

ABSTRACT

Title of Document: PRECIPITATING HEALTH BEHAVIOR
CHANGE: THE ROLE OF TECHNOLOGY
AND THE SOCIAL ENVIRONMENT

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Health behaviors represent the largest determinant of a person's health and impact healthcare practice and delivery. Responding to the need to uncover mechanisms that instigate health behavior change, in this dissertation I investigate the effects of two important drivers of variation: health information technology and social health influence. I conduct empirical analyses using a unique medical and administrative dataset on 820,000 U.S. Army soldiers over four years.

In the first study, I examine the effects of a patient portal implemented by the Army in 2011. Patient portals are used to facilitate greater patient engagement with health and increase patient activation, defined as the ability and desire to improve one's health. A critical, overlooked factor is the reciprocal of patient activation: "provider activation," the provider's knowledge and desire to get patients more activated. I

examine the discrete and complementary effects of patients' healthcare needs and provider activation and demonstrate each significantly impact patient activation. Using a novel matching method to minimize selection bias, I investigate the impacts of a patient portal on healthcare utilization and outcomes. Patient portal usage is shown to complement healthcare utilization, improve access to services, and increase medication adherence.

In study two, I investigate social health influence within Army units. Large variations in health behaviors have been observed across different locations. I assert this variation is a result of distinct "health cultures" or norms of health behaviors, influencing individual soldier behaviors. To examine the effect of these health cultures on soldiers' health behaviors, while minimizing selection bias, I exploit a unique feature of the Army: the exogenous assignment of soldiers to units. The hierarchical structure inherent to the Army provides an opportunity to examine leader and subordinate effects, in addition to peer effects, which I demonstrate have significant, differential impacts on the spread of obesity, tobacco use, and alcohol abuse.

This dissertation contributes to the field's understanding of drivers of health behavior change, through the examination of patient and provider activation and the role of social influence in health behaviors. It offers important recommendations for policy makers seeking to improve the effectiveness and efficiency of healthcare systems.

PRECIPITATING HEALTH BEHAVIOR CHANGE: THE ROLE OF
TECHNOLOGY AND THE SOCIAL ENVIRONMENT

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Preface

The views expressed in this dissertation are those of the author and do not necessarily reflect the views or official policies of the U.S. Government, Department of Defense, Defense Health Agency, Department of the Army, or the U.S. Army Medical Department.

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Chapter 1: Dissertation Overview

Modifiable health behaviors represent the largest determinant of a person's health, with poor behavioral choices causing nearly one million deaths each year in the United States (McGinnis et al. 2002). Chronic conditions, such as diabetes, hypertension, and heart disease, account for as much as 84% of healthcare costs (Anderson 2010) and can be effectively managed, and often, prevented, through deliberate patient actions (Frosch et al. 2010; Shively et al. 2013). The primary aim of this dissertation is to examine the impacts of drivers that have the potential to trigger behavior changes that improve individuals' healthcare and health outcomes. I investigate the effects of two distinct drivers: a health information technology (IT) intervention in the form of a patient portal with secure messaging and a personal health record, and the social context within which a person is embedded. For my empirical analyses, I use a unique and rich dataset containing administrative, medical, and training data on 820,000 U.S. Army soldiers across four years.

Study 1: Critical Complements: Patient and Provider Engagement with Technology

In recent years, in an effort to improve healthcare quality and control expenses, many U.S. healthcare organizations have tried to involve patients more in the delivery of their care. In particular, substantial effort has been dedicated to understand how to increase patient activation. Patient activation is a patient's ability and desire to take charge of their health and healthcare (Hibbard and Greene 2013). Patients who are more activated are significantly more likely to exhibit healthy behaviors, such as nutritious diets, moderate exercise, and preventive health screenings, and to avoid

unhealthy behaviors, such as excessive drinking and smoking (Greene and Hibbard 2011; Hibbard and Greene 2013). In other words, activated patients are more committed to their health and wellness. Such patients also have lower costs of care than less activated ones (Greene and Hibbard 2011; Hibbard and Greene 2013; Hibbard et al. 2013). Research suggests that interventions can be implemented to engage patients and increase their activation levels (Hibbard and Greene 2013; Hibbard et al. 2007).

The growing national discourse on the digital transformation of healthcare suggests that health information technology-based interventions may play an important role in patient activation. The patient portal is one such intervention implemented by healthcare organizations. It provides secure, digital access to many healthcare services and resources (Otte-Trojel et al. 2014). Within patient portals, patients are able to exchange asynchronous, secure messages with their healthcare providers, record personal health information in a personal health record (PHR), request appointments, and view educational materials (Otte-Trojel et al. 2014).

The importance of patient portals is recognized government legislation, which provided substantial financial incentives to help accelerate the implementation of patient portals by U.S. healthcare organizations. The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 specified a set of requirements for the “Meaningful Use” of health IT. One key objective of the Stage 2 in Meaningful Use is that healthcare organizations provide patients with the ability to send secure messages to their healthcare providers and the ability to access and share their health information (Centers for Medicare and Medicaid 2012).

While patient portals have significant potential to activate patients and improve health outcomes, we still lack a deep understanding of how to realize this potential. The evidence so far is ambiguous: some researchers find that patient portals improve health outcomes (Harris et al. 2009; Lau et al. 2014; Zhou et al. 2010), while others report no effect on health outcomes (Bavafa et al. 2013; Grant et al. 2008; McCarrier et al. 2009; Ralston et al. 2009; Wagner et al. 2012). I argue that these mixed results are plausibly a result of a critical factor missing from extant literature on patient portals: the utilization of patient portals by healthcare providers, which doubtless influences patients' utilization. In this study, I investigate the impact of provider activation on patient portal usage and the impact of patient portals on patients' healthcare utilization and outcomes. Additionally, through the use of a robust method, look-ahead matching (Jung et al. 2014), in which users in one-time period are matched to users in a future time period and outcomes examined prior to the future users' adoption, I minimize the self-selection bias present in most patient portal studies.

Study 2: Social Influence on Health Behaviors: Evidence from a Natural Experiment

Implementing and maintaining behavior change is a difficult process, and social support is essential to most successful health behavior change (Amick and Ockene 1994; Verheijden et al. 2005; Wing and Jeffery 1999). For example, it is estimated that only 4-7% of smokers successfully quit on an attempt without medication or support (“Guide to Quitting Smoking” 2014), but reach much higher success rates with support groups (Ford et al. 2013) and smoke-free homes (Messer et al. 2008).

Fundamentally, humans are social beings. We live within families, communities, and workplaces. Therefore, it is not surprising that our social environments influence our thoughts, actions, and overall health. Individuals may update their beliefs and attitudes toward healthy behaviors through peer influence, where information from peers influences an individual's expected utility and likelihood of engaging in a specific behavior (Aral 2011).

Over the past decade, researchers have tried to better understand the person-to-person nuances involved in the spread of healthy and unhealthy behaviors (Smith and Christakis 2008). Although there is ongoing debate on the identification methods used in many of these studies due to concerns of self-selection and contextual effects (Cohen-Cole and Fletcher 2008a, 2008b; J. H. Fowler and Christakis 2008; Lyons 2010; Shalizi and Thomas 2011; VanderWeele 2011), it is widely accepted that peer influence plays an important role in an individual's health behaviors and lifestyle choices (VanderWeele 2011).

In this study, I examine how the local social network affects soldiers' health behaviors, namely obesity, tobacco use, and alcohol abuse. These three health outcomes were purposively selected as they are of great concern to the U.S. Military. Despite the perception that soldiers are all fit and healthy, in 2014, 24% of soldiers were identified as obese, 36% reported using tobacco, and 17% of soldiers struggled with alcohol abuse. Interestingly, even though the Army has a unified health system with common policies and procedures, as well as similar patient populations throughout, surprisingly large variations in these behaviors have been observed across different locations and organizations. I argue that military organizations have

developed distinct “health cultures,” or norms of acceptable health behaviors, which both influence new entrants into the culture and further reinforce certain behavioral choices.

Research on social health influence has focused on peer effects, not distinguishing between different types of connections in the network and treating all potential levels of influence as equal. In addition to methodological improvements that my study offers, I also extend the current network influence literature beyond “peer effects.” It is easy to think of a scenario in which there may be leaders in the network, perhaps work supervisors or community leaders, with greater influence on personal decisions. Opinions and behaviors of the leaders in a network may have a different impact than those of peers. The hierarchical nature of the military enables examination of influence of leaders on subordinates’ behaviors, that I term “leader effects” and the reverse influence of subordinates on leaders’ behavior, termed “subordinate effects.”

Identifying social influence can be very difficult as the formation of social ties is typically endogenous. To address this empirical challenge, I leverage a unique feature of my empirical setting: the exogenous displacement of soldiers to new units. Every few years, soldiers are required by the Army to move to a different unit and/or installation. The concerns that network formations are endogenous and homophilous are reduced because of the near-random assignment of soldiers to units, as determined by the needs of the Army. In other words, the new location and the timing of this movement are largely out of a soldier’s control. In addition, by using the longitudinal data across four years, including a record of health behaviors prior to the soldiers’ new unit assignments, I can further minimize the concern that the outcomes are

merely reflecting the inherent individual behaviors in the network and not causing the behaviors (i.e. “the reflection problem” (Manski 1993)).

This dissertation contributes to healthcare literature on consumer health information technology and activation as the first study to propose the influence of provider activation on patient activation. Additionally, I minimize self-selection that normally limits conclusions in the patient portal literature. This dissertation also contributes to the literature on social network effects by determining how leader, subordinate, and peer effects impact health behaviors, and how these effects are different depending on the specific behavior and source of social influence.

Chapter 2: Critical Complements: Patient and Provider

Engagement with Technology

2.1 Introduction

Given the significance of patient portals, many researchers have examined their effectiveness in improving healthcare. Prior literature consists of empirical investigations on patients' adoption, usage, and outcomes, and contradictory results emerge. Some researchers have demonstrated patient portals improve health outcomes (Harris et al. 2009; Lau et al. 2014; Zhou et al. 2010), while others have shown patient portals have no effect on health outcomes (Bavafa et al. 2013; Grant et al. 2008; McCarrier et al. 2009; Ralston et al. 2009; Wagner et al. 2012). Similarly, in examining the impacts of patient portal on healthcare services utilization, many researchers have concluded they do not affect utilization (Bergmo et al. 2005; North et al. 2014; Ralston et al. 2009; Wagner et al. 2012), while others observe both decreased utilization (Zhou et al. 2007) and increased utilization (Bavafa et al. 2013; Harris et al. 2009; Palen et al. 2012).

All studies in the literature focus on the link between patient use of the portal and the healthcare utilization and outcomes. While patient activation as reflected in portal use is recognized as critical, researchers have paid surprisingly limited attention to provider activation. Similar to patient activation, I define provider activation as a provider's knowledge, ability, and motivation to get his or her patients more involved in their healthcare. To the degree that the healthcare provider is a critical actor in healthcare delivery, what happens when a patient is engaged in using technology but

their provider and healthcare team are not? Patients may lose interest if providers are not encouraging use of the electronic tools or involved in using the tools themselves (Wells et al. 2014). Indeed, it has been suggested that physicians might not be enthusiastic about patient portals due to concerns that patient portals amplify the workload for already overworked medical professionals, a concern which thus far is not supported (Crotty et al. 2014; Garrido et al. 2014; Kittler et al. 2004; Wells et al. 2014).

The patient-provider relationship is at the center of healthcare delivery, with both parties representing critical components of the dyad. A supportive patient-provider relationship has been shown to increase patient compliance (Francis et al. 1969); decrease pain (Gryll and Katahn 1978); and shorten recovery (Olsson et al. 1989). Opportunities to interact with one another are at the center of the development of ideal patient-provider relationships (Baur 2000). In “Crossing the Quality Chasm,” the Institute of Medicine (2001) recommended the use of phone and email communication between appointments as a visit extender to support a continuous patient-provider relationship (Baur 2000; Matusitz and Breen 2007), as contrasted with an episodic relationship that is triggered only by an infrequent office visit. Secure messaging could facilitate the development of stronger relationships by increasing interaction time, making patients more comfortable asking questions and discussing embarrassing issues, and allowing physicians to provide better advice and education (Houston et al. 2004). However, such benefits will only be realized if patients and providers are both activated to utilize the technology.

It is therefore, important to consider provider adoption and use of health information technology systems and the impact on patients. Indeed, the importance of provider activation is reflected in a qualitative study interviewing Veterans Affairs healthcare providers: “Although PHRs are designed as consumer-oriented tools intended to engage and empower patients, study findings suggest that engagement must be a reciprocal process.” (Nazi 2013, pg 17). Providers must endorse and actively use patient portals for them to be effective (Nazi 2013).

Motivated by these considerations, I address two specific research questions in this study: (1) How does provider activation influence patient activation? and (2) What are the effects of a patient portal on patients’ healthcare utilization and outcomes? The empirical context for the study is the implementation of the Army Medicine Secure Messaging Service (AMSMS) by the U.S. Army Medical Department (AMEDD), initiated in January 2011. Patients use AMSMS to securely message their primary care and medical teams to request medical advice, appointments, lab results, referrals, and prescription renewals; record medical information; and access educational materials. The rollout of the system was conducted in a consistent manner across Army hospitals and clinics, with a team visiting each location to conduct training and provide system access. The AMEDD is an excellent setting for this study because it is a large, integrated organization with common policies and procedures and similar patient populations across medical facilities.

This research study makes two important contributions. Theoretically, it is the first to propose the significance of and examine the important role of provider activation in patient activation. By examining the actual usage logs of the patient portal,

combined with a detailed longitudinal data set, I am able to identify the independent and significant effects that provider activation and patients' healthcare needs have on patient messaging rates. An empirical contribution of this study is the use of a more rigorous control for patient self-selection of portals. Previous studies have accounted for self-selection by matching portal users to those adopters who did not use the system (Bavafa et al. 2013; Harris et al. 2009). However, there is still unobserved heterogeneity between adopters who choose to use the portal versus those who do not. This is the first study in the patient portal literature to use look-ahead matching (Jung et al. 2014) to control for patient self-selection of the portal. The use of look-ahead matching, in which adopters during one time-period are matched to users in a future time period and outcomes are examined prior to adoption by the future users, minimizes self-selection bias.

This chapter is organized as follows: In section 2.2, I provide the conceptual background and review the patient portal literature. In section 2.3, I describe the methodology for the research study, giving an overview of the Army Medical Department, the large, rich dataset utilized, and the empirical specification. In section 2.4, I present the findings from my analyses. Finally, in section 2.5, I discuss the contributions and limitations of the study.

2.2 Conceptual Background and Literature Review

I examine the impacts of patient portals by focusing on the interactions of patients and providers with each other and with the patient portal. See figure 2.1 for a high-level depiction of the research model.

[Insert Figure 2.1]

Previous studies have demonstrated that patient usage of patient portals is low with only 10-32% of patient portal adopters actually using the portal (Bavafa et al. 2013; Lau et al. 2014; Weppner et al. 2010). In fact, the Centers for Medicare & Medicaid Services recently proposed a change to the HITECH Act from requiring 5% of patients send a secure message to only the presence of the feature because providers are having a difficult time engaging their patients in this way (Centers for Medicare and Medicaid 2014).

Clearly one could argue that patients will use a portal only when their medical conditions and/or healthcare needs necessitate it and that this occurs infrequently. However, the impact of health status on patient health IT acceptance is not established in the literature (Or and Karsh 2009). And the opposite could be argued as well: that unhealthy patients are less likely to use a portal than healthy patients because unhealthy patients are busy dealing with their medical conditions.

The nature of the relationship between patient use and provider use of a portal is not clear, *ex ante*. Low patient usage could be influenced by low provider activation. If a patient sends his provider a message and does not receive a response, he could

become frustrated with his provider and stop using the system. Alternatively, it is plausible that high provider activation discourages patient use. Patients may be intimidated by the elevated status of physicians (Mishra et al. 2012) and the messages themselves could be written at a health literacy level much higher than that of the patient (Mirsky et al. 2015). Both of these scenarios would leave a patient feeling inadequate to respond to providers' messages.

Existing studies on patient portals are largely empirical in nature, focusing primarily on whether or not patient portals improve the effectiveness and efficiency of healthcare. The findings in these areas are mixed and the effects of patient portals are unclear (Giardina et al. 2013). Additionally, with the exception of Kim Nazi's qualitative interview study (Nazi 2013), previous patient portal researchers have focused exclusively on patient use and outcomes, without considering providers' use and support of such systems. Table 2.1 summarizes the major patient portal studies that examine impacts, to date.

[Insert Table 2.1]

Scholars have studied the effects of patient portals on utilization of healthcare services. Some researchers claim that patient portals increased services utilization, including in-person visits and telephone calls (Bavafa et al. 2013; Harris et al. 2009; Palen et al. 2012; Zhou et al. 2007). Surprisingly, Palen and colleagues (2012) found that emergency room visits and in-patient hospitalizations also increased for patient portal users. Meanwhile, others showed that patient portals had no effect on

utilization (Bergmo et al. 2005; North et al. 2014; Ralston et al. 2009; Wagner et al. 2012). Kumar and Telang (2012) explored this variation in impacts by distinguishing between the ambiguity of the information accessed. When the information accessed in a patient portal was ambiguous, calls to the healthcare organization increased by 66%, but when the information was clear, telephone calls decreased by 29% (Kumar and Telang 2012).

