Essays on Human Capital, the Labor Market, and Social Interaction

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by

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APPROVAL OF THE DISSERTATION

This dissertation, *Essays on Human Capital, the Labor Market, and Social Interaction*, has been approved by the Graduate Faculty of the Curry School of Education in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

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For Hillary and Emmy Lou.

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Miller, Chris Nicholas, Pete Peters, Dan Reed, Mihai Sofronie, Daniel Stanton, and others over the last three years; each one listened to me vent at times and never stopped offering encouragement. The handful of fly fishing days with Dan and Brian – in addition to the short ski trips to Snowshoe with my brother Matt – gave me a break and some much-needed perspective.

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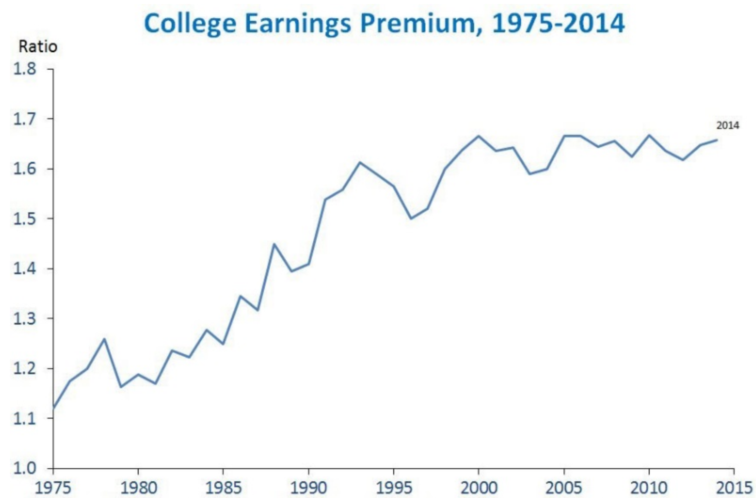
This dissertation examines individual decision-making in higher education and the workforce by using the detailed nature of military personnel data and natural experiments that occur within the military. Investments in human capital – particularly in higher education – are among the most consequential made in a person's lifetime. The underlying decision processes are complex and merit rigorous analysis. While the military and its members are an important subject of study outright, the military experience additionally provides sources of quasi-experimental variation that support the causal study of these topics.[1]

In the first chapter of the dissertation, I examine social influences and the new employee's decision to participate in a generous subsidized continuing education program – the US Army's Tuition Assistance program. I rely on the random assignment of soldiers to companies with varying participation rates in order to identify a causal effect. In the second chapter, my co-authors and I consider an employee's decision to transfer to a family member a generous education benefits package – from the post-9/11 GI Bill – in exchange for continued labor supply in a hazardous profession. In the third chapter, I extend the random assignment methodology used in the first chapter to study the effects of randomly-assigned exposure to peers with adverse characteristics, caused by a temporary surge in the granting of morality waivers to enlist in the US Army.

[1] The views expressed throughout this dissertation – the linking document as well as Chapters 1, 2, and 3 – are those solely of the author and co-authors. We do not purport to represent the positions of the University of Virginia, the Office of Economic and Manpower Analysis, the U.S. Military Academy, the Department of the Army, or the Department of Defense. My co-authors and I obtained institutional review board (IRB) approval through the U.S. Military Academy for all human subjects study conducted as part of the dissertation research. Documentation of IRB approval is available from the author upon request.

Perhaps the simplest way to measure the payoff from higher education is to compare the earnings of those with a bachelor's degree to the earnings of those without. As Figure L.1 below shows, the ratio of those earnings has increased over the last four decades and is currently greater than 1.6.

Figure L.1: Earnings Premium from Holding a Bachelor's Degree[2]



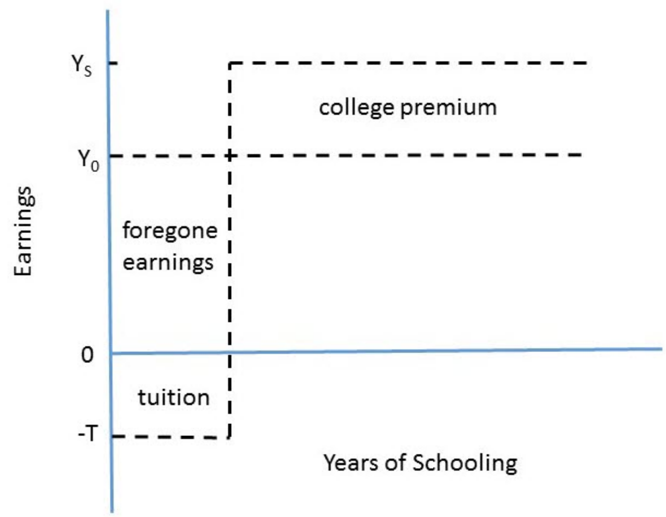
There are also non-pecuniary returns to higher education – benefits that are in addition to the wage premium. Such benefits may include higher job satisfaction, lower unemployment risk, better health and new friend sets and networks (Baum, Ma, and Payea, 2013).

Even though investing in college promises, on average, a large return, there are still costs incurred and uncertainty. Thus, it is helpful to analyze higher education decision-making through a human capital investment framework that models the tradeoffs among the costs of education, foregone earnings in the short-run, and increased future earnings and other potential benefits (see Lovenheim and Turner, 2015, for instance). Figure L.2 below provides a visualization of this cost-benefit tradeoff. In a

[2] Source: Bureau of Labor Statistics, www.bls.gov.

simple model, the costs include only tuition and fees plus the opportunity cost of foregone earnings and the only benefit is in higher future earnings; all of these quantities are known to the would-be student before she makes the human capital investment decision. She also knows the relevant interest rate for discounting future revenue streams and it is assumed that she will successfully complete the educational program.

Figure L.2: A Simple Model of the Human Capital Investment Decision



In the case of perfect information (and certain success in the education program) as above, the would-be student compares the net present values of investing in more education versus not investing. In a simple four-period model in which schooling lasts only one period[3], those cost-revenue streams to compare are:

$$NPV_0 = \frac{Y_0}{(1+r)} + \frac{Y_0}{(1+r)^2} + \frac{Y_0}{(1+r)^3} + \frac{Y_0}{(1+r)^4} \tag{L.1}$$

$$NPV_{school} = -T + \frac{Y_S}{(1+r)^2} + \frac{Y_S}{(1+r)^3} + \frac{Y_S}{(1+r)^4} \tag{L.2}$$

where Y_0 and Y_S are non-school and post-school wages, respectively, T is the (tuition and fees) cost of attending school, and r is the relevant discount rate. Subtracting (L.2) from

[3] A four-period model captures the full tradeoffs in this investment decision. The model can easily be extended to many periods or even condensed into just two periods without loss of generality.

(L.1) yields:

$$NPV_{net} = -T - \frac{Y_0}{(1+r)} + \frac{(Y_S - Y_0)}{(1+r)^2} + \frac{(Y_S - Y_0)}{(1+r)^3} + \frac{(Y_S - Y_0)}{(1+r)^4} \tag{L.3}$$

The would-be student invests in more education if NPV_{net} is positive and does not invest (i.e. – continues to work at the Y_0 wage rate) if NPV_{net} is negative. Another way to think about the investment decision is in terms of the college premium, $Y_S - Y_0$. The would-be student invests if the time-discounted value of the college premium exceeds the cost of tuition plus foregone earnings while the student is in school.

In the real word, students face uncertainty and other factors that complicate human capital investment. The would-be student realistically has no guarantee of her earnings post-education (this is Y_S in the model above) nor does she know for certain that she will complete the educational program. She might not even know the true cost of tuition and fees.[4] Moreover, there could be psychic costs involved due both to the uncertainty just discussed and stress related to postponing labor force entry, learning new material, taking tests, etc. These informational and behavioral challenges are a significant complication to the classic human capital investment model and they have received much overdue attention in recent research; Page and Scott-Clayton (2016) provides an excellent survey of barriers to access in higher education.

Social influence may partly mitigate the role of these barriers in higher education; this is the topic of the first chapter of this dissertation. For example, maybe a would-be student is initially skeptical or even uninformed about the downstream value of a postsecondary degree – this is an information problem. Likewise, perhaps a second

[4] There is a crucial distinction to be made between sticker price and net price in higher education, with financial aid representing the difference between the two. Many institutions follow a high-tuition, high-aid pricing strategy, which allows price discrimination but adds further complication to modeling the college-going process. As Anthony, Page and Seldin (2016) discuss, net tuition and fees can vary widely across students, even at the same institution for would-be students who are similar socioeconomically.

would-be student is very worried about the psychic toll and stress of being in the classroom and shuts down in the face of the college opportunity – this is a behavioral idiosyncrasy. It could be that a well-informed peer might convince the student in the first scenario that going to college pays while the attitude and example of a peer group convinces the second student that she too can overcome her fears of being in the classroom again.

Each of the scenarios above suggests that peers and the associated environment could in fact play an important role in shaping the individual's decision to pursue additional education. While there is widespread evidence of how peers affect outcomes within an educational setting like primary school or college (Hoxby, 2000; Sacerdote, 2001; Kremer and Lavy, 2008; Duflo, Dupas, and Kremer, 2011), less is known about how peers influence the decision to invest in education (Bifulco, Fletcher, and Ross, 2011; Hoxby and Avery, 2013). It may be helpful to think of the former as the intensive margin of education while the latter is the extensive margin.

In the first chapter of this dissertation, I investigate the role of social influence at the extensive margin of education by analyzing participation in continuing education against the backdrop of randomly assigned peer groups. Specifically, I leverage the random assignment of new soldiers to companies in the US Army that vary substantially in their participation rates in the Tuition Assistance program. I estimate the causal effect of the existing participation rate on the new soldier's own participation decision and then decompose that overall effect into neighborhood, leadership, and peer influences.

The second chapter of the dissertation examines intrafamily decision-making in education. A further complication to the human capital investment framework lies in the intergenerational dimension, which concerns educational correlations and decisions of transfer between parents and children. Parent-child schooling correlations approach 0.5 in the United States and Europe and are higher than 0.6 in some countries in South America (see Black and Devereux, 2010, for a survey). These correlations indicate that the children of college graduates are far more likely to attend college than are children of parents who never attended college.

Partly motivated by these high intergenerational correlations, numerous researchers have considered models in which parents make investments in their children. The key tradeoffs in this model are current consumption for the older generation (the parents) versus future consumption and educational attainment for the newer generation (the children). Becker and Tomes (1986) and Acemoglu and Pischke (2001) provide economics of the household models that analyze these tradeoffs. The general form of these models considers a unitary household that maximizes discounted intrafamily utility across a multiperiod horizon:

$$U = \ln(c) + \delta * \ln(\widehat{c}) \tag{L.4}$$

In equation (L.4), c is the consumption of the parents and $\widehat{(c)}$ is the consumption of the offspring. The parameter δ weights the relative importance of future (children's) consumption versus current (parental) consumption. The parents can make investments in the education of the children, but thereby reduce current period consumption to increase the expected value of future consumption. These choices by the parents occur against the backdrop of a standard intertemporal budget constraint (not shown for brevity).

