close friends who initiate sex increased the probability an individual initiates sex by 5%, while a 10% increase in the number of sexual partners among close friends increased own-sexual partners by 5% (Ali and Dwyer, 2011). This sexual activity has demonstrated consequences: a 10 percentage point increase in peer pregnancies was associated with a 2-5 percentage point increase in own pregnancy (Fletcher and Yakusheva, 2016). To mitigate that effect, a 10% increase in peer contraception use increased own contraception use by about 5% (Ali et al., 2011b). Pregnancy, while not considered risky in adults, also has peer effects in the workplace. In Germany, for instance, in the year after a colleague in the same firm gave birth, the rates of first pregnancy among female employees doubled; the peer spillover decreased over time and disappears after two years (Pink et al., 2014).

Among 18-year-olds, there was no relationship between randomly assigned college roommate behavior and own behavior for risky activities of gambling or having multiple sexual partners (Eisenberg et al., 2014). However, other bad behavior might be spread: at the US Air Force Academy, random assignment to a squadron with less-fit peers decreased health outcomes (Carrell et al., 2011). The opposite was also true, but the effects were mainly driven by the least fit cadets pulling others down (Carrell et al., 2011).

2.4 Other Areas for Peer Effects

2.4.1 Program Take Up

Peer effects also matter for program take-up. In Norway following the introduction of paid paternity leave, coworkers and brothers were much more likely to take up available paternity leave if their peer was induced into taking up paternity leave (Dahl et al., 2014). The authors argued that the mechanism in this case was informational, including the knowledge of how an employer reacts to a male taking on paternity leave. Notably, in the case of Norway, the estimated peer effect expanded over time, as more and more males took advantage of the policy. Similarly, individuals watch the retirement decisions of their peers: retirement-age teachers were more likely to retire if a retirement-age teacher in their school retired the prior year (Brown and Laschever, 2012). A 2005 Israeli reform shifted the ability to choose savings programs from employers to individuals. Though funds performed similarly, savings decisions were strongly influenced by the choices of coworkers with the same ethnic background (Mugerman et al., 2014). Information transmission may be the mechanism behind these peer effects. In the context of military pensions, individuals must choose between an upfront lump sum payment of $30,000 with a reduced future pension payment, or no upfront payment with a higher future pension payment. Previous peer take-up of the upfront lump sum was negatively associated with own take-up of that option, perhaps because their peers who chose the myopic lump-sum payment convinced the next round of choosers to consider the more farsighted-option (Cunha and Veith, 2018). In the context of programs aimed at limiting substance abuse and suicide, this may hold lessons for the DoD: peers are watchful of what choices peers make and what happens to coworkers who take up new programs designed to assist them. [2]

[2] Training programs can also improve the productivity of un-treated peers in the workplace. For instance, one work-related training program increased own performance by 10%, and a 10 percentage-point increase in treated coworkers increased other workers' performance by 0.51% (De Grip and Sauermann, 2012). For the Department of Defense, trained individuals can disperse knowledge to their untrained peers.

2.4.2 Productivity

In general, better-performing peers in a workplace are associated with better own-performance (Herbst & Mas, 2015). Peer effects could transfer in a variety of ways, including knowledge transfer, social pressure, and social support (or, conversely, antagonism) (Chiaburu and Harrison, 2008). There is some evidence that effects are larger in the type of low-skill occupations where the mechanism is likely social pressure, while there is little wage effect in high-skilled occupations where the mechanism is social pressure (Cornelissen et al., 2017). For instance, putting highly productive grocery store staff onto a shift was associated with a boost in performance for the whole team, especially for workers who saw each other frequently and only when the workers' productivity was observed by others on the team (Mas and Moretti, 2009). This social pressure improved the performance of everyone on the team, on average.

Peer social pressure may apply even when one person's effort is unrelated to the productivity of the other people on the team, and each person is paid per piece rates based on individual productivity. Compared to cases when a worker had no social ties to coworkers, a given worker's productivity significantly increased when working with a more-productive friend (Bandiera et al., 2010). At the same time, a given worker's productivity decreased when working with less-productive friends. For the firm studied in this research, the net effect of social incentives was positive when averaged across all workers (Bandiera et al., 2010). This may differ in cases where individual productivity affects other workers. Heterogeneity of worker ability may improve team performance in team-based pay systems, while heterogeneity may harm overall team performance if individuals are competing against each other (Chan et al., 2014).[3]

2.4.3 Ethics

Peers can even influence the ethics of individuals. As vehicle emissions inspectors worked across different organizations, they adjusted the rate at which they passed vehicles to more closely match their current coworkers. Still, individual inspectors had persistent ethical stances that limited the magnitude of this influence (Pierce and Snyder, 2008). That is, stringent inspectors remained fairly stringent regardless of where they worked, but they were somewhat less stringent at loose organizations than when they were at strict ones.

[3] Working with an elite cast also increases the probability that an actor received an Academy Award (Rossman et al., 2010), and there was positive offensive productivity spillovers among professional basketball players (Arcidiacono et al., 2017, Kendall, 2003) and in track and field heats (Hill, 2014). In the elite world of the National Spelling Bee, the current speller performed better if the predecessor was incorrect than when the predecessor was correct (Smith, 2013). Though, we note, peer spillover does not extend to professional golfers' performance, as playing partners' ability does not affect own performance (Guryan et al., 2009).

Relatedly, working near peers constrains unethical behavior in laboratory-based settings, though if enough peers appear to cheat then unethical behavior returns to the level of an individual's unsupervised cheating levels (Pascual-Ezama et al., 2015). The military is not exempt from this behavior. Using data from 1959-2002, adding one additional student who cheated in high school to a cohort induced 0.33-0.47 additional college students to cheat at the three major service academies (Air Force, Army, and Navy) (Carrell et al., 2008). Adding one additional student who cheated while at a service academy to a cohort induced 0.61-0.75 additional college students to cheat (Carrell et al., 2008). When thinking about substance abuse, it may be important to know that ethical stances may change as individuals are exposed to more- or less-virtuous peers.

3 Research Strategy

3.1 Overview

Our first task was to assemble a comprehensive analytical file at the individual-month level that links more than 10 different administrative databases. We assigned a unique study ID to each service member in each database in order to facilitate the merging of databases and to allow us to track individuals over time. We then defined units within each service as the empirically tractable grouping of individuals that would expect to interact with each other on a daily basis. Using these unit identifiers, we aggregated the individual-month data into unit-quarter level variables. Finally, we used the TRICARE administrative data to create variables at the individual level that identify engagement in destructive behaviors, and then we aggregated these behaviors to the unit level.

3.2 Overall Study Population and Data Sources

Our study population includes all active-duty service members between 2003 and 2015[4], including reservists and members of the national guard who were activated for at least 30 consecutive days. We analyze each specific aim for both the Navy only and the overall sample that includes all services (Navy, Marine Corps, Army, and Air Force).

[4]For objective #3, the analysis period is 2002 and 2011 due to availability of certain individual data elements

Figure 1: Sources of data and linkages between sources

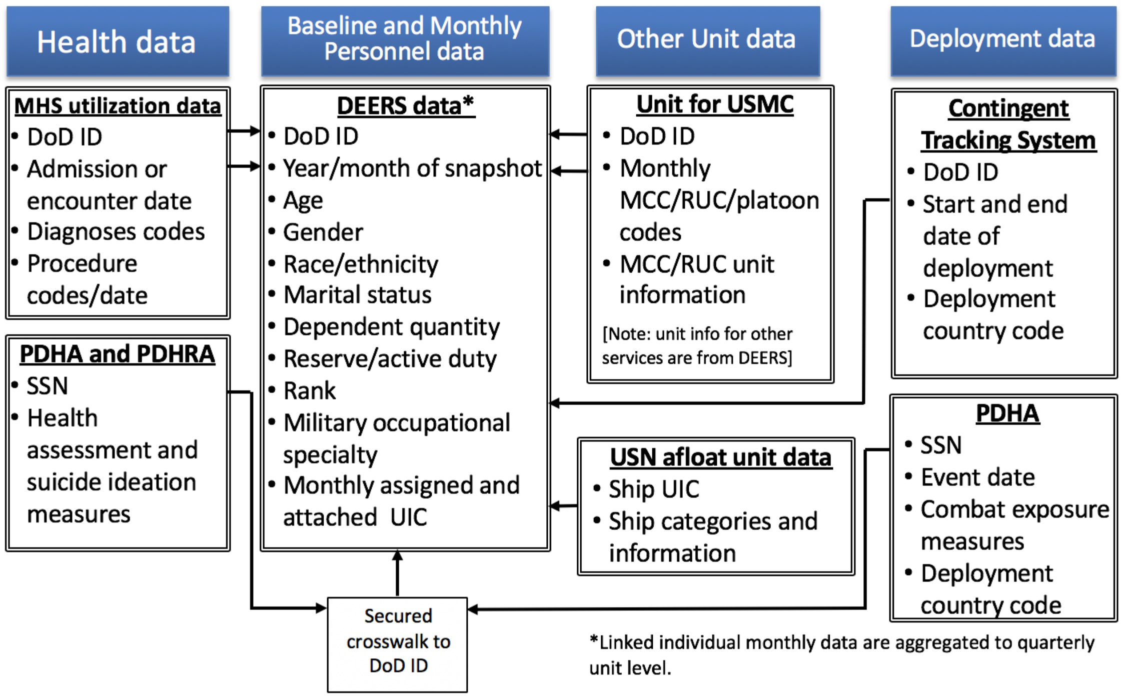


Figure 1 presents the linkages across the individual- and unit-level datasets that were used in our analysis. We have approval to access all data assets per DHA DSA #18-2000 and our research is covered by the Naval Postgraduate School (NPS) IRB protocol (#NPS.2013.0088-CR04-EP5-A). Below we summarize each data asset in more detail.

- *Monthly demographic and service information of individuals.* From the Defense Enrollment Eligibility Reporting System (DEERS), we obtained demographic characteristics (such as race, gender, marital status, number of dependents) and service information (such as rank, service branch, active duty status, military occupational specialty), which forms the population of our analytical sample.

- *Health and behavioral outcomes.* Health care utilization/claims data captured all service members, who are automatically enrolled in TRICARE, and provided clinical diagnoses of mental health conditions from all medical visits (care provided through direct care and purchased care; care provided in outpatient and inpatient settings) during years of service from the Military Health System (MHS) Data Repository.

- *Deployment history and combat exposure.* We use two sources of data to capture unit members' deployment history. First, the Contingency Tracking System (CTS) identifies dates and locations of deployments under Operation Enduring Freedom and Operation

Iraqi Freedom. Second, we supplement the CTS information with the Post-Deployment Health Assessment (PDHA) to capture deployments that were not part of the operations collected by CTS. The PDHA captures dates and locations of deployments, along with measures of exposure to combat and the intensity of that exposure.

- *Individual monthly unit assignment.* We obtain monthly unit information from two sources: monthly assigned and attached Unit Identification Code (UIC) for Army, Navy, and Air Force come from the DEERS database, while the monthly Major Command Codes (MCC) and Reporting Unit Codes (RUC) for the Marine Corps come from the Marine Total Force Data Warehouse (TFDW).

- *Unit geographical and installation information.* We obtain unit information (such as location, installation names, type of units) from three sources: TFDW data (for the Marine Corps) and Defense Manpower Data Center (DMDC) data (for all other services) identify geographical locations of the units, and we use the Center for Naval Analysis Integrated Ship Database to identify homeports and identities of Navy ships.

3.3 Defining Military Units and Key Variables

Military unit definition

A critical task for our project is to define units and peer groups for each service. We have consulted with various stakeholders and subject matter experts across all four services to determine the conceptual framework for, and the empirical definition of, units for our analysis. To understand how peers might influence individual behavior, we ideally would like to identify *units* as the workplace in which service members have meaningful professional and organizational interactions with other members in the same unit. For example, for Army and Marine Corps infantry, platoons seem to be reasonable operational units. On Navy afloat platforms, closer interactions occur among sailors of similar rank groups and rating groups, while Air Force units are organized based on job type, command, and unit codes.

Empirically, we face several major challenges. First, we would like to develop a common metric whenever possible that allows us to compare comparable units across all services. Second, we want to conduct our analysis at the population level so our results can be generalizable. Given the large scale nature of the analysis, the metric we choose to define units and peer groups would not capture unique and nuanced features that are specific to certain units. Third, we must rely on centralized administrative data that are available for all services. Given these conceptual and empirical parameters, the closest proxy for these peer groups is the unit identification codes, except for the Marines: the MCC/RUC codes more appropriately identify units in the Marine Corps than does the UIC. Consultation with experts from each of the services, service stakeholders, and from the prior literature (Ursano et al., 2017) led us to adopt the following empirical rules for defining units:

- *Army.* The 6-digit attached unit identification codes (UIC); if attached UIC is unavailable, then use the assigned UIC. The 6-digit UIC codes is the closest proxy to platoon level groups.
- *Marine Corps.* A combination of MCC/RUC codes, with additional breakdown into platoons for larger units.
- *Navy afloat platforms.* The unique UIC assigned to each ship. We further separate out the enlisted and officers so that each afloat platform has 2 separate groups.
- *Navy ashore platforms.* The 6-digit attached UIC; if attached UIC is unavailable, then use the assigned UIC.
- *Air Force.* The 8-digit Personnel Accounting Symbol (PAS) code that groups airmen by job type, command, and units.