A similar pattern emerges about the effects of patient portals on health outcomes. Many of them have found that health outcomes, such as glycemic index, blood pressure, and cholesterol, are unaffected by patient portals (Bavafa et al. 2013; Grant et al. 2008; McCarrier et al. 2009; Ralston et al. 2009; Wagner et al. 2012). Others have concluded that patient portals improved health outcomes, including glycemic index, cholesterol, and Healthcare Effectiveness Data and Information Set (HEDIS) measures (Harris et al. 2009; Lau et al. 2014; Zhou et al. 2010).

Multiple reasons can explain differences in findings reported in the patient portal literature. The first is differences in the activation levels of both patients and providers, reflected in their specific use of the portal. For example, one would expect that an overweight patient with a highly activated provider who sends her frequent, encouraging messages to improve her nutrition and activity levels, to be more successful in losing weight than another patient with a less activated provider that only communicates during in-person visits. Likewise, a patient whose provider by default, always instructs their patients in their secure message reply to make an in-person appointment may have different utilization rates than a patient whose provider does not respond to the message at all.

The second reason for differences in findings I believe is due to the various methodologies employed in prior literature and whether or not these methodologies control for self-selection. There are likely to be systematic differences between patients that decide to use a patient portal compared to those that do not. This is demonstrated by the result of Palen and colleagues (2012) that patient portal users' emergency room visits and hospitalizations increased, compared to the control group of non-users. It is highly unlikely that a patient portal would cause this negative outcome. There must have been unobserved heterogeneity *ex ante* between the two groups of patients that influenced the outcome. Palen and colleagues are not alone in their insufficient control for self-selection. This is a fairly common limitation in the retrospective cohort studies in the patient portal literature. In the literature review above, this is also the case in Harris et al. (2009), Kumar and Telang (2012), and North et al. (2014).

Other scholars went to the effort to control for self-selection through the use of matching users to non-users, controlling for *observable* differences in patients (Lau et al. 2014; Palen et al. 2012; Zhou et al. 2007, 2010). Matching patients on observable characteristics, such as demographics and medical conditions, is a step in the right direction to control for self-selection effects. However, there are likely many characteristics that could affect outcomes that are unobserved, such as motivation to change behavior and attitude toward technology. In this study, I address these shortcomings through the use of look-ahead matching. I match patients that adopt and use the portal in one time period (treatment) with patients that adopt and use the portal in a similar way in a future time period (control), observing differences in

outcomes during the earlier time period. One patient portal study did control for observed and unobserved heterogeneity through the use of an instrumental variable of provider message rates with other patients, under the assumption that this impacts the focal patient's portal usage (Bavafa et al. 2013). I employ this methodology as a robustness check that confirms my results from the primary analysis.

2.3 Methodology

2.3.1 Setting

The setting for this study is the United States Army Medical Department, which provides health care to the Army's 3.95 million service members, retirees, and family members, across 8 medical centers, 27 community hospitals, and numerous clinics ("Introduction to the U.S. Army Medical Department" 2015). In January 2011, the Army Medical Department began implementation of a patient portal, the Army Medicine Secure Messaging Service (AMSMS), which includes secure messaging and a personal health record. See figures 2.2 through 2.4 for screen shots of the system. An implementation team visited each of 50 Army medical facilities to conduct training and initiate system access, with implementation completed in primary care locations in March 2013.

[Insert Figures 2.2-2.4]

2.3.2 Data

The primary data set consists of de-identified administrative, medical, and training data from military information systems. It was established at the University of Maryland Center for Health Information and Decision System (CHIDS) as the Military Medical Informatics Data Set (MMIDS). The MMIDS contains 25 million person-month observations, with data on over 820,000 Active Duty soldiers from January 2011 through December 2014. Data elements in the data set include among other variables, age, deployment history, time-in-service, rank, race, marital status, body mass index, self-reported health measures, medical diagnoses, medical appointment data, prescription medications, physical fitness test scores, and tobacco use. Additionally, I obtained the usage logs from AMSMS since implementation through November 2014. This includes 727,951 secure messages and 362,283 PHR actions for 439,368 patient users, of which 81,645 are Active Duty soldiers, and 2,983 provider and staff users. See table 2.2 for a description of the data sources.

[Insert Table 2.2]

Dependent Variables

The dependent variable for the first research question is the number of patient-initiated messages in one month. For the second research question the dependent variables include healthcare utilization, medications, tobacco use, body mass index (bmi), and physical fitness levels. See table 2.3 for a description of the dependent variables.

[Insert Table 2.3]

Independent and Control Variables

As a measure of provider activation, I calculate number of messages a patients' provider sends to other patients in a month. This measure is exogenous to the focal patient and therefore, uncorrelated with their outcomes, and provides an estimate of how much a provider is using the portal. The provider activation variable is used in the first part of the analysis to examine impact on patient messaging and is used as an instrumental variable robustness check, described below.

To estimate patient activation, I calculate patients' overall observed use from time of adoption through November 2014. I then divide patients into low and high users according to their rank among all patient portal adopters.

In the first part of the analysis, I include healthcare utilization measures as independent variables. I control for a number of patient factors including patient demographics, recent medical conditions (the conditions which are the most common in the U.S. Army), and location. Table 2.4 includes a description of independent and control variables.

[Insert Table 2.4]

2.3.3 Empirical Strategy

Research Question 1

I compare the impact of provider activation with the impacts of patient healthcare utilization and medical conditions to understand why a patient sends a secure message at the time they do so. Is it only because of a specific health need or does provider activation with the portal have an impact? To answer this question the following negative binomial regression model with patient fixed effects is used:

$$\begin{aligned} \log(\text{patientmsg}_{it}) &= \beta_0 + \beta_1 \text{provactcat}_{it-1} + \beta_2 \text{primcaretot}_{it-1} + \beta_3 \text{ervisit}_{it-1} \\ &+ \beta_4 \text{speccaretot}_{it-1} + \beta_5 [\text{Patient Medical Conditions}_{it}] \\ &+ \beta_6 \text{installation} + \beta_7 \text{month} + \varepsilon_{it} \end{aligned}$$

Research Question 2

In order to determine the impacts of a patient portal on patient level outcomes, I construct a control group to serve as a baseline of expected outcomes in the absence of treatment. Because patients self-select into using the portal, I employ two strategies to control for self-selection: Coarsened Exact Matching (Iacus et al. 2011) and Look-Ahead Matching (Jung et al. 2014). I use Coarsened Exact Matching (CEM) to create a control group that is similar to the treatment group in terms of specified, observable characteristics. CEM uses bins of operator-determined size to match treatment and control groups in order to maximize the number of matches and create balance between the groups (Iacus et al. 2011). For example, rather than matching on exact

age, which would decrease the number of possible matches and not significantly improve the estimation, age groups are specified, such as 25-30 year olds, to match patients within. This is done for all combinations of specified characteristics and bin sizes, creating numerous strata containing treatment and control patients. Any bins without treatment patients are discarded.

To account for unobserved heterogeneity, I use Look-Ahead Matching (LAM) (Jung et al. 2014). Jung, Umyarov, Bapna, and Ramaprasad (2014) demonstrated the effectiveness of this method in the area of mobile channel adoption. It was observed in the analysis that only 33% of all portal adopters and 21% of Active Duty soldier adopters actually use the portal at least one time. Therefore, the analyses focus on patient portal users, not just adopters. The patient portal users are split into two groups based on their chronological time of adoption. The users from April 2013 to August 2013 serve as the treatment group and are matched to users from June 2014 to September 2014 with similar characteristics to serve as the control group. The outcomes are observed from September 2013 to May 2014, prior to the control group's adoption. See Figure 2.5 for a visual depiction of this method. The treatment and control groups do not differ in terms of adoption timelines. Due to the incremental rollout of the system across military installations and due to the transitory nature of the soldiers, I am able to match users according to the quarter after the system was available to them at their specific clinic in which the user adopted.

[Insert Figure 2.5]

I match on the following observable demographics and bin sizes in December 2012: age (18-29 / 30-44 / 45-62), gender (M / F), education (High School Diploma / At least Some College), number of years of military service (<4 / 4-10 / 10-16 / >16), military rank category (Junior Enlisted / Junior Non-Commissioned Officer (NCO) / Senior NCO / Warrant Officer, Officer), mental health diagnosis in three months prior to match (No / Yes), mental health diagnosis in three months prior to match (No / Yes), musculoskeletal diagnosis in three months prior to match (No / Yes), sleep apnea diagnosis in three months prior to match (No / Yes), hypertension diagnosis in three months prior to match (No / Yes), dyslipidemia diagnosis in three months prior to match (No / Yes), pregnancy in three months prior to match (No / Yes), patient activation category (low/ high), and adoption timeline quarter.

To ensure ample time to observe outcomes, I exclude soldiers without at least 9 months of observation in the pre-period (period 0) and 9 months of observations in the post-period (period 2). This reduces the study population from 17,345 Active-duty users to 5,263 patients, with 3,208 in the treatment group because they adopted in period 1 and 2,055 in the control group because they adopted in period 3. Matching further reduces the sample to 1,856 total soldiers, with 1,013 in the treatment group and 843 in the control group.

Matching methods are not intended to be used as statistical estimators, but serve as a way to preprocess the data (Iacus et al. 2011). Therefore, it is necessary to use an estimator to make causal claims after matching is complete. Different estimators are required based on the structure of each outcome variable (e.g. negative binomial for count outcome variables, logistic for binary outcome variables). In each case I use a

difference-in-difference model to detect the treatment effect, which takes the difference of each of the differences between the treatment and control groups before and after treatment. The difference-in-differences coefficient is β_3 in the regression model below.

$$\begin{aligned}
 y_{it} = & \beta_0 + \beta_1 Treatment\ Group + \beta_2 PostPeriod \\
 & + \beta_3 (Treatment\ Group * PostPeriod) \\
 & + \beta_4 [Patient\ Medical\ Conditions_{it}] + \beta_5 installation \\
 & + \beta_6 month + \varepsilon_{it}
 \end{aligned}$$

As a robustness check, I perform an instrumental variable analysis using the linear two-stage least squares model shown below. The first stage uses *provactivation* as an instrument to estimate a variable called *portaluse*. The variable *portaluse* turns to one in the patients' first month of portal use and remains one thereafter. As will be demonstrated by answering the first research question, *provactivation* has a significant impact on patients' portal usage. Because *provactivation* is a measure of messaging with the providers' other patients, it will only impact patient outcomes through the variable, *portaluse*. The first stage regression has an F stat greater than 10 and all tests for under-identification demonstrate models are not under-identified.

Stage 1:

$$\begin{aligned}
 portaluse_{it} = & \beta_0 + \beta_1 provactivation_{it} + \beta_2 [Patient\ Medical\ Conditions_{it}] \\
 & + \beta_3 installation + \beta_4 month + \varepsilon_{it}
 \end{aligned}$$

Stage 2:

$$\begin{aligned}
 y_{it} = & \beta_0 + \beta_1 \widehat{portaluse}_{it} + \beta_2 [Patient\ Medical\ Conditions_{it}] + \beta_3 installation \\
 & + \beta_4 month + \varepsilon_{it}
 \end{aligned}$$

For this analysis, I examine all patients who adopt the portal (users and non-users) and have at least 9 months before and after adoption. This reduces the sample size to 29,662. I examine outcomes in the 9 months both before and after a patients' adoption.

Descriptive Statistics

Table 2.5 provides descriptive statistics of the CHIDS MMIDS. Table 2.6 provides descriptive statistics of the portal non-adopters, adopters, and users. Table 2.7 describes portal usage by patients. Table 2.8 provides descriptive statistics of portal usage by providers. Table 2.9 provides descriptive statistics of the treatment group after matching. Table 2.10 provides descriptive statistics of the sample used in the instrumental variable analysis.

[Insert Tables 2.5 – 2.10]

2.4 Results

2.4.1 Impacts of Provider Activation on Patients' Portal Use

Table 2.11 displays the results from the regression analysis of patient initiated messages. Healthcare utilization and medical conditions significantly impact patient messaging. For every additional primary care visit the month prior, patients send 13.9% more messages. Specialty care and emergency room visits in the month prior do not impact the number of messages a patient sends. Having a musculoskeletal or

dyslipidemia diagnosis in the previous three months significantly increases the number of patient messages by 15.4% and 13.9%, respectively. But, mental health, hypertension, and sleep apnea do not impact patient messaging habits.

We see that patients with activated providers are significantly more likely to initiate a secure message. Those with highly activated providers send 174% more messages than those with non-activated providers. Low activated providers increase messages by 63% and medium activated providers increase message by 103% over non-activated providers. These findings provide strong evidence and underscore the significant role that provider activation plays in patient portal use.

[Insert Table 2.11]

2.4.2 Impacts of Patient Portal on Patients' Healthcare Utilization and Outcomes

The defining assumption of a difference-in-differences model is that the treatment and control groups have similar expected trends for each of the outcome variables in the absence of treatment. This allows the control group to serve as a valid baseline with which to compare the treatment group. I compared the dependent variables' trends of the treatment and control groups in the pre-period and confirmed that this assumption was satisfied.

Tables 2.12 – 2.21 display all results from the main analysis of the impacts of the patient portal on patients' utilization and health outcomes. I first explain the results for healthcare utilization. Table 2.12 displays the regression results for primary care visits. Primary care visits increase 13.7% more for the treatment group in the post-

period than for the control group. Results in tables 2.13 and 2.14 show that there are no differences between the two groups in emergency room visits or specialty care visits. Regression results displayed in table 2.15 demonstrate that pain clinic visits increase 140.4% more for patients in the treatment than in the control group in the post-period. Patient portal impacts on medications on displayed in tables 2.16 and 2.17. From these we see that patients in the treatment group are 27% more likely to have an opioid prescription. Similarly, psychotropic medications increase 34% more for the treatment group in the post-period than for the control group. Means of outcomes with significant differences are graphed by group over the study period in figures 2.6 to 2.9.

Patient health outcome results are displayed in tables 2.18 through 2.21. There are no significant differences between treatment and control groups in terms of BMI or odds of obesity, whether or not the patient was obese at the start of period 1. The analysis also reveals there are no differences between the groups for odds of passing the physical fitness test and odds of tobacco use. I do not detect any effects of the patient portal on patient health outcomes in the look-ahead matching analysis.

[Insert Tables 2.11-2.21]

[Insert Figures 2.6-2.9]

The instrumental variable robustness analysis results are displayed in tables 2.22 and 2.23. These results confirm that patient portal use increases primary care visits and opioid prescriptions. In this analysis, primary care visits increase by 42%

following portal use and opioid use increases by 11.8%. The instrumental variable analysis also confirms that emergency room visits are not affected by patient portal usage. However, we do not see a significant difference in pain clinic visits or psychotropic medications and we see a 60.6% increase in specialty care visits. Additionally, the two-stage least squares regression confirms patient portals do not impact obesity, fitness, or tobacco use. There is a significant impact on body mass index, with a 68.1% decrease in BMI from portal usage.

[Insert Tables 2.22-2.23]

In summary, patients initiate messages as their healthcare needs and medical conditions dictate. Perhaps more notable, patient usage significantly increases with providers' activation levels. The analysis of the overall impacts of patient portals on patients' healthcare utilization and outcomes demonstrates that patient portal usage complements healthcare utilization and does not directly impact patient health outcomes. It is likely that primary care providers are instructing patients to come in for an in-person visit when they receive a message or when multiple messages cannot resolve the issue. Because the U.S. Military does not operate on a fee-for-service model, we know the providers are not driven by monetary incentives to increase visit rates, so the portal may be improving access. In as much as pain clinic visits improve care for patients, patients receive improved healthcare through patient portal use. Medication rates also increase due to use of the portal. This can be attributed to more

prescribing and therefore, improved treatment of medical conditions, and/or more medication refills by patients, which means increased adherence to treatment plans.

2.5 Discussion and Conclusions

Patient portals have been recognized by the U.S. Government and healthcare organizations as having the potential to activate patients and improve outcomes. However, research exploring their impacts has resulted in ambiguous findings. With a unique and detailed dataset, I examine a patient portal implemented among a large sample of patients at a unified healthcare organization and study their specific portal usage and resulting outcomes.

This study introduces the concept of provider activation, or a provider's motivation and ability to get patients more involved in their health. I conceptualize provider activation by examining providers' secure messaging patterns. I demonstrate that in addition to a patient's healthcare utilization and medical needs, increasing provider activation significantly increases patient messaging.

Additionally, through the use of a robust matching method, as well as an instrumental variable analysis, I reduce selection bias that is rampant in the patient portal literature. I establish that patient portal usage complements utilization of healthcare services, while increasing access and improve medication rates and/or adherence.

There are three practical implications from this study that are noteworthy. The first is that in order to encourage portal usage among their patients, healthcare organizations can focus on increasing provider engagement. They can also expect

increased secure messaging from patients following primary care visits and recent diagnoses of musculoskeletal issues and dyslipidemia. Second, despite the expectation by many that secure messages replace visits, healthcare organizations should expect an increase in utilization after patient portal implementation. Finally, providers can use patient portals to improve medication adherence among their patients.

There are also limitations of this study to consider. The first is that the setting is the U.S. Army, with a younger, more male population than the general public and its own private healthcare system. However, there are still ample observations of patients over the age of 45 and females. Additionally, the patient portal software used is the same software used in many civilian healthcare settings. The second limitation is that while look-ahead matching controls for observed and time-invariant unobserved heterogeneity, it does not control for time-variant unobserved heterogeneity (Jung et al. 2014). I make the assumption that any time-variant unobserved heterogeneity does not impact the outcomes.

Chapter 3: Social Influence on Health Behaviors: Evidence from a Natural Experiment

3.1 Introduction

Despite physical fitness and general health requirements for U.S. Army soldiers, the Army struggles with improving soldiers' health behavioral choices, which impact military readiness and effectiveness, as well as further increase healthcare costs that are already prohibitive. Approximately 24% of soldiers were considered obese in 2014, and that is not including those that would qualify as overweight due to a higher than normal body mass index. Additionally, in 2014, 36% of soldiers report using tobacco and 17% of soldiers were identified as alcohol abusers. Understanding how these behaviors spread in social networks throughout the Army may help to control them.