In the second chapter, my co-authors and I adapt this intergenerational framework to examine a new provision within the post-9/11 GI Bill that allows service members to transfer a generous post-secondary educational benefits package to a family member. The service member must already have at least six years of service and agree to serve four more years on active duty in order to transfer benefits. The transfer policy's implementation in 2009 – at the height of US involvement in ground combat in Afghanistan and Iraq – amplifies the dilemma for service members weighing benefits transfer against continued service in a hazardous profession. Moreover, the service member who transfers benefits to a family member foregoes using the education package for himself. We model this dilemma as a multi-period household optimization problem and test predictions from the economic model against rich observational data that includes transfer decisions made by US Army service members in the early years of the program. We also rely on the policy's differential appeal to service members with dependent family members versus those without in order to estimate a retention effect in the Army.

In the third chapter, I extend the social influences framework from the first chapter in order to investigate how exposure to adverse peers affects the individual's workplace performance and longevity. While some authors have examined workplace peer effects in contemporaneous productivity (Mas and Moretti, 2009; Ichino and Falk, 2006), there is less evidence on if or how much adverse peers affect workplace outcomes. I am particularly interested in estimating spillover effects onto high-quality workers when a firm loosens hiring standards and allows lower-quality individuals into the workforce. This is an important question that could have both theoretical implications for the study of peer effects mechanisms and also practical applications for hiring decisions, admissions standards, and the reintegration into society and the workforce of those with criminal backgrounds.

I study US Army enlisted accessions in the years around 2005-2008. During this period, the Army struggled to meets its recruiting goals at a time of intense and prolonged ground combat in Iraq and Afghanistan and against the backdrop of low domestic unemployment, at least through mid-2008. To meet recruiting goals, the Army granted large numbers of enlistment waivers to otherwise unqualified candidates who had low aptitude scores or criminal backgrounds or both. I am particularly interested in the effects of the waivered soldiers on higher-quality peers who enlisted under normal procedures. As in Chapter 1, the random assignment of soldiers to companies and therefore peer groups allows me to estimate a causal effect. I also conduct a simple network analysis of misconduct events by month within companies in order to explore mechanisms underlying the peer effect.

I plan to continue to improve these chapters based on guidance from the dissertation committee and feedback that I hope to receive at conference presentations. My co-authors and I would like to submit Chapter 2 for publication in a policy or education-related journal sometime in 2017. I plan to refine both peer effects papers over the coming year and submit these to either field journals in economics (labor economics; economics of education; crime) or to relevant education and public policy journals.

CHAPTER 1

Social Influences on Human Capital Investment: Evidence from a Continuing Education Program in the US Army

Abstract

Human capital investment represents a complex and far-reaching individual decision that may be influenced by the educational choices made by others, yet we know far less about peer effects at this extensive margin than we do at the intensive margin of education production itself. In this paper, I rely on a unique source of exogenous variation in which individuals randomly receive exposure to different levels of peer investment in human capital and then must make their own education participation decisions. Specifically, I study new US Army soldiers who are randomly assigned to companies that vary substantially in their existing participation rates in a subsidized continuing education program. I find that a new soldier assigned to a high-participation company is far more likely to take classes than a soldier assigned to a low-participation company. Building on prior work examining neighborhood and peer effects, I decompose this overall impact into neighborhood, leadership, and peer influences. The decomposition suggests that differences across Army locations and other common shocks are largely responsible for the impacts I observe, though I also find a modest peer effect on participation.

Introduction

For at least 50 years, social scientists have wrestled with the question of how environments and peers influence individual decision making and outcomes in education, health, and other important policy domains. The well-known Coleman Report (1966) notes the correlation between a pupil's achievement and the educational backgrounds and aspirations of the other students in the school. Recent work by Raj Chetty and co-authors (2016) shows significant geographic variation in lifetime health outcomes across income groups. For example, low-income males living in Detroit have life expectancy that is 5 to 6 years lower than low-income males in New York or San Francisco. While researchers suspect that environmental and peer differences may contribute to these geographic disparities, there is still much to learn about how external influences affect individual decision-making and outcomes.

Estimating the causal impact of neighborhood and peer influences is inherently challenging given that individuals typically select the environments in which they live and the peers with whom they associate. For instance, a family that prioritizes high-quality primary education might choose to live in a neighborhood that features highly regarded and well-resourced elementary schools. Such neighborhoods may also have additional resources (e.g. better-funded libraries) that support educational pursuits and neighbors who similarly value and promote education. Although we are interested in individual student outcomes that may be influenced by these inputs, selection problems make it difficult to isolate the causal impact of those environmental and peer influences.

Despite these selection challenges, many authors have examined the influence of environments and peers in education and other outcomes. Case and Katz (1991) find strong neighborhood influence on outcomes such as crime involvement, drug and alcohol use, and church attendance. A series of papers analyzes the Moving to Opportunity (MTO) project, in which residents of housing projects were randomly assigned vouchers they could use to purchase housing in other communities. The early MTO papers[5] find that moving to a lower-poverty neighborhood results in better short-run outcomes for young females and improved health outcomes for adults, but that there are no detectable effects on child math and reading achievement. A new MTO paper by Chetty, Hendren, and Katz (2016), however, finds that children who moved to a low poverty neighborhood at a young age are far more likely to attend college.

Many studies in the last two decades have estimated peer effects in education. Several authors have found evidence of peer effects on the intensive margin of education; these studies typically rely on randomness generated within the process of organizing for school (like assignment to a classroom in primary school or to a roommate in college). Hoxby (2000), Duflo, Dupas, and Kremer (2011), and Imberman, Kugler, and Sacerdote (2012) find that stronger peers have a positive effect on individual performance in primary school. The effects often vary across the ability distribution, with students at either tail benefitting more greatly from better peers. Sacerdote (2001), Kremer and Lavy (2008), and Carrell, Fullerton, and West (2009) study social interaction in college and find relatively larger impacts from peers on non-academic outcomes, such as the decision to join a fraternity or sorority, as well as modest evidence of nonlinear peer effects on academic outcomes.

A small recent literature addresses peer influences in education investment decisions, like going to college. Bifulco, Fletcher, and Ross (2011) relies on within-

[5] See Kling, Ludwig, and Katz (2005), Kling, Liebman, and Katz (2007), and Sanbonmatsu et al. (2006).

school, across-cohort variation in high school classmate characteristics and finds that an increase in the percent of peers with college-educated mothers increases own likelihood of college-going. In a field experiment examining peer *pressure*, Bursztyn and Jensen (2015) finds that high school students are less likely to sign up for a free SAT preparatory class if told that their signup decision will be made public.

In this paper, I rely on a unique source of exogenous variation in human capital investment in which new US Army soldiers are randomly assigned to companies that vary substantially in their participation rates in a subsidized continuing education (CE) program. The Army is like many large corporations that subsidize continuing education programs for their employees (Flaherty, 2007). Given that junior soldiers live in military dormitories by unit of assignment and have nearly around-the-clock workplace and off-duty interaction, I hypothesize that existing participation rates will affect the new member's own decision to participate in the CE program. The exogeneity of the military assignment process allows me to estimate a causal effect. I then decompose that estimate into effects from educational markets, leadership, local mentors, and peer effects. Gauging the relative importance of such mechanisms is important because it could guide the design and implementation of effective policies to encourage human capital investment.

This work makes several contributions to the existing literature. First, I add to the rigor of current research on social interaction by exploiting, as does MTO, random assignment to study the impact of environmental and peer influences on important individual decisions and outcomes. Second, I estimate the effect of the peer continuing education participation rate on the new member's own CE participation decision, thereby providing causal evidence at the extensive margin of education. Third, this study examines the social context of education decisions made by young, working adults – a non-traditional student population that is growing across higher education (Seftor and Turner, 2002; Deming, Goldin, and Katz, 2012).

I find that a new soldier assigned to a high-participation company is 16 percentage points more likely to use CE than a soldier assigned to a low-participation company. This is a sizable impact given that only 11 percent of the new soldiers in the sample participate in CE. Building on prior work examining neighborhood and peer effects, I decompose this overall impact into neighborhood, leadership, and peer influences. This decomposition suggests that differences across Army locations and other common shocks are largely responsible for the impacts I observe, though I also find a modest peer effect on continuing education participation.

The rest of the paper proceeds as follows. Section II provides background information on the Army and its subsidized continuing education program. Section III describes the data. Section IV details the empirical strategy. I present results and discussion in Section V. Finally, Section VI concludes.

II. Background

A. US Army Structure

The US Army is a large and structured organization consisting of brigades, battalions, and companies. Figure 1.1 depicts the structure of a brigade, which consists of about 4,500 soldiers. The hierarchical level of interest in this study is the company, of which there are about 30 in a brigade. Within a company, the officers and sergeants are responsible for day-to-day operations as well as the training and mentorship of the soldiers in the company. The approximately 60 junior enlisted soldiers in the company are the peer group that I study in this paper. New junior soldiers join the company after completing their initial military training, commonly referred to as "boot camp." In Section IV of the paper, I discuss the military assignment process for these junior soldiers, with special attention to the resulting randomness.

When the unit is at home station and not deployed overseas, unmarried junior soldiers reside by company in Army-provided dormitories (or "barracks") that feature two- or three-person rooms, administrative offices, and indoor and outdoor leisure spaces. Since the soldiers living in barracks have nearly around-the-clock interaction, both during the work day and in their off-duty time, it is reasonable to expect that they are a prominent information source for and peer influence on one another. Moreover, a soldier who lives in an Army barracks cannot help but to notice how his peers down the hall are allocating their off-duty time – whether for continuing education participation, physical fitness, or other leisure activities. The combination of these elements creates a social environment at the company level that is suitable for studying peer influence.

B. Tuition Assistance

Tuition Assistance is a voluntary continuing education (CE) program that subsidizes college classes for service members. The program is subject to subsidy caps by credit hour and total expenditure per year by soldier, but the generous benefit levels easily cover part-time participation in college – taking one or two classes at a time – for the participating soldier.[6] The Army administers the Tuition Assistance program through its on-post Army Education Centers, staffed by civilian personnel who are independent of

[6] Since the subsidy caps are at the level of the individual soldier only, there is no risk that soldiers may "crowd out" one another or be forced to compete for resources within the program.

the officers and sergeants to whom the soldier reports at the company level. Soldiers who want to participate in the CE program must seek out information either online or from a counselor at the Education Center, formally request Tuition Assistance, enroll in class, and then complete coursework during off-duty hours. Soldiers commit to only one class at a time, are able to start at any time in the calendar year, pending the availability of classes, and can either pursue individual courses or enroll in a degree program. Army Education Centers, working in partnership with institutions of higher education, offer classes in both online and traditional brick-and-mortar formats.[7] Among soldiers assigned to brigades in 2013, 12 percent took at least one Tuition Assistance course during that year while 24 percent had ever taken a course; those figures are 16 percent and 32 percent, respectively, if we consider only soldiers with at least 3 years of service in the Army.[8]

Given the generous subsidy available through Tuition Assistance, the low take-up levels for continuing education may seem surprising. However, participation requires an off-duty time commitment, since a soldier's work day (and sometimes his night) is full of military training and there are no modifications to his duty requirements to support completing CE coursework. There is also some risk of financial obligation: soldiers must repay the subsidy if they fail or withdraw from a class for reasons unrelated to military duty.[9] Moreover, many new soldiers (almost 90% - see Table 1.1) join the Army having

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[7] CE is wholly separate from and has no effect on GI Bill benefit eligibility (used after leaving the service) and Army skills-based educational programs, like parachutist training or military leadership training in conjunction with promotion to sergeant.