Destructive behavior and mental health outcomes

The clinical codes that allow us to capture destructive behavior and mental health outcomes from the available clinical encounter data are the International Classification of Diseases, 9th edition (ICD-9). Our data ends as of September 30, 2015, after which the clinical records switched to the 10th edition of ICD. After consulting with clinicians and the extant literature,(Centers for Medicare and Medicaid Services, 2017, National Center for Health Statistics, 2011, Shen et al., 2016) we have identified clinical codes that are suitable to identify the outcomes for our current effort. These codes and definitions are detailed in Table 1. We separate out substance us disorder into two categories: alcohol use or drug disorder (where we expect such condition would impair job performance) and tobacco use disorder (where we expect no impairment but a potentially different type of interaction among peers compared to alcohol or drug use).

For cross-unit variation analysis (Aims 1 and 2), we examine all 5 outcomes. For peer influence analysis (Aim 3), we exclude general anxiety from the analysis. Our conversation with clinicians indicated that general anxiety tends to be the “catch-all” diagnosis for all things that cannot be precisely diagnosed. Given that we do see that peer influence can go opposite direction depending on the specific diagnosis, we want to focus on outcomes that are narrowly defined.

For each individual service member, we first identify whether he or she was diagnosed with each of the conditions in Table 1 in a given quarter based on his or her admission or encounter dates. We then define a variety of measures that capture history and recency of the diagnoses, as explained in more details in Section 5. For unit-level analysis, we aggregate the number of members in a given unit that had the condition in a given quarter.

Defining work and life stressors for individual service members

In our previous work, we found that stressors in workplace and personal life are associated with higher probability of individuals diagnosed with a variety of mental health conditions and suicide(Shen et al., 2010, 2012, 2016). In our current work, we capture the following four stressful events.

- Demotion: we use rank change between quarters as reported in DEERS to identify whether a service member was demoted in a given quarter.
- Divorce: we use marital status change between quarters in DEERS to identify whether a service member was divorced in a given quarter.
- Deployment to any location: we use a combination of CTS and PDHA deployment dates to identify whether a service member was deployed anywhere in the world.
- Deployment to combat zone: we use a combination of CTS and PDHA deployment dates and country codes to identify whether a service member was deployed to combat zone (proxied by deployment to Iraq or Afghanistan) in a given quarter.

4 Descriptive Statistics of the Study Population

4.1 Individual level summary statistics

Table 2 shows that at the individual service member level, we captured 19,603,792 person-quarter observations representing 895,983 Navy active-duty service members who served between 2003 and 2015. Our entire sample, when combining all four services, includes approximately 81 million person-quarter observations representing 3.63 million unique service members.

Table 3 summarizes the demographic and service characteristics at the individual level. As we observe the entire active-duty population (including the reservists who became activated), this data is represents the military as a whole. Relative to the other three services, the Navy underutilizes the PDHA by a large margin. While we do expect to see a discrepancy in the percent deployed when comparing records from CTS and from PDHA, the differences tend to be small in Army, Marines, and Air Force (the discrepancy is under three percentage points). However, at the person-quarter level, CTS indicated that on average, about 10% of sailors are deployed in a given quarter, whereas the PDHA only identified 3% of sailors being deployed.

Table 4 shows crude rate per 10,000 service members for each outcome (measured as number of unique person with a given outcome divided by total number of unique service members). For the Navy, we further break out the crude rate by ashore and afloat platforms. We expect to see lower crude rates from service members who were stationed in afloat units, since medical records might not be3 fully transmitted from afloat units. It is interesting to note that while crude rates of all outcomes are substantially lower from service members in afloat units, the crude rate for alcohol or drug misuse is similar between ashore and afloat units.

4.2 Unit level summary statistics

By design, we exclude units that had fewer than four members, as units with very few members likely have different group dynamics than larger groups.[5] This excludes 1-2% of our individual analytical sample, depending on service. Table 5 shows the sample size of our unit-level analysis. Table 6 shows member characteristics at the unit level and the geographic distribution of units.

We want to highlight two panels in particular: the distribution of stressful events and unit size. The first panel shows the percent of units that have members who experienced a given stressor in the past four quarters. For each stressful event, we report two measures, the percent of units that have at least one member experiencing the stressor in the past four quarters and the mean rate of each stressor. Take the Navy as an example: amongst all Navy units (afloat or ashore), 28% of units have at least one member who was demoted in the past four quarters, and the mean rate of demotion across all Navy units is 0.8%. In comparison, the Army has the highest percent of units with members that were demoted (45%) while the Marine Corps has the highest mean rate of demotion (2.4%). Table 6 also shows that 41% of Navy units have at least one member who was divorced in the past 4

[5]Our analysis would not be meaningful for the non-trivial number of units that only have one member.

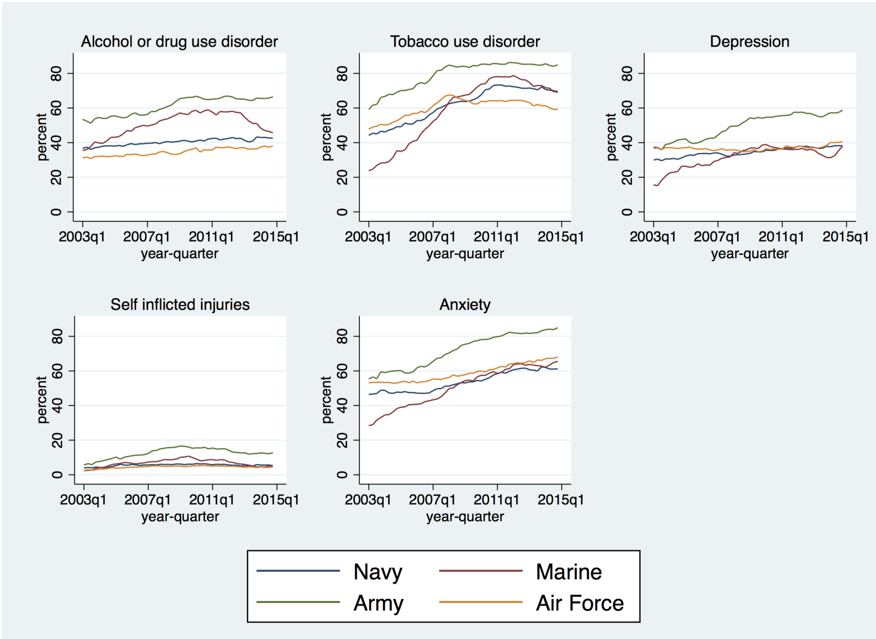
quarters with a mean divorce rate of 1.6%. The Army again has the highest percent of units with members who underwent divorce in the past four quarters (59% with a mean divorce rate of 2.6%). The Navy has the lowest mean rate of deployment as captured by CTS and PDHA (16%) while the Army and the Marine Corps have a mean rate of deployment of over 30%. Not surprisingly, relatively few Navy active duty service members were deployed to Iraq or Afghanistan (on average, 4% of members in a unit were deployed to these two countries), whereas in the Army and the Marine Corps on average about a quarter of members in a unit had been deployed to those two countries.

The distribution of unit size is similar across the four services, where the most common unit size is 11-50 members. For Aims 1 and 2, we analyze all unit sizes reported in Table 6. For the peer influence analysis, we limited our analysis to units that had 4-150 members. The choice of 150 as a maximum size was motivated by Dunbar's Number, the cognitive ceiling beyond which our ability to have individual relationships is hindered by neocortical limitations (de Ruiter et al., 2011). Lastly, it should be noted that while reservists or members of the national guard represent a small share of the overall active duty workforce (a mean rate of 2-4% across units), the presence of reservists or guard members is widespread: 43% of Navy units have at least one reservist or national guard member present in a given quarter.

Unit level outcome trends

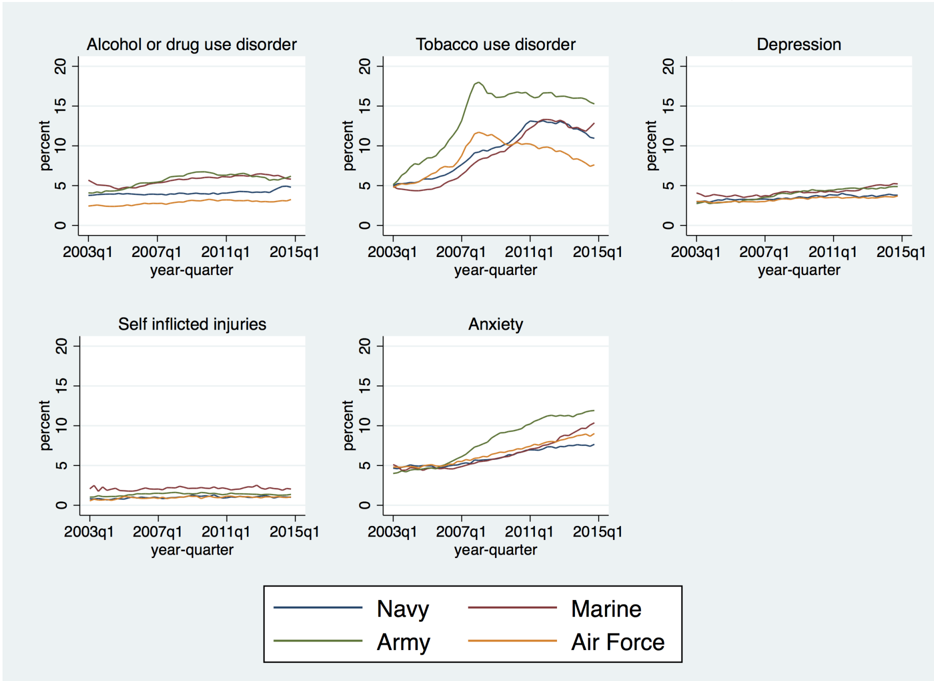
Figure 2 displays the percent of units that contained members diagnosed with a given outcome, and several observations are of note. First, in any given quarter, there is a large share of units with at least one member who was diagnosed with the given mental health diagnoses in the past four quarters. The first panel shows that about 40% of Navy units had positive incidents of alcohol or drug use disorder while about 60% of Army units had positive incidents of these disorders. Second, there is generally an increasing trend over time across all four services. For example, the percent of Navy units with members who were diagnosed with tobacco use disorder in the past four years increased from 40% in 2005 to almost 70% in 2015. The largest increase in tobacco use disorder is observed in Marine Corps units: percent of units with positive incidents increased from 20% to 70% between 2003 and 2015. Third, among all four services, the Army (the green line in Figure 2) tends to have a higher percent of units with members with recent past diagnoses across all five outcomes.

Figure 2: Percent of units with at least one diagnosis



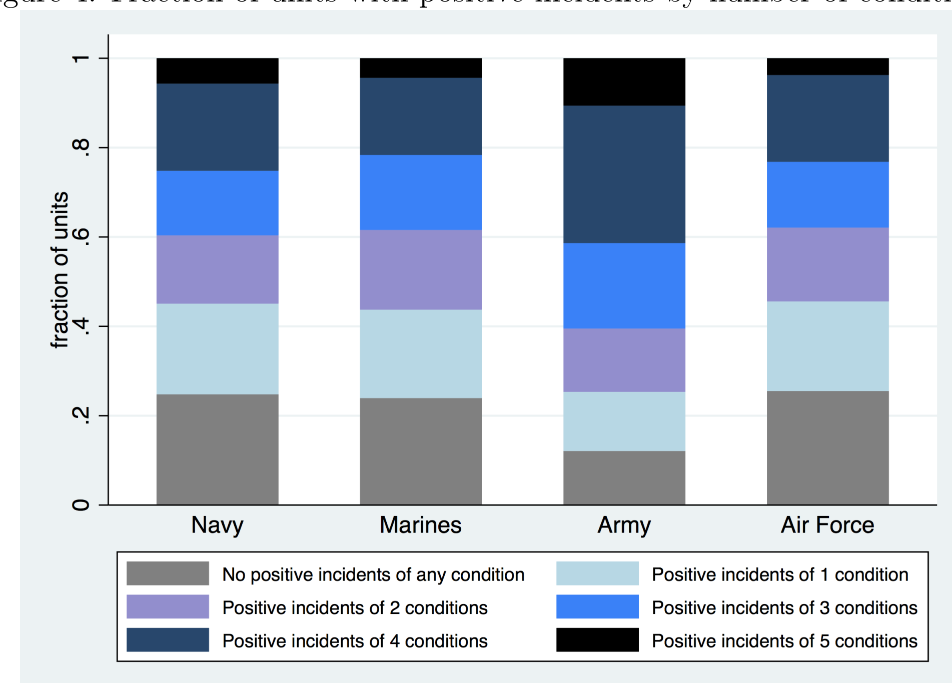
Next, we condition only on units with any positive diagnoses of a given outcome and we explore the conditional mean unit-level prevalence rates, as seen in Figure 3. Among units with positive incidents of the disorder, the mean prevalence rate is fairly steady across years for alcohol or drug use disorder (between 3 and 5%), depression (between 4 and 5%), and self inflicted injuries (around 2%). On the other hand, the mean prevalence rate increased substantially for tobacco use disorder in the first half of the study period (the prevalence rate ranged from 5 to 17%) and for anxiety in the second half of the study period (ranging from 5 to 12%).