This study examines peer, leader, and subordinate health effects in randomly assigned networks of U.S. Army soldiers. The U.S. Army provides an excellent setting for the study of social health influence for several reasons. First, U.S. Army soldiers are required to move to a different unit and/or installation every few years, according to the needs of the Army. I argue this movement is exogenous to the soldier and that exposure to the new health culture may trigger a change in health behaviors. Second, the hierarchical structure of the military provides an unambiguous and straightforward way to examine leader and subordinate effects and how they may differ from peer effects. Finally, through the use of individual and longitudinal

medical and administrative data across four years on over 820,000 active duty soldiers, including a record of health behaviors prior to the soldiers' new unit assignments, I minimize the concern that the outcomes are merely reflecting the inherent individual behaviors in the network and not causing the behaviors (i.e. “the reflection problem” (Manski 1993)). The research question addressed in this study is: How do leaders, peers, and subordinates influence one another’s health behaviors?

This study makes two important contributions to the literature. The first contribution is that it is the first to examine leader and subordinate health effects, in addition to peer effects. Social influence from leaders and subordinates differs from that of peers and the effects vary with the type of behavior. The second contribution this study makes is empirical in nature. This is the first study to make use of a natural experiment of random network assignment to eliminate selection bias, outside of the college roommate scenario (Carrell et al. 2011; Duncan et al. 2005; Yakusheva et al. 2014). This will enable generalizability of findings to broader populations. From a policy perspective, understanding how health behaviors spread through a social network and what people are possible key influencers could help policymakers more effectively design interventions to have the largest impact on health behavior change.

This chapter is organized as follows: In section 3.2, I provide a literature review of the social health influence literature with a brief overview of some of the controversy surrounding empirical approaches and reported effects. In section 3.3, I summarize mechanisms that may drive social influence and provide hypotheses for the study. Then, in section 3.4 I describe the methodology for the study, the dataset, and

empirical strategy. In section 3.5, I present and discuss results. Finally, section 3.6, summarizes the contributions and limitations of the study.

3.2 Literature Review

The social influence literature has exploded in recent years in the area of health behaviors, thanks in large part to influential studies by Nicholas Christakis and James Fowler (Christakis and Fowler 2013). Christakis and Fowler, along with fellow collaborators conducted a series of studies examining social health influence in the Framingham Heart Study (FHS) data (“History of the Framingham Heart Study” 2015). The Framingham Heart Study was initiated in 1948 with 5200 people from Framingham, Massachusetts, to study factors that contribute to cardiovascular disease (“History of the Framingham Heart Study” 2015). The FHS researchers expanded the study to include later generations of people from Framingham, many of which are related to one another and the original cohort (“History of the Framingham Heart Study” 2015). Because the unique data set contains health outcomes and behaviors and social contacts of participants across 32 years, Christakis, Fowler, and collaborators were able to create the social networks of study participants and examine peer effects of obesity (Christakis and Fowler 2007), smoking (Christakis and Fowler 2008), happiness (Fowler and Christakis 2008), loneliness (Cacioppo et al. 2009), alcohol use (Rosenquist et al. 2010), eating habits (Pachucki et al. 2011), and depression (Rosenquist et al. 2011). In these studies they found clusters of the various health behaviors and psychological traits, common among peers, that were more concentrated than by chance alone (Christakis and Fowler 2013). Additionally,

they found in all of these studies, people connected up to three degrees of separation (“friends of friends of friends”) were influenced by their peers (Christakis and Fowler 2013). For an overview of the Christakis, Fowler, and colleagues' studies, see table 3.1.

[Insert Table 3.1]

While Christakis and Fowler have made significant advances on the field's understanding of social health influence, their identification strategies have been widely criticized due to two main concerns: selection effects and contextual effects (Cohen-Cole and Fletcher 2008a; Shalizi and Thomas 2011). Self-selection of peers is a concern because people could select friends based on factors correlated with health traits that influence the outcome of interest (Cohen-Cole and Fletcher 2008a). Contextual effects are also a concern in the Christakis and Fowler studies because there may be common environmental factors that are simultaneously driving the changes in both people and therefore, community level controls are necessary (Cohen-Cole and Fletcher 2008a).

To overcome the selection bias commonly present in social influence studies, some researchers have used social relationships that are a result of random assignment, namely the random assignment of college freshman roommates (Carrell et al. 2011; Duncan et al. 2005; Yakusheva et al. 2014). See table 3.2 for an overview of these studies. These studies demonstrate that even in randomly assigned social relationships, peers influence fitness and alcohol use. Carrell, Hoekstra, and West

(2011) examine peer effects at the U.S. Air Force Academy and are able to study much larger peer groups than only roommates due to random assignments of cadets to squadrons, whom they spend the majority of their time with. However, while these studies are able to effectively control for selection bias, they are fairly limited in scope, with the findings possibly applying only to college campus settings. In this study, I utilize the rigorous and established technique of random social network assignment, in a much broader population.

[Insert Table 3.2]

In addition, a comprehensive literature review reveals that the social health influence literature is concentrated on peer effects, treating all social contacts as having equal influence. I argue that examining connections with superior and subordinate social standing is important to understanding how behaviors spread through social networks.

3.3 Theory and Hypotheses

Social Influence

Social influence is thought to arise with social proximity. Due to social interactions, people exert influence on each other (Marsden and Friedkin 1993). The influence can be direct, which is an intentional act to change behavior; or indirect, which involves imitation by others without any intent by the initiator (Marsden and

Friedkin 1993). Social health influence likely occurs through a number of pathways, including: social norms, social learning, cues, and access to resources.

In uncertain social situations, people use social norms to understand how to properly behave in that particular situation (Cialdini and Goldstein 2004), such as how to dress for a social event versus a job interview. Social norms influence people through subtle awards of acceptance for conformity and / or punishments for nonconformity (Friedkin 2001). Because of these subtle awards and punishments, over time unique norms begin to develop within organizations. Research shows that social norms directly influence people's behavior (Cialdini and Goldstein 2004). As expressed by Berkman and colleagues (2000, pg 849), "Shared norms around health behaviors (e.g. alcohol, and cigarette consumption, health care utilization, treatment adherence or dietary patterns) might be powerful sources of social influence with direct consequences for the behaviors of network members." Social norms may also impact people's anchors. The anchoring heuristic is when a person makes an estimate by thinking of an initial value (an "anchor") and adjusting it to compute a final value (Tversky and Kahneman 1974). This initial value selected, however, biases the final estimate (Tversky and Kahneman 1974). The way in which anchoring could play a role in social health influence is by changing the people's initial estimate of expected utility. For example, if many of your friends are overweight, you may increase your anchor of what an acceptable weight is (Christakis and Fowler 2007). I believe varying social health norms or "health cultures" have developed across the Army, as evidenced by the observed large variations in health behaviors.

Social learning (Bandura 1971) is widely accepted as one way in which social influence occurs. The idea behind social learning is that people can learn about the utility of behaviors by observing others (Bandura 1971). For example, I may learn about the benefits of consuming a more nutritious diet by observing the weight loss and energy gain of a friend that is eating well.

Cue theory provides another possible avenue for social influence. Personal preferences are sensitive to environmental cues because cues increase the expected utility of the behavior by triggering a craving (Liabson 2001). Seeing someone else's pack of cigarettes may serve as a cue that stimulates a person's desire to smoke (Kremer and Levy 2008).

Further, spending time with other people also provides access to resources (Berkman et al. 2001). These resources could be material, such as cigarettes (Ann 2015) or informational, such as knowledge about smoking cessation classes.

Soldiers within a military unit perform work and training together and spend many hours a day together. Most of this work and training involve extensive social interactions, providing opportunities for the development of social norms, learning from each other, observing cues in the setting, and facilitated access to the resources others within the unit possess. In other words, all of the mechanisms of social influence identified above are likely to be present. This leads to the first hypothesis:
H1: Military unit leaders, peers, and subordinates exert social health influence on one another.

In much the same way that network externalities (Katz and Shapiro 1985) cause the marginal utility one derives from certain products to increase by others using the product, social interaction increases the utility of select behaviors, termed “socially enhanced behaviors.” For example, the utility one derives from drinking alcohol is likely higher when it is consumed with others than when it is consumed alone.

Socializing between rank categories is considered fraternization and is prohibited in the military. Therefore, peer influence should be stronger than leader or subordinate influence in the examined outcomes, which are all socially-enhanced, as stated in my second hypothesis:

H2: Peer effects are stronger than leader and subordinate effects.

3.4 Methodology

3.4.1 Setting

The empirical setting for this study is the U.S. Army. “The Army’s mission is to fight and win our Nation’s wars by providing prompt, sustained land dominance across the full range of military operations and spectrum of conflict in support of combatant commanders” (“Organization” n.d.). The Army represents the largest component of the Department of Defense and had 494,000 Active Duty soldiers at the end of 2014. Due to the physical demands of service, the U.S. Army does have a younger population, with an average age of 30; and more men (86%) than the general U.S. population, which reduces the generalizability of findings. However, there are sufficiently high numbers of soldiers aged 45 or more (28,866 as of May 2014) and women (70,796 as of May 2014) in the Army.

The Army provides an excellent setting to investigate social health influence for a number of reasons. First, there is a wealth of self-reported behaviors that are recorded at medical appointments and annual physical exams, including drinking and smoking habits. I was able to obtain this data, along with other detailed medical and administrative data, covering all active duty soldiers over four years. This allows for a rich, longitudinal analysis of social health influence. Second, even though the Army has a common healthcare system and consistent standards of fitness throughout its duty locations, large variations in healthcare and behaviors have been observed. I believe these variations are due to local “health cultures” with norms of acceptable health behaviors that have developed over time. Finally and most importantly, the Army provides a natural experiment for this study. Every few years soldiers are required by the Army to change military units. The specific unit assignment is according to the needs of the Army and is largely out of a soldier’s control. This creates exogenous social networks at military units and eliminates selection bias concerns.

3.4.2 Data

The data set utilized in this study consists of de-identified administrative and medical data from military information systems, including the military’s electronic health record (EHR). It was compiled from disparate systems and established at the University of Maryland Center for Health Information and Decision System (CHIDS) as the Military Medical Informatics Data Set (MMIDS). The MMIDS contains

820,000 Active Duty soldiers observed monthly from January 2011 to December 2014. See table 2.3 for a description of the data sources.

[Insert Table 2.3]

The most basic organizational unit within the Army is a company, an organization comprised of approximately 100-150 soldiers. Typically, 3-5 companies combine to form a battalion, with approximately 800 soldiers. The data set includes assigned unit identification codes (UIC) for each soldier throughout the covered time-period, identifying which company or battalion the soldier belongs to at any given point in time.

For the purposes of this analysis, soldiers are categorized as “junior rank” if they are junior enlisted (E1-E4), “mid-level rank” if they are a junior non-commissioned officers (NCO) (E5-E6) and as “senior rank” if they are senior NCOs (ranks E7-E9), warrant officers (WO1-CW5), junior commissioned officers (ranks O1-O3), or senior commissioned officers (ranks O4-O10). Peer effects are defined as those occurring in the same rank category. Leader effects are defined as those moving from senior ranks to mid-level and junior ranks. And subordinate effects are defined as those moving from junior ranks to mid-level and senior ranks and from mid-level to senior ranks.

Table 3.3 provides descriptive statistics of the CHIDS-MMIDS, overall and by rank group. Table 3.4 provides descriptive statistics at the unit level. Table 3.5 provides a sampling of mean annual statistics at the 31 largest Army installations

between 2011 and 2014 to demonstrate the differences observed in health behaviors across the Army.

[Insert Tables 3.3-3.5]

Dependent Variables

The dependent variables for this study include tobacco use and cessation, alcohol abuse, and obesity. As noted before, these particular health behaviors and conditions are of specific concern to the military. For a description of how the variables were derived, refer to table 3.6.

[Insert Table 3.6]

Independent Variables

Independent variables in the analysis include demographics, military occupation, and military installation. See table 3.7 for a description of independent variables. The unit rank mean variables refer to the behavior rate (i.e. tobacco use) in each of the unit's rank groups in a three month time period. Newly-arrived soldiers are not included in the unit rank means in their month of arrival and three months following arrival. The unit rank means are standardized by calculating the distance from all unit's rank means (separately at each rank) and dividing by the standard deviation. This allows me to take into account what is a normal behavior pattern for the Army.

[Insert Table 3.7]

3.4.3 Empirical strategy

To examine the peer, leader, and subordinate effects on health behaviors, I explore how unit rank means influence a soldier's behavior after they arrive to a new unit. There are nine possibilities of social influence type and direction when a new soldier is assigned to a unit: (1) unit junior soldiers on new junior ranking soldier (peer effect), (2) unit junior soldiers on new mid-level ranking soldier (subordinate effect), (3) unit junior soldiers on new senior ranking soldier (subordinate effect), (4) unit mid-level ranking soldiers on new junior ranking soldier (leader effect), (5) unit mid-level ranking soldiers on new mid-level ranking soldier (peer effect), (6) unit mid-level ranking soldiers on new senior ranking soldier (subordinate effect), (7) unit senior ranking soldiers on new junior ranking soldier (leader effect), (8) unit senior ranking soldiers on new mid-level ranking soldier (leader effect), (9) unit senior ranking soldiers on new senior ranking soldier (peer effect). See Figure 3.1 for a visual description of the examined social influence types.

[Insert Figure 3.1]

The logistic regression models below are used to detect peer, leader, and subordinate effects on newly arrived junior, mid-level, and senior soldiers. A soldier is included in the study if there are six months of observations in the data set before the move to the new unit and three months of observation after the move to the new unit. This allows for consistent time for outcomes and controls. The six months prior to a move to a new unit also eliminates brand new soldiers in the Army reporting

from Basic Training, where soldiers are not allowed to use tobacco or alcohol and are in high levels of fitness, which would bias the results. The sample size is 378,209 soldier-arrivals with 304,621 soldiers at 2,297 units. See table 3.8 for the descriptive statistics of the new soldiers by rank category.

$$\begin{aligned} \ln\left(\frac{p_{i,t+3}^{new\ junior\ soldier}}{1 - p_{i,t+3}^{new\ junior\ soldier}}\right) \\ = \beta_0 + \beta_1 PeerMean_{t-3} + \beta_2 MidLeaderMean_{t-3} \\ + \beta_3 SeniorLeaderMean_{t-3} + \beta_4 y_{i,t-3} + \beta_5 y_{i,t-6} \\ + \beta_6 SoldierDemographics_i + \beta_7 Installation \\ + \beta_8 Time\ Controls + \varepsilon \end{aligned}$$

$$\begin{aligned} \ln\left(\frac{p_{i,t+3}^{new\ mid\ soldier}}{1 - p_{i,t+3}^{new\ mid\ soldier}}\right) \\ = \beta_0 + \beta_1 PeerMean_{t-3} + \beta_2 LeaderMean_{t-3} \\ + \beta_3 SubordinateMean_{t-3} + \beta_4 y_{i,t-3} + \beta_5 y_{i,t-6} \\ + \beta_6 SoldierDemographics_i + \beta_7 Installation \\ + \beta_8 Time\ Controls + \varepsilon \end{aligned}$$

$$\begin{aligned} \ln\left(\frac{p_{i,t+3}^{new\ senior\ soldier}}{1 - p_{i,t+3}^{new\ senior\ soldier}}\right) \\ = \beta_0 + \beta_1 PeerMean_{t-3} + \beta_2 MidSubordinateMean_{t-3} \\ + \beta_3 JuniorSubordinateMean_{t-3} + \beta_4 y_{i,t-3} + \beta_5 y_{i,t-6} \\ + \beta_6 SoldierDemographics_i + \beta_7 Installation \\ + \beta_8 Time\ Controls + \varepsilon \end{aligned}$$

where $p = \Pr(y = 1|x)$

The unit rank mean variables are lagged to the three-month time period prior to arrival of the new soldier. The assumption is that the unit norms will not change much between the previous time period and the period in which the new soldier arrives. Lagging these variables eliminates the “reflection problem” because the new soldier was not yet assigned to the unit and therefore, could not have influenced the unit rank means. These unit rank mean variables are the variables of interest in the regression equations because they demonstrate how much peer, leader, and subordinate effects impact the new soldiers’ odds of the behavior. The outcome variable is defined as the odds (the probability of success divided by the probability of failure) of the new soldier performing the particular behavior in the three months after arrival. Additionally, the new soldier’s behavior in the three months and six months before arrival are included to account for already established behaviors. A soldier who reported tobacco use in one of these previous periods is much more likely to report tobacco use in the next time period. Tables 3.9 to 3.12 contain the results from these regressions for each of the outcome variables. Tables 3.13 and 3.14 provide a summary of results.

[Insert Tables 3.8 – 3.14]

3.5 Results

3.5.1. Main Results

First, I examine the impacts of peer, subordinate, and leader effects on the odds of newly-arrived soldiers becoming obese in the three months after arrival. As shown in column (1) of table 3.9, junior new soldiers have a 17.3% increase in the odds of obesity for every one-unit increase in the standard deviation of the unit junior mean. This is a peer effect. (For each column peer effects are in the dotted box.) Junior new soldiers also have a 14.5% increase and 2.8% increase in the odds of obesity for every one-unit increase in the standard deviations of the unit mid and senior means, respectively. These are both leader effects. Column (2) of table 3.9 shows that mid-level new soldiers have an obesity peer effect of 21.2%, a subordinate effect of 11.3%, and a leader effect of 5.3%. The coefficients in column (3) of table 3.9 demonstrate that senior new soldiers experience an increase in the odds of obesity of 22.1% for every one-unit increase in the standard deviations of the unit rank means from peers, a 13.0% increase from mid-level subordinates, and a 5.5% increase from junior-level subordinates. These results allow me to conclude that as soldiers move to new units of increasing obesity rates, they are more likely to become obese, through social influence from their peers, leaders, and/or subordinates, as applicable.