[8] Analysis is based on 153,746 enlisted soldiers assigned to brigades in 2013; 87,339 of those soldiers had 3 or more years of service in the Army. Tuition Assistance use by officers is uncommon because they incur extra time in the service for taking classes, whereas the enlisted do not.

[9] If a soldier fails or withdraws for a military-related reason (such as intensive home-station training prior to a combat deployment), the soldier can request a memorandum from his commanding officer to waive subsidy repayment.

completed high school and no college, so they may be unfamiliar with or have misconceptions about higher education in general. Also, since CE is not administered through his assigned company, there is no guarantee that the new soldier even knows about the program, particularly given that CE is a less prominent educational benefit than the longstanding and well-known GI Bill. As such, while CE presents a promising human capital investment opportunity, many soldiers might be unaware of or hesitant to pursue the benefit.[10] Thus, the attitudes and participation behavior around the company could be very influential in shaping individual CE outcomes – both for the new member and those soldiers already in the peer group.

III. Data

A. Sources

I rely on data from two sources. First, I draw administrative military data on enlisted soldiers from the US Army's Office of Economic and Manpower Analysis (OEMA); these records contain rich soldier-level demographic, financial, and occupational data from the point of entry into the service as well as through subsequent military assignment. Importantly, these data also include the specific dates when soldiers enter into and depart from the assigned company. Second, I draw individual-level data on CE course participation from Headquarters, Army Continuing Education Services (ACES). The CE data include start and end dates for each class taken, so I observe program participation by month for each soldier. One limitation of the CE data is that

[10] Castleman (2015) and Hoxby and Turner (2015) note that a lack of visibility of opportunities in higher education likely constrains participation in those opportunities. This information problem and other types of barriers to higher education have received increased attention in the recent college access literature; Page and Scott-Clayton (2016) provides an excellent survey.

many (nearly 40%) course grades are missing while others are simply pass/fail. Accordingly, I analyze only participation and not performance in this study.

B. Sample

I focus on new soldiers assigned to any active Army brigade that did not deploy overseas in the years 2012-2013; there are seven such brigades. The purpose of this sample selection is to establish baselines both for access to CE and personal discount rate, both of which are important for educational decision-making and might be influenced by a current or impending combat deployment. First, soldiers have little to no access to Army Education Centers and CE courses while deployed overseas. Second, any investment in education requires accepting present cost in the hope of gaining future benefit; a soldier who is anticipating a combat deployment might evaluate this tradeoff with a high personal discount rate given the imminent risk of personal harm that he faces. Thus, while new soldiers who did not deploy in 2012-2013 are not systematically different at entry from those who did deploy, I condition my sample on this critical unit-level treatment (deployment) for the reasons just described. Appendix 1A contains more details on sample selection.

Across the seven brigades and two years in my preferred sample, I identify 10,141 junior enlisted non-married soldiers who were newly assigned to a company in the brigade and stayed in that company for at least 9 months.[11] These soldiers were newly assigned across 186 companies in those brigades during that time period. Table 1.1

[11] I exclude married junior soldiers from this study because they reside with their families in private quarters and are away from important social interaction that occurs after duty hours in Army-provided company-level barracks. The 9-month window ensures that each new soldier, regardless of what month he joins the company, will get exposure to that company's existing CE environment <u>and</u> experience two traditional quarter-based course starts. Later in the paper, I test the robustness of the results to each of these design considerations.

provides summary statistics on these soldiers and the companies that they joined. As shown in Panel A, the new soldiers are young (21 years old) on average and about 90% have completed no college. Approximately 60% of the new soldiers are white and more than 90% are male.[12] The outcome of interest is a binary variable for each newly assigned soldier indicating whether he has participated in CE – taking at least one class – by the 9 month mark of assignment to the company; 11% in this sample participated in CE within that timeframe. An advantage of focusing on new soldiers is that I know their earlier exposure to Army CE to be zero; these soldiers were previously in boot camp, where there is no access to CE, and so they had no prior exposure to the CE program. The company-level statistics in Panel B are averages across the 186 companies and 24 months of observation. The key explanatory variable is the percentage of junior soldiers that either were currently using or had recently used CE while assigned to that same company; the mean of this variable is 5.7% across all companies in the sample.[13] Figure 1.2 shows that there is significant variation in this treatment variable.

IV. Empirical Strategy

A. Social Influence and Military Assignments

I quantify each Army company's human capital investment environment on a monthly basis as the CE participation rate of the soldiers already assigned to that company. This company participation rate – the basis for estimating the causal effect of social influence – is the product of all factors that may in turn influence the individual's

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[12] The sample is disproportionately male (relative to overall Army demographics) because of Army regulations concerning how females can be assigned to small units with direct combat missions (such as within a combat brigade) – please see footnote 14 for more details.

[13] I expect the average recent CE use rate (5.7%) to be lower than the average outcome variable (11% CE use rate for new soldiers) because of the strictness by which each figure is measured: I define recent use as occurring within the last 3 months whereas the outcome variable measures any CE use within 9 months.

CE participation decision: peer effects, but also differences in educational markets across Army locations, differences in command emphasis on continuing education, differences in local mentor CE participation, etc. In subsequent sections I attempt to decompose the overall social influence into specific mechanisms, such as neighborhood-level effects and peer effects.

To estimate a causal effect attributable to social influence, I rely on Army conditional random assignment (CRA) of soldiers to companies. The Army arbitrarily assigns its junior enlisted members to companies based on established personnel processes that prioritize the "needs of the Army,"[14] not based on the preferences of the soldier and certainly without regards to variation in CE participation across companies. For example, the Army may assign two soldiers with tank driver specialty to two different companies, one with high CE participation and the other low. Those assignments are conditional on the soldiers' specialties (tank driving) and the companies' needs (tank drivers), but otherwise arbitrary and therefore unrelated to anything else about either soldier.

In addition to the established personnel processes that underlie CRA, there are three further reasons to expect randomness in the assignment of new soldiers to company CE rates. First, as already mentioned, entry-level soldiers have no exposure to CE in boot camp – so even if they could influence their assignment to a company, they would have no basis to angle for placement in a high participation company. Second, since

[14] Department of Defense Directive 1315.07 and Army Regulation 600-14 provide the regulatory basis for CRA. Other researchers have used versions of this identification strategy, including Angrist and Johnson (2000), Carrell and Zinman (2014), Carter and Skimmyhorn (2016), and Carter et al. (2016). Army Regulation 600-13 provides the further stipulation that female soldiers cannot be assigned to units that have a routine mission to engage in direct combat, or to units which co-locate with units assigned a direct combat mission. Many of the units depicted in Figure 1.1 – like the tank battalion or an infantry company – are assigned direct combat missions and so are male-only during the time period considered.

basic training soldiers do not receive individual performance reports and there is no interview process for the next job, there is no clear means by which a company commander might measure the quality of or attempt to influence the assignment of the new tank driver (or any other new soldier) that the company is due to receive. Third, the only organization that could calculate unit CE participation rates – ACES, which provided me the soldier participation data – has no role in the military assignment process. Thus, it is reasonable to expect random assignment of soldiers to companies with varying CE participation rates.

I confirm that a natural experiment results from CRA by comparing, in Table 1.2, the baseline characteristics of soldiers assigned to companies with differing levels of CE participation. Column 1 presents a regression of the existing CE participation rate – measured in the company the month before[15] a new soldier arrives – on the assignment controls: rank, career field, time and their interactions along with gender. In column 2, I add a vector of entry characteristics – including AFQT, education level, and age – to the assignment controls. None of the entry characteristics added in column 2 is statistically or economically significant; they are also jointly insignificant at conventional statistical levels (F=1.52, p-value = 0.136). These analyses confirm that soldiers, conditional on rank, career field, Army requirements, and gender, are randomly assigned to companies. Put another way, personnel managers in the Army are <u>not</u> considering the personal characteristics of new soldiers – beyond what is mandated by normal assignment regulations – when placing them into CE participation environments.

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[15] The use of a lagged peer measure – here the CE rate the month before the new soldier arrives – is a strategy that some authors (Hanushek et al, 2003; Burke and Sass, 2013) have used to deal with simultaneity issues in peer effects studies. I discuss this empirical challenge in the next section.

Figure 1.3 demonstrates the timeline by which I use the plausible exogeneity stemming from Army CRA to test for the effect of social influence on individual CE participation. I measure the *ex ante* CE rate of the company at time t-1, or the month before the new soldier joins the company. The soldier joins the unit at time 0 and then I observe him again in the future for a CE outcome, with a binary cumulative assessment of his participation at 9 months.

Given the randomness resulting from the military assignment process and the timeline in Figure 1.3, I estimate an OLS model to test for the causal effect of social influence on CE participation:

$$CEPart_{ijt} = \alpha_0 + \alpha_1 * \overline{CEPart}_{j,t-1} + \alpha_2 * X_{ij,t-1} + \alpha_3 * A_{crt} + e_{ijt} \qquad (1.1)$$

In equation (1), $CEPart_{ijt}$ is the outcome of interest: a binary variable indicating CE participation for soldier i assigned to Army company j at time t. α_0 is the regression intercept. $\overline{CEPart}_{j,t-1}$ measures the existing CE participation in the company, the month before new soldier i arrives; $\overline{CEPart}_{j,t-1}$ can be either a rate or a set of indicator variables for quartile of assignment, where quartile is based on the relative CE rate of the company (see Figure 1.2). $X_{ij,t-1}$ is a vector of individual characteristics (like aptitude, entry education level, and age). A_{crt} are the assignment control fixed effects, which are career field, rank, time (month*year), and gender. Given the randomness resulting from Army CRA, α_1 provides an unbiased estimate of the pre-assignment environment's effects ("social influence") on the individual's future CE decision.

B. Decomposing the Social Effect

To inform policy and resourcing decisions, it is important to distinguish among the mechanisms driving any social influence on individual human capital investment decisions. Whereas I argue above that the estimate for social influence is internally valid due to CRA, I acknowledge here that disentangling any potential peer effect from the overall social effect is a more challenging empirical problem. Manski (1993) provides a well-known framework for understanding why individuals who belong to the same social group might behave in the same way or make similar choices. The mechanisms he considers are peer actions, peer characteristics, and correlated effects. In the current context, the peer action is contemporary CE participation; peer characteristics include group measures such as aptitude, education, and age that might influence human capital investment; and correlated effects are common background factors such as the local Ed Center and the proximity of colleges and universities to each battalion. Some authors (Lyle, 2007; Angrist, 2014) refer to the correlated effects as "common shocks" to emphasize the effect these factors have on all members of the social group.