Figure 3: Unit-level prevalence rate conditional on having positive incidents



When examining all outcomes together, Figure 4 shows that only about 20% of units have zero incidents of any kind (for the Army, only 10% of units have no reports of any conditions). Most units have positive incidents of multiple conditions in any given quarter.

Figure 4: Fraction of units with positive incidents by number of conditions



5 Statistical Methods and Results

5.1 Aim 1. Determine whether there are systematic relationships between unit composition and unit-level incidences of destructive behaviors

Overview

Our first aim was to empirically investigate whether there are systematic differences across units in unit-level incidences of the destructive behavioral outcomes outlined in Table 1. The unit of observation is the unit-quarter; thus, for example, a unit that existed in all 12 years of the study period would appear 48 times in this analysis. The outcome of interest is whether a unit is ranked in the top decile of the distribution of unit-level incident rates: we define such units as "high-risk" units. The key independent variables include unit level stressors and other unit-level factors as described below, and the statistical model is a linear probability model (estimated via Ordinary Least Squares) with heteroskedasticity-robust standard errors that are clustered at the unit level to take into account intracorrelation of observations from the same units (Stock and Watson, 2008).

Defining outcomes for Aim 1

The focus of Aim 1 is to investigate whether units with a high prevalence of a given disorder systematically differ from other units in terms of unit composition and other unit characteristics. To achieve this goal, we first rank the unit level prevalence rate of each condition across all observations. We then define a unit-quarter observation as a "high risk" observation if its prevalence rate is in the top decile of that empirical distribution. We choose this metric over alternatives (such as using the mean prevalence rate directly) because this binary outcome allows us to compare results consistently across outcomes with wide ranges of prevalence rates.

Independent variables in the model

Our key independent variables for Aim 1 are the unit level prevalence of members who recently (in the past four quarters) experienced each of the four stressors defined in section 3.3. For ease of interpretation, we grouped each stressor into three levels. Take demotion as an example, the three categories are (1) units with no members being demoted in the past four quarters (the reference group), (2) low rate units, defined as units where percent of members who experienced demotion was in the bottom 50th percentile among units with non-zero cases of demotion, and (3) high rate units, defined as units where the unit level demotion rate was in the upper 50th percentile among units with non-zero cases of demotion. Our last set of key variables are indicators for the geographical locations of units: Overseas, the 4 Census regions (Northeast, Midwest, South, West[6]), and unknown location, which servers as the reference group. For the Navy, we further disaggregate unit platforms as follows: air craft carriers (the reference group), cruisers, destroyers, frigates, submarines, other afloat platforms, and land based units.

Other independent variables include the unit size (4-10 is reference group, 51-100, 101-150, 151-400, 401-1000, 1000+), unit member specialty distribution (presence of combat arms specialists, aviation, or medical, each classified into three levels in the same way that we classified the prevalence of stressors), the presence of reservists or members of the national guards (three levels with no reservists or guards in the unit as the reference group), unit member demographics (percent that are male, Black, Hispanic, and Asian or Pacific islanders). Lastly, we include year fixed effects which control for macro trends that apply to all units

Findings

Table 7 reports our multivariate findings of the key variables for the Navy population (complete results for the Navy are included in Appendix Table A1). Units that have high rates of demotion are more likely to be high-risk units for all five outcomes, although the magnitude of the association varied quite a bit across outcomes. Take alcohol or drug disorder for example, if a unit's demotion rate is in the "high rate" category (mean demotion rate is 4.6% and 14% of Navy units quarters fall into this category), its probability of being a high=risk unit for alcohol and drug disorder would be 6.189 percentage points (off the base of 10%) higher than *similar* units (in terms of characteristics that we control for in the models) with no demotions (which represent 72% of Navy unit quarter observations). It is important to note that our Aim 1 analysis only establishes associations, not causality. That is, we do not know, for example, whether demotions are causing destructive behaviors or whether destructive behaviors are causing demotions.

For Navy units that have experienced a high rate of divorce among its members (this category contains 20% of all Navy unit quarters, and the mean divorce rate is 6.7%), we see

[6]Map of Census regions and their corresponding states are included in Appendix Figure A1

a higher probability of being high-risk units for tobacco misuse and anxiety (by 1.17 and 0.61 percentage points, respectively; off a base of 10 percent), but slightly lower probability of being high-risk units for self-inflicted injury (by 0.38 percentage point) compared to similar units with no divorce (units with no divorce represents 59% of all Navy unit quarter observations).

For the Navy, high level of deployment per se does not appear to be associated with higher probability of being high-risk units. However, if a unit has a high percent of members returning from combat deployment (22% of Navy unit quarter observations all into this category, mean deployment rate is 17%), its probability of being a high-risk unit is higher than units with no members returning from combat deployment by 1.8, 2.3, and 0.5 percentage points for depression, anxiety, and self-inflicted injuries, respectively.

Table 7 also shows that high-risk land-based units are concentrated in certain geographical regions. For example, the Northeast regions have higher probability of having high-risk Navy units in tobacco misuse, depression, and anxiety compared to similar land based units in other geographical locations, whereas the West region have higher probability of having high-risk units in self inflicted injuries. For drug and alcohol misuse disorder, we see a higher concentration of high-risk units for whom we cannot identify their geographical locations.

Amongst afloat platforms, we noted that while submarines have the lowest probability of being high-risk unit for tobacco misuse, this category has the highest probability for alcohol and drug misuse compared to other platforms (by 7 percentage points compared to air craft carriers, the reference platform), assuming similar unit member composition. On the other hand, destroyers have the highest probability of being high-risk units for self inflicted injuries (by 10 percentage points compared to carriers).

We report our results on the key variables for the Marine Corps in Table 8 and find that results on life and job stressors are very similar between the Navy and the Marine Corps populations. The magnitude of the estimates is similar between the two populations, except that Marine Corps units with high level of demotion rate has higher likelihood of being high-risk units in tobacco misuse and self inflicted injuries. For the Marine Corps, high-risk units for tobacco misuse tend to be concentrated in oversea units, followed by units in the Northeast region. high-risk units for depression and anxiety tend to be concentrated in the Midwest regions.

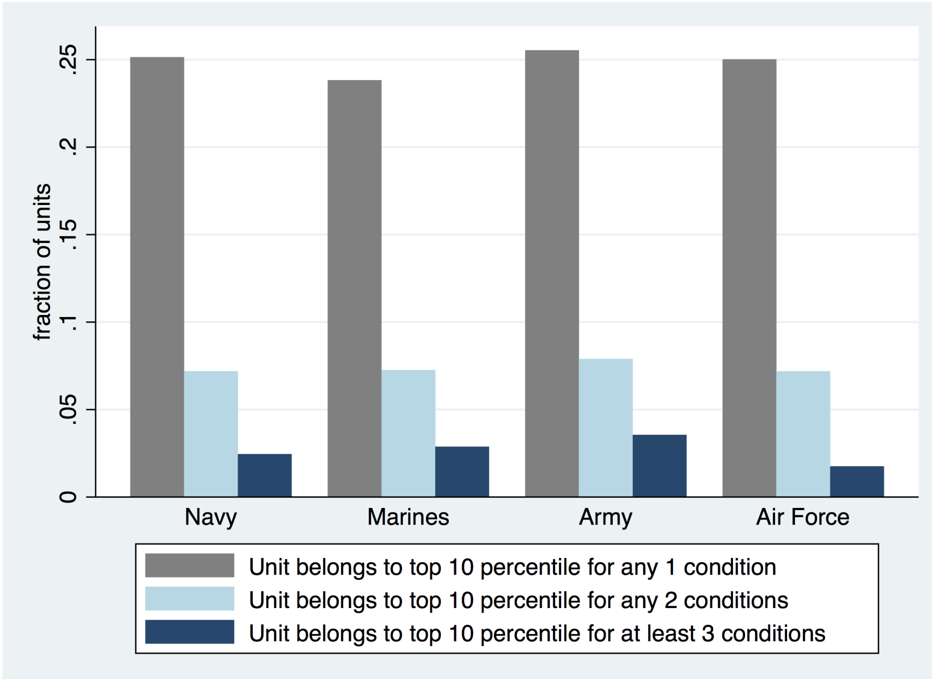
To compare the Naval only results to the US military as a whole, we repeat the analysis using the entire study population. The independent variables are the same except for the following: we include indicators for each service branch (Navy is the reference group) and we group Navy afloat units into an overall "ship" category instead of breaking them out in finer details. Table 9 shows that results on life and job stressors are very similar whether we examined Navy, Marines, or the overall U.S. military. Geographic concentration of high-risk units is quite different when comparing Navy and the overall U.S. military, but similar between the Marines and the overall U.S. military. For example, when looking at all four services together, overseas units have the highest probability of being high-risk units for tobacco misuse (by 12 percentage points when compared to unknown location), whereas overseas units among the Navy have the lowest probability. Lastly, among the overall U.S. military, units in the Midwest Census region had the highest probability of being high-risk units for depression and anxiety, followed closely by units in the Northeast.

5.2 Aim 2. Identify units identified as "high-risk" units across multiple destructive behaviors

Overview

Aim 2 examines the extent to which units are high-risk (i.e., prevalence rate is in top 10 percentile for a given condition) across multiple outcomes. Figure 5 shows the fraction of units that were identified as high-risk units by number of conditions. For example, 25% of Navy units were identified as high-risk units for precisely one outcome, 7% for two outcomes, and 2% for three or more outcomes. In general, across services, about 25% of units are high-risk units in one outcome whereas about 10% of units are high-risk units in two or more outcomes.

Figure 5: Distribution of high-risk units by number of conditions



Based on the above empirical distribution, we define the a binary dependent variable for Aim 2 as follows: a unit takes on the value 1 if it was identified as a high-risk unit in at least two outcomes and 0 otherwise. The empirical model for this analysis is analogous to the models in Aim 1 described above.

Findings

Table 10 shows that among the four life and job stressors, results are remarkably similar across Navy, Marines, and the overall U.S. military. Recall that about 10% of all units are identified as high-risk units for at least two outcomes. Column 1 of Table 10 shows that for the Navy, a unit with a high rate of demotion is 4.4 percentage points more likely to be a high-risk units with multiple outcomes. The magnitude is slightly larger when we examine the entire U.S. military (5.8 percentage points, or 58% higher compared to a unit that was not identified as high-risk for any outcomes). Results for the rest of the covariates are presented in Appendix Table A2. Units in which there was a high percentage of members that were demoted, divorced, or returned from combat deployment within the past four quarters have a higher probability of being high-risk units in at least two destructive behavior outcomes compared to units with no members experiencing those events in the past four quarters. Amongst the four stressors, the difference in high-risk unit probability is largest when looking at demotions.

Within the Navy, units with multiple high risks tend to be concentrated in the Northeast region (5.5 percentage points higher than units in unknown location, the reference group). Overseas and afloat units tend to have a lower probability of being multiple high-risk units. When looking at the Marines or the U.S. military as a whole, units with multiple high risks tend to be concentrated in the Midwest regions, although the variation across Census regions tend to be smaller in magnitude when examining the entire active-duty population.

5.3 Aim 3. Estimate the influence of peers have on each other to engage in destructive behaviors

Overview

Our third aim was to empirically estimate the extent to which group members influence each other's propensity to engage in destructive behaviors. The decision to misuse substances may be influenced by one's surroundings, and military personnel work and live in close proximity to each other in tight-knit units. In contrast to aims 1 and 2, the unit of observation for this analysis is the individual service member. The outcome of interest is whether an individual had a positive diagnosis of one of four destructive behaviors within four quarters of joining a new unit: tobacco abuse, alcohol or drug abuse, depression disorder, and self-injury disorder. The key independent variables include both individual-level and unit-level factors as described below, and the statistical model is a "linear-in-means" model including unit fixed effects (Graham and Hahn, 2005).

Analytical sample

In order to identify meaningful peer influences within units, we restrict our sample to only those units with at least 5 members and no more than 150 members. Units with very few members likely have different group dynamics than larger groups, while individuals may never interact with each other in very large groups. The choice of a minimum group size of five is motivated by an empirical structural break in the distribution of unit size at 5 members, with relatively few units having two, three, or four members. The choice of 150 as a maximum size was motivated by Dunbar's Number, the cognitive ceiling beyond which the ability to have individual relationships is hindered by neocortical limitations (de Ruiter et al., 2011). In practice, these restrictions only eliminate approximately 10% of units, thus still preserving the generalizability of our findings to the military as a whole, especially as most service members would rotate into and out of large and small units throughout their service.[7]

At the individual level, we limit the sample to those person-quarters in which a service member newly joins a unit. By focusing only on new arrivals, we are able to isolate the impact of the peers in the new unit a person is joining separate from the impact of the individual of study's impact on others (this is known as the reflection problem). As with the restriction on units, this restriction on individuals does not invalidate the generalizability of our findings to the military as a whole because all service members rotate into and out of units on set rotation schedules.