Next, I examine the social influence of tobacco use by examining the results in table 3.10. From the first column we see that junior new soldiers experience a tobacco use peer effect of 7.4%, mid-level leader effect of 2.8%, and a senior leader effect of 2.5%. Mid-level new soldiers' peer, subordinate, and leader effects are in column (2). Mid-level new soldiers have an 8.7% increase in the odds of tobacco use for every

one-unit increase in the standard deviation of the unit's mid-level mean. Mid-level new soldiers have a 6.3% increase in the odds of tobacco use from subordinates. However, their leaders do not impact their tobacco use. Senior new soldiers, as displayed in column (3), have a 6.3% peer effect, a 3.9% mid-level subordinate effect, and a 3.0% junior-level subordinate effect on their odds of tobacco use. From these results, I conclude that junior, mid-level, and senior new soldiers' peers influence their tobacco use. Leaders also influence junior new soldiers' tobacco use. And subordinates influence both mid-level and senior new soldiers' tobacco use.

Tobacco cessation social influence results are displayed in table 3.11. Junior new soldiers have a 10.8% increase in the odds of tobacco cessation as the unit junior mean increases by one standard deviation. Mid-level new soldiers have an 11.9% increase in the odds of tobacco cessation from peer effects, a 5.8% increase from subordinate effects, and a 9.4% increase from leader effects. Peers and subordinates do not influence senior new soldiers in their tobacco cessation. I conclude that there are tobacco cessation peer effects present for junior and mid-level new soldiers, as well as subordinate and leader effects for mid-level new soldier.

The final outcome variable examined is alcohol abuse, shown in table 3.12. Junior new soldiers have a 7.0% increase and a 4.7% increase in the odds of alcohol abuse for every standard deviation increase in unit junior and senior means, respectively. Mid-level new soldiers experience a peer effect of 5.2% and a leader effect of 6.1%. Senior new soldiers only experience a peer effect of 8.9%. Alcohol abuse social influence appears to flow down from senior unit leaders and across amongst peers, with the strongest effects coming from peers.

In summary, I observe the presence of peer, leader, and subordinate effects on new soldiers' odds of obesity, tobacco use and cessation, and alcohol abuse, thereby finding strong evidence for H1. As suggested in H2, among all outcomes and ranks of the new soldiers, peer effects have the largest impact. Tobacco cessation appears to not spread as easily as other behaviors, with leaders not impacting junior new soldiers and senior new soldiers not being impacted by any relationships. In contrast, obesity spreads the most easily within and between rank groups. Alcohol abuse social influence only flows from senior leaders downward and within peers.

3.5.2 Robustness

The analysis up to this point included soldiers that changed units both within and between military installations. Moving to another installation represents 68% of the unit changes in the sample. When a soldier moves to another installation, it is likely a major event because they have to move their household and establish themselves in a new location. To determine if the observed peer, leader, and subordinate effects are largely driven by soldiers moving to a new installation and perhaps experiencing more stress and therefore being more easily influenced by members of the new unit, I repeat the analyses among within-installation unit changes only. This involves 122,837 soldier arrivals, among 116,967 soldiers. Regression results are found in tables 3.15-3.18, with summary results in table 3.19. Major differences between the two analyses are bolded and underlined in table 3.19.

[Insert Tables 3.15-3.19]

Considering the obesity social influence effects first, peer and subordinate effects at each rank group on new soldiers remain fairly consistent, with small increases or decreases compared to the main analysis. Leader effects appear to decrease and in the case of senior leaders impact on junior new soldiers, the leader effect also becomes insignificant. For tobacco use, I observe a decrease in peer and leader effects among junior new soldiers. There is also a decrease in peer and subordinate tobacco use effects on senior new soldiers. However, there is an increase in subordinate and peer effects among mid-level new soldiers for tobacco use. Interestingly, for tobacco cessation, leader effects increase for both junior and mid-level new soldiers and subordinate effects increase nearly three-fold for mid-level new soldiers. For alcohol abuse, peers effects also increase three-fold for mid-level new soldiers, and increase slightly for junior and senior new soldiers. Leader effects increase for junior and mid-level new soldiers. And mid-level subordinate effects increase for senior new soldiers. Overall, this sub-analysis among soldiers moving to new units on the same installation confirms that peers, leaders, and subordinates do impact the health behavior decisions of new soldiers.

3.6 Discussion and Conclusion

Using a rich data set in a unique setting of frequent displacement into exogenous networks, I uncover the presence of strong peer, leader, and subordinate effects on health behaviors. Peer effects are the strongest social influences in this setting. Obesity spreads easily to new soldiers arriving to units for all relationship types. Tobacco use spreads moderately through peers and less through subordinates and

leaders. Tobacco cessation does not spread to new senior soldiers and only spreads through peers for junior soldiers. All types of relationships strongly impact mid-level new soldiers' tobacco cessation. Finally, alcohol abuse spreads between peers and down from senior leaders.

This study makes two important contributions to the study of social influence. This is the first study to examine leader and subordinate effects on health behaviors, an important aspect of understanding social health influence. This study also makes an empirical contribution through the use of randomly formed social networks, beyond the previous narrow setting of college campuses. The setting does however create a limitation to the study. That is, the U.S. Army has a younger, more male population than the general public, but there are ample observations of patients over the age of 45 and females.

The findings in this study yield two important policy implications. The first is they could help military leaders focus in on specific units with poor health cultures and intervene through social channels to improve behavioral choices. Second, the results could serve as an early warning system for soldiers reporting to units with poor health cultures to help them be less susceptible to the influences.

Tables

Table 2.1: Patient Portal Literature

Study	Study Design and Population	Intervention	Outcome Measures	Main Findings
Bavafa, Hitt, & Terwiesch, 2013	Design: Retrospective cohort study with matched-controls Population: Patients in major US Healthcare Organization (N=143,025)	Treatment: Patients that used secure messaging system Control: Matched patients that adopted and did not use system	- Outpatient visits - Telephone consults - ER Visits - Glycemic control - Cholesterol	The number of office visits and telephone visits increased considerably from use of the portal. Portal adoption did not affect health outcomes.
Bergmo et al., 2005	Design: Randomized Controlled Trial Population: Primary care patients from clinic in Norway (N=200)	Treatment: Access to secure messaging system Control: Standard care	- Outpatient visits - Telephone consults	Treatment group primary care appointments significantly decreased more than the control group. No difference in telephone consults.
Grant et al. 2008	Design: Randomized Controlled Trial Population: Patients with Diabetes (N=244)	Treatment: Access to a diabetes-specific electronic personal health record with clinical data, patient decision support, and ability to submit diabetes care plan to physicians Control: Basic PHR with no pre-populated data, basic health maintenance journal	- Glycemic Control - Blood pressure - Cholesterol	No overall differences between treatment and control groups in glycemic control, blood pressure, or cholesterol. Treatment group patients without good glycemic control at baseline were more likely than the control group to achieve glycemic control at conclusion of study. Treatment patients that submitted a diabetes care plan prior to their appointment were more likely to have a medication adjustment than those control patients that submitted a maintenance journal.
Harris et al., 2009	Design: Retrospective cohort study Population: Adult patients with diabetes	Treatment: Patients that used secure messaging system (n=2,924) Control: Patients that adopted and did not use system (n=2,350)	- Glycemic Control - Blood pressure - Cholesterol - Outpatient visits	Patients in the user group had better glycemic control and slightly better LDL cholesterol than those in the non-user group. No differences in blood pressure control. Patients in the user group also had higher outpatient visits.
Kumar & Telang, 2012	Design: Retrospective cohort study Population: Random samples of customers	Treatment: customers that adopted web portal with access to health insurance plans, claims,	- Number of calls to call center	Web portal usage increased calls to call center by 14% When information and actions were unambiguous, web portal

	of U.S. health insurance firm (N=60,000)	personal health records, and general health education resources Control: customers that did not adopt portal		usage decreased calls by 29% When information was ambiguous, web portal usage increased calls by 66%
Lau et al., 2014	Design: Retrospective cohort study with matched controls Population: Adult patients with diabetes (N=100)	Treatment: Patients that used patient portal with secure messaging Control: Matched patients that did not use system	- Glycemic Control	56% of patients in the portal user group achieved glycemic control compared to only 32% in the non-user group.
McCarrier et al., 2009	Design: Randomized Controlled Trial Population: Diabetes Clinic patients with type 1 diabetes and recent high glycohemoglobin test (N=77)	Treatment: Access to nurse case manager and a disease management electronic portal with EMR access, personal health record, feedback on blood glucose and general health, and educational material Control: Standard care	- Glycemic Control - Diabetes self-efficacy	No significant differences in glycemic control between treatment and control groups. Diabetes self-efficacy significantly increased in treatment group and decreased in control group.
North et al., 2014	Design: Retrospective cohort study Population: Adult primary care patients (N=2,357)	Treatment: Patients that used secure messaging or e-visit through patient portal Control: Same patients in time prior to use	- Outpatient visits	No significant change in number of primary care appointments following secure messaging / e-visit use.
Palen et al., 2012	Design: Retrospective cohort study with matched-controls Population: Adult members of Kaiser Permanente Colorado (N=88,642)	Treatment: Active users of an electronic personal health record with secure messaging, appointment scheduling, and medication refill Control: Matched control of non-users	- Outpatient visits - Telephone consults - ER visits - Inpatient stays	Significant increase in primary care visits and telephone consults in PHR user group over non-user group. Significant increase in per-1000 member rates of emergency room visits and hospitalizations in PHR user group over non-user group.
Ralston et al., 2009	Design: Randomized Controlled Trial Population: Patients with type 2 diabetes and recent high glycohemoglobin tests	Treatment: Access to care manager and web-based care management system with personal health record, secure messaging, feedback	- Glycemic Control - Blood pressure - Cholesterol - Health care utilization	Glucose levels declined significantly in treatment group (0.7%) and increased in the control group. No difference in blood pressure, cholesterol, and healthcare utilization between groups.

	(N=83)	on blood glucose levels, and educational material Control: Standard care		
Ross et al., 2004	Design: Randomized Controlled Trial Population: Specialty clinic patients with heart failure (N=107)	Treatment: Access to electronic personal health record with access to electronic medical record, secure messaging, and educational material Control: Standard care	Self-reported measures of: - Doctor-patient communication - Medical Adherence - Self-efficacy - Health status - Health care utilization	Patients in the treatment group reported higher increases in general adherence and satisfaction with doctor-patient communication than patients in the control group. No differences in self-efficacy.
Wagner et al., 2012	Design: Randomized Controlled Trial Population: Ambulatory Clinic patients with hypertension (N=443)	Treatment: Access to electronic personal health record with access to electronic medical record, secure messaging, health diaries, educational material, and appointment assistance Control: Standard care	- Blood pressure - Patient activation - Patient perception of quality of care - Self-reported Health services utilization	No significant differences in blood pressure control, patient activation, perceived quality of care, or medical utilization. Self-identified active PHR users had a 5.25-point reduction in blood pressure. PHR use associated with baseline activation scores and satisfaction with provider communication.
Zhou et al., 2007	Design: Retrospective cohort study with matched-controls Population: Adult members of Kaiser Permanente Northwest (N=6,402)	Treatment: Patients that accessed electronic personal health record with secure messaging Control: Matched control of non-users	- Outpatient visits - Telephone consults	Primary care appointments significantly decreased 6.7% more for the PHR users than the non-users. PHR users' telephone consults increased 13.7% less than non-users.
Zhou et al., 2010	Design: Retrospective cohort study with matched-controls Population: Adult members of Kaiser Permanente Southern California with diabetes and/or hypertension (N=35,423)	Treatment: Patients that used secure messaging Control: Matched control of non-users	HEDIS measures: - Glycemic screening and control - LDL cholesterol screening and control - Retinopathy screening - Blood pressure control	Secure messaging users had a 2.0 to 6.5 percent higher improvement in HEDIS measures than non-users.

Table 2.2: Description of Data Sources

Defense Manpower Data Center (DMDC):

- Active Duty File: Demographic and military service data
- Active Duty Transaction File: Details of changes of duty status, such as discharges from active service

Digital Training Management System (DTMS):

- Army Physical Fitness Test Scores
- Height and weight
- Weapons Qualification

Medical Data Repository (MDR):

- Combined Ambulatory/ Professional Encounter Record (CAPER): Outpatient diagnoses and care in military facilities
- Standardized Inpatient Data Record (SIDR): Inpatient diagnoses and care in military facilities
- Tricare Encounter Data, Non-Institutional (TED-NI): Outpatient diagnoses and care in civilian facilities
- Tricare Encounter Data, Institutional (TED-I): Inpatient diagnoses and care in civilian facilities
- Pharmacy Detail Transaction Service (PDTS): Prescription medication information
- Clinical Data Repository Radiology Results (CDR Rads): Imaging study results and details
- Clinical Data Repository Vitals (CDR Vitals): Vital signs including height and weight taken during care in military facilities
- Appointment Data File: Details of outpatient appointments in military facilities, such as whether kept, “no-show” or canceled

Medical Operational Data System (MODS):

- eProfile: Digitally-recorded temporary and permanent work restrictions
- Periodic Health Assessment (PHA): Details of annual health surveys and associated physical examinations
- Pre-Deployment Health Assessment (PDHA): Details of health surveys and associated clinical actions preceding combat duty

Army Medicine Secure Messaging Service (AMSMS):

- Usage logs for all Army users: patients, providers, and staff
- Secure messages sent, type of message, date/time stamp, recipient, sender
- PHR access, action type, date/time stamp, accessor role

Table 2.3: Dependent Variables

Variable Name	Description
Patient Portal Usage	
<i>patientmsg</i>	Number of patient initiated messages in a month, derived from patient portal usage logs
Healthcare Utilization Measures	
<i>primecaretot</i>	Number of monthly primary care visits
<i>ervisit</i>	If patient had an emergency room visit that month (0/1)
<i>speccaretot</i>	Number of monthly specialty care visits
<i>painclinctot</i>	If the patient had a pain clinic visit that month (0/1)
Medication Rates	
<i>opioid</i>	If patient had an opioid prescription that month (0/1)
<i>psychotrope</i>	Number of monthly psychotropic prescriptions
Tobacco Use Measures	
<i>tobaccouse</i>	Binary variable that indicates whether or not the soldier has reported tobacco use at a healthcare encounter or during the annual Periodic Health Assessment (PHA), an annual physical required of all soldiers that includes a health questionnaire.
Physical Fitness Measures	
<i>fitnesspass</i>	Biannual measure of physical fitness consisting of two minutes of pushups, two minutes of situps, and a two-mile run, according to specified standards. The test is required of all soldiers twice a year. This variable is whether or not the soldier has a valid, passing physical fitness test score that month. (0 / 1)
<i>bmi</i>	The soldier's body mass index as calculated by height / weight measures taken during a healthcare encounter or physical fitness test.
<i>obesity</i>	Composite binary variable derived from: (1) Body mass index (BMI) - calculated by height / weight measures taken during a healthcare encounter or Army physical fitness test. Obesity is indicated as having a BMI over 30. (2) Body fat test – During Army physical fitness tests, soldiers who do not meet the Army height/weight requirements are required to undergo a body fat test. Obesity is indicated as exceeding the Army maximum allowable percent body fat standards, which are as follows: Age Group 17-20: Male 20% / Female 30% Age Group 21-27: Male 22% / Female 32% Age Group 28-39: Male 24% / Female 34% Age Group 40+: Male 26% / Female 36% (3) Diagnosis of obesity during healthcare encounter – derived from Electronic Health Record

Table 2.4: Independent and Control Variables
(Matching Variables in Bold)

Variable Name	Description
Demographics	
<i>agegroup</i>	Age group of soldier that month (18-30 / 31-45 / 46-62)
<i>gender</i>	Gender of soldier
<i>education</i>	Education level of soldier 1: GED / High School Diploma 2: Some College / Bachelor's Degree / Graduate Degree
<i>rankcat</i>	Military rank: 1: Junior Enlisted (E1-E3) / Specialist (E4) 2: Junior Non-Commissioned Officer (NCO) (E5-E6) 3: Senior NCO (E7-E9) 4: Officer: Warrant Officer (WO1-CW5) / Junior Commissioned Officer (O1-O3) / Senior Commissioned Officer (O4-O10)
<i>servicetime</i>	Number of years in Army (<4 / 4-10 / 10-16 / >16)
Medical Conditions	
<i>mentaldx3</i>	Whether or not the soldier has a diagnosis of anxiety disorder, adjustment disorder, personality disorder, depression, or post-traumatic stress disorder in last 3 months (0 / 1)
<i>muskdx3</i>	Whether or not the soldier has a diagnosis of musculoskeletal issue (e.g. back injury, joint pain) in last 3 months (0 / 1)
<i>sleepapndx3</i>	Whether or not the soldier has a diagnosis of sleep apnea in last 3 months (0 / 1)
<i>hypertensiondx3</i>	Whether or not the soldier has a diagnosis of hypertension in last 3 months (0 / 1)
<i>dyslipidemiadx3</i>	Whether or not the soldier has a diagnosis of dyslipidemia in last 3 months (0 / 1)
<i>pregnancy3</i>	Whether or not the soldier is pregnant in last 3 months (0 / 1)
Healthcare Utilization Measures	
<i>primecaretot</i>	Number of monthly primary care visits
<i>ervisit</i>	Number of monthly emergency room visits
<i>speccaretot</i>	Number of monthly specialty care visits
Portal Usage Factors	
<i>adoptcat</i>	Patient's portal adoption quarter
<i>patactcat</i>	Ranking of overall observed patient's portal usage, categorized low and high
<i>provactivation</i>	The number of messages the patients' provider sends to other patients in a month, representing the providers' activation level