I start with a traditional linear-in-means specification, capturing the elements in Manski's model and similar to that used by Sacerdote (2001) and other authors:

$$CEPart_{ijt} = \alpha + \beta * \overline{CEPart}_{-jt} + \gamma * X_{ij,t-1} + \sigma * A_{crt} + \delta * \bar{X}_{j,t-1} + \mu * Z_{jt} + \varepsilon_{ijt} \qquad (1.2)$$

Although this specification resembles equation (1.1), there are a few important differences. First, $\overline{CEPart}_{-jt}$, the explanatory variable of interest, measures *contemporaneous* peer participation: the average CE participation rate among soldier i's peers in the company at time t, excluding individual i. In the core model discussed earlier, I use the *ex ante* rate first to establish random assignment and then second to identify a causal effect. Here, to explore mechanisms in the framework put forth by Manski, I use the contemporaneous rate in order to provide a precise measure of what the peers are doing in the current period. Next, $\bar{X}_{j,t-1}$ are the mean characteristics of the company peers the month before new soldier i joins; this is the peer characteristics channel of influence. Finally, Z_{jt} are correlated effects – background factors such as the local educational environment and leaders that potentially impact the CE participation decision of all members of the company. ε_{ijt} is the error term. While this model is more complex than that in equation (1.1), it helps me to separate underlying mechanisms whereas the core model identifies only the overall impact of social influence.

As is well documented in the peer effects literature (Sacerdote, 2001; Hanushek et al, 2003; Angrist, 2014), there are some empirical challenges in causal interpretation of the contemporaneous peer effects parameter β from equation (1.2). Even though Army CRA removes worry of selection into the peer group, there are two other potential problems. First, there is risk of unobserved correlated effects that might not be picked up in the vector Z_{jt}. These could relate to organizational culture, attitudes about continuing education, or another unobservable factor related to CE participation both by the peer group and the new soldier; failing to account for these could create a source of bias. Second, the simultaneity of $CEPart_{ijt}$ and $\overline{CEPart}_{-jt}$ presents a major identification challenge in estimating (1.2). This is what Manski terms the "reflection problem," insomuch as the researcher cannot be sure whether the peer group is influencing the individual, the individual is influencing the peer group, or both.[16] Nonetheless, estimating (1.2) can give a rough idea of the relative sizes of mechanisms, and, in the case of a large and statistically significant estimate for β, suggests that the researcher can reject a null hypothesis that there are no peer effects present.

[16] The reflection problem is a significant empirical concern in the well-known scenario of two peers who are college roommates. It may be less of a concern in the current setting, in which the new soldier is junior to 59 peers who are already assigned to the company – I investigate this possibility at the end of Section V.

Within the Manski model, I can apply a fixed-effects framework to address potential bias stemming from unobservable correlated factors. The hierarchical structure of the military makes such a framework particularly effective, as demonstrated in Lyle (2007). Army base and time fixed effects within Z_{jt} soak up location-specific or time-specific determinants of continuing education participation, which could include differences in the density of participating higher education institutions around different Army bases. Another important factor unique to any given Army base is the local Education Center, which may have different course offerings and outreach capability – like from education counselors – when compared to other Ed Centers at other Army locations. There could also be seasonal factors that influence CE participation, perhaps related to when courses typically start. The Army base and time fixed effects control for all of these possible confounders. Additional fixed effects at the battalion level account for the intensity of unit training and day-to-day operations, leader emphasis on continuing education, and barracks location relative to the Army Education Center. Finally, I add the CE participation rate of the sergeants by unit and month to allow for the influence of a natural mentor network as well as local attitudes and encouragement for education within the assigned company.

The reflection problem, on the other hand, remains an enduring challenge in analyses of social interaction. Some authors (Gaviria and Raphael, 2001; Fletcher, 2015) have turned to instrumental variables (IV) methods to enable causal estimation of equation (1.2), while others (Brock and Durlauf; 2001, 2007) have examined identification within structural models of binary choice.[17] The simultaneous equations

[17] In the IV case, it is difficult to justify the exclusion restriction in this setting, namely that the instrument affects CE participation only through the participation rate of the group. The Brock and Durlauf model

approach used by Case and Katz (1991) and Sacerdote (2001) provides a middle ground to addressing the reflection problem and has become a convention in the peer effects literature. Using this approach, the simultaneity of peer outcomes gives a second equation – very similar to (1.2) – that captures the influence of the individual on the group outcome. I present both equations below for ease of visual comparison:

$$CEPart_{ijt} = \alpha + \beta * \overline{CEPart}_{-jt} + \gamma * X_{ij,t-1} + \sigma * A_{crt} + \delta * \bar{X}_{j,t-1} + \mu * Z_{jt} + \varepsilon_{ijt} \tag{1.2}$$

$$\overline{CEPart}_{-jt} = \tilde{\alpha} + \tilde{\beta} * CEPart_{ijt} + \tilde{\gamma} * X_{ij,\,t-1} + \tilde{\sigma} * \mathrm{A_{crt}} + \tilde{\delta} * \bar{X}_{j,t-1} + \tilde{\mu} * Z_{jt} + \tilde{\varepsilon}_{ijt} \tag{1.3}$$

Combining (1.2) and (1.3) gives the following reduced-form equation:

$$CEPart_{ijt} = \pi_0 + \pi_1 * X_{ij,t-1} + \pi_2 * \bar{X}_{j,t-1} + \pi_3 * Z_{jt} + \nu_{ijt} \tag{1.4}$$

Equation (1.4) still includes measures of peer *characteristics* within the vector $\bar{X}_{j,t-1}$ but excludes the simultaneous term, $\overline{CEPart}_{-jt}$, that is a measure of contemporary peer action. This step mechanically removes the reflection problem and concerns about simultaneity. The reduced-form coefficients in (1.4), such as π_2, are composite of parameters from (1.2) and (1.3). More precisely,

$$\pi_2 = \frac{\beta\tilde{\delta}+\delta}{1-\beta\tilde{\beta}} \tag{1.5}$$

after inserting (1.3) into (1.2) and collecting terms. The β terms measure the peer actions channel while the δ terms are from the peer characteristics channel. Based on the complexity of the relationship in equation (1.5), the researcher would need to make very strong assumptions about several parameters to identify any one structural parameter of interest, say β, even after first obtaining an estimate for π_2 from equation (1.4). Nonetheless, the estimate for π_2 gives well-identified evidence of peer effects (i.e. – free

argues that the reflection problem does not arise in the binary choice setting as long as a large support assumption holds for the observable peer characteristics vector. Under such a condition, the expected value of the peer group choice, bounded between -1 and 1, cannot be linearly dependent on the peer group characteristics.

of simultaneity bias) in the reduced form, even though it does not completely untangle the mechanisms of peer influence that the estimation of equations (1.2) and (1.3) attempts to address.

V. Results

A. Social Influence

Using least squares estimation of equation (1.1), I find that existing company participation has a strong effect on the CE investment decision of a newly assigned soldier. When the treatment variable $\overline{CEPart}_{j,t-1}$ is a rate of unit participation, the point estimate for the causal parameter is 1.02. This linear-in-means result indicates nearly one-for-one movement between the new soldier's CE outcome and the corresponding peer participation rate. Given a standard deviation in unit participation rates of 0.06, the effect size is slightly larger than 6 percentage points (pp). This is a sizeable effect given that only 11 percent of the new soldier sample use CE during the period of observation. These regression results appear in Appendix 1B.

My preferred model for social influence uses a more flexible specification in which the treatment variable $\overline{CEPart}_{j,t-1}$ is a set of indicator variables for quartile of CE assignment. These results appear in Table 1.3. Using this nonlinear specification allows the treatment effect (from the *ex ante* CE participation rate) to vary at different points across the distribution of company CE participation. As suggested by the histogram in Figure 1.2, a top quartile CE company has participation rates of 10 percent or greater while a bottom quartile company has rates lower than 2 percent. In a company of 60 junior enlisted soldiers, these rates equate to a half-dozen or more peers taking classes in a top company versus none or maybe only one using CE in a bottom company. Upon estimating equation (1.1) with the indicator variables for CE quartile, the results are once again large and statistically significant: a soldier assigned to a top quartile CE company is 16 percentage points more likely to use CE than a new soldier assigned to a bottom quartile CE company, where only 5 percent of new soldiers on average will participate in CE. Similarly, a soldier assigned to the second highest quartile of CE participation is 7 percentage points more likely to use CE. Soldiers assigned to either of the bottom two quartiles of CE participation companies are far less likely to use the benefit. The estimates in Table 1.3 are robust to the full set of new soldier demographic controls (added in columns 2 and 3), confirming the conditional exogeneity via military assignment that was discussed in Section IV.[18] [19]

Estimation of equation (1.1) also reveals some heterogeneity in CE participation, as shown in Table 1.3. Service members who already have a college degree – only about 3% of the sample – are far less likely to use CE. The likelihood of participation increases slightly in the age of the new soldier: about 0.4 of a percentage point per year. Nonwhite soldiers and females are more likely to use CE than their white male counterparts; these results are consistent with descriptive findings in earlier studies of CE programs both in the military (Garcia, Arkes, and Trost, 2002; Sticha et al., 2003) and outside the military (Flaherty, 2007).[20]

[18] Probit marginal effects, evaluated at the means of explanatory variables, return similar estimates.
[19] The existing CE rate in the company has no impact on the number of courses taken - I find influence only on the decision to take a first class, and not on how many courses to take.
[20] As an immediate robustness check, I estimate equation (1.1) for only the male soldiers in the sample; these results appear in column 4 of Table 1.3. As discussed in footnote 12, Army assignment policies forbid the assignment of females to direct combat units and so females are therefore assigned to non-direct combat units with peers that may have better access to and inclination to use CE. Moreover, since females in this study are more likely to participate in CE, it could be that this subset of soldiers is driving the results thus far. This is clearly not the case here, as shown in column 4 of Table 1.3. The strong social effects are identical for the male soldiers alone as for the entire sample, which is not entirely surprising since the sample is more than 90% male.

B. Decomposing the Social Effect

In this section, I shift to the more complex specification in equation (1.2) in an attempt to separate out the mechanisms driving the overall social effects just discussed. I separately estimate the full peer effects model in (1.2) using each of the *ex ante* and contemporaneous peer participation rates. I address some advantages and disadvantages of each approach.

First, I first estimate a modified version of equation (1.2) in which I include the mean peer characteristics and common shocks as regressors alongside the *ex ante* CE participation rate and individual characteristics. One advantage of this approach, as noted earlier, is to circumvent the reflection problem by using a lagged peer treatment rather than the contemporaneous measure. For this estimation, I increasingly layer on covariates in order to address the confounding influence of peer characteristics and correlated effects. The covariates that I add are mean peer characteristics by company, fixed effects for Army base, fixed effects for the battalion (higher headquarters) to which the company is assigned, and finally the contemporary CE rate of the sergeants assigned to the company. With the full set of these confounders included, the impact of the *ex ante* peer rate decreases by more than 80% and loses statistical significance at conventional levels (results in Table 1B.1 in the appendix). This initial estimation suggests that common shocks from location, leadership, and mentors play a large role in the effects observed and that peer effects are small or negligible.