Methodology

The main challenge in estimating the influence of individuals on each other is to separate other factors that influence these behaviors but are common to all members of a unit. In the language of Manski (Manski, 1993), these common influences are known as "correlational" and "exogenous" factors. Our model can identify the causal influence of peers by including the following factors:

- **Unit fixed effects to control for common shocks:** In the context of the military, all unit members experience similar correlational influences due to the similar nature of their jobs and the common physical environment in which they live. For example, all Marines in a combat platoon are infantry fighters and they live in the same geographic location, and that job or area could influence one's decision to engage in destructive behavior. We can separate out this impact empirically by focusing on variation in outcomes within a unit as opposed to across units. We achieve this goal by including unit fixed effects in the regression model—these fixed effects remove common shocks to the same unit that all members experienced.

- **Individual risk factors:** We control for influences that are not due to the unit-specific environment by including individual-level risk characteristics as regressors in a multivariate regression framework. This set of variables includes individual service members' mental health history, their demographics, and their rank, and their service (in the cross-service models).

[7] In the Navy, the units that with more than 150 members are disproportionately located on larger ships, such as air craft carriers and amphibious assault ships; nonetheless, there are non-negligable numbers of these "large" units in all ship types and on land based Navy commands.

- **Peer influence factors within a unit:** After controlling for unit fixed effects and individual risk factors, the influence of peers on each other is identified by the relationship between the proportion of group members who have had a variety of mental health diagnoses in the recent past – precisely, one year before joining the unit - and one's own diagnosis. This peer influence is generally what policy-makers and clinicians are interested in identifying, as it is the direct influence of one's peers on one's own decision to engage in destructive behavior. In the standard linear-in-means model, the independent variable is a fraction (0 to 1). However, the coefficients of such a model are difficult to interpret, and so we instead present a more parsimonious model that includes two binary regressors indicating whether the unit is has a "low" or "high" fraction of peers with past diagnoses. The omitted indicator is thus being in a unit no peers who have had past diagnoses. We define "low" and "high" as below and above the median fraction of the outcome, conditional on having any peers with past diagnoses. Thus, the indicators vary by condition. In addition, we only consider peer diagnoses that were made while service members were at a different unit than the one in which they currently serve. If we included diagnoses that were made at the current unit, we run the risk of incorrectly identifying peer effects when in fact a medical provider happened to be systematically over- or under-diagnosing conditions.

We estimate the linear-in-means model by Ordinary Least Squares separately for each of the four outcomes: tobacco disorder, alcohol or drug disorder, depression disorder, and self-injury disorder. For ease of presentation, we multiply each of these outcomes by 100 (so a diagnosis is represented by 100 and no diagnosis is represented by 0): this reduces the number of decimal places in the estimated coefficients as shown below, but does not impact the ultimate interpretation of the findings.

It is important to emphasize that this empirical framework hinges on the fact that individuals are assigned to units without regard to their past medical history, which is in fact a defining characteristic of the formation of military units (effectively, individuals are randomly assigned to units, conditional on rank, experience, and occupation).[8]

Findings

We first present results for the Navy and then show a subset of the results for the Marine Corps and the DoD as a whole. Additional results for the DoD and any results for any other services separately are available upon request.

[8]Interestingly, one of the recommendations we offer below is to consider using past medical history when assigning individuals to units.

Column 1 of Table 11 presents estimates from a model of the impact of peers past tobacco use disorder on a Navy service member's propensity to be diagnosed with a tobacco use disorder. This column presents the estimated coefficients and standard errors of the two main independent variables: indicators for whether there was a high fraction of peers in the unit who had past tobacco diagnoses and whether there was a low fraction of such peers. The omitted variable is whether there were no peers who had a tobacco disorder diagnosis in the past fours quarters prior to joining the unit, and thus the interpretation of the coefficients presented is the impact of being in a unit with either a high or a low fraction of peers with past diagnoses, compared to being in a unit with no peers with past diagnoses. The coefficient of 0.0154 on "low fraction" implies that being in a unit with below median (conditional on having any diagnoses) number of diagnoses increased the likelihood of being diagnosed oneself by 0.0154 percentage points relative to being in a unit with no peers with diagnoses. This is a very small number: it is both insignificantly different from zero at conventional levels and it is small relative to the prevailing rate of tobacco disorder diagnoses of 2.41 percent in the population. Being in a unit with a high fraction of diagnosed peers is associated with a greater peer influence - the coefficient of 0.1866 is an order of magnitude higher than the coefficient for the low-fraction units, although it is still insignificant at conventional levels.

The remainder of our findings have similar interpretations, and so we proceed to discuss them at a more general level. Column 2 of Table 11 presents results of peer influences on alcohol or drug disorders. Compared to tobacco, the overall prevalence of drug and alcohol is lower by about half: 1.21 incidents per person-quarter compared to 2.41 incidents for tobacco. While a low fraction of peers with recent diagnoses has an insignificant effect, a high fraction of peers has a large positive effect of 0.14, representing an increase in the likelihood of diagnosis by almost 10%. Depression and self-injury have even lower prevalence rates in the population, at 0.34 and 0.05 diagnoses per person-quarter, and they show negative peer influences of large magnitudes, especially for self-injury. For example, being in a high-fraction unit implies that the likelihood of one being diagnosed drops by almost four times the mean diagnosis rate.

Some readers may be interested in the correlations of the other covariates with the outcomes in our models. We did not include those estimated coefficients for the sake of parsimony, but they can be found for the main models (Table 11) in Appendix Table A3.

Heterogeneity of results

Next we explore how peer influences vary among different sub-populations of the active-duty Navy, separating the population by whether they have had past diagnoses of destructive behaviors (Table 12), by age categories (Table 15), by officer status (Table 16), and by race/ethnicity (Table 17).

As it may be that the influence of peers is different for those with a past history of a destructive behavior, we first split the sample between those service members who have and have not had a past diagnosis of the outcome of interest. Table 12 contains the results. Comparing across columns, there does not appear to be much difference in peer influence among those with and without past diagnoses, except for self-injury (columns 7 and 8): albeit this is a very small sample (4,067 service members). Specifically, a sailor with a history of self harm has a substantially higher propensity to inflict injury upon himself (by 5 percentage points, off the base of 27%) when he joined a unit with a high fraction of peers who were diagnosed with self inflicted injuries in the past four quarters.

Next, we split the sample into three categories that roughly reflect the developmental stages of adulthood: 21 years old and younger, 22 to 29 years of age, and 30 years of age and older. Table 15 contains the results for each of the outcomes of interest. One result that stands out is that the youngest population (21 and under) see some of the largest positive influences of peers, with many coefficients being significantly different from zero despite the small sample size in this group. In particular, there is a strong positive influence of peers in tobacco diagnoses, and strong negative influences of peers in alcohol/drug, depression, and self-injury diagnoses. The middle age group (22-29 years old) sees peer influences only in self-injury, while the oldest age group only sees influences in alcohol/drug diagnoses.

Comparing officers and enlisted personnel, Table 16 shows robustly that all of the peer influences are concentrated among enlisted personnel. And, naturally, the estimated coefficeints for the enlisted are larger in magnitude than for the population as a whole. We see here that there are meaningful, positive peer influences on tobacco and alcohol/drug disorders amongst the enlisted, while there are negative peer inflences on depresesion and self-injury.

Finally, we show how peer inflences vary across race/ethnicity in Table 17. We separate the sample into four categories: white, black, Hispanic, or other race/ethnicity. Taking into account the fact that standard errors are larger for models other than for white service members, due to smaller sample sizes, there do not seem to be meaningful differences in diagnoses across these racial/ethnic groups.

Results for the Marine Corps

Tables 13 and 14 replicate Tables 11 and 12 for the Marine Corps. Compared to the Navy, Table 13 shows positive - and now statistically significant - impact of past tobacco disorders on current peer's use of tobacco. Interestingly, for alcohol and drug disorder, the sign is reversed, with a negative and significant coefficient in the Marine Corps, which suggests a protective influence of peers. The coefficients for depression and self-injury have the same (negative) sign as in the Navy. When we split the sample into those who have had and have not had a diagnosis of the destructive behavior in question in the past (Table 14), we see: similar results for both groups for tobacco. We also see that most of the negative impact of peer's alcohol/drug, depression, and self-injury diagnoses is among those with a past diagnosis.

Results for the DoD as a whole

Finally, we present the main results for the DoD as a whole. Compared to the Navy and the Marine Corps, Table 18 shows many more statistically significant results for the DoD as a whole, although it must be kept in mind that the sample size has also increased by about a factor of 4. Nonetheless, the magnitudes of the coefficients are large and meaningful. For example, the positive impact of peer's past tobacco diagnoses on one's own diagnosis is 0.08 for a low fraction of peers and 0.09 for a high fraction of peers, and this represents an increased likelihood of diagnosis of about 5 percentage points. Alcohol/drugs, depression, and self-injury, on the other hand, show a negative influence of peers. Again, given the lower prevalence rates of these diagnoses, the magnitudes of the impacts are quite large.

We also split the sample into those who have had and have not had a diagnosis of the destructive behavior in question in the past, and the results are displayed in Table 19. Keeping in mind the differences in sample sizes, there does not appear to be meaningful differences across these two population groups for tobacco and alcohol/drugs, but we do see that the impact of peers is concentrated in those with past diagnoses of depression and self-injury.

Robustness analysis

This empirical exercise required multiple, nuanced modelling decisions, and we were diligent in assessing whether our conclusions are robust to various choices. We present the results of one important decision in Appendix Table A4, which contains estimates from a model that uses the linear fraction of peers with past diagnoses instead of indicators for units with high and low fractions of peers with past diagnoses. The only significant coefficient is for self-injury, and this lack of significance underlies our reason for using the categorical variables in our main model, in that the linear specification can mask important heterogeneity across the distribution of the stock of peers' diagnoses across units.

Summary of findings

We have developed and implemented a robust and precise methodology for identifying the influence of peers on one's propensity to engage in destructive behaviors. In general, we found that for some diagnoses and for some sub-groups, peers with past diagnoses meaningfully change the likelihood of a service member being diagnosed themselves. Peer influences seem to be the strongest in the enlisted population and among the youngest age group (21 years old and younger), and there does not appear to be much meaningful difference amongst different races/ethnicities or amongst those with or without past diagnoses. The results for the DoD as a whole suggest that peer influences are stronger in the other services than in the Navy.

Interestingly, peer influences are both positive and negative, suggesting both a destructive and a protective influence of peers. In general, the more peers that have past diagnoses of tobacco and alcohol/drug disorder diagnoses, the more likely a service member is to be diagnosed with those conditions. On the other hand, the more peer that have past diagnoses of depression or self-injury, the less likely is a service member to be diagnosed with those conditions.

5.4 Limitations

Our study has several limitations. First, we rely on clinical diagnoses to capture behavioral outcomes, records that can only be captured if a service member seeks, or is forced to seek, professional medical help. In the peer analysis in particular, this is problematic for several reasons: first, receiving a diagnosis involves both disclosing the condition to a clinician (or diclosing the condition to a superior who forces the service member to see a doctor) and the clinician correctly diagnosing the condition; second, we do not observe less-than-severe instances of destructive behaviors, such as tobacco abuse that does not arise to a diagnosable level; and third, we do not know whether peers were cured of their destructive behavior before they began interacting with the service member who newly joined their unit (simpley consider the difference between a peer who was diagnosed with alcohol abuse disorder, began treatment, and now can impart to others the downsides of drinking excessively with a peer who was diagnosed with alcohol abuse disorder and is still drinking heavily).

Second, the ICD-9 clinical code - which we observe in our medical data - might be inadequate to fully capture some of the outcomes. For example, there is no specific code in the ICD-9 that captures self-harm. This limitation can be mitigated in future research because new encounters are coded with the ICD-10, which does have a specific code for self harm history (Z91.5–personal history of self-harm). Relatedly, anecdotoal evidence suggested that some physicians might code self-harm as an adjustment disorder to protect the service member in a medical board. Adjustment disorder made up a large portion of the "other mental health" categories, ranging from 69% of diagnoses in that category in the Army to 54% in the Air Force; however, we have no way to differentiate whether an adjustment disorder reflects a true adjustment disorder or whether it was marked as such in order to mitigate negative consequence on a service member's career.

Third, among all the administrative data available to us, the PDHA and PDHRA are the only ones that capture suicide ideation. However, we were not able to utilize the PDHA and PDHRA as we had originally planned due to poor matching rates with the master personnel file, especially within the Navy. Another potential data to capture this important outcome is the periodic health assessment–these data resided with each service individually, and it is beyond our scope to obtain the PHA from each service separately.

Fourth, given the available administrative data, we can reliably capture four stressor events. However, there are other life stressors that might have larger influences on the health of units that we were not able to obtain, such as financial hardship among members (this is especially salient during economic downtime), death in the family, and special needs among dependents.

6 Discussion and Recommendations

As requested by OPNAV N17, we pursued three specific aims in our research: 1) to study the relationship between unit composition and unit-level incidences of destructive behaviors, 2) to identify units at "high-risk" of destructive behaviors, and 3) to study how peers within a unit influence each other to engage in destructive behaviors. We have developed an emprical framework which allows military policy makers to understand the variation in destructive behaviors at the unit level. Resources can be targeted at either the individual or the unit, and this framework and set of results covering the past decade give military policy makers vital information which can be used to make more informed choices about the optimal allocation of preventative resources. Below we discuss our major findings, lessons learned from the project, and their implications for current and future efforts to strengthen our armed forces.