<i>provactcat</i>	<i>provactivation</i> variable compared to all providers' distribution. Three categories: low, medium, and high
<i>portaluse</i>	Used in first stage of two-stage least squares for instrumental variable analysis. Variable turns to 1 in the month of patients' first use of the patient portal (e.g. patient sends a message or uses PHR) and remains a 1 thereafter.
Other Factors	
<i>installation</i>	Patient's military locations, one of 32 possible locations
<i>month</i>	Monthly dummies for time controls

Table 2.5: Descriptive Statistics of CHIDS-MMIDS

	All Soldiers
	N=827,265
	Percent
Gender	
Male	86.39
Female	13.61
Age Category	
18-22 years old	25.09
23-27 years old	27.02
28-35 years old	24.69
36+ years old	23.21
Education Level	
High School Equivalency	7.477
High School Diploma	58.42
Some College	13.59
Bachelor's Degree	13.52
Graduate Degree	6.994
Race	
Caucasian	68.70
African-American	20.84
Asian / Pacific Islander	4.140
Other	6.324
Marital Status	
Never Married	34.70
Married	59.35
Divorced	5.953
Military Occupational Specialty	
Category	
Medical	9.835
Infantry	14.09
Armor / Cavalry	4.467
Air and Field Artillery	7.436
Chaplain	0.593
Aviation	6.185
Special Forces / Civil Affairs	2.355
Administration / Finance / Legal /	5.751
Public Affairs	
Engineer	4.596
Supply / Logistics	10.87
Signal	7.466
Ordinance / Maintenance	10.22
Transportation	4.100
Military Police	3.797
Intelligence / Psychological	6.101

Operations	
Chemical	1.534
Other / Unknown	0.600
Dyslipidemia diagnosis in last 3 months	2.112
Hypertension diagnosis in last 3 months	0.676
Mental Health diagnosis in last 3 months	2.251
Musculoskeletal diagnosis in last 3 months	6.443
Sleep Apnea diagnosis in last 3 months	1.741
Obese in last 3 months	11.36
Tobacco Use reported in last 3 months	24.06

Table 2.6: Comparison of Characteristics among Patient Portal Adopter Types

	Portal Non- Adopter	Portal Adopter	Portal Non- Using Adopter	Portal User
	Percent	Percent	Percent	Percent
Gender				
Male	87.57	78.64	80.70	72.13
Female	12.43	21.36	19.30	27.87
Age Category				
18-22 years old	26.39	16.53	19.41	7.393
23-27 years old	27.84	21.62	23.30	16.27
28-35 years old	24.12	28.40	28.15	29.20
36+ years old	21.65	33.45	29.14	47.14
Education Level				
High School Equivalency	7.843	5.074	5.555	3.545
High School Diploma	60.04	47.79	51.25	36.79
Some College	13.10	16.82	16.05	19.26
Bachelor's Degree	12.79	18.32	17.15	22.03
Graduate Degree	6.232	12.00	9.992	18.37
Military Rank:				
Private E1-E3	20.42	13.09	15.46	5.563
Specialist (E4)	26.21	18.04	19.91	12.09
Junior Sergeant (E5-E6)	26.56	27.89	28.06	27.34
Senior Sergeant (E7-E9)	9.918	14.30	12.62	19.63
Warrant Officer (WO1-CW5)	2.810	3.711	3.294	5.034
Junior Officer (O1-O3)	8.774	12.73	12.26	14.20
Senior Officer (O4-O10)	5.314	10.25	8.388	16.14
Marital Status				
Never Married	36.00	26.17	29.02	17.14
Married	58.27	66.45	64.11	73.86
Divorced	5.736	7.381	6.870	9.003
Dyslipidemia diagnosis in last 3 months (before adoption for adopters)	1.914	3.415	2.693	5.703
Hypertension diagnosis in last 3 months	0.643	0.894	0.689	1.547
Mental Health diagnosis in last 3 months	2.266	2.154	1.758	3.409
Musculoskeletal diagnosis in last 3 months	6.198	8.054	6.634	12.56
Obese in last 3 months	10.98	13.87	11.14	17.95
Sleep Apnea diagnosis in last 3 months	1.654	2.314	1.830	3.847
Tobacco Use reported in last 3 months	24.46	21.44	21.94	19.83

Table 2.7: Descriptive Statistics of AMSMS Usage by Patients (N=439,368)

MONTHLY VARIABLES	(1) mean	(2) sd	(3) min	(4) max
Any Action	0.0395	0.317	0	180
Any Message	0.0358	0.286	0	38
Appointment Request	0.00547	0.0847	0	10
Note to Office	0.00265	0.0659	0	26
Note to Provider	0.0193	0.194	0	35
Lab Result Request	0.00233	0.0535	0	14
Referral Request	0.00132	0.0411	0	6
Prescription Renewal	0.00446	0.109	0	24
WebVisit Msg	0.000295	0.0185	0	7
Any PHR action	0.00362	0.104	0	179
Added to PHR	0.000212	0.0583	0	129
Changed PHR	0.00341	0.0755	0	50
Provider Activation	8.682	46.05	0	2,384

Table 2.8 Descriptive Statistics of AMSMS Usage by Providers (N=2,983)

MONTHLY VARIABLES	(1) mean	(2) sd	(3) min	(4) max
Provider Initiated Messages				
Messages Sent	2.327	18.52	0	2,384
Appointment Reminder	0.0325	1.166	0	132
Care Reminder	0.564	14.95	0	2,382
Patient Message	1.716	9.169	0	386
Provider Received Messages				
Messages Received	6.915	21.01	0	287
Appointment Request	1.033	3.763	0	136
Note to Office	0.514	2.661	0	117
Note to Provider	3.741	12.75	0	199
Lab Result Request	0.450	1.524	0	31
Referral Request	0.254	1.003	0	21
Prescription Renewal	0.867	3.154	0	63
WebVisit Msg	0.0558	0.327	0	13
Number of Patients Enrolled	92.60	312.8	0	3150

Table 2.9: Descriptive Statistics of Treatment Group in Look-Ahead Matching Analysis
(As of March 2012)

	Treatment Group
	Percent
Gender	
Male	76.90
Female	23.10
Age Category	
18-22 years old	7.009
23-27 years old	14.22
28-35 years old	30.01
36+ years old	48.77
Education Level	
High School Equivalency	3.554
High School Diploma	30.21
Some College	21.42
Bachelor's Degree	24.98
Graduate Degree	19.84
Military Rank	
Private E1-E3	4.936
Specialist (E4)	9.872
Junior Sergeant (E5-E6)	22.51
Senior Sergeant (E7-E9)	22.41
Warrant Officer (WO1-CW5)	4.738
Junior Officer (O1-O3)	15.89
Senior Officer (O4-O10)	19.64
Marital Status	
Never Married	13.72
Married	78.48
Divorced	7.799
Dyslipidemia diagnosis in 3 months before adoption	2.764
Hypertension diagnosis in 3 months before adoption	0.0987
Mental Health diagnosis in 3 months before adoption	0
Musculoskeletal diagnosis in 3 months before adoption	2.962
Obese in 3 months before adoption	14.41
Sleep Apnea diagnosis in 3 months before adoption	0
Tobacco Use reported in 3 months before adoption	22.21

Table 2.10: Descriptive Statistics of Sample in Instrumental Variable Analysis

	N=29,662
	Percent
Gender	
Male	75.71
Female	24.29
Age Category	
18-22 years old	9.301
23-27 years old	18.29
28-35 years old	30.47
36+ years old	41.94
Education Level	
High School Equivalency	4.278
High School Diploma	38.46
Some College	20.67
Bachelor's Degree	20.63
Graduate Degree	15.96
Military Rank	
Private E1-E3	6.065
Specialist (E4)	15.06
Junior Sergeant (E5-E6)	29.48
Senior Sergeant (E7-E9)	17.76
Warrant Officer (WO1-CW5)	4.191
Junior Officer (O1-O3)	12.52
Senior Officer (O4-O10)	14.92
Marital Status	
Never Married	18.90
Married	72.52
Divorced	8.577
Dyslipidemia diagnosis in 3 months before adoption	5.003
Hypertension diagnosis in 3 months before adoption	1.200
Mental Health diagnosis in 3 months before adoption	2.525
Musculoskeletal diagnosis in 3 months before adoption	10.03
Obese in 3 months before adoption	16.65
Sleep Apnea diagnosis in 3 months before adoption	2.882
Tobacco Use reported in 3 months before adoption	22.09

Table 2.11: Impact of Patients' Healthcare and Providers' Portal Usage on Patient Messaging

VARIABLES	Patient Initiated Messages
	Incident Rate Ratio (IRR)
Monthly Provider Activation (ref: none)	
Low Provider Activation last month	1.630** (0.0299)
Medium Provider Activation last month	2.028** (0.0374)
High Provider Activation last month	2.744** (0.0624)
Primary care visits last month	1.139** (0.00609)
Emergency room visits last month	1.018 (0.0267)
Specialty care visits last month	1.002 (0.00274)
Musculoskeletal diagnosis in last 3 months	1.154** (0.0219)
Mental Health diagnosis in last 3 months	1.023 (0.0309)
Hypertension diagnosis in last 3 months	1.004 (0.0385)
Sleep Apnea diagnosis in last 3 months	1.031 (0.0299)
Dyslipidemia diagnosis in last 3 months	1.139** (0.0268)
Constant	0 (8.41e-06)
Installation FE	YES
Month FE	YES
Patient FE	YES
Observations	331,973

** p<0.01, * p<0.05

Table 2.12: Impact of Patient Portal on Primary Care Visits

	Primary Care Visits	Primary Care Visits
	Coefficient	IRR
Treatment Group*	0.129**	1.137**
PostPeriod	(0.0371)	(0.0422)
Constant	0.313**	1.368**
	(0.104)	(0.143)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	32,652	32,652

** p<0.01, * p<0.05

Table 2.13: Impact of Patient Portal on Emergency Room Visits

	Emergency Room Visit or not (0/1) Coefficient	Emergency Room Visit or not (0/1) Odds Ratio
Treatment Group*	-0.290	0.748
PostPeriod	(0.436)	(0.326)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	3,690	3,690

** p<0.01, * p<0.05

Table 2.14: Impact of Patient Portal on Specialty Care Visits

	Specialty Care Visits	Specialty Care Visits
	Coefficient	IRR
Treatment Group*	0.0632	1.065
PostPeriod	(0.137)	(0.146)
Constant	-3.944**	0.0194**
	(0.238)	(0.00461)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	12,204	12,204

** p<0.01, * p<0.05

Table 2.15: Impact of Patient Portal on Pain Clinic Visits

	Pain Clinic Visit or not (0/1)	Pain Clinic Visit or not (0/1)
	Coefficient	Odds Ratio
Treatment Group*	0.877*	2.404*
PostPeriod	(0.354)	(0.850)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	2,304	2,304

** p<0.01, * p<0.05

Table 2.16: Impact of Patient Portal on Opioid Use

	Opioid Prescription or not (0/1)	Opioid Prescription or not (0/1)
	Coefficient	Odds Ratio
Treatment Group* PostPeriod	0.239*	1.270*
	(0.104)	(0.132)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	17,586	17,586

** p<0.01, * p<0.05

Table 2.17: Impact of Patient Portal on Psychotropic Medication Prescriptions

	Psychotropic Prescriptions	Psychotropic Prescriptions
	Coefficient	IRR
Treatment Group* PostPeriod	0.292**	1.339**
	(0.0736)	(0.0985)
Constant	-0.0202	0.980
	(0.264)	(0.258)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	13,464	13,464

** p<0.01, * p<0.05

Table 2.18: Impact of Patient Portal on Body Mass Index

	Body Mass Index	Body Mass Index Among Obese at start of Period 1
	Coefficient	Coefficient
Treatment Group*	-0.120	-0.536
PostPeriod	(0.111)	(0.374)
Constant	0.117	30.80**
		(0.308)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	11,615	2,165

** p<0.01, * p<0.05

Table 2.19: Impact of Patient Portal on Obesity

	Obesity	Obesity	Obesity Among Obese at start of Period 1	Obesity Among Obese at start of Period 1
	Coefficient	Odds Ratio	Coefficient	Odds Ratio
Treatment Group*	0.0665	1.069	0.0737	1.076
PostPeriod	(0.108)	(0.115)	(0.150)	(0.161)
Month FE	YES	YES	YES	YES
Installation FE	YES	YES	YES	YES
Person FE	YES	YES	YES	YES
Medical Condition Controls	YES	YES	YES	YES
Observations	12,366	12,366	5,094	5,094

** p<0.01, * p<0.05

Table 2.20: Impact of Patient Portal on Passing the Army Physical Fitness Test

	Pass APFT	Pass APFT
	Coefficient	Odds Ratio
Treatment Group*	0.185	1.203
PostPeriod	(0.351)	(0.422)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	1,378	1,378

** p<0.01, * p<0.05

Table 2.21: Impact of Patient Portal on Tobacco Use

	Tobacco Use among Tobacco Users at start of Period 1	Tobacco Use among Tobacco Users at start of Period 1
	Coefficient	Odds Ratio
Treatment Group*	-0.0678	0.934
PostPeriod	(0.129)	(0.121)
Month FE	YES	YES
Installation FE	YES	YES
Person FE	YES	YES
Medical Condition Controls	YES	YES
Observations	6,498	6,498

** p<0.01, * p<0.05

Table 2.22: Instrumental Variable Analysis on Healthcare Utilization

	Primary Care Visits	Emergency Room Visits	Specialty Care Visits	Pain Clinic Visits or not	Opioid Use	Psychotropic Medication
	Coeff	Coeff	Coeff	Coeff	Coeff	Coeff
Portal Use	0.423** (0.123)	0.0399 (0.0226)	0.606** (0.219)	0.129 (0.0944)	0.118* (0.0525)	0.124 (0.0663)
Constant	0.202 (0.361)	-0.00898 (0.0663)	-0.0608 (0.641)	-0.0108 (0.277)	0.175 (0.154)	0.0484 (0.194)
Month FE	YES	YES	YES	YES	YES	YES
Installation FE	YES	YES	YES	YES	YES	YES
Person FE	YES	YES	YES	YES	YES	YES
Medical Condition Controls	YES	YES	YES	YES	YES	YES
Obs.	418,594	418,594	418,594	418,594	418,594	418,594

Table 2.23: Instrumental Variable Analysis on Health Outcomes

	Body Mass Index	Obesity	Pass APFT	Tobacco Use
	Coeff	Coeff	Coeff	Coeff
Portal Use	-0.681** (0.241)	0.0625 (0.0369)	-0.0175 (0.0349)	0.0135 (0.0322)
Constant	27.79** (0.636)	0.0779 (0.108)	1.179** (0.131)	0.140 (0.0944)
Month FE	YES	YES	YES	YES
Installation FE	YES	YES	YES	YES
Person FE	YES	YES	YES	YES
Medical Condition Controls	YES	YES	YES	YES
Obs.	166,784	418,594	195,870	418,594

Table 3.1: Christakis and Fowler Framingham Heart Study Data Studies

Study	Objective	Findings
Christakis and Fowler, 2007	Determine how obesity spreads in a social network	A person with an obese friend is 57% more likely to become obese themselves. Obese siblings increase the odds of obesity by 40% and spouses by 37%. The Spread of smoking cessation and geographic distance did not explain results.
Christakis and Fowler, 2008	Determine how smoking behavior spreads in a social network	There is evidence of people quitting smoking together. A person whose spouse quits smoking is 67% less likely to smoke, whose sibling quits, 25% less likely, and whose friend quits, 36% less likely to smoke.
Fowler and Christakis, 2008	Determine how happiness spreads in a social network	A person is 25% more likely to be happy if they have a happy friend that lives within a mile of them. Co-resident happy spouses increase odds of happiness by 8% and next-door happy neighbors by 34%. The spread of happiness decreases over time and distance.
Cacioppo, Fowler, and Christakis, 2009	Determine how loneliness spreads in a social network	A person with a lonely friend is 52% more likely to be lonely. The effect of a lonely person at two degrees of separation is 25%, and at three degrees, 15%. People with more friends are less likely to be lonely in the future, with each additional friend reducing number of lonely days by 0.04 days per week.
Rosenquist, Murabito, Fowler, and Christakis, 2010	Determine how alcohol use spreads in a social network	A person whose friend is a heavy drinker is 50% more likely to be a heavy drinker. Friends of friends have an effect of 36%. Three degrees of separation has an effect of 15%. A person whose friend does not drink alcohol is 29% more likely to not drink alcohol. This abstinence effect is 21% for two degrees of separation and 5% for three degrees of separation.
Pachucki, Jacques, and Christakis, 2011	Determine how eating habits spread in a social network	Spouse's food choices most closely predicted ego's food choices. Siblings and friends were most likely to share the "alcohol and snacks" category eating

		habits.
Rosenquist, Fowler, and Christakis, 2011	Determine how depression spreads in a social network	A person with a depressed friend is 93% more likely to be depressed. Depression at two degrees of separation has an effect of 43% and at three degrees, 37%. People with more friends are less likely to experience depression in the future.