Next, I estimate the canonical linear-in-means peer effects model in equation (1.2), with peer actions entering now through the *contemporaneous* participation rate, consistent with the social interactions framework discussed in Section IV. Regression results appear in Table 1.4. The outcome is still the binary CE participation outcome of the newly assigned soldier. Per equation (1.2), the explanatory variable of interest is the contemporaneous CE participation[21] of the new soldier's peers during the 9-month window – this is the peer actions channel of influence from Manski's framework. As I progress across regression specifications in Table 1.4, I increasingly layer on covariates in order to address the confounding influence of peer characteristics and correlated effects. In column 2 of Table 1.4, I add peer mean characteristics (aptitude, education, age) to the regression; there is a small decrease in the estimated effect of peer actions on new soldier CE participation. However, in column 3, the inclusion of Army base controls lowers the coefficient on the peer CE rate from 1.372 to 0.734 – nearly a 50% reduction. Since the location control is a fixed effect only, it is not possible to pinpoint the exact mechanism at work, but the local education market (on-post Education Center, counselors at that center, course offerings, etc.) may be an important factor. I discuss the importance of local education markets and common shocks in more detail in Section VI. Adding the battalion controls in column 4 further reduces the topline coefficient to 0.554. Again, since this control is a fixed effect only, I am unable to identify a mechanism, but it could be that the intensity of day-to-day operations or the leadership attitudes towards CE in the higher headquarters are important factors in individual decision-making. Finally, adding the participation rate of the sergeants in column 5 reduces the coefficient on the peer CE rate to 0.439, indicating that these local mentors affect both the new soldier and the junior soldier peer group. With the full covariate set included, the point estimate on the contemporary CE rate indicates that exposure to a 10 percentage point increase in

[21] The results of applying fixed effects for the decomposition are similar whether the peer CE variable is the company rate (linear-in-means model) or the set of indicators for company participation quartile (non-linear specification in section A above). I present and discuss results here using the former for ease of exposition.

peer CE participation increases the likelihood of own CE participation by 4.39 percentage points.

Even though there are concerns about simultaneity when estimating peer effects with the contemporaneous rate, as above, there are two important takeaways from the results in Table 1.4. First, even with the reflection problem potentially present, the point estimate in column 5 provides suggestive evidence against any null hypothesis that there are no peer effects present. Second, the "decay" in coefficient on the peer CE rate across specifications is indicative of the role played by common shocks; this is consistent with results in Hanushek et al. (2003) and Lyle (2007). Thus, taken collectively, my analyses indicate that environmental and social factors have a substantial influence on individual human capital investment decisions, but that even after controlling for these factors, peers still appear to influence the participation decisions of individuals when they join a new group.

C. Exploring the Reflection Problem

In this section, I examine the potential for simultaneity problems in this context when estimating the peer effects model with the contemporaneous rate. The analysis that follows suggests that the reflection problem in this setting is nonzero but perhaps less prominent than in other previously studied environments.

In some higher education settings, the reflection problem is symmetric: the simultaneity of outcomes occurs as two peer roommates – often both freshmen in college – influence one another. The current setting is different insomuch as the newly-assigned soldier joins approximately 59 peers who have already been in the company, some for multiple years. To test whether that new soldier influences the longer-tenured peers, I estimate equation (1.3), in which the outcome is the contemporaneous peer CE rate at 9 months and the key explanatory variable is the new soldier's binary participation decision.[22] Estimation proceeds similarly to that in the section above and I layer on the same confounding covariates here that appear in the columns of Table 1.4. Results for this analysis appear in Table 1.5. The new soldier's CE choice is significant in all models; the movement in topline coefficient from 0.0285 (column 1) to 0.00846 (column 5) is reminiscent of results observed in Table 1.4 and again suggests prominent common shocks. The point estimate in column 5 of Table 1.5 reveals that CE use by the new soldier is associated with a nearly 1 pp increase in the peer CE rate. While it may seem surprising that the new soldier has this influence on the incumbent peer group, the magnitude of the effect (0.00846 x 59 peers) suggests that the induced takeup is, on average, only one half of one person in each company. Data limitations prevent me from examining whether that new user is a roommate or a friend who lives a few doors down, as we might expect in a dormitory-like setting. Nonetheless, this important result confirms that simultaneity (the reflection problem) plays a small but non-trivial role in this setting.

D. Reduced-Form Peer Effect

In this section, I estimate equation (1.4) in order to provide evidence of a peer effect that is fully identified – this is complementary to the main analysis of peer effects already discussed. I find that new soldiers assigned to older peers are more likely to participate in CE. This reduced-form peer effect is modest in magnitude and statistically significant at conventional levels. See Appendix 1C for more details.

[22] Calculation of the peer CE rate at 9 months excludes the new soldier. It is important to caution that this is exploratory analysis, since the parameters in (1.3) are not fully identified due to the same simultaneity concerns discussed in Section IV for equation (1.2).

E. Robustness Checks

Finally, in this section, I vary some important design features of this study in order to explore the robustness of the results. First, throughout the paper, I measured the new soldier's CE participation outcome at the end of 9 months in the company. The purpose of this timeframe is to permit adequate time for receipt of existing CE rate "treatment" plus the passing of two traditional quarter course starts.[23] As a robustness check, I re-estimate (1.1) and (1.2) with different durations of observation for each new soldier, since the summary statistics in Panel A of Table 1.1 show that some new soldiers do take up CE almost immediately. With CE use by the 3 month mark as the outcome, the environment effect is small and the estimated endogenous peer effect coefficient is null. For the 6 month time horizon, the effects are statistically significant but smaller than those observed for the 9 month outcome. The results for 12 months mirror those for 9 months (results also not shown). The results for the shorter time horizons make intuitive sense: the "early takers" of the CE benefit are making participation decisions in the first 3 months that are unrelated to social influence. Participation decisions made in the 6 or 12 month timeframe reveal a similar role for social influence when compared to estimation at 9 months. I do not estimate effects for longer time horizons – such as 18 months – since more than a third of the soldiers in the sample change companies before that timeframe. The models with a 9-month outcome remain my preferred specification.

I also excluded married soldiers from the preferred sample in order to ensure uniform "full" treatment that includes those important off-duty social interactions that

[23] Although the CE courses start throughout the calendar year, the four most common starting months (January, March, August, October) account for more than 50% of course starts. Any new soldier staying in a company for 9 consecutive months will see at least 2 of these most common starting months. Analysis of CE course timeframes is based on more than 780,000 courses from 2010 through 2015.

occur in Army barracks (recall that married soldiers, even if junior enlisted, reside in separate living quarters with their spouses, away from the company barracks). As a second robustness check, I re-estimate the main results with the married soldiers included; this step increases the sample size by about 20%. For the test of social effects in equation (1.1), including the married soldiers reduces the treatment effect about 10% in the linear specification. The reduction is steeper – about 20% – in the nonlinear specification: the top quartile company participation effect is 13 pp instead of 16 pp. Interestingly, the peer effects results are much smaller with the married soldiers included. The linear-in-mean peer effects specification in (1.2) returns a coefficient of 0.254 for this larger sample, compared to 0.439 for the non-married soldiers only. The reduced-form coefficient on peer mean age from equation (1.4) also decreases by more than 25% and loses statistical significance (p-value=0.15). It is unsurprising that these estimates appear to be "watered down" when compared to the main results that exclude the married soldiers; these individuals are away from the company barracks during those critical off-duty times when peers might be working on coursework or at least discussing the potential costs and benefits of the CE program. Thus, these results are as expected and confirm the importance of the round-the-clock social interaction in contributing to the main effects observed in this study.

In a final robustness exercise, I apply the models discussed in this paper to the new soldiers and Army units excluded from my preferred sample because of a combat deployment in 2012-2013. I find much lower participation in CE and no evidence of peer effects in CE uptake among these soldiers in the deployed units. There is only weak evidence of overall social influence on CE participation – this is the baseline measure as estimated in equation (1.1). These results suggest that combat deployment or impending deployment has a strong negative impact on continuing education, as hypothesized, both on takeup as well as on the social context that might encourage takeup. Please see section B of Appendix 1A for more analysis and discussion of these supplemental results.

VI. Discussion

In this paper, I study new US Army soldiers who are randomly assigned to companies that vary substantially in their existing participation rates in a subsidized continuing education program. I find that a new soldier assigned to a high-participation company is far more likely to take classes than a soldier assigned to a low-participation company. I find that differences across Army locations and other common shocks are largely responsible for the impacts I observe, while peers exert a smaller yet nonetheless significant effect.

I find evidence of social influence and peer effects in this study in spite of the generally low use of the Army's generous CE benefit, i.e. – a company at the 75th percentile of participation shows only 10% of its soldiers as recent program users. Similarly, even when excluding the most junior personnel (two or fewer three years in the Army), no more than 1/3 of soldiers have *ever* used the CE benefit. As mentioned in Section II, the low participation rates could be related to the risk of financial obligation (upon failing a class or withdrawing), general unawareness, time use constraints, or more likely a combination of all of these factors. It is an open question whether higher overall takeup would lead to stronger social influence and peer effects – particularly on new group members. This is a topic for future research.

My work also finds that peer actions are but one component of the larger social influence that can shape the human capital investment decisions of a new group member. Even in the unique environment that I study – featuring random assignment and voluntary CE participation in military barracks during off-duty time – peer effects are modest and certainly not independent of correlated factors that define the educational environment. This finding is consistent with the common shocks results in Hanushek et al (2003) and Lyle (2007) and reinforces the need for a total-environment approach to the study of peer effects and social interaction in general.

Finally, the paper demonstrates that a new worker is unlikely to use firm-sponsored CE if she does not have many peers who are using the program. This result may generalize to other academic settings and populations beyond just continuing education and the military. These potential learners – whether adolescents or adults – who are in environments that are not encouraging of investment in education could be another type of the "missing student" described in Hoxby and Avery (2013). This is a significant policy concern. Since it can be costly or even infeasible to re-shuffle peers to improve exposure to human capital investment, it is important to remember that peers only partially account for the CE outcome of the adult learner. Specifically, in the context of this study, I find that the educational environment exerts a large influence on participation and I suggest that factors within that local environment such as the density of local institutions, Education Center counselors, and local mentors could be particularly important.

Of general interest, it is important to assess which factors – peers but also other common shocks – in other settings are likewise influential in human capital investment decisions, whether for attending college, using CE in the workplace, or leveraging other opportunities to learn. Such assessments should guide resource allocation (say, for guidance counselors or course offerings) or even the design of interventions to encourage participation in education (like that for high-achieving, low income high school students discussed in Hoxby and Turner, 2013). Thus, a fruitful topic for future research is to investigate which specific aspects of the educational environment might encourage participation, particularly in general settings outside continuing education and the military, and to quantify their effect on promoting investment in human capital.

Appendix 1A – Sample Selection

A. Military Deployment

I base my sample selection on two confounding factors related to individual decision-making in higher education – program access and personal discount rate – that may be especially important in a military context. First, soldiers have little to no access to Army Education Centers and CE courses while deployed overseas.[24] Second, any investment in education requires accepting present cost in the hope of gaining future benefit; a soldier who is anticipating a combat deployment might evaluate this tradeoff with a high personal discount rate given the imminent risk of personal harm that he faces.