We found that destructive behaviors are widespread across units: in about 80% of unit-quarters, we observe at least one member being diagnosed with one of the conditions we study. But, conditional on having any positive diagnoses in a unit, incident rates are low for most units. For these low-incident units, a minimally invasive program that monitors the stress level of members along with basic resilience training might be sufficient to prevent escalation of destructive behaviors.

More importantly, there are about 10% of units that display a high risk of destructive behavior across multiple conditions. Using our methodology to target these units, policy-makers may find it effective to target them with additional interventions.

Our analysis revealed that cross-unit variation due to common life stressors are similar across all services and are systematically associated with destructive behaviors. Given the available administrative data, we were not able to capture other life stressors, such as financial hardship, deaths in the family, or dependents with special needs. If the data were available, they should be incorporated in the Commander Risk Mitigation Dashboard.

We observed that high-risk units are not evenly spread out across geographic regions or platform types. Future research should study whether this variation is driven by the supply of mental health providers in each region, and whether mental health resource capacities are adequate to meet the demand for services in regions that have a high prevalence of high-risk units. In fact, we are working with the Defense Health Agency on a two-year project that would allow us to partially address this mental health resource capacity issue.

Within units, we found that peers impact each other's destructive behaviors in both positive and negative ways. For example, the abuse of tobacco and alcohol/drugs appear to spread in a negative manner across peers in a unit, while peers past experiences with depression and self-injury appear to have protective effects. Intervention policies - especially those that are targeted to the unit as a whole - should be designed with these potential peer influences in mind, for example, by informing individuals of the dangers of "following the crowd," while at the same time informing them of "learning from past experiences of your peers." Personnel planners may also consider using one's medical history in determining the assignment of individuals to units.

More broadly, the fact that peers do have some influence on individual behavior suggests that efforts to change social norms on certain behaviors (such as tobacco use and pornography consumption) would be more effective with buy-in of peer groups. But it is important to recognize that our analysis also revealed a large degree of heterogeneity in peer influences across different sub-groups. For example, younger and enlisted populations tend to be more readily influenced by peers. Any policies or intervention initiatives should recognize that a uniform policy across populations may not be effective.

When comparing the Navy and the Marine Corps with the rest of the armed forces, we found that peer influences tended to be weaker in those two services compared to the Army and Air Force. Policy interventions that intend to leverage peers to influence individual behavior are likely to vary in their effectiveness across services.

An important limitation of our work is that clinical diagnoses capture only a subset of destructive behaviors and mental health problems - in particular, they capture the most severe cases and cases from people who are *willing* to seek care. Future efforts should be made to capture less-severe instances of substance abuse, suicide ideation, and mental health issues that may precipitate destructive behavior. For example, the PDHA (Post-Deployment Health Assessment) contains such data, but it is not applied in a consistent enough manner in the Navy to be of use for the study of the Navy as a whole; similarly, the PHA (Periodic Health Assessment) also contains such data, but we were not able to obtain access for this study.

Our analysis was retrospective, and not predictive. Future research could develop a machine learning algorithm that can predict which units are the most likely to be high risk *in the future*. Such an algorithm extends the analysis we performed examining the cross-unit risk factors by allowing the functional form of the estimated relationship to be fully flexible. The vast database we have assembled, covering all available risk factors and the entire population of the U.S. armed services, permits sufficient statistical power to build high-dimension, highly-predictive models. This line of research would directly support Navy's current effort to integrate administrative databases to form a comprehensive picture of the sailor's career and health and use it to enhance the Commander Risk Mitigation Dashboard that allows unit commanders to assess the health of his or her own unit.

Currently there is major push toward using machine learning and artificial intelligence to manage and shape our end-strength. The machine learning algorithm proposed above, as well as the Dashboard initiative, are among those efforts. However, it is critical to recognize that the results of these efforts are only as good as the underlying data. One important lesson from our analysis is that while some databases may be rich in information, they may be of limited use to the Navy if coverage is not complete. In particular, assessment data such as the PDHA and PDHRA are severely underutilized by the Navy, leaving them of little use when studying the population as a whole. One potential data source that might be useful to capture the another dimension of health (aside from clinical data) is the Periodic Health Assessment (PHA), as every service member is required to complete the PHA regardless of his or her deployment status.

It would also be important to gather force wide information on potential protective factors at the unit level and understand their roles in reducing destructive behaviors. For example, understanding how variations in various types of counselings (pastoral, social workers) are linked to unit level risks of destructive behaviors would provide much needed insight on the resource allocation of Chaplains and social workers.

Another important facets of unit dynamic is leadership roles. As explained in Section 3.3, we define units in the broadest sense to allow for uniform definition across all services and all units. In particular, we identify people by their assigned units regardless of their role in the unit, and we cannot isolate impact of supervisor of each unit. Such "near peer" and similar leadership analysis would be important next step to understand peer dynamics within the unit. Some changes inevitably would have to come from the near peer group. Conversations with Navy officers indicated that it is OK to take smoke breaks on the ship but not any other types of breaks. Such culture inevitably lead to more sailors picking up smoking just so they can have breaks. To change such cultural norm would need buy-in from the supervisors and not just the peer groups.

Future research can apply the analytical framework we have developed to other behaviors that harm the mission of the DoD, such as sexual assault and physical violence. If data were available from physical evaluation boards and pay records, our framework could also be applied to less severe but more widespread outcomes that affect unit readiness, such as missed training days, muscular and skeletal injury rates, and non-deployable rates. Additional in-depth analysis on Naval communities that might be high risk communities of these other outcomes (for example, muscular and skeletal injuries are high in helicopter communities) might also be warranted. The accumulation of insights learned from a study of all adverse outcomes - not just those in our current study - would allow for the identification of units that are "high-risk" in a holistic set of destructive behaviors.

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Tables

Table 1: Clinical codes and descriptions of the outcomes of study

Outcome description	**Definition based on ICD-9 code**
Substance use disorder	
Alcohol use or drug disorder	291, 303,292, 304, 305 (exclude 305.1)
Tobacco use disorder	305.1
Major depression	296.2-296.3
General anxiety	300
Suicide attempts (self-inflicted injuries)	E950-E958

Table 2: Individual sample size

	Total number of person-quarter observations		Total number of unique person	
Navy	19,603,792	24%	895,983	25%
Marine Corps	10,239,762	13%	449,299	12%
Army	31,938,092	39%	1,490,766	41%
Air Force	19,179,847	24%	800,121	22%
Overall	80,961,493	100%	3,636,169	100%

Table 3: Demographic and service characteristics of individual analytical sample, 2003-2015

	Navy		Marine Corps		Army		Air Force	
	N	%	N	%	N	%	N	%
Demographics								
male	16,514,402	84	9,588,542	94	27,454,036	86	15,441,518	81
Race/ethnicity								
white	10,753,525	55	7,062,910	69	18,056,475	57	13,693,990	71
black	3,311,907	17	1,101,204	11	6,649,097	21	2,820,539	15
hispanic	2,626,602	13	1,399,377	14	3,493,298	11	969,560	5
asian	1,382,475	7	385,280	4	3,373,203	11	873,261	5
native	781,438	4	174,664	2	414,770	1	164,800	1
other races	797,915	4	144,677	1	379,751	1	711,334	4
Family status								
married	10,281,218	52	4,880,343	48	18,475,814	58	11,243,612	59
divorced	710,117	4	427,621	4	1,853,519	6	1,407,944	7
ever divorced	1,234,087	6	759,582	7	3,713,357	12	2,391,346	12
Service characteristics								
Rank								
enlisted	16,607,691	85	9,142,053	89	26,547,287	83	15,416,011	80
officer	3,009,803	15	1,105,016	11	5,402,900	17	3,770,109	20
Deployment status								
deployed (CTS)	2,083,222	11	1,550,898	15	6,361,608	20	1,794,069	9
ever deployed (CTS)	8,817,975	45	5,197,996	51	18,891,085	59	8,397,327	44
deployed (PDHA)	663,594	3	1,250,264	12	5,811,060	18	1,595,065	8
ever deployed (PDHA)	4,174,254	21	4,677,075	46	18,011,260	56	7,429,256	39
MOS categories								
Combat arm	1,093,394	6	2,515,481	25	7,885,423	25	955,913	5
Combat support	2,473,562	13	1,004,429	10	2,224,718	7	902,689	5
service support	3,411,650	17	1,905,797	19	6,784,004	21	7,490,125	39
aviation	2,195,714	11	1,286,562	13	1,173,962	4		
medical	486,608	2			2,686,933	8	681,276	4
other	1,433,829	7	42,690	0	1,913,445	6	809,477	4
Unit information								
Unit size (shore only if Navy)								
4-10	342,046	2	329,012	3	527,216	2	430,847	2
11-50	1,634,500	8	2,396,302	23	3,425,406	11	2,146,656	11
51-100	1,596,549	8	2,087,688	20	6,216,658	19	2,662,908	14
101-150	1,157,275	6	1,109,142	11	6,862,833	21	1,995,638	10
151-400	6,212,942	32	3,021,043	30	11,856,499	37	6,544,941	34
401-1000	3,052,542	16	1,114,649	11	1,771,201	6	4,064,365	21
>=1000	4,231,350	22	30,810	0.3	980,230	3	1,061,119	6
Ship category (Navy only)								
Carriers	1,808,934	9						
Cruisers	415,197	2						
Destroyers	853,327	4						
Frigates	273,139	1						
Minesweeper	23,474	0.1						
Submarines	449,973	2						
Patrol	6,881	0.0						
All other float platform	1,140,505	6						
Total number of observations	19,603,792		10,239,762		31,938,092		19,179,847	
Total number of unique person	895,984		449,299		1,490,766		801,646	

Table 4: Crude rate per 10,000 members

Crude Rates per 10,000 members					
	Navy Shore	Navy Afloat	Marine Corps	Army	Air Force
Sub. Use Disorder (any)	1,914	1,176	2,507	3,289	2,176
Alcohol or drugs	661	623	1,073	1,316	583
Tobacco	1,553	791	1,880	2,727	1,875
Depression	365	196	409	598	447
Anxiety	891	396	1,004	1,653	1,211
Self-inflicted injury	40	46	75	101	39

Table 5: Unit sample size

	Total number of unit-quarter observations		Total number of unique units	
Navy	198,435	19%	6,425	12%
Marine Corps	195,721	19%	15,881	30%
Army	413,578	39%	21,656	40%
Air Force	241,550	23%	9,543	18%
Overall	1,049,284	100%	53,505	100%

Table 6: Member composition and unit characteristics across services, 2003-2015

	Navy	Marine Corps	Army	Air Force
Unit member experience in the past 4 quarters				
have at least 1 member demoted	28%	41%	45%	20%
Mean rate of demotion	0.8%	2.4%	1.7%	0.4%
Have at least 1 member divorced	41%	37%	59%	48%
Mean rate of divorce	1.6%	1.9%	2.6%	2.3%
have at least 1 member deployed to anywhere	73%	78%	82%	76%
Mean rate of deployment to anywhere	16%	32%	31%	17%
have at least 1 member deployed to Iraq or Afghanista	44%	71%	77%	63%
Mean rate of deployment to Iraq or Afghanistan	4%	25%	26%	8%
Unit Census region				
Unknown	13%	7%	32%	23%
Northeast	4%	2%	3%	3%
Midwest	3%	3%	5%	8%
South	34%	44%	38%	33%
West	21%	38%	12%	21%
Oversea	13%	7%	8%	12%
On ship	11%			
Platform type (Navy only)				
Carriers	1%			
Cruisers	1%			
Destroyers	3%			
Frigates	1%			
Submarines	3%			
All other afloat platform	3%			
Land	89%			
Unit size				
4-10	28%	26%	21%	28%
11-50	38%	47%	32%	36%
51-100	12%	15%	20%	15%
101-150	6%	5%	13%	7%
151-400	13%	7%	13%	11%
401-1000	3%	1%	1%	3%
>=1000	1%	0%	0%	0%
Unit occupation/reserve distribution				
Combat arms occupation	6%	31%	27%	9%
Combat service occupation	17%	13%	10%	10%
Combat service support occupation	39%	25%	28%	48%
Aviation occupation	8%	13%	5%	
Medical occupation	5%		10%	8%
Other occupation	6%	3%	9%	7%
Unknown occupation	19%	15%	11%	18%
have at least 1 member from reserve/guard componer	43%	41%	53%	42%
Percent of member from reserve/guard component	3%	4%	4%	2%
Unit demographics				
male	85%	93%	85%	78%
Black	16%	12%	22%	15%
Hispanic	11%	14%	11%	6%
Asian	7%	4%	10%	5%
Total number of unit-quarter observations	198,435	195,721	413,578	241,550