Table 3.2: Studies Examining Social Health Influence with Random Relationship Assignment

Study	Objective	Findings
Carrell, Hoekstra, and West, 2011	Study effects of peers' high school fitness levels on own physical fitness at U.S. Air Force Academy	Peers' high school fitness levels have a significant impact on own fitness score and has 40-70% as large an effect as own high school fitness level. The least fit peers have largest impact (negative) on fitness scores and fitness test failure chances. The least fit students are most affected by their peers.
Duncan, Boisjoly, Kremer, Levy, and Eccles, 2005	Investigate peer effects of alcohol use, drug use, and sexual behavior on college students	Male students who reported being a binge drinker in high school are likely to drink more alcohol in college if assigned a binge-drinking roommate. The effect is not true for female students and there is no peer effect observed for drug use or sexual behavior.
Yaskusheva, Kapinos, Eisenberg	Examine peer effects of weight gain on college students	For every pound increase in their roommate, female students gain 0.034 pounds. Roommates' weight is not found to significantly influence males.

Table 3.3: Descriptive Statistics of CHIDS-MMIDS

	All Soldiers	Junior Soldiers	Mid-level Soldiers	Senior Soldiers
	N=827,265 Percent	N=509,227 Percent	N=241,708 Percent	N=201,261 Percent
Gender				
Male	86.39	85.81	88.13	85.68
Female	13.61	14.19	11.87	14.32
Age Category				
18-22 years old	25.09	52.37	4.310	2.035
23-27 years old	27.02	32.34	32.95	13.22
28-35 years old	24.69	11.84	41.54	28.94
36+ years old	23.21	3.444	21.20	55.81
Education Level				
High School Equivalency	7.477	10.23	9.870	0.967
High School Diploma	58.42	77.90	66.91	20.25
Some College	13.59	7.066	17.26	20.31
Bachelor's Degree	13.52	4.416	5.378	35.25
Graduate Degree	6.994	0.391	0.582	23.23
Race				
Caucasian	68.70	72.33	65.72	65.83
African-American	20.84	20.93	22.38	19.26
Asian / Pacific Islander	4.140	4.182	3.978	4.224
Other	6.324	2.558	7.926	10.68
Marital Status				
Never Married	34.70	57.04	15.76	17.63
Married	59.35	40.20	75.13	74.39
Divorced	5.953	2.757	9.109	7.981
Military Occupational Specialty Category				
Medical	9.835	8.732	8.277	13.00
Infantry	14.09	17.41	13.78	9.230
Armor / Cavalry	4.467	4.418	4.799	4.233
Air and Field Artillery	7.436	7.359	7.215	7.760
Chaplain	0.593	0.311	0.459	1.156
Aviation	6.185	5.441	5.301	8.165
Special Forces / Civil Affairs	2.355	1.005	1.763	5.005
Administration / Finance / Legal / Public Affairs	5.751	3.209	5.773	9.683
Engineer	4.596	4.943	4.560	4.088
Supply / Logistics	10.87	11.62	11.50	9.122
Signal	7.466	7.857	7.913	6.441
Ordinance / Maintenance	10.22	12.82	10.56	5.870

Transportation	4.100	4.689	5.134	2.222
Military Police	3.797	3.988	4.410	2.930
Intelligence / Psychological Operations	6.101	4.841	6.770	7.436
Chemical	1.534	1.344	1.793	1.586
Other / Unknown	0.600	0.0100	0.000827	2.074
Obese in last 3 months	11.36	9.745	13.85	11.57
Tobacco Use reported in last 3 months	19.65	27.47	29.14	14.04
Tobacco Cessation in last 3 months	0.322	0.279	0.432	0.286
Alcohol Abuse in last 3 months	10.41	8.520	12.99	10.93

Table 3.4: Descriptive Statistics of Army Units in the CHIDS-MMIDS

	Mean	SD	Min	Max
Overall Obesity in last 3 months	0.128	0.0731	0	1
Junior Obesity in last 3 months	0.127	0.119	0	1
Mid-level Obesity in last 3 months	0.145	0.113	0	1
Senior Obesity in last 3 months	0.116	0.106	0	1
Overall Tobacco Use in last 3 months	0.215	0.104	0	1
Junior Tobacco Use in last 3 months	0.262	0.149	0	1
Mid-level Tobacco Use in last 3 months	0.246	0.139	0	1
Senior Tobacco Use in last 3 months	0.131	0.111	0	1
Overall Tobacco Cessation in last 3 months	0.00417	0.00945	0	0.250
Junior Tobacco Cessation in last 3 months	0.00447	0.0231	0	1
Mid-level Tobacco Cessation in last 3 months	0.00516	0.0208	0	1
Senior Tobacco Cessation in last 3 months	0.00327	0.0158	0	1
Overall Alcohol Abuse in last 3 months	0.0796	0.0611	0	1
Junior Alcohol Abuse in last 3 months	0.0755	0.0910	0	1
Mid-level Alcohol Abuse in last 3 months	0.0947	0.0947	0	1
Senior Alcohol Abuse in last 3 months	0.0760	0.0901	0	1
Unit turnover	0.117	0.170	0	1.963
Unit size	257.3	365.4	25	8,441
Number of units	2496			

Table 3.5: Varying Health Cultures across the Army

Installation	Average Monthly Obesity Rate in 2013	Average Monthly Tobacco Use Rate in 2013	Average Monthly Tobacco Cessation Rate in 2013	Average Monthly Alcohol Abuse Rate in 2013	Average Monthly Obesity Rate in 2014	Average Monthly Tobacco Use Rate in 2014	Average Monthly Tobacco Cessation Rate in 2014	Average Monthly Alcohol Abuse Rate in 2014
Ft Bragg, NC	0.120	0.176	0.003	0.067	0.123	0.184	0.005	0.073
Ft Hood, TX	0.141	0.239	0.008	0.102	0.142	0.227	0.010	0.094
Ft Lewis, WA	0.133	0.257	0.002	0.097	0.138	0.254	0.002	0.112
Ft Campbell, KY	0.118	0.261	0.004	0.079	0.120	0.260	0.000	0.069
Ft Bliss, TX	0.137	0.254	0.001	0.100	0.144	0.236	0.001	0.097
Ft Carson, CO	0.115	0.224	0.003	0.084	0.112	0.208	0.001	0.069
Ft Stewart, GA	0.152	0.242	0.001	0.068	0.173	0.250	0.002	0.066
Ft Riley, KS	0.138	0.261	0.000	0.059	0.153	0.281	0.000	0.062
Ft Benning, GA	0.132	0.226	0.001	0.105	0.155	0.198	0.000	0.093
Hawaii	0.121	0.240	0.001	0.123	0.117	0.216	0.001	0.112
Ft Drum, NY	0.145	0.259	0.000	0.115	0.138	0.248	0.000	0.104
Ft Sill, OK	0.163	0.292	0.002	0.122	0.168	0.277	0.000	0.109
Ft Polk, LA	0.157	0.284	0.013	0.090	0.172	0.282	0.016	0.105
Ft Sam Houston, TX	0.183	0.177	0.020	0.081	0.198	0.172	0.004	0.067
Ft Leonard Wood, MO	0.152	0.294	0.000	0.093	0.162	0.291	0.000	0.087
Alaska	0.119	0.254	0.008	0.090	0.120	0.263	0.010	0.104
Ft Knox, KY	0.166	0.251	0.002	0.110	0.153	0.236	0.002	0.095
Ft Gordon, GA	0.180	0.201	0.001	0.100	0.181	0.188	0.001	0.085
Ft Jackson, SC	0.177	0.156	0.001	0.082	0.159	0.139	0.000	0.099
Ft Lee, VA	0.175	0.185	0.007	0.099	0.181	0.188	0.005	0.105
Ft Irwin, CA	0.132	0.242	0.001	0.129	0.141	0.253	0.000	0.123
Ft Eustis, VA	0.193	0.249	0.012	0.092	0.193	0.241	0.006	0.085
National Capital Region	0.133	0.117	0.007	0.067	0.142	0.120	0.002	0.075
Europe	0.141	0.237	0.006	0.133	0.136	0.220	0.005	0.118
Ft Leavenworth, KS	0.170	0.249	0.000	0.105	0.173	0.243	0.001	0.095
Ft Meade, MD	0.188	0.174	0.006	0.085	0.185	0.158	0.001	0.089
Ft Huachuca, AZ	0.137	0.194	0.006	0.109	0.145	0.179	0.002	0.091
Korea/Japan	0.118	0.204	0.005	0.089	0.109	0.192	0.004	0.086
Ft Rucker, AL	0.157	0.175	0.000	0.072	0.168	0.187	0.000	0.094
West Point, NY	0.154	0.177	0.000	0.110	0.119	0.157	0.000	0.112
Presidio, CA	0.079	0.135	0.003	0.072	0.087	0.140	0.005	0.082
Eglin AFB, FL	0.106	0.111	0.001	0.071	0.107	0.078	0.000	0.055

Table 3.6: Dependent Variables

Variable Name	Description
Tobacco Use Measures	
<i>tobaccocessation</i>	Binary variable that indicates whether or not the soldier attended tobacco cessation counseling and/or has a tobacco cessation medication prescription .
<i>tobaccouse</i>	Binary variable that indicates whether or not the soldier has reported tobacco use at a healthcare encounter or during the annual Periodic Health Assessment (PHA), an annual physical required of all soldiers that includes a health questionnaire.
Alcohol Use Measure	
<i>alcoholabuse</i>	Composite binary variable that includes a diagnosis of alcohol abuse from a healthcare encounter and/or a high AUDIT-C alcohol abuse survey score indicating alcohol abuse. The validated AUDIT-C alcohol abuse survey (Bush et al. 1998) is part of the PHA health questionnaire.
Physical Fitness Measure	
<i>obesity</i>	Composite binary variable derived from: (1) Body mass index (BMI) - calculated by height / weight measures taken during a healthcare encounter or Army physical fitness test. Obesity is indicated as having a BMI over 30. (2) Body fat test – During Army physical fitness tests, soldiers who do not meet the Army height/weight requirements are required to undergo a body fat test. Obesity is indicated as exceeding the Army maximum allowable percent body fat standards, which are as follows: Age Group 17-20: Male 20% / Female 30% Age Group 21-27: Male 22% / Female 32% Age Group 28-39: Male 24% / Female 34% Age Group 40+: Male 26% / Female 36% (3) Diagnosis of obesity during healthcare encounter – derived from Electronic Health Record

Table 3.7: Independent Variables

Variable Name	Description
Unit Rank Means	
<i>UnitJuniorMean</i>	Number of junior ranking soldiers in unit with outcome behavior in last 3 months divided by number of junior ranking soldiers in unit and then normalized with mean at 0
<i>UnitMidMean</i>	Number of mid-level ranking soldiers in unit with outcome behavior in last 3 months divided by number of mid-level ranking soldiers in unit and then normalized with mean at 0
<i>UnitSeniorMean</i>	Number of senior ranking soldiers in unit with outcome behavior in last 3 months divided by number of senior ranking soldiers in unit and then normalized with mean at 0
Soldier Demographics	
<i>age</i>	Yearly age of soldier that month
<i>gender</i>	Gender of soldier
<i>education</i>	Education level of soldier 1: GED 2: High School Diploma 3: Some College 4: Bachelor's Degree 5: Graduate Degree
<i>race</i>	1: White 2: Black 3: Asian / Pacific Islander 4: Other
<i>marriage</i>	1: Married 2: Never Married 3: Separated / Divorced
<i>mos</i>	Military occupational specialty 1: Medical 2: Infantry 3: Armor / Cavalry 4: Air and Field Artillery 5: Chaplain 6: Aviation 7: Special Forces / Civil Affairs 8: Administration / Finance / Legal / Public Affairs 9: Engineer 10: Supply / Logistics 11: Signal 12: Ordnance / Maintenance 13: Transportation 14: Military Police 15: Intelligence / Psychological 16: Operations

	17: Chemical 18: Other / Unknown
Other Factors	
<i>installation</i>	Patient's military locations, one of 32 possible locations
<i>month</i>	Time controls

Table 3.8: Descriptive Statistics of Study Population

	Junior New Soldiers (N=105,328) Percent	Mid-level New Soldiers (N=120,918) Percent	Senior New Soldiers (N=151,963) Percent
Gender			
Male	83.76	87.21	85.60
Female	16.24	12.79	14.40
Age Category			
18-22 years old	42.53	4.625	1.187
23-27 years old	38.17	32.78	13.31
28-35 years old	14.61	42.15	30.55
36+ years old	4.683	20.45	54.95
Education Level			
High School Equivalency	11.12	9.866	0.884
High School Diploma	76.78	66.08	17.65
Some College	7.809	18.47	18.90
Bachelor's Degree	3.958	5.107	38.12
Graduate Degree	0.341	0.481	24.45
Race			
Caucasian	69.95	64.05	65.81
African-American	22.64	23.89	19.50
Asian / Pacific Islander	4.175	4.111	4.475
Other	3.235	7.948	10.22
Marital Status			
Never Married	46.00	14.41	16.58
Married	50.15	76.40	75.78
Divorced	3.858	9.195	7.635
Military Occupational Specialty Category			
Medical	8.478	8.201	11.99
Infantry	12.16	13.04	9.711
Armor / Cavalry	3.683	4.406	4.562
Air and Field Artillery	7.402	7.455	8.582
Chaplain	0.424	0.556	1.373
Aviation	4.466	4.391	6.964
Special Forces / Civil Affairs	0.259	1.964	4.691
Administration / Finance / Legal / Public Affairs	4.455	6.221	9.247
Engineer	4.565	4.634	4.643
Supply / Logistics	12.54	11.73	8.940
Signal	8.932	8.208	6.646
Ordinance / Maintenance	14.05	10.48	5.570
Transportation	5.269	4.993	2.200
Military Police	6.108	4.946	3.261
Intelligence / Psychological	5.206	6.877	7.866

Operations			
Chemical	2.001	1.902	1.714
Other / Unknown	0.00190	0	2.042
Obese in 3 months before moving to new unit	7.082	7.933	5.807
Obese in 6 months before moving to new unit	21.43	25.07	22.26
Tobacco Use reported in 3 months before moving to new unit	13.61	11.41	4.858
Tobacco Use reported in 6 months before moving to new unit	52.73	52.32	29.25
Tobacco Cessation in 3 months before moving to new unit	0.131	0.128	0.0954
Tobacco Cessation in 6 months before moving to new unit	1.006	1.293	0.856
Alcohol Abuse in 3 months before moving to new unit	2.805	2.793	1.961
Alcohol Abuse in 6 months before moving to new unit	16.95	20.63	17.94
Obese in 3 months after moving to new unit	15.46	16.26	12.76
Tobacco Use reported in 3 months after moving to new unit	35.81	31.82	15.06
Tobacco Cessation in 3 months after moving to new unit	0.470	0.486	0.274
Alcohol Abuse in 3 months after moving to new unit	13.95	15.81	12.88

Table 3.9: Social Influence on Odds of Obesity for Newly-Arrived Soldiers

VARIABLES	(1)	(2)	(3)
	Junior new soldier	Mid-level new soldier	Senior new soldier
	Obesity Odds Ratios	Obesity Odds Ratios	Obesity Odds Ratios
Unit Junior Standardized Mean in last period	1.173** (0.0194)	1.113** (0.0133)	1.055** (0.0102)
Unit Mid Standardized Mean in last period	1.145** (0.0181)	1.212** (0.0173)	1.130** (0.0151)
Unit Senior Standardized Mean in last period	1.028* (0.0137)	1.053** (0.0138)	1.221** (0.0186)
Obese in last period	2.851** (0.0881)	2.492** (0.0689)	2.472** (0.0699)
Obese in last two periods	8.448** (0.190)	8.732** (0.181)	9.798** (0.205)
Constant	0.0331** (0.00331)	0.0207** (0.00195)	0.0144** (0.00189)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	104,415	115,955	135,854

** p<0.01, * p<0.05

Table 3.10: Social Influence on Odds of Tobacco Use for Newly-Arrived Soldiers

VARIABLES	(1)	(2)	(3)
	Junior new soldier Tobacco Use Odds Ratios	Mid-level new soldier Tobacco Use Odds Ratios	Senior new soldier Tobacco Use Odds Ratios
Unit Junior Standardized Mean in last period	1.074** (0.0155)	1.063** (0.0122)	1.030** (0.0114)
Unit Mid Standardized Mean in last period	1.028* (0.0141)	1.087** (0.0144)	1.039* (0.0159)
Unit Senior Standardized Mean in last period	1.025* (0.0112)	0.996 (0.0115)	1.063** (0.0182)
Tobacco Use in last period	3.719** (0.0929)	3.897** (0.0957)	3.412** (0.104)
Tobacco Use in last two periods	17.96** (0.379)	24.21** (0.570)	28.87** (0.727)
Constant	0.0699** (0.00632)	0.0312** (0.00285)	0.0213*** (0.00264)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	104,415	115,955	135,854

** p<0.01, * p<0.05

Table 3.11: Social Influence on Odds of Tobacco Cessation for Newly-Arrived Soldiers

VARIABLES	(1)	(2)	(3)
	Junior new soldier Tobacco Cessation Odds Ratios	Mid-level new soldier Tobacco Cessation Odds Ratios	Senior new soldier Tobacco Cessation Odds Ratios
Unit Junior Standardized Mean in last period	1.108** (0.0371)	1.058** (0.0157)	0.939 (0.0554)
Unit Mid Standardized Mean in last period	1.095 (0.0505)	1.119** (0.0358)	1.079 (0.0491)
Unit Senior Standardized Mean in last period	1.080 (0.0456)	1.094** (0.0318)	1.093 (0.0540)
Tobacco Use in last period	2.650** (0.294)	3.860** (0.406)	6.914** (1.016)
Tobacco Use in last two periods	3.340** (0.506)	3.437** (0.498)	4.195** (0.768)
Tobacco Cessation in last period	10.38** (2.627)	11.91** (2.967)	15.62** (4.753)
Tobacco Cessation in last two periods	7.278** (1.166)	6.138** (0.897)	12.78** (2.131)
Constant	0.000534** (0.000238)	0.000526** (0.000235)	0.000112** (7.44e-05)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	90,995	103,670	121,131