To control for these factors, I rely on two major Army events that bookend the period of study and guide my sample selection. First, the US military completed its planned withdrawal from Iraq in December 2011. This withdrawal subsequently reduced the number and pace of unit deployments to the Middle East and therefore reasonably reduced enlisted soldiers' expectations of future combat deployments, particularly if serving in a unit that just returned to home station. Second, in a policy change effective January 1, 2014, soldiers became ineligible to participate in CE within the first twelve months of their assignment to a company, meaning that any initial peer effect on an impressionable new soldier would have at best a one-year lagged effect. Accordingly, I focus on new soldiers in brigades in 2012 and 2013 that did not deploy in order to create baselines both for access to CE and for a soldier's own personal discount rate; each of these factors would otherwise be affected by deployment, impending deployment, or the one-year waiting period if assigned after 2014.

[24] The Army has at different times maintained a few Education Centers in the Middle East theaters of operation, but only at major air bases. As such, these facilities were unavailable to the majority of Army soldiers serving in combat brigades on deployment and so home-station access to the CE program is an important consideration in this study.

I include in the preferred sample all seven brigades that did not deploy for any part of the years 2012-2013, per the non-deploying and benefit access criteria described above. Four of these are traditional US Army ground combat brigades that returned to home station from a rotational combat deployment to either Iraq or Afghanistan in late 2011, one underwent a significant equipment transformation and retraining at home station between the years 2011-2013, and the remaining two conduct permanent mission functions for the Army that almost surely could not be interrupted for a deployment to the Middle East. Each of these circumstances not only precluded combat deployment for that brigade in 2012-2013, but also reasonably created an expectation that deployment was very unlikely: these are important conditions for human capital investment, as discussed. Table 1A.1 shows that new soldiers assigned to brigades that did not deploy in 2012-2013 have slightly lower AFQT scores and more likely to be nonwhite, but otherwise are not systematically different at entry into the service from soldiers assigned to brigades that did deploy.

B. Social Influence in the Deployed Brigades

To explore the effects of deployment or impending deployment on human capital investment, I compare in Figure 1A.1 companies and new soldiers from the seven brigades that meet the no deployment criterion ("sample") versus those from the 29 brigades that do not ("non-sample").[25] Each of the 29 non-sample brigades was deployed to the Middle East – with duty in Afghanistan or Kuwait – for some portion of 2012-2013. Here, unlike in Table 1A.1, the differences are striking. These non-sample

[25] The 36 brigades discussed in this section are brigade combat teams: deployable units that feature the permanent assignment of soldiers to companies. There are also training brigades in the Army's force structure, but I exclude these from the analysis entirely since most of their manning consists of transient soldiers who cycle in and out of the unit based on start and end dates of military training. The units that conduct boot camp for new enlistees are an example of this type of training brigade.

companies show lower aggregate CE participation and a compressed distribution of CE rates. New soldiers assigned to units in the non-sample also use CE with less frequency at every point of measurement (3 months, 6 months, 9 months). These descriptive findings are to be expected given that soldiers would have reduced (if any) access to CE during a combat deployment and presumably would think about human capital investments differently in the months before impending deployment. Unsurprisingly, when I estimate equations (1.1), (1.2), and (1.4) for the non-sample soldiers, there is only weak evidence of a social effect on CE participation and no evidence of peer effects.[26]

Appendix 1B – Linear Model for Social Influence

This appendix presents regression results from estimation of equation (1.1), in which the peer treatment variable is a rate of unit participation. As shown in column 4 of Table 1B.1, the point estimate for the causal parameter is 1.02, meaning that a 10 percentage point (pp) increase in the peer CE rate leads to a 10.2 pp increased likelihood that the new soldier will himself use CE. The more general, nonlinear model whose results I presented in Table 1.3 remains my preferred specification for social influence.

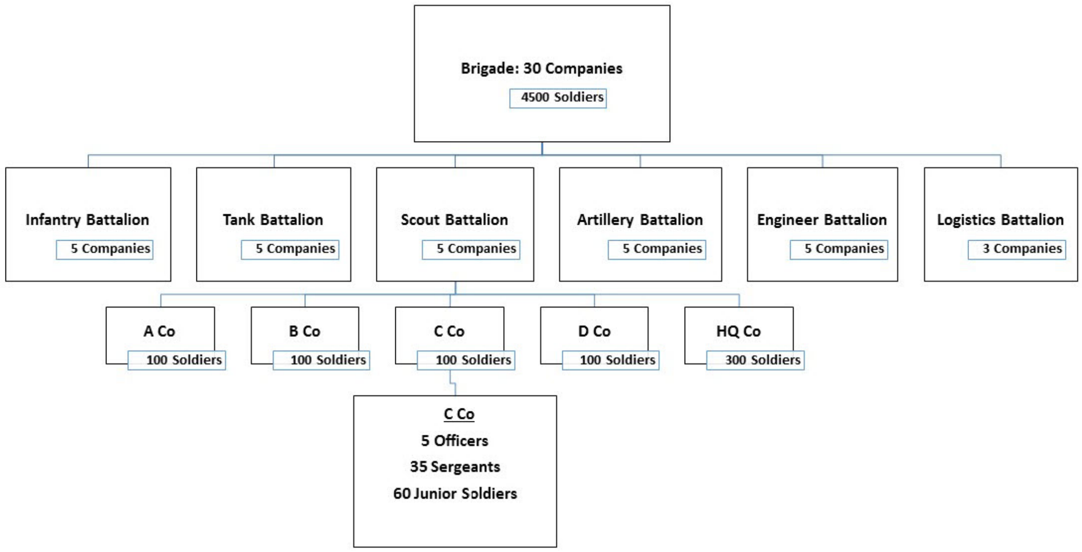
Appendix 1C – Reduced-Form Peer Effect

In this appendix, I estimate equation (1.4) in order to provide evidence of a peer effect that is fully identified – this is complementary to the analysis of the endogenous peer effect already discussed. The estimates here are in the reduced form because it was an algebraic combination of structural equations that removed the simultaneity of CE participation outcomes and resulted in equation (1.4). As discussed in Section IV, the coefficients are composite of several structural parameters, meaning that any peer effect detected here acts through the multiple channels of peer actions and peer characteristics

[26] Results available from the author on request.

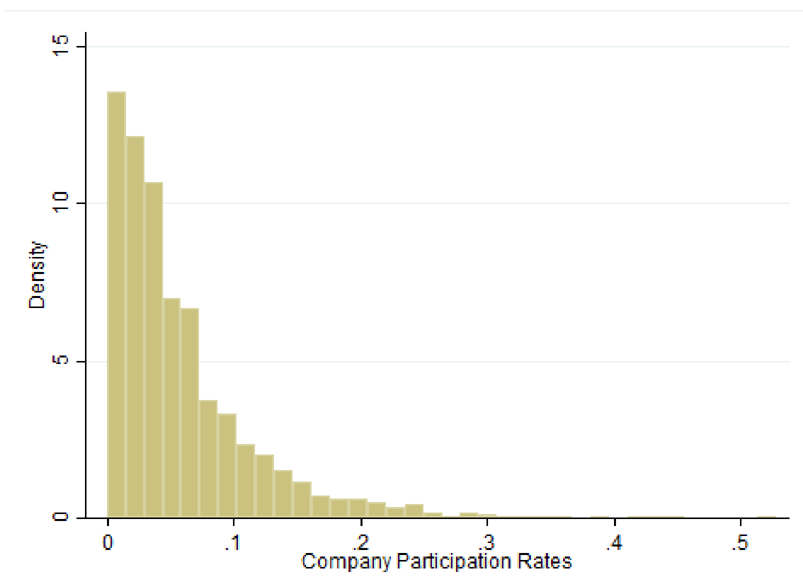
as in (1.5). Regression results for equation (1.4) appear in Table 1C.1. The full specification in column 3 reveals that a one-year increase in the mean age of company peers leads to a 1.3 pp increased likelihood of own participation in CE (this is the coefficient on *peer mean age* in Table 1C.1). This peer effect is about three times as large as the increased likelihood for a one-year increase in own age. Across the entire sample of companies, the average mean peer age is 24 as shown in the summary statistics in Table 1.1. The 25^{th} percentile and 75^{th} percentile values for mean peer age are 23.3 and 24.9, respectively. Thus, the 75-25 difference is 1.6 years and the associated CE participation effect comparing assignment to 75^{th} percentile versus 25^{th} percentile peer mean age is approximately 2 pp. This is a modest peer effect – particularly when compared to the overall social effects found earlier that are much larger – but still noteworthy given that only 11 percent of the sample uses the CE benefit. It is important to remember that this effect occurs through both the peer action and peer characteristics channels because of the reduced-form coefficient.

Figure 1.1: Organization of a US Army Brigade



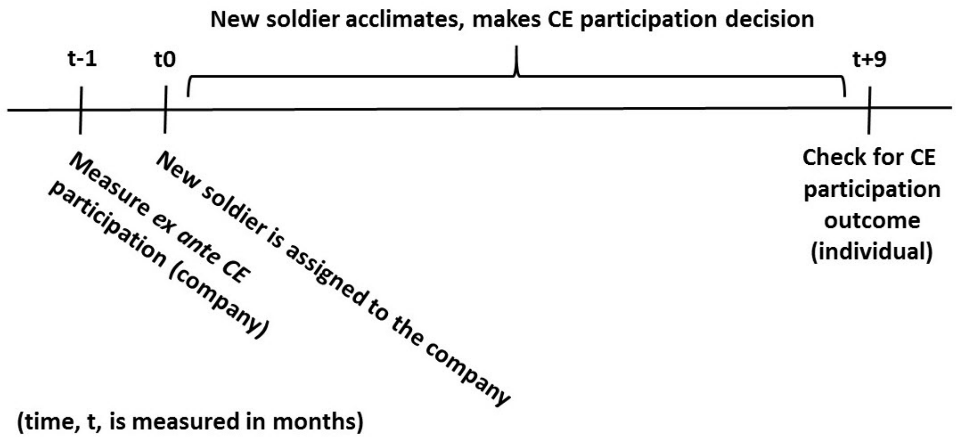
Note: Figure depicts the structure of a typical brigade in the US Army. The company is the hierarchical level of interest in this study, with the 60 junior soldiers as the peer group whose members are making human capital investment decision.

Figure 1.2: Monthly CE Participation Rates in Sample Companies, 2012-2013



Note: DoD Data. Analysis is by month for companies that new US Army soldiers joined in 2012 and 2013. Horizontal axis measures fraction of assigned peer group in that company that are recent CE users. Histogram contains 36 bins, width 0.015. 14% of company-months show zero recent participation as of that month.