Table 7: Cross-unit variations on destructive behaviors in the Navy

	Units where the given diagnoses' prevalence rate is in the top 10 percentile				
Outcome =	Tobacco	Alcohol or drug	Depression	Anxiety	Self injury
Life Stressor					
Percent demoted over the past 4 qtrs					
(ref group is unit with no demotion)					
low rate unit	0.651+	1.474**	0.912*	0.187	2.582**
	(0.340)	(0.386)	(0.423)	(0.307)	(0.438)
high rate unit	1.068*	6.189**	2.666**	1.367**	3.886**
	(0.420)	(0.515)	(0.488)	(0.409)	(0.331)
Percent divorced over the past 4 qtrs					
(ref group is unit with no divorce)					
low rate unit	-0.450	-1.231**	-0.068	0.221	1.509**
	(0.312)	(0.326)	(0.327)	(0.250)	(0.351)
high rate unit	1.171**	-0.243	0.434	0.614*	-0.375*
	(0.298)	(0.289)	(0.310)	(0.288)	(0.167)
Job Stressor					
Percent member deployed anywhere over the past 4 qtrs					
(ref group is unit with no member deployed)					
low rate unit	0.566	0.650+	0.387	-0.962**	-0.071
	(0.358)	(0.355)	(0.358)	(0.356)	(0.199)
high rate unit	-0.377	0.250	-0.486	-1.341**	-0.259
	(0.385)	(0.370)	(0.364)	(0.390)	(0.187)
Percent member deployed to combat zone over the past 4 qtrs					
(ref group is unit with no member deployed)					
low rate unit	0.663*	-1.383**	-0.500	-0.362	1.218**
	(0.326)	(0.317)	(0.338)	(0.272)	(0.308)
high rate unit	0.526	0.319	1.810**	2.335**	0.544*
	(0.378)	(0.371)	(0.402)	(0.386)	(0.218)
Unit locations					
Land based unit location					
(ref group is unknown location)					
Northeast	6.072**	0.496	4.195**	6.532**	-0.398
	(1.324)	(0.921)	(1.090)	(1.272)	(0.428)
Midwest	0.470	-1.971*	1.774	3.333**	-0.809
	(1.432)	(0.897)	(1.115)	(1.145)	(0.595)
South	0.707	-2.033**	2.317**	1.789**	-0.290
	(0.527)	(0.440)	(0.510)	(0.471)	(0.274)
West	-2.316**	-0.750	0.814	0.893+	0.756*
	(0.533)	(0.516)	(0.526)	(0.509)	(0.326)
Oversea	-12.756**	-3.744	2.888	-0.707	0.526
	(1.847)	(3.987)	(5.934)	(5.059)	(1.283)
Navy duty platforms					
(ref group is Carriers)					
Cruisers	-4.407**	-0.060	-4.147**	-4.573**	7.141*
	(1.034)	(1.750)	(1.370)	(0.905)	(3.138)
Destroyers	-4.354**	-1.330	-3.145*	-5.821**	10.009**
	(1.040)	(1.354)	(1.230)	(0.797)	(2.907)
Frigates	-3.147**	5.026*	2.697+	-2.317*	3.423
	(1.159)	(1.967)	(1.441)	(0.932)	(2.906)
Submarine	-6.186**	7.037**	1.618	-2.679**	4.761+
	(1.159)	(1.666)	(1.394)	(0.886)	(2.793)
All other	-3.365**	2.593+	-2.548*	-4.639**	6.973*
	(1.046)	(1.420)	(1.058)	(0.819)	(3.039)
Land based units	1.749	3.993**	1.776	-1.109	2.401
	(1.120)	(1.250)	(1.209)	(0.852)	(2.724)
Observations	198,673	198,673	198,673	198,673	198,673

Notes: ** p<0.01, * p<0.05, + p<0.1 Standard errors in parentheses clustered within unit groups. Complete resiults are presented in Appendix.

Table 8: Cross-unit variations on destructive behaviors in the Marine Corps

	Units where the given diagnoses' prevalence rate is in the top 10 percentile				
Outcome =	Tobacco	Alcohol or drug	Depression	Anxiety	Self injury
Life Stressor					
Percent demoted over the past 4 qtrs					
(ref group is unit with no demotion)					
low rate unit	0.146	2.478**	0.109	-0.363	1.057**
	(0.287)	(0.253)	(0.287)	(0.249)	(0.280)
high rate unit	0.049	7.929**	3.523**	2.909**	1.611**
	(0.287)	(0.314)	(0.322)	(0.311)	(0.206)
Percent divorced over the past 4 qtrs					
(ref group is unit with no divorce)					
low rate unit	-0.042	-1.310**	-0.983**	-0.857**	0.515+
	(0.261)	(0.251)	(0.273)	(0.222)	(0.305)
high rate unit	2.603**	0.390	1.903**	1.879**	-0.748**
	(0.289)	(0.258)	(0.284)	(0.282)	(0.171)
Job Stressor					
Percent member deployed anywhere over the past 4 qtrs					
(ref group is unit with no member deployed)					
low rate unit	1.645**	0.637	0.454	-0.078	-1.850**
	(0.431)	(0.412)	(0.429)	(0.451)	(0.234)
high rate unit	-2.005**	-0.227	-1.186*	-2.809**	-2.307**
	(0.480)	(0.481)	(0.467)	(0.488)	(0.296)
Percent member deployed to combat zone over the past 4 qtrs					
(ref group is unit with no member deployed)					
low rate unit	1.040**	0.776*	1.128**	1.316**	-0.828**
	(0.401)	(0.387)	(0.395)	(0.394)	(0.241)
high rate unit	0.608	1.176**	1.712**	1.803**	-0.423
	(0.423)	(0.447)	(0.421)	(0.421)	(0.276)
Unit locations					
(ref group is unknown location)					
Northeast	5.276**	-2.754*	2.235+	4.121**	-0.533
	(1.411)	(1.104)	(1.217)	(1.334)	(0.492)
Midwest	9.785**	-1.720+	3.151*	8.311**	0.078
	(1.777)	(0.988)	(1.257)	(1.568)	(0.593)
South	0.619	-1.531**	-0.360	0.646	0.392
	(0.572)	(0.520)	(0.609)	(0.557)	(0.379)
West	-0.862	-1.440**	-2.184**	-0.090	1.167**
	(0.541)	(0.521)	(0.602)	(0.554)	(0.382)
Oversea	12.345**	-0.875	-5.962**	-3.742**	0.233
	(1.121)	(0.706)	(0.700)	(0.690)	(0.566)
Observations					195,721

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses clustered within unit groups. Models control for unit size, unit demographics, specialty and reservist distribution, rank distribution, and time dummies.

Table 9: Cross-unit variations on destructive behaviors in the entire US military

	Units where the given diagnoses' prevalence rate is in the top 10 percentile				
Outcome =	Tobacco	Alcohol or drug	Depression	Anxiety	Self injury
Life Stressor					
Percent demoted over the past 4 qtrs					
(ref group is unit with no demotion)					
low rate unit	0.973**	1.501**	0.014	0.020	2.807**
	(0.145)	(0.135)	(0.141)	(0.125)	(0.164)
high rate unit	2.434**	7.687**	2.798**	2.575**	3.666**
	(0.161)	(0.180)	(0.177)	(0.166)	(0.139)
Percent divorced over the past 4 qtrs					
(ref group is unit with no divorce)					
low rate unit	0.430**	-0.672**	-0.944**	-0.396**	1.016**
	(0.125)	(0.127)	(0.125)	(0.110)	(0.131)
high rate unit	2.283**	0.524**	1.185**	0.818**	-0.229**
	(0.121)	(0.117)	(0.127)	(0.121)	(0.080)
Job Stressor					
Percent member deployed anywhere over the past 4 qtrs					
(ref group is unit with no member deployed)					
low rate unit	0.841**	1.418**	0.997**	0.018	-0.819**
	(0.180)	(0.170)	(0.181)	(0.190)	(0.107)
high rate unit	0.334	0.716**	-0.525*	-1.832**	-1.672**
	(0.209)	(0.195)	(0.206)	(0.217)	(0.121)
Percent member deployed to combat zone over the past 4 qtrs					
(ref group is unit with no member deployed)					
low rate unit	0.460**	0.193	0.818**	0.452**	-0.947**
	(0.166)	(0.163)	(0.170)	(0.160)	(0.124)
high rate unit	0.863**	0.700**	1.267**	1.885**	-0.571**
	(0.193)	(0.186)	(0.200)	(0.192)	(0.122)
Unit locations					
(ref group is unknown location)					
Northeast	1.639**	-0.305	2.425**	2.874**	-2.449**
	(0.496)	(0.416)	(0.492)	(0.505)	(0.279)
Midwest	3.728**	-1.094**	2.467**	3.057**	0.537*
	(0.511)	(0.321)	(0.407)	(0.408)	(0.259)
South	0.501*	-0.501**	0.991**	0.815**	0.439**
	(0.195)	(0.169)	(0.187)	(0.179)	(0.140)
West	-2.170**	-0.466*	-0.131	0.201	1.062**
	(0.210)	(0.208)	(0.212)	(0.211)	(0.166)
Oversea	11.656**	0.585	-3.301**	-2.487**	0.414
	(0.979)	(0.543)	(0.559)	(0.551)	(0.439)
On ship	-8.005**	-0.297	-3.695**	-4.221**	2.598**
	(0.323)	(0.526)	(0.402)	(0.298)	(0.513)
Observations	1,049,522	1,049,522	1,049,522	1,049,522	1,049,522

Notes: *** p<0.01, ** p<0.05, * p<0.1 Standard errors in parentheses clustered within unit groups. Models control for unit size, unit demographics, specialty and reservist distribution, rank distribution, and time dummies.

Table 10: Cross-unit variations in units with multiple high risks

Outcome=	units that are high risks in at least 2 conditions		
	Navy	Marine Corps	All services
Life stressor			
Percent demoted over the past 4 qtrs			
(ref group is unit with no demotion)			
low rate unit	1.667**	1.092**	1.302**
	(0.424)	(0.255)	(0.141)
high rate unit	4.397**	4.980**	5.831**
	(0.483)	(0.310)	(0.178)
Percent divorced over the past 4 qtrs			
(ref group is unit with no divorce)			
low rate unit	0.065	-0.863**	-0.050
	(0.314)	(0.254)	(0.123)
high rate unit	0.545+	1.829**	1.536**
	(0.289)	(0.269)	(0.119)
Job Stressor			
Percent member deployed anywhere over the past 4 qtrs			
(ref group is unit with no member deployed)			
low rate unit	0.226	0.330	0.811**
	(0.332)	(0.418)	(0.169)
high rate unit	-0.640+	-2.389**	-0.676**
	(0.348)	(0.461)	(0.193)
Percent member deployed to combat zone over the past 4 qtrs			
(ref group is unit with no member deployed)			
low rate unit	-0.109	1.119**	0.526**
	(0.305)	(0.380)	(0.156)
high rate unit	1.711**	1.370**	1.361**
	(0.362)	(0.405)	(0.182)
Unit location			
(ref group is unknown location)			
Northeast	5.507**	2.531*	1.433**
	(1.195)	(1.217)	(0.482)
Midwest	0.637	6.186**	2.500**
	(1.004)	(1.423)	(0.384)
South	0.907*	0.302	0.651**
	(0.460)	(0.559)	(0.177)
West	0.289	-0.802	-0.449*
	(0.504)	(0.552)	(0.208)
Oversea	-5.521**	-0.315	0.961+
	(1.948)	(0.724)	(0.543)
On ship	-2.915**		-4.607**
	(0.510)		(0.368)
Observations	198673	195721	1049522

Notes: ** p<0.01, * p<0.05, + p<0.1 Standard errors in parentheses clustered within unit groups. Complete resiults are presented in Appendix.

Table 11: Peer impacts on destructive behaviors in the Navy

	Diagnosed with … disorder			
Outcome =	Tobacco	Alcohol or drug	Depression	Self injury
	(1)	(2)	(3)	(4)
Low fraction of peers with	0.0154	-0.0515	-0.0854**	-0.0504**
recent diagnosis	(0.0490)	(0.0460)	(0.0429)	(0.0198)
High fraction of peers with	0.1866	0.1407*	-0.0392	-0.2019***
recent diagnosis	(0.1150)	(0.0790)	(0.0738)	(0.0419)
Observations	594,474	594,430	594,527	594,530
Mean of outcome	2.41	1.21	0.34	0.05

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for person demographics, peer demographics, and unit fixed effects. Peer diagnoses only include those made while attached to a different unit. Omitted category is no peers with recent diagnosis.

Table 12: Peer impacts on destructive behaviors in the Navy, by past diagnosis

	Diagnosed with … disorder							
Outcome =	Tobacco		Alcohol or drug		Depression		Self injury	
Past diagnosis of outcome?	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low fraction of peers	0.0622	-0.0235	-0.0515	-0.0249	-0.0151	-2.9560	0.0122	-3.2122
with recent diagnosis	(0.0384)	(0.3697)	(0.0460)	(0.0381)	(0.0327)	(2.0124)	(0.0339)	(3.0225)
High fraction of peers	0.1179	0.0858	0.1407*	0.1189**	-0.0563	-0.6829	-0.0157	5.0949*
with recent diagnosis	(0.0858)	(0.5091)	(0.0790)	(0.0589)	(0.0471)	(1.6799)	(0.0669)	(3.0355)
Observations	550,244	44,230	594,430	575,495	587,875	6,652	590,491	4,067
Mean of outcome	1.28	11.50	1.21	0.73	0.23	8.89	0.43	27.24

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for person demographics, peer demographics, and unit fixed effects. Omitted category is no peers with recent diagnosis.