** p<0.01, * p<0.05

Table 3.12: Social Influence on Odds of Alcohol Abuse for Newly-Arrived Soldiers

VARIABLES	(1)	(2)	(3)
	Junior new soldier Alcohol Abuse Odds Ratios	Mid-level new soldier Alcohol Abuse Odds Ratios	Senior new soldier Alcohol Abuse Odds Ratios
Unit Junior Standardized Mean in last period	1.070** (0.0261)	1.017 (0.0163)	1.017 (0.0129)
Unit Mid Standardized Mean in last period	1.021 (0.0219)	1.052** (0.0199)	1.024 (0.0187)
Unit Senior Standardized Mean in last period	1.047* (0.0190)	1.061** (0.0179)	1.089** (0.0235)
Alcohol Abuse in last period	19.02** (2.064)	37.32** (5.048)	70.70** (13.23)
Alcohol Abuse in last two periods	72.66** (2.146)	82.98** (2.428)	96.25** (2.994)
Constant	0.0306** (0.00426)	0.0400** (0.00487)	0.0325** (0.00519)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	104,413	115,955	135,854

** p<0.01, * p<0.05

Table 3.13: Detailed Summary of Social Influence Results

	Junior new Soldier	Mid-level new Soldier	Senior new Soldier
Junior-level Subordinate Effects		<p>11.3% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>6.3% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>5.8% increase in odds of tobacco cessation for every 1 unit increase in standard deviation of unit rank mean</p> <p>No impact on odds of alcohol abuse</p>	<p>5.5% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>3.0% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>No impact on odds of tobacco cessation</p> <p>No impact on odds of alcohol abuse</p>
Mid-level Subordinate Effects			<p>13.0% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>3.9% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>No impact on odds of tobacco cessation</p> <p>No impact on odds of alcohol abuse</p>
Peer Effects	<p>17.3% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>7.4% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>10.8% increase in odds of tobacco cessation for every 1 unit increase in standard deviation of unit rank mean</p> <p>7.0% increase in odds of alcohol abuse for every 1 unit</p>	<p>21.2% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>8.7% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>11.9% increase in odds of tobacco cessation for every 1 unit increase in standard deviation of unit rank mean</p> <p>5.2% increase in odds of alcohol abuse for every 1 unit</p>	<p>22.1% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>6.3% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>No impact on odds of tobacco cessation</p> <p>8.9% increase in odds of alcohol abuse for every 1 unit increase in standard deviation of unit rank mean</p>

	increase in standard deviation of unit rank mean	increase in standard deviation of unit rank mean	
Mid-level Leader Effects	<p>14.5% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>2.8% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>No impact on odds of tobacco cessation</p> <p>No impact on odds of alcohol abuse</p>		
Senior-level Leader Effects	<p>2.8% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>2.5% increase in odds of tobacco use for every 1 unit increase in standard deviation of unit rank mean</p> <p>No impact on odds of tobacco cessation</p> <p>4.7% increase in odds of alcohol abuse for every 1 unit increase in standard deviation of unit rank mean</p>	<p>5.3% increase in odds of obesity for every 1 unit increase in standard deviation of unit rank mean</p> <p>No impact on odds of tobacco use</p> <p>9.4% increase in odds of tobacco cessation for every 1 unit increase in standard deviation of unit rank mean</p> <p>6.1% increase in odds of alcohol abuse for every 1 unit increase in standard deviation of unit rank mean</p>	

Table 3.14: Brief Summary of Social Influence Results

		Obesity	Tobacco Use	Tobacco Cessation	Alcohol Abuse
Junior New Soldier	Peer Effects	YES	YES	YES	YES
	Leader Effects	YES	YES	NO	YES* *senior only
Mid-level New Soldier	Subordinate Effects	YES	YES	YES	NO
	Peer Effects	YES	YES	YES	YES
	Leader Effects	YES	NO	YES	YES
Senior New Soldier	Subordinate Effects	YES	YES	NO	NO
	Peer Effects	YES	YES	NO	YES

Table 3.15: Social Influence on Odds of Obesity for Newly-Arrived Soldiers at Unit within Installation

VARIABLES	(1)	(2)	(3)
	Junior new soldier	Mid-level new soldier	Senior new soldier
	Obesity Odds Ratios	Obesity Odds Ratios	Obesity Odds Ratios
Unit Junior Standardized Mean in last period	1.199** (0.0339)	1.147** (0.0275)	1.077** (0.0188)
Unit Mid Standardized Mean in last period	1.127** (0.0297)	1.198** (0.0305)	1.135** (0.0253)
Unit Senior Standardized Mean in last period	1.030 (0.0225)	1.020 (0.0233)	1.170** (0.0281)
Obese in last period	4.240** (0.215)	3.597** (0.171)	3.131** (0.140)
Obese in last two periods	8.337** (0.326)	9.353** (0.363)	10.13** (0.352)
Constant	0.0370** (0.00649)	0.0152** (0.00273)	0.0153** (0.00352)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	35,133	34,411	53,293

Table 3.16: Social Influence on Odds of Tobacco Use for Newly-Arrived Soldiers at Unit within Installation

	(1) Junior new soldier Tobacco Use Odds Ratios	(2) Mid-level new soldier Tobacco Use Odds Ratios	(3) Senior new soldier Tobacco Use Odds Ratios
VARIABLES			
Unit Junior Standardized Mean in last period	1.003 (0.00163)	1.004** (0.00145)	1.001 (0.00130)
Unit Mid Standardized Mean in last period	1.004* (0.00162)	1.007** (0.00165)	1.003 (0.00174)
Unit Senior Standardized Mean in last period	1.005** (0.00157)	1.002 (0.00177)	1.008** (0.00234)
Tobacco Use in last period	3.263** (0.127)	3.795** (0.158)	3.607** (0.173)
Tobacco Use in last two periods	19.17** (0.749)	23.09** (1.029)	25.39** (1.025)
Constant	0.0678** (0.0107)	0.0282*** (0.00487)	0.0182*** (0.00393)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	35,133	34,408	53,293

Table 3.17: Social Influence on Odds of Tobacco Cessation for Newly-Arrived Soldiers at Unit within Installation

VARIABLES	(1)	(2)	(3)
	Junior new soldier Tobacco Cessation Odds Ratios	Mid-level new soldier Tobacco Cessation Odds Ratios	Senior new soldier Tobacco Cessation Odds Ratios
Unit Junior Standardized Mean in last period	1.109** (0.0439)	1.160** (0.0511)	0.912 (0.113)
Unit Mid Standardized Mean in last period	1.062 (0.0762)	1.096 (0.0559)	0.999 (0.0892)
Unit Senior Standardized Mean in last period	1.124** (0.0429)	1.129** (0.0496)	0.975 (0.104)
Tobacco Use in last period	2.313** (0.353)	2.913** (0.457)	9.366** (2.127)
Tobacco Use in last two periods	2.832** (0.625)	4.935** (1.302)	2.594** (0.780)
Tobacco Cessation in last period	8.215** (2.566)	17.73** (5.629)	15.94** (6.391)
Tobacco Cessation in last two periods	10.55** (2.042)	5.106** (1.096)	23.61** (6.069)
Constant	0.00154** (0.00104)	0.000591** (0.000440)	2.78e-05** (3.46e-05)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	29,793	28,271	42,253

Table 3.18: Social Influence on Odds of Alcohol Abuse for Newly-Arrived Soldiers at Unit within Installation

VARIABLES	(1)	(2)	(3)
	Junior new soldier Alcohol Abuse Odds Ratios	Mid-level new soldier Alcohol Abuse Odds Ratios	Senior new soldier Alcohol Abuse Odds Ratios
Unit Junior Standardized Mean in last period	1.119** (0.0441)	1.037 (0.0341)	1.042 (0.0220)
Unit Mid Standardized Mean in last period	1.093** (0.0374)	1.155** (0.0364)	1.098** (0.0317)
Unit Senior Standardized Mean in last period	1.066* (0.0321)	1.066* (0.0302)	1.123** (0.0364)
Alcohol Abuse in last period	5.331** (0.738)	11.70** (1.960)	32.96** (7.672)
Alcohol Abuse in last two periods	59.86** (3.106)	53.06** (2.787)	77.15** (3.888)
Constant	0.0560** (0.0131)	0.0686** (0.0145)	0.0388** (0.0100)
Installation Controls	YES	YES	YES
Soldier Controls	YES	YES	YES
Time Controls	YES	YES	YES
Observations	35,133	34,411	53,293

Table 3.19: Summary of Social Influence Results for Newly-Arrived Soldiers at Unit within Installation

(major changes from main analysis bolded and underlined)

		Obesity	Tobacco Use	Tobacco Cessation	Alcohol Abuse
Junior New Soldier	Peer Effects	YES	<u>NO</u>	YES	YES
	Leader Effects	YES* *mid-level only	YES	<u>YES*</u> *senior only	YES
Mid-level New Soldier	Subordinate Effects	YES	YES	YES	NO
	Peer Effects	YES	YES	<u>NO</u>	YES
	Leader Effects	<u>NO</u>	NO	YES	YES
Senior New Soldier	Subordinate Effects	YES	<u>NO</u>	NO	YES* *senior only
	Leader Effects	YES	YES	NO	YES

Figures

Figure 2.1: Research Model

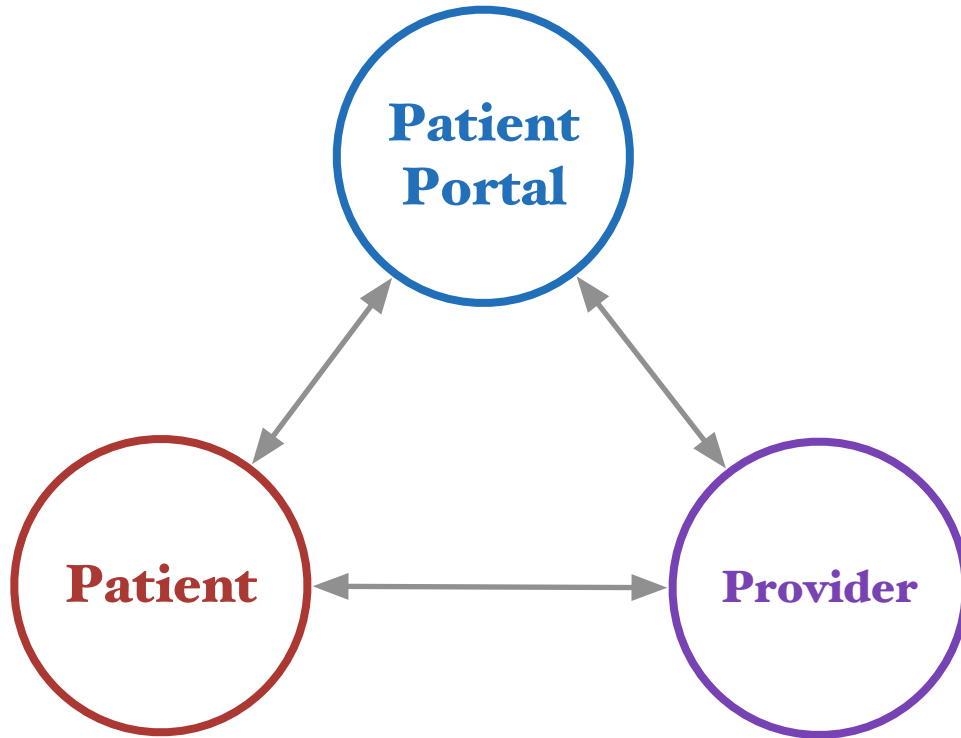


Figure 2.2: Home Page of AMSMS

The screenshot displays the home page of the AMSMS (Advanced Message System) interface. At the top, a blue navigation bar contains the following tabs: Home, Your Doctors, Message Center, Health Records, Education, and Account. The main content area is divided into several sections:

- Message Options:** A vertical list of links including Appointments, Prescriptions, Lab/Test Results, Referrals, Message the Office Staff, Message Your Provider, and webVisit®.
- Quick Links:** A section with links for Update Your E-mail Address, Change Your Password, and Change Your User ID.
- Provider Web Pages:** A section with a link for Dr. [redacted].
- Export or Download Health Data:** A section featuring a blue button labeled "Download My Data".
- Do You Like This Service?:** A section with links for Tell a Doctor and Tell a Friend.

The central area of the page features a "Welcome [redacted]" message. Below this, a paragraph explains that users can begin a message to their healthcare provider through the options on the left, and that they will be notified at [redacted]. A note states, "Use this service only for non-urgent communications." Below the welcome message, a "No New Messages" section indicates that all messages can be viewed in the Message Center. A "Reminders" section contains three items: "Link to a New Doctor", "Add a Family Member to your account to send messages on their behalf", and "Set Up Your Account". The "Health Records" section at the bottom right shows a "Last Updated" timestamp and a row of [redacted] information.

Figure 2.3: Personal Health Record Section of AMSMS

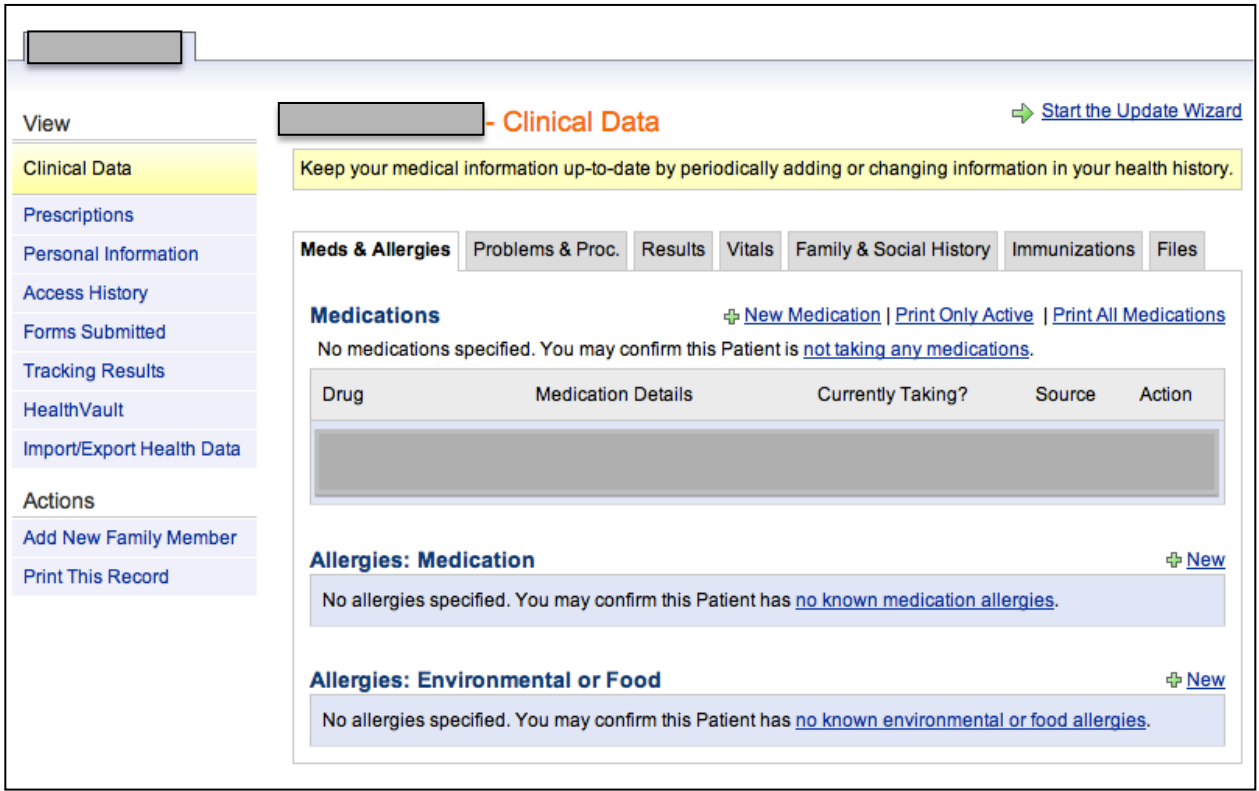


Figure 2.4: Secure Message Center Section of AMSMS

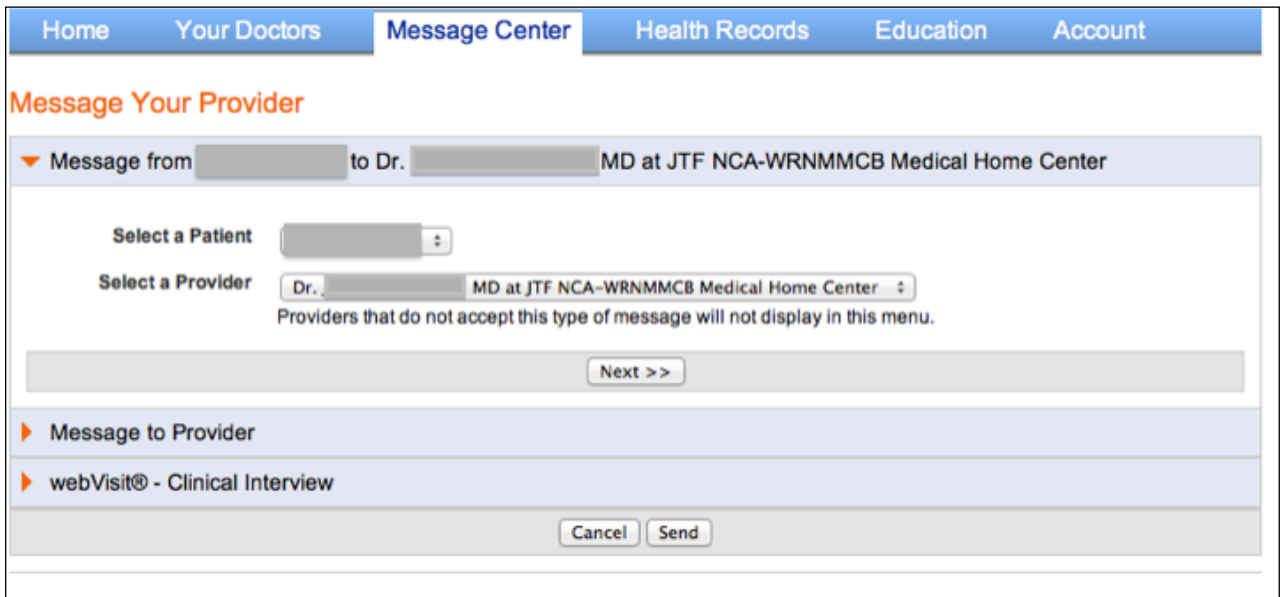


Figure 2.5: Look-Ahead Matching Methodology

Period 0 Pre-Period		Period 1 Treatment Group	Period 2 Post-Period (outcomes)	Period 3 Control Group		
July 12	Mar 13	Apr-Aug 13	Sept 13	May 14	Jun 14	Sep 14