Figure 1.3: Timeline for Identifying the Effect of *Ex Ante* CE Participation on the New Soldier's CE Decision

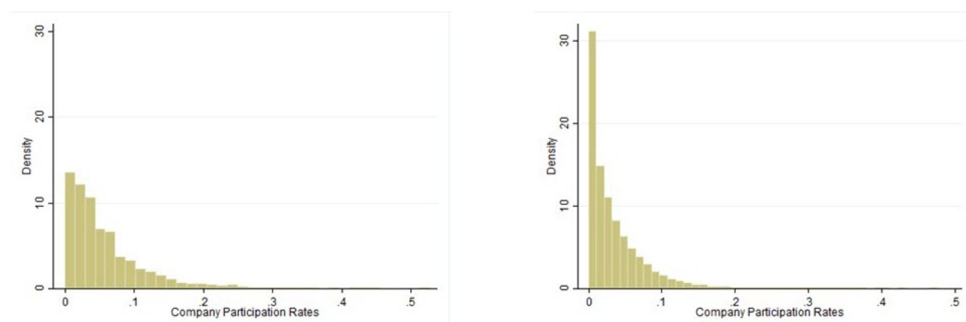


Note: Figure depicts a timeline by month for social influence on human capital investment. The key peer variable, the CE participation rate, is measured the month before the new soldier joins the company.

Figure 1A.1: CE Participation and Deployment, 2012-2013

Monthly CE rates – sample brigades

Monthly CE rates – non-sample brigades



New soldier CE use – sample brigades

	n	mean	sd
CE user by month 3	10141	0.06	(0.25)
CE user by month 6	10141	0.10	(0.29)
CE user by month 9	10141	0.11	(0.32)

New soldier CE use – non-sample brigades

	n	mean	sd
CE user by month 3	41763	0.02	(0.15)
CE user by month 6	41763	0.03	(0.18)
CE user by month 9	41763	0.05	(0.21)

Note: DoD Data. Analysis is by month for companies that new US Army soldiers joined in 2012 and 2013. Sample brigades are those that did not deploy in 2012-2013 (as in Figure 1.2) while non-sample brigades deployed to the Middle East for some portion of 2012-2013. Horizontal axis measures fraction of assigned peer group in that company that are recent CE users. Histograms contain 36 bins, width 0.015. 14% of company-months show zero recent participation as of that month in the sample brigades; 31% are zero in the non-sample brigades.

Table 1.1: Summary Statistics for Preferred Sample

Panel A. Newly Assigned Soldiers Who Spend at Least 9 Months in the Company

	n	Mean	SD	Min	Max
AFQT	10141	57	18	22	99
GED	10141	0.03	0.18	0	1
high school graduate	10141	0.88	0.33	0	1
some college	10141	0.05	0.23	0	1
college graduate	10141	0.03	0.18	0	1
age	10141	21	2.83	18	44
white	10141	0.59	0.49	0	1
black	10141	0.21	0.40	0	1
Hispanic	10141	0.14	0.34	0	1
other race	10141	0.07	0.25	0	1
male	10141	0.92	0.28	0	1
female	10141	0.08	0.28	0	1
combat career field	10141	0.61	0.49	0	1
logistics career field	10141	0.39	0.49	0	1
CE user by month 3	10141	0.06	0.25	0	1
CE user by month 6	10141	0.1	0.29	0	1
CE user by month 9	10141	0.11	0.32	0	1

Panel B. Company*Month Average Values (186 Companies x 24 Months)

	n	Mean	SD	Min	Max
company size (enlisted only)	4408	123	52	49	408
junior soldiers					
AFQT	4408	57	6	44	75
high school only	4408	0.90	0.05	0.61	1
some college only	4408	0.07	0.04	0	0.28
college degree	4408	0.03	0.03	0	0.20
age	4408	24	1.24	21	29
recent CE users	4408	0.06	0.06	0	0.53
sergeants					
AFQT	4408	55	6	41	75
high school only	4408	0.78	0.12	0.32	1
some college only	4408	0.17	0.10	0	0.63
college degree	4408	0.04	0.04	0	0.31
age	4408	32	2.00	27	38
recent CE users	4408	0.09	0.06	0	0.47

Sources: Office of Economic and Manpower Analysis and Army Continuing Education System.
"Recent CE users" denotes either currently using CE or having used CE in last quarter.

Table 1.2: Conditional Random Assignment Test

Dependent variable is ex ante CE participation rate of assigned company
Explanatory variables are characteristics of the newly assigned soldier

	(1)	(2)
AFQT		0.000
		(0.000)
GED only		0.009
		(0.020)
high school only		0.006
		(0.019)
some college		-0.001
		(0.020)
college degree		0.012
		(0.020)
age		0.000
		(0.000)
black		0.001
		(0.002)
Hispanic		-0.000
		(0.002)
other race		0.003
		(0.002)
assignment controls (rank, career field, time and interactions; gender)	Yes	Yes
p-value for joint significance of entry characteristics		0.136
Observations	10141	10141

Standard errors in parentheses. I measure the dependent variable the month before the new soldier joins the company. This table demonstrates that personal characteristics of the new soldier have no bearing on treatment when assignment controls are included in the regression. This result underlies the identification strategy. Assignment controls are based on the applicable regulations that govern general assignment of service members (AR 600-14) and assignment of females to units with a direct combat mission (AR 600-13). The separately listed covariates are entry characteristics of the new soldier that are not considered in the assignment process.
* p<0.10, ** p<0.05, *** p<0.01

Table 1.3: New Soldier CE Participation and the Existing Company Human Capital Environment (Nonlinear Specification)

Ex ante CE participation is measured by indicators for quartile of assignment
Binary dependent variable is new soldier CE use by month 9

	(1)	(2)	(3)	(4)
4th qtile (top) CE	0.156***	0.157***	0.157***	0.155***
(junior enlisted)	(0.019)	(0.019)	(0.019)	(0.020)
3rd qtile CE	0.066***	0.066***	0.067***	0.069***
(junior enlisted)	(0.013)	(0.013)	(0.013)	(0.014)
2nd qtile CE	0.009	0.009	0.009	0.007
(junior enlisted)	(0.008)	(0.008)	(0.008)	(0.008)
AFQT		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
some college		0.023	0.009	-0.000
		(0.015)	(0.016)	(0.016)
college degree		-0.088***	-0.118***	-0.121***
		(0.016)	(0.018)	(0.017)
age			0.004**	0.004*
			(0.001)	(0.001)
black			0.040***	0.040***
			(0.009)	(0.010)
Hispanic			0.024*	0.019*
			(0.009)	(0.009)
other race			0.045**	0.050***
			(0.014)	(0.013)
female	0.0730***	0.0768***	0.065***	n/a
	(0.0144)	(0.0146)	(0.016)	
assignment controls	Yes	Yes	Yes	Yes
Observations	10141	10141	10141	9289

For columns 1-4, standard errors are clustered at the company level. 4th quartile CE companies have CE participation rates above 10 percent; 3rd quartile above 6 percent; 2nd quartile above 2 percent. Assignment controls include military occupation and year-month of initial assignment to the company. I exclude females from column 4 as an initial robustness check.
* p<0.10, ** p<0.05, *** p<0.01

Table 1.4: New Soldier CE Participation and Contemporary Peer CE Participation

Contemp CE rate is measured by participation within last 3 mos
Binary dependent variable is new soldier CE use by month 9

	(1)	(2)	(3)	(4)	(5)
contemp CE rate	1.437***	1.372***	0.734***	0.554***	0.439**
(junior enlisted)	(0.159)	(0.136)	(0.199)	(0.160)	(0.169)
AFQT	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
some college	0.008	0.009	0.011	0.012	0.011
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
college degree	-0.114***	-0.115***	-0.114***	-0.113***	-0.114***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
age	0.004**	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
race indicators	Yes	Yes	Yes	Yes	Yes
assignment controls	Yes	Yes	Yes	Yes	Yes
peer mean characteristics	No	Yes	Yes	Yes	Yes
location controls	No	No	Yes	Yes	Yes
battalion controls	No	No	No	Yes	Yes
sergeants CE rate	No	No	No	No	0.299***
					(0.103)
Observations	10141	10141	10141	10141	10141

Standard errors are clustered at the company level in all regressions. Assignment controls include military occupation and year-month of initial assignment to the company. Peer mean characteristics are by company for junior enlisted and include aptitude, education, and age. Location and and battalion controls are fixed effects based on Army base and higher headquarters to which the company is assigned, respectively. Sergeants CE rate is the contemporary participation rate of the sergeants who are assigned to the company.
* p<0.10, ** p<0.05, *** p<0.01

Table 1.5: Incumbent Peer CE Use and New Soldier Participation

New soldier CE use by month 9 is a binary independent variable
Dependent variable is incumbent peer group CE rate 9 months after new soldier arrives

	(1)	(2)	(3)	(4)	(5)
new soldier CE use by month 9	0.029***	0.027***	0.014***	0.009***	0.008***
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)
AFQT	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
some college	-0.004	-0.004**	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
college degree	-0.001	-0.002	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
age	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
race indicators	Yes	Yes	Yes	Yes	Yes
assignment controls	Yes	Yes	Yes	Yes	Yes
peer mean characteristics	No	Yes	Yes	Yes	Yes
location controls	No	No	Yes	Yes	Yes
battalion controls	No	No	No	Yes	Yes
sergeants CE rate	No	No	No	No	0.123**
					(0.048)
Observations	10141	10141	10141	10141	10141

Standard errors are clustered at the company level in all regressions. Assignment controls include military occupation and year-month of initial assignment to the company. Peer mean characteristics are by company for junior enlisted and include aptitude, education, and age. Location and battalion controls are fixed effects based on Army base and higher headquarters to which the company is assigned, respectively. Sergeants CE rate is the contemporary participation rate of the sergeants who are assigned to the company.
* p<0.10, ** p<0.05, *** p<0.01

Table 1A.1: Summary Statistics for New Soldiers across Samples

These are newly assigned soldiers who spent at least 9 months in the company.
Non-sample soldiers are excluded from main analysis because of assignment to a brigade that had a combat deployment for some part of 2012-2013.

	sample soldiers			non-sample soldiers		
	n	Mean	SD	n	Mean	SD
AFQT	10141	57	18	41763	59	19
GED	10141	0.03	0.18	41763	0.04	0.20
high school graduate	10141	0.88	0.33	41763	0.86	0.35
some college	10141	0.05	0.23	41763	0.06	0.24
college graduate	10141	0.03	0.18	41763	0.04	0.19
age	10141	21	2.83	41763	22	2.95
white	10141	0.59	0.49	41763	0.65	0.48
black	10141	0.21	0.40	41763	0.16	0.37
Hispanic	10141	0.14	0.34	41763	0.13	0.34
other race	10141	0.07	0.25	41763	0.05	0.23
male	10141	0.92	0.28	41763	0.93	0.25
female	10141	0.08	0.28	41763	0.07	0.25
combat career field	10141	0.61	0.49	41763	0.62	0.48
logistics career field	10141	0.39	0.49	41763	0.38	0.48

Source: Office of Economic and Manpower Analysis.