Table 13: Peer impacts on destructive behaviors in the Marine Corps

	Diagnosed with ... disorder			
Outcome =	Tobacco	Alcohol or drug	Depression	Self injury
	(1)	(2)	(3)	(4)
Low fraction of peers with recent diagnosis	0.2162***	-0.0547	-0.1224**	-0.0622
	(0.0669)	(0.0674)	(0.0624)	(0.0407)
High fraction of peers with recent diagnosis	0.1513	-0.1338*	-0.0998	-0.1195***
	(0.1137)	(0.0704)	(0.0744)	(0.0304)
Observations	570,459	570,495	570,557	570,583
Mean of outcome	2.405	1.209	0.340	0.0465

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for person demographics, peer demographics, and unit fixed effects. Peer diagnoses only include those made while attached to a different unit. Omitted category is no peers with recent diagnosis.

Table 14: Peer impacts on destructive behaviors in the Marine Corps, by past diagnosis

	Diagnosed with ... disorder							
Outcome =	Tobacco		Alcohol or drug		Depression		Self injury	
Past diagnosis of outcome?	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low fraction of peers with recent diagnosis	0.2343***	0.3546	0.0251	-0.9598	-0.0263	-4.3174	-0.0384	-5.6985
	(0.0541)	(0.5465)	(0.0567)	(1.0010)	(0.0500)	(4.0179)	(0.0404)	(8.4600)
High fraction of peers with recent diagnosis	0.1037	0.2195	-0.0167	-1.4875*	-0.0312	-3.2054	0.0802**	-0.9951
	(0.0910)	(0.5981)	(0.0577)	(0.7875)	(0.0477)	(2.6140)	(0.0216)	(3.1921)
Observations	535,141	35,318	546,850	23,645	565,202	5,355	569,227	1,356
Mean of outcome	1.275	11.50	0.733	12.22	0.231	8.887	0.0366	4.150

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for person demographics, peer demographics, and unit fixed effects. Omitted category is no peers with recent diagnosis.

Table 15: Heterogeneous impacts of peers in the Navy, by age categories

Age range =	< 21	22-29	30+
Outcome =	Diagnosed with tobacco disorder		
Low fraction of peers with	0.2660*	0.0383	-0.0660
recent diagnosis	(0.1527)	(0.0726)	(0.0679)
High fraction of peers with	0.3684	0.2415	0.0806
recent diagnosis	(0.3645)	(0.1605)	(0.1487)
Observations	68,976	241,759	283,739

Age range =	< 21	22-29	30+
Outcome =	Diagnosed with alcohol or drug disorder		
Low fraction of peers with	-0.4154**	-0.0228	0.0356
recent diagnosis	(0.1764)	(0.0741)	(0.0467)
High fraction of peers with	-0.0543	0.1401	0.1924*
recent diagnosis	(0.2746)	(0.1253)	(0.0997)
Observations	68,976	241,747	283,707

Age range =	< 21	22-29	30+
Outcome =	Diagnosed with depression disorder		
Low fraction of peers with	-0.3916**	-0.0499	-0.0614
recent diagnosis	(0.1705)	(0.0710)	(0.0595)
High fraction of peers with	-0.1702	-0.1519	0.1086
recent diagnosis	(0.2370)	(0.1127)	(0.1065)
Observations	68,978	241,788	283,761

Age range =	< 21	22-29	30+
Outcome =	Diagnosed with self-injury disorder		
Low fraction of peers with	-0.1346	-0.0660**	-0.0114
recent diagnosis	(0.1370)	(0.0258)	(0.0070)
High fraction of peers with	-0.6734***	-0.1862***	-0.0585
recent diagnosis	(0.1993)	(0.0560)	(0.0397)
Observations	68,976	241,796	283,758

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for unit fixed effects. Peer diagnoses only include those made while attached to a different unit. Omitted category is no peers with recent diagnosis.

Table 16: Heterogeneous impacts of peers in the Navy, by officer status

Sample =	Officer	Enlisted
Outcome =	Diagnosed with tobacco disorder	
Low fraction of peers with recent diagnosis	0.0067	0.0356
	(0.0428)	(0.0720)
High fraction of peers with recent diagnosis	-0.1137	0.2759*
	(0.1052)	(0.1465)
Observations	185,986	408,488

Sample =	Officer	Enlisted
Outcome =	Diagnosed with alcohol or drug disorder	
Low fraction of peers with recent diagnosis	-0.0121	-0.0667
	(0.0342)	(0.0731)
High fraction of peers with recent diagnosis	0.0930	0.1721*
	(0.0931)	(0.1009)
Observations	185,980	408,450

Sample =	Officer	Enlisted
Outcome =	Diagnosed with depression disorder	
Low fraction of peers with recent diagnosis	0.0583	-0.2347***
	(0.0513)	(0.0698)
High fraction of peers with recent diagnosis	0.1211	-0.1022
	(0.1295)	(0.0898)
Observations	185,980	408,547

Sample =	Officer	Enlisted
Outcome =	Diagnosed with self-injury disorder	
Low fraction of peers with recent diagnosis	-0.0029	-0.1120**
	(0.0031)	(0.0447)
High fraction of peers with recent diagnosis	0.0004	-0.2322***
	(0.0016)	(0.0500)
Observations	186,042	408,488

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for unit fixed effects. Peer diagnoses only include those made while attached to a different unit. Omitted category is no peers with recent diagnosis.

Table 17: Heterogeneous impacts of peers in the Navy, by race/ethnicity

Race/ethnicity =	White	Black	Hispanic	Other
Outcome =	Diagnosed with tobacco disorder			
Low fraction of peers with	0.0293	0.0007	0.2704*	-0.2231
recent diagnosis	(0.0612)	(0.0962)	(0.1405)	(0.1702)
High fraction of peers with	0.2385*	-0.1354	-0.1367	0.5594*
recent diagnosis	(0.1419)	(0.1916)	(0.2624)	(0.3382)
Observations	384,580	97,582	59,076	55,649

Race/ethnicity =	White	Black	Hispanic	Other
Outcome =	Diagnosed with alcohol or drug disorder			
Low fraction of peers with	-0.0547	-0.1167	-0.0579	0.0309
recent diagnosis	(0.0526)	(0.1123)	(0.1549)	(0.1630)
High fraction of peers with	0.2662**	-0.2530	0.2525	-0.1958
recent diagnosis	(0.1100)	(0.1574)	(0.2877)	(0.2267)
Observations	384,552	97,572	59,070	55,649

Race/ethnicity =	White	Black	Hispanic	Other
Outcome =	Diagnosed with depression disorder			
Low fraction of peers with	-0.0841	-0.1827*	0.0241	-0.0446
recent diagnosis	(0.0538)	(0.0971)	(0.1709)	(0.1584)
High fraction of peers with	0.0401	-0.2235	-0.1588	-0.0272
recent diagnosis	(0.1009)	(0.1387)	(0.1918)	(0.2142)
Observations	384,608	97,587	59,086	55,659

Race/ethnicity =	White	Black	Hispanic	Other
Outcome =	Diagnosed with self-injury disorder			
Low fraction of peers with	-0.0207	-0.0646	-0.0792*	-0.2473*
recent diagnosis	(0.0255)	(0.0408)	(0.0424)	(0.1291)
High fraction of peers with	-0.1771***	-0.2186**	-0.2169**	-0.2922**
recent diagnosis	(0.0644)	(0.0948)	(0.1047)	(0.1186)
Observations	384,612	97,596	59,079	55,656

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for unit fixed effects. Peer diagnoses only include those made while attached to a different unit. Omitted category is no peers with recent diagnosis.

Table 18: Peer impacts on destructive behaviors in all four services

	Diagnosed with … disorder			
Outcome =	Tobacco	Alcohol or drug	Depression	Self injury
	(1)	(2)	(3)	(4)
Low fraction of peers with	0.0875***	-0.0086	-0.0462***	-0.0477***
recent diagnosis	(0.0259)	(0.0224)	(0.0170)	(0.0153)
High fraction of peers with	0.0962***	-0.1000***	-0.0525**	-0.0860***
recent diagnosis	(0.0357)	(0.0273)	(0.0230)	(0.0190)
Observations	4,513,472	4,513,425	4,513,702	4,513,647
Mean of outcome	2.41	1.21	0.34	0.05

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. All services included. Models control for person demographics, peer demographics, and unit fixed effects. Peer diagnoses only include those made while attached to a different unit. Omitted category is no peers with recent diagnosis.

Table 19: Peer impacts on destructive behaviors in all four services, by past diagnosis

	Diagnosed with … disorder							
Outcome =	Tobacco		Alcohol or drug		Depression		Self injury	
Past diagnosis of outcome?	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low fraction of peers	0.1554***	0.0651	0.0131	-0.2304	0.0092	-1.5837***	-0.0112	-1.8856
with recent diagnosis	(0.0212)	(0.1503)	(0.0186)	(0.2863)	(0.0140)	(0.5949)	(0.0127)	(1.9585)
High fraction of peers	0.0133	0.1963	-0.0416**	-0.6101**	-0.0040	-1.5637***	-0.0140	-2.2783*
with recent diagnosis	(0.0269)	(0.1346)	(0.0211)	(0.2471)	(0.0165)	(0.5014)	(0.0155)	(1.2692)
Observations	4,010,229	503,243	4,326,078	187,347	4,456,529	57,173	4,502,723	10,924
Mean of outcome	1.275	11.50	0.733	12.22	0.231	8.887	0.0366	4.150

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. All services included. Models control for person demographics, peer demographics, and unit fixed effects. Omitted category is no peers with recent diagnosis.

Appendix Figures and Tables

Figure A1: United States Census Division Map

Source: reproduced from
www.bts.gov/archive/publications/america_on_the_go/us_business_travel/figure_02

Table A1: Cross unit variations on destructive behaviors in the Navy, all covariates

	Units where the given diagnoses' prevalence rate is in the top 10 percentile				
Outcome =	Tobacco	Alcohol or drug	Depression	Anxiety	Self injury
Percent demoted over the past 4 qtrs					
(ref group is unit with no demotion)					
lower 50 percentile	0.651+	1.474**	0.912*	0.187	2.582**
	(0.340)	(0.386)	(0.423)	(0.307)	(0.438)
upper 50 percentile	1.068*	6.189**	2.666**	1.367**	3.886**
	(0.420)	(0.515)	(0.488)	(0.409)	(0.331)
Percent divorced over the past 4 qtrs					
(ref group is unit with no divorce)					
lower 50 percentile	-0.450	-1.231**	-0.068	0.221	1.509**
	(0.312)	(0.326)	(0.327)	(0.250)	(0.351)
upper 50 percentile	1.171**	-0.243	0.434	0.614*	-0.375*
	(0.298)	(0.289)	(0.310)	(0.288)	(0.167)
Percent member deployed anywhere over the past 4 qtrs					
(ref group is unit with no member deployed)					
lower 50 percentile	0.566	0.650+	0.387	-0.962**	-0.071
	(0.358)	(0.355)	(0.358)	(0.356)	(0.199)
upper 50 percentile	-0.377	0.250	-0.486	-1.341**	-0.259
	(0.385)	(0.370)	(0.364)	(0.390)	(0.187)
Percent member deployed to combat zone over the past 4 qtrs					
(ref group is unit with no member deployed)					
lower 50 percentile	0.663*	-1.383**	-0.500	-0.362	1.218**
	(0.326)	(0.317)	(0.338)	(0.272)	(0.308)
upper 50 percentile	0.526	0.319	1.810**	2.335**	0.544*
	(0.378)	(0.371)	(0.402)	(0.386)	(0.218)
Presence of combat arms specialists					
(ref group is unit with no presence)					
lower 50 percentile	0.505	0.588	0.615	0.186	0.317
	(0.479)	(0.421)	(0.486)	(0.406)	(0.331)
upper 50 percentile	-2.119**	0.310	-0.822+	-1.510**	0.308
	(0.526)	(0.448)	(0.467)	(0.442)	(0.263)
Presence of aviation specialists					
(ref group is unit with no presence)					
lower 50 percentile	0.472	0.449	0.138	-0.554	1.086**
	(0.440)	(0.431)	(0.508)	(0.391)	(0.363)
upper 50 percentile	2.004**	-0.505	-2.489**	-1.949**	-0.190
	(0.605)	(0.474)	(0.467)	(0.453)	(0.312)
Presence of medical specialists					
(ref group is unit with no presence)					
lower 50 percentile	-4.736**	0.993*	-1.182*	0.316	0.224
	(0.527)	(0.475)	(0.481)	(0.342)	(0.507)
upper 50 percentile	-4.043**	1.619**	6.759**	7.628**	1.336**
	(0.483)	(0.482)	(0.645)	(0.615)	(0.297)
Presence of reserve components					
(ref group is unit with no presence)					
lower 50 percentile	-0.733*	-0.960**	-0.346	-0.227	-0.133
	(0.319)	(0.315)	(0.346)	(0.264)	(0.281)
upper 50 percentile	-1.527**	0.930**	1.308**	0.841*	0.374*
	(0.303)	(0.327)	(0.369)	(0.334)	(0.180)
Officer presence					
(ref group is unit with no presence)					