Figure 2.6: Graph of Primary Care Visit Trends by Group during Study Periods

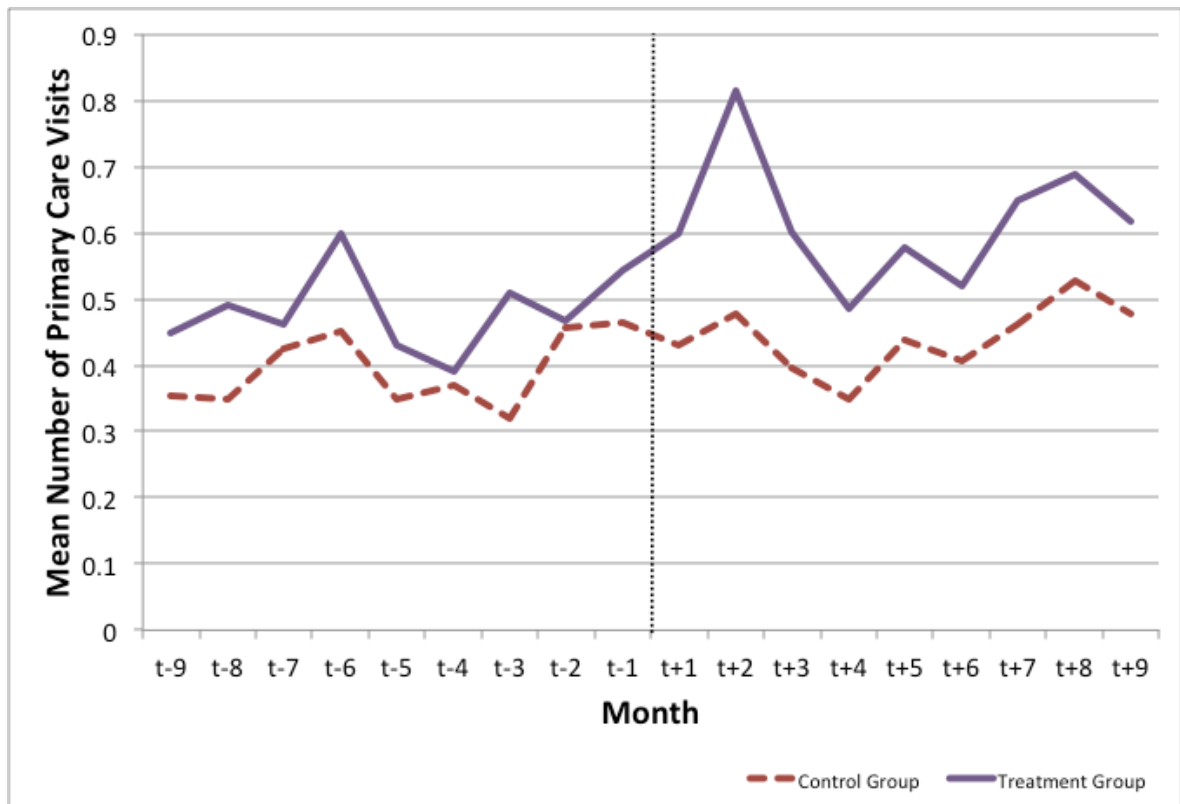


Figure 2.7: Graph of Pain Clinic Visit Trends by Group during Study Periods

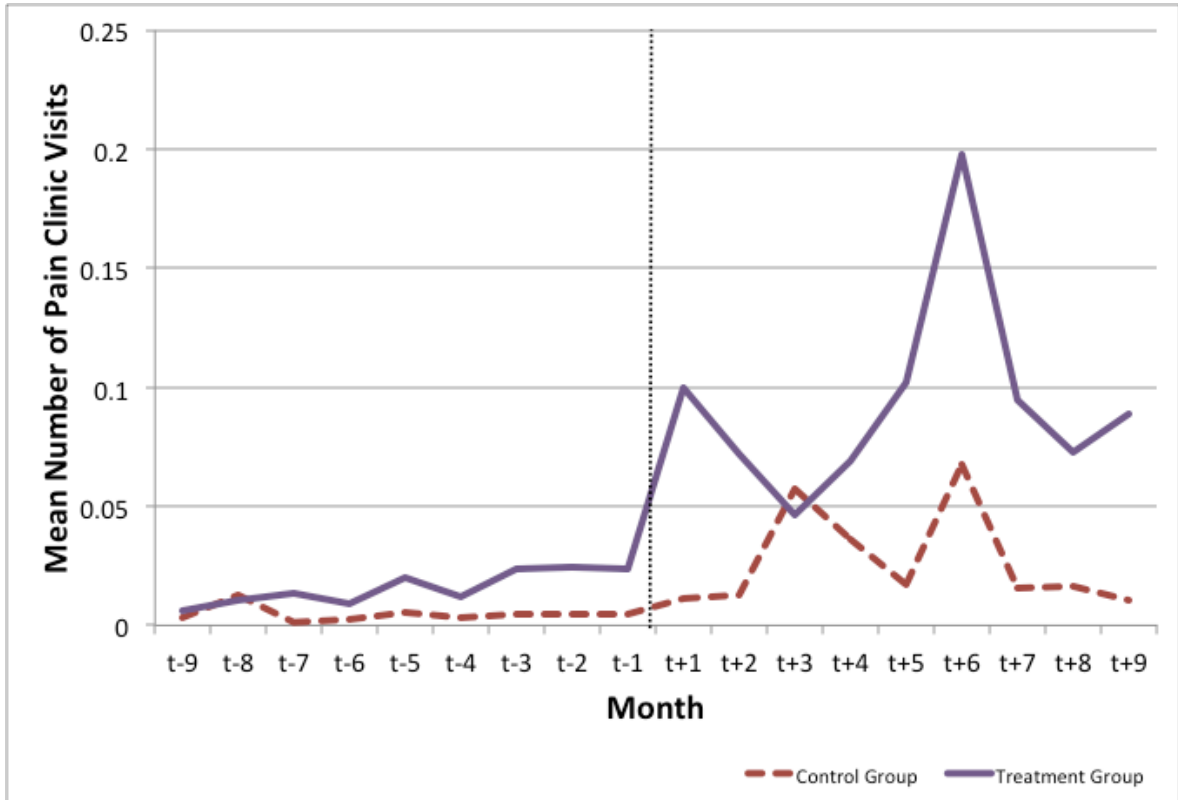


Figure 2.8: Graph of Opioid Prescription Trends by Group during Study Periods

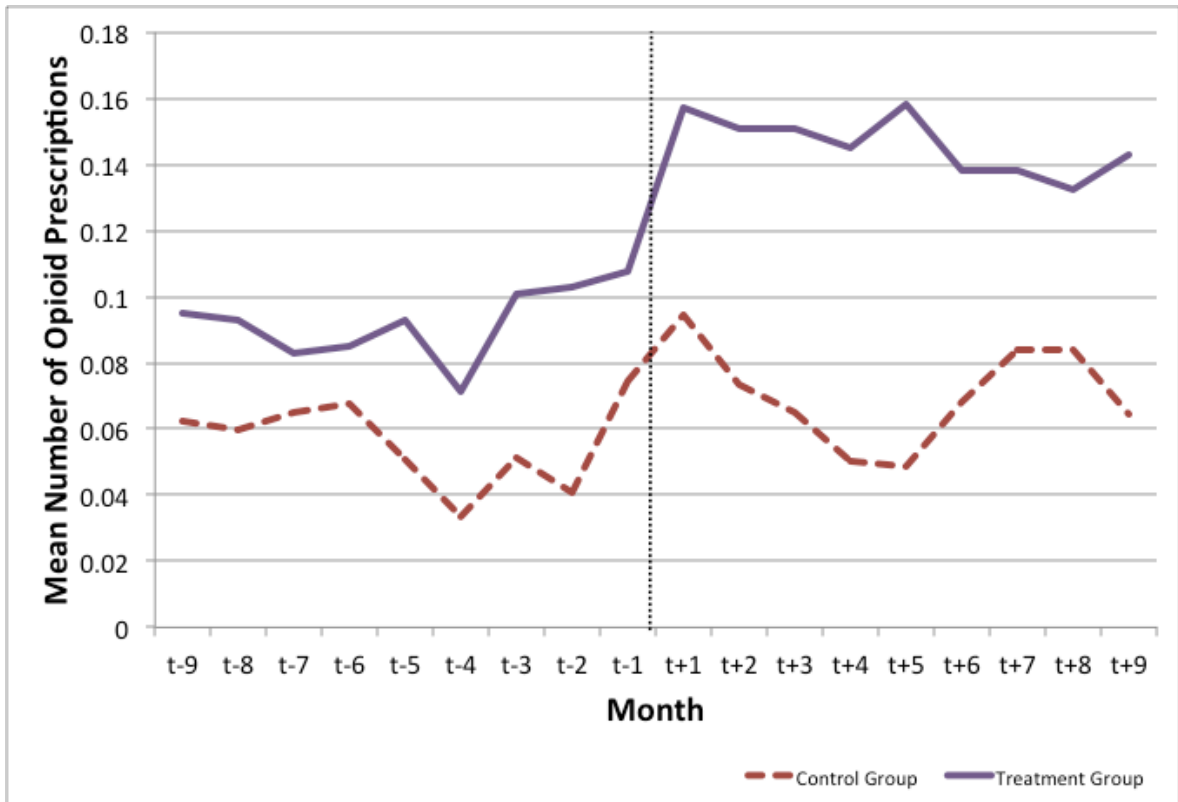


Figure 2.9: Graph of Psychotropic Medication Trends by Group during Study Periods

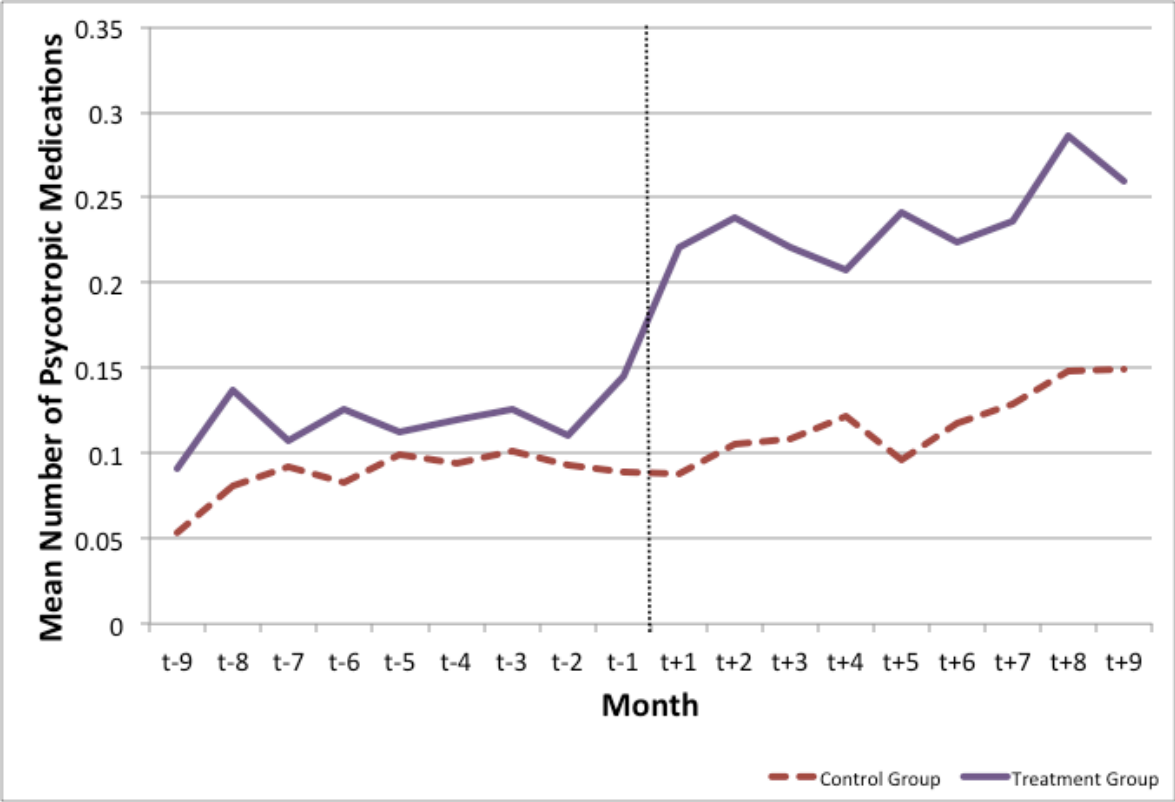
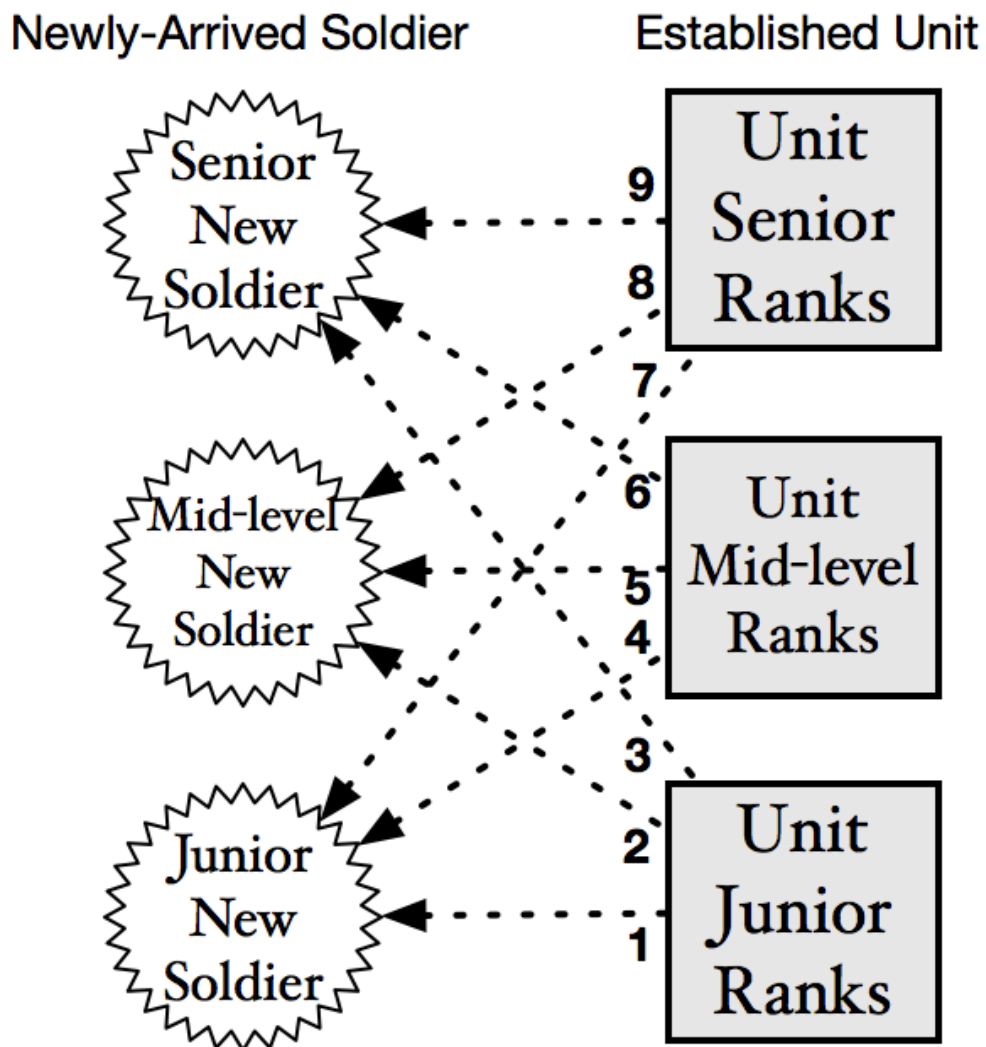


Figure 3.1: Possible Social Health Effects Examined



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