Table A1 continues

Outcome =	Tobacco	Alcohol/drug	Depression	Anxiety	Self injury
lower 50 percentile	-4.267**	-4.600**	-0.196	-1.431**	-2.644**
	(0.606)	(0.537)	(0.554)	(0.546)	(0.309)
upper 50 percentile	-15.028**	-10.746**	-3.281**	-5.850**	-3.015**
	(0.601)	(0.516)	(0.542)	(0.557)	(0.271)
Land based unit location (ref group is unknown)					
Northeast	6.072**	0.496	4.195**	6.532**	-0.398
	(1.324)	(0.921)	(1.090)	(1.272)	(0.428)
Midwest	0.470	-1.971*	1.774	3.333**	-0.809
	(1.432)	(0.897)	(1.115)	(1.145)	(0.595)
South	0.707	-2.033**	2.317**	1.789**	-0.290
	(0.527)	(0.440)	(0.510)	(0.471)	(0.274)
West	-2.316**	-0.750	0.814	0.893+	0.756*
	(0.533)	(0.516)	(0.526)	(0.509)	(0.326)
Oversea	-12.756**	-3.744	2.888	-0.707	0.526
	(1.847)	(3.987)	(5.934)	(5.059)	(1.283)
Unit size (ref group is 4-10 members)					
11 - 50	-4.165**	6.019**	7.928**	-6.557**	0.433**
	(0.474)	(0.409)	(0.432)	(0.466)	(0.149)
51 - 100	-7.568**	1.192*	2.783**	-12.505**	2.843**
	(0.704)	(0.578)	(0.639)	(0.605)	(0.392)
101 - 150	-8.238**	-0.849	-0.956	-13.941**	6.599**
	(0.982)	(0.776)	(0.852)	(0.731)	(0.661)
151 - 400	-10.907**	-3.074**	-2.060**	-14.666**	14.818**
	(0.808)	(0.717)	(0.780)	(0.690)	(0.744)
401 - 1000	-11.073**	-4.921**	-3.673**	-17.161**	37.779**
	(1.156)	(1.003)	(1.425)	(0.875)	(1.760)
GT 1000	-18.667**	-10.290**	-2.520	-17.394**	77.879**
	(1.116)	(1.490)	(2.247)	(1.248)	(2.992)
Unit demographics					
Percent male	-0.014	0.000	-0.254**	-0.276**	-0.067**
	(0.013)	(0.011)	(0.015)	(0.015)	(0.007)
Percent black	-0.005	-0.003	0.027*	0.003	0.020**
	(0.015)	(0.012)	(0.014)	(0.014)	(0.006)
Percent Hispanic	-0.043*	0.089**	0.065**	0.026	0.033**
	(0.018)	(0.016)	(0.018)	(0.019)	(0.007)
Percent Asian or Pacific Islanders	-0.049**	-0.070**	-0.030+	-0.058**	0.007
	(0.018)	(0.016)	(0.017)	(0.019)	(0.007)
Navy duty platforms (ref group is Carriers)					
Cruisers	-4.407**	-0.060	-4.147**	-4.573**	7.141*
	(1.034)	(1.750)	(1.370)	(0.905)	(3.138)
Destroyers	-4.354**	-1.330	-3.145*	-5.821**	10.009**
	(1.040)	(1.354)	(1.230)	(0.797)	(2.907)
Frigates	-3.147**	5.026*	2.697+	-2.317*	3.423
	(1.159)	(1.967)	(1.441)	(0.932)	(2.906)
Submarine	-6.186**	7.037**	1.618	-2.679**	4.761+
	(1.159)	(1.666)	(1.394)	(0.886)	(2.793)
All other	-3.365**	2.593+	-2.548*	-4.639**	6.973*
	(1.046)	(1.420)	(1.058)	(0.819)	(3.039)
Land based units	1.749	3.993**	1.776	-1.109	2.401
	(1.120)	(1.250)	(1.209)	(0.852)	(2.724)
_cons	23.874**	10.018**	25.692**	43.473**	3.977
	(1.757)	(1.678)	(1.828)	(1.728)	(2.815)
Observations	198,673	198,673	198,673	198,673	198,673

Table A2: Cross unit variations on units with multiple high risks, all covariates

Outcome=	units that are high risk units in at least 2 conditions		
	Navy	Marine Corps	All services
Percent demoted over the past 4 qtrs			
(ref group is unit with no demotion)			
lower 50 percentile	1.667**	1.092**	1.302**
	(0.424)	(0.255)	(0.141)
upper 50 percentile	4.397**	4.980**	5.831**
	(0.483)	(0.310)	(0.178)
Percent divorced over the past 4 qtrs			
(ref group is unit with no divorce)			
lower 50 percentile	0.065	-0.863**	-0.050
	(0.314)	(0.254)	(0.123)
upper 50 percentile	0.545+	1.829**	1.536**
	(0.289)	(0.269)	(0.119)
Percent member deployed anywhere over the past 4 qtrs			
(ref group is unit with no member deployed)			
lower 50 percentile	0.226	0.330	0.811**
	(0.332)	(0.418)	(0.169)
upper 50 percentile	-0.640+	-2.389**	-0.676**
	(0.348)	(0.461)	(0.193)
Percent member deployed to combat zone over the past 4 qtrs			
(ref group is unit with no member deployed)			
lower 50 percentile	-0.109	1.119**	0.526**
	(0.305)	(0.380)	(0.156)
upper 50 percentile	1.711**	1.370**	1.361**
	(0.362)	(0.405)	(0.182)
Presence of combat arms specialists			
(ref group is unit with no presence)			
lower 50 percentile	1.056*	0.604+	-0.239
	(0.441)	(0.349)	(0.153)
upper 50 percentile	-1.236**	0.632	0.629**
	(0.435)	(0.387)	(0.166)
Presence of aviation specialists			
(ref group is unit with no presence)			
lower 50 percentile	0.641	-0.865*	-0.118
	(0.448)	(0.351)	(0.212)
upper 50 percentile	-1.368**	-3.451**	-2.909**
	(0.468)	(0.382)	(0.192)

Table A2 continues

Outcome=	units that are high risk units in at least 2 conditions		
	Navy	Marine Corps	All services
Presence of medical specialists			
(ref group is unit with no presence)			
lower 50 percentile	-1.986**		0.476**
	(0.470)		(0.165)
upper 50 percentile	4.702**		3.354**
	(0.592)		(0.222)
Presence of reserve components			
(ref group is unit with no presence)			
lower 50 percentile	-0.464	-1.564**	-0.799**
	(0.314)	(0.279)	(0.128)
upper 50 percentile	0.955**	-0.717*	0.943**
	(0.327)	(0.290)	(0.135)
Officer presence			
(ref group is unit with no presence)			
lower 50 percentile	-3.202**	-2.488**	-2.057**
	(0.562)	(0.348)	(0.219)
upper 50 percentile	-10.278**	-3.208**	-7.903**
	(0.548)	(0.361)	(0.206)
Military branch (Ref group is Navy)			
Marines			0.518+
			(0.273)
Army			0.555*
			(0.240)
Air Force			-2.028**
			(0.246)
Land based unit location			
(ref group is unknown location)			
Northeast	5.507**	2.531*	1.433**
	(1.195)	(1.217)	(0.482)
Midwest	0.637	6.186**	2.500**
	(1.004)	(1.423)	(0.384)
South	0.907*	0.302	0.651**
	(0.460)	(0.559)	(0.177)
West	0.289	-0.802	-0.449*
	(0.504)	(0.552)	(0.208)
Oversea	-5.521**	-0.315	0.961+
	(1.948)	(0.724)	(0.543)
On ship			-4.607**
			(0.368)

Table A2 continues

Outcome=	units that are high risk units in at least 2 conditions		
	Navy	Marine Corps	All services
Navy duty platforms			
(ref group is Carriers)			
Cruisers	0.734		
	(1.861)		
Destroyers	-0.839		
	(1.625)		
Frigates	3.257+		
	(1.784)		
Submarine	3.250+		
	(1.767)		
All other	0.910		
	(1.555)		
Land based units	4.201*		
	(1.642)		
Unit size (ref group is 4-10 members)			
11 - 50	1.550**	-1.687**	-1.336**
	(0.404)	(0.374)	(0.171)
51 - 100	-3.421**	-5.644**	-5.416**
	(0.573)	(0.456)	(0.221)
101 - 150	-4.672**	-6.677**	-5.953**
	(0.795)	(0.587)	(0.276)
151 - 400	-5.610**	-6.925**	-6.521**
	(0.736)	(0.585)	(0.288)
401 - 1000	-4.738**	-5.289**	-4.144**
	(1.421)	(1.187)	(0.633)
GT 1000	-7.167**	11.079	-8.975**
	(2.420)	(9.159)	(1.287)
Unit demographics			
Percent male	-0.193**	-0.227**	-0.150**
	(0.013)	(0.015)	(0.005)
Percent black	-0.005	0.000	-0.029**
	(0.013)	(0.012)	(0.005)
Percent Hispanic	0.034*	0.006	0.016*
	(0.016)	(0.013)	(0.007)
Percent Asian or Pacific Islanders	-0.061**	-0.062**	0.009+
	(0.016)	(0.023)	(0.005)
_cons	26.485**	33.295**	27.135**
	(2.068)	(1.561)	(0.603)
Observations	198673	195721	1049522

Notes: ** p<0.01, * p<0.05, + p<0.1 Standard errors in parentheses clustered within unit groups. Time dummies included in the model.

Table A3: Peer impacts on destructive behaviors in the Navy, all covariates

	Diagnosed with … disorder			
Outcome =	Tobacco	Alcohol or drug	Depression	Self injury
	(1)	(2)	(3)	(4)
Low fraction of peers with recent diagnosis	0.0154	-0.0515	-0.0854**	-0.0504**
High fraction of peers with recent diagnosis	0.1866	0.1407*	-0.0392	-0.2019***
Low fraction of peers with recent other diagnosis	0.0862	-0.0815**	-0.0057	-0.0087*
High fraction of peers with recent other diagnosis	0.0588	-0.0939	-0.0342	0.0026
Ever diagnosed with the outcome	6.3061***	9.7231***	10.0324***	3.1374***
Ever diagnosed with other outcome	1.9894***	0.8782***	0.2538***	0.0261**
Low fraction of peers with past deployment	0.0914**	-0.0671**	-0.0259	-0.0039
High fraction of peers with past deployment	0.1188*	-0.0725*	-0.0501*	-0.0025
Low fraction of peers with past demotion	0.0300	0.1001	0.0178	0.0223*
High fraction of peers with past demotion	0.0268	-0.0501	-0.0028	0.0005
Low fraction of peers with past divorce	-0.0449	-0.0026	0.0073	-0.0008
High fraction of peers with past divorce	0.0474	0.0611	-0.0070	-0.0170**
Male	-0.0152	0.2760***	-0.2635***	-0.0214***
Black	-0.6734***	-0.0985***	-0.0787***	0.0007
Hispanic	-0.4868***	0.0068	-0.0257	-0.0012
Asian	-0.4659***	-0.4627***	-0.1535***	-0.0069
Other race	0.1377	0.1822**	0.0685	0.0196
Married	-0.1580***	-0.1336***	0.0622***	0.0021
Age < 22	-0.3259***	-0.4330***	-0.0911***	-0.0359***
Age 22 - 25	-0.4440***	-0.8394***	-0.1365***	-0.0508***
Age 26-30	-0.4933***	-0.9605***	-0.1857***	-0.0544***
Age 31-35	-0.4169***	-0.9767***	-0.1591***	-0.0568***
Age 36-40	-0.4341***	-0.8980***	-0.1438***	-0.0569***
1 dependent	0.0860*	-0.1695***	-0.0451*	0.0019
2 dependents	0.0496	-0.1731***	-0.0702**	-0.0029
3 or more dependents	0.1205**	-0.2231***	-0.0310	-0.0024
Officer	-0.8441***	-0.2667***	-0.0687***	-0.0087**
Observations	594,474	594,430	594,527	594,530
Mean of outcome	2.41	1.21	0.34	0.05

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Models control for unit fixed effects. Omitted categories include White race, age category 41 years and older, and having no dependents. Peer diagnoses only include those made while attached to a different unit.

Table A4: Peer impacts on destructive behaviors in the Navy, linear specification

	Diagnosed with … disorder			
Outcome =	Tobacco	Alcohol or drug	Depression	Self injury
	(1)	(2)	(3)	(4)
Fraction of peers with recent diagnosis	1.6888	0.6697	0.3586	-2.2038**
	(1.1466)	(0.8461)	(0.5868)	(0.8619)
Observations	594,474	594,430	594,527	594,530
Mean of outcome	1.378	0.837	0.322	0.0256

Notes: *** p<0.01, ** p<0.05, * p<0.1 Outcomes multiplied by 100. Standard errors in parentheses clustered within peer groups. Models control for person demographics, peer demographics, and unit fixed effects. Peer diagnoses only include those made while attached to a different unit. Omitted category is no peers with recent diagnosis.