Table 1B.1: New Soldier CE Participation and the Existing Company Human Capital Environment (Linear Specification, with Common Shocks Analysis)

Ex ante CE participation is measured by the percentage using CE in company
Binary dependent variable is new soldier CE use by month 9

	(1)	(2)	(3)	(4)	(5)
ex ante CE rate	1.022***	0.955***	0.350***	0.163*	0.132
(junior enlisted)	(0.074)	(0.069)	(0.131)	(0.084)	(0.091)
AFQT	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
some college	0.010	0.011	0.012	0.012	0.012
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
college degree	-0.115***	-0.112***	-0.110***	-0.109***	-0.108***
	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)
age	0.004***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
race indicators	Yes	Yes	Yes	Yes	Yes
assignment controls	Yes	Yes	Yes	Yes	Yes
peer mean chars	No	Yes	Yes	Yes	Yes
location controls	No	No	Yes	Yes	Yes
battalion controls	No	No	No	Yes	Yes
sergeants CE rate	No	No	No	No	Yes
Observations	10141	10141	10141	10141	10141

Standard errors are clustered at the company level in all regressions. Assignment controls include military occupation and year-month of initial assignment to the company. Peer mean characteristics are by company for junior enlisted and include aptitude, education, and age. Location and battalion controls are fixed effects based on Army base and higher headquarters to which the company is assigned, respectively. Sergeants CE rate is the contemporary participation rate of the sergeants who are assigned to the company.
* p<0.10, ** p<0.05, *** p<0.01

Table 1C.1: New Soldier CE Participation and Peer Mean Characteristics

This is reduced form estimation - equation (1.4) in the paper
Binary dependent variable is new soldier CE use by month 9

	(1)	(2)	(3)
AFQT	0.001**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
some college	0.010	0.011	0.011
	(0.016)	(0.016)	(0.016)
college degree	-0.114***	-0.113***	-0.113***
	(0.017)	(0.018)	(0.018)
age	0.004**	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
race indicators	Yes	Yes	Yes
assignment controls	Yes	Yes	Yes
peer mean age	0.008	0.013*	0.013*
	(0.006)	(0.007)	(0.007)
other peer mean characteristics	Yes	Yes	Yes
location controls	Yes	Yes	Yes
battalion controls	No	Yes	Yes
sergeants CE rate	No	No	Yes
Observations	10141	10141	10141

Standard errors are clustered at the company level in all regressions. Assignment controls include military occupation and year-month of initial assignment to the company. Other peer mean characteristics are by company and include aptitude and education. Location controls and battalion controls are fixed effects based on Army base and higher headquarters to which the company is assigned, respectively. Sergeants CE rate is the contemporary participation rate of the sergeants who are assigned to the company.
* p<0.10, ** p<0.05, *** p<0.01

CHAPTER 2

Marching Across Generations? An Analysis of the Benefits Transfer Provision of the Post-9/11 GI Bill

with Benjamin L. Castleman and William L. Skimmyhorn

Abstract

The post-9/11 GI Bill provides a unique form of deferred compensation in which the employee receives generous education benefits that can be transferred to a family member in exchange for additional military service. Whether soldiers should transfer benefits to a spouse or children is essentially a multi-period optimization problem. We test predictions from our economic model of benefits transfer against rich observational data from the program. Our analysis reveals clear socioeconomic differences in patterns of transfer: utilization rates are highest among senior service members who earn higher wages, are near or beyond pension eligibility, and have already completed their education. Leveraging variation across cohorts in eligibility for the transfer provision, we use difference-in-differences estimation to find that the policy had a small stabilizing effect on Army retention.

Introduction

Various public and private policies encourage employees to incur additional labor in the near term for financial benefits in the future. For instance, workers may qualify for a defined-benefit (DB) pension or accumulate stock options by choosing to remain with the same firm for an extended period; similarly, aging workers can draw higher Social Security payments later in life by working more or delaying the timing of their initial benefits claim. From the firm perspective, deferred compensation plans reduce personnel turnover, encourage worker effort, and regulate retirement flows (Gustman, Mitchell, and Steinmeier, 1994; Lazear, 1979, 1990). From a public policy perspective, programs such as delayed social security receipt may increase labor force participation and reduce present strain on social welfare programs (Diamond and Gruber, 1999). In some occupations, such as emergency response or the military, deferred compensation programs may be particularly necessary for the employer to retain workers – given the high costs of firm-specific training and the risks faced by employees.

For the individual, however, these benefits programs and policies pose an economic dilemma: the worker must weigh the value of the benefit against the opportunity cost of the additional time spent working—and in hazardous professions, ongoing risk of injury or death. On the one hand, these policies offer workers the opportunity to accumulate additional expected financial benefits for themselves or their families. On the other hand, such policies induce workers both to forego the benefits of other employment opportunities and to potentially take on additional hazard. Existing research across general occupations shows that workers covered by pension plans have lower turnover rates than workers without pensions (Gustman and Steinmeier, 1993;

Ippolito, 1987) and that a small but non-trivial fraction of workers delays social security benefits receipt (Coile et al, 2002; Shoven and Slavov, 2012). Studies of retention in the military confirm the prominent role of retirement benefits in stay-or-leave decisions faced by service members (Daula and Moffitt, 1995; Ausink and Wise, 1996). The literature on the role of deferred compensation in retention in hazardous occupations is otherwise limited.[27]

In the current paper, we examine a new form of deferred compensation introduced in the post-9/11 GI Bill that allows currently serving military service members to transfer a generous post-secondary educational benefits package to a spouse or child. In order to transfer benefits, the service member must already have at least six years of service and agree to serve four more years on active duty. The transfer policy's implementation in August 2009 – near the height of US involvement in ground combat in Afghanistan and Iraq – amplifies the dilemma for service members weighing benefits transfer against continued service in a hazardous profession. We model this dilemma as a multi-period household optimization problem and test predictions from the economic model against rich observational data that includes transfer decisions made by hundreds of thousands of US Army service members. We also estimate, using a difference-in-differences estimation strategy, whether the transfer policy led to an increase in retention for eligible soldiers with dependents relative to a variety of comparison groups who were either ineligible for the transfer benefit or less likely to be responsive to its provisions.

Our work makes several contributions to the existing literature. First, we develop an economic model for how individuals weigh intrafamily benefits against additional

[27] Numerous authors document the positive relationship between present-time compensation – measured by wages – and hazardous work conditions. See, for instance, Garen (1988), Kniesner and Leeth (1991), and Dorman and Hagstrom (1998).

labor, especially when faced with the prospect of injury or death in a hazardous profession. Second, we provide descriptive evidence on patterns of benefit transfer by education level, occupational experience, prior hazard exposure, and potential value of the benefit to the individual, to investigate whether groups who appear to benefit from the transfer policy take it up at high rates, or whether information frictions and hassle costs may impede use of the policy for certain groups. Finally, we present plausibly causal evidence on how deferred compensation policies that trade an intrafamily benefit for additional labor impact retention in a very large firm with hazardous employment.

Our analysis reveals that the GI Bill transfer provision is most highly utilized by senior service members who earn higher wages, have tenure near or beyond pension eligibility, and have already completed their education. Takeup rates among eligible soldiers are lowest for junior enlisted service members who earn the lowest wages and typically have completed only a high school education. We find that the transfer provision had a modest but positive retention effect for midcareer enlisted soldiers in the years immediately following program implementation, indicating some willingness of parents to extend hazardous military careers in exchange for future educational benefits for their children.

The remainder of the paper proceeds as follows. In the next section, we provide background information on the GI Bill and the military personnel system. Section III summarizes our economic model of benefits transfer. Section IV describes the data while Section V presents our main descriptive findings on who transfers benefits. Section VI details our empirical strategy for estimating a causal retention effect and Section VII presents those results. Section VIII concludes.

II. Background

A. GI Bills

The GI Bill is an education benefits program that has for decades facilitated the retraining and reintegration of American military service members into society and the workforce. Although Congress has updated the GI Bill numerous times since its inception in 1944, the focus on education and retraining has remained unchanged. The first GI Bill of Rights was signed into law as the Servicemen's Readjustment Act of 1944 by President Franklin D. Roosevelt on June 22, 1944.[28] Once legislation was approved, the Veterans Administration (VA) bore responsibility for implementing the key provisions of the GI Bill: education and training, loan guaranty for homes, farms, or businesses, and unemployment pay. By the time the first GI Bill ended in 1956, nearly half of the 16 million returning World War II veterans had used its educational or training benefits in some form.[29]

There have been two significant updates to the GI Bill in the four decades since the US moved to an all-volunteer force in 1973. First, in 1984, former Mississippi Congressman Gillespie V. "Sonny" Montgomery revamped the GI Bill and it has borne his last name ever since as the Montgomery GI Bill, or MGIB. This program was opt-in, requiring the service member to forego $100 in monthly pay the first twelve months of active duty, and mandated completion of continuous active duty service for at least two years in order to gain benefit eligibility. In the most recent update to the GI Bill, under

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[28] The impetus for the bill was the perceived mismanagement of millions of US veterans returning home from World War I decades earlier; many received only $60 allowance and a train ticket home, with the mass of returning veterans linked to high unemployment on return from service. Nevertheless, there was intense debate in Congress about how and when to implement a program of veterans' benefits.
[29] See "Education and Training: History and Timeline," U.S. Department of Veterans Affairs website, available at www.benefits.va.gov/gibill/history.asp.

the Veterans Educational Assistance Act of 2008, or post-9/11 GI Bill, benefits reached greater levels of generosity: 36 months paid tuition at the most expensive public university in the state home of record (or its monetary equivalent at a private institution) in addition to a monthly housing allowance and stipend for books and supplies. Moreover, for the first time, benefits eligibility was extended to commissioned officers. The primary objectives of the new legislation were to provide benefits to reservists on par with what active duty service members receive and to update benefits comprehensively in light of rising costs in higher education. Secondary goals were to support military recruiting goals and to increase service member retention through the transfer provision.[30]

Most relevant for our analyses, under the post-9/11 GI Bill, all active-duty service members with six or more years of service gained the option to transfer educational benefits to a spouse or child. Service members are required to commit to serving four more years on active duty in order to transfer benefits. An eligible service member can transfer up to 36 months of benefits and distribute that benefit among multiple dependent family members. To initiate transfer, the service member need only transfer at least one month of benefits[31] to one family member; he can subsequently change the recipients and distribution of benefits. The implementation date for establishing benefits transfer was August 1, 2009.

[30] See Dortch (2012), which is a Congressional Research Service report that summarizes the debate over the framing of the new legislation, including its founding objectives, and also presents other issues related to the bill.

[31] Many service members transfer only one month of benefits to one recipient, knowing that they can re-allocate the full 36 months at a later date. The observed data therefore reflect a downward bias in the amount of benefits transferred. As a result, the analysis that follows focuses only on the extensive margin of transfer (initial transfer of any benefit) and does not address the intensive margin (how much was transferred and to whom).

The GI Bill has been the subject of multiple academic studies given how it relates to the important topics of educational subsidy, veterans welfare, and public finance. Numerous studies of the early GI Bills have found positive effects on college enrollment or attainment for veterans, see for instance: Bound and Turner (2002) and Angrist and Chen (2011). A more recent paper by Simon, Negrusa, and Warner (2010) focuses on veterans who separated after 1990 and finds small effects from the enhanced benefit levels of the MGIB relative to older bills. Barr (2015) finds that the higher level of benefits introduced with the post-9/11 GI Bill increased college enrollment of veterans by as much as 20 percent, while also encouraging more enrollments in four-year educational institutions.

B. Key Features of the Military Personnel System

There are several unique features of the military personnel system that are relevant to this study. Enlisted members serve on contracts of fixed length, typically of three or four years; when the current contract ends, the soldier must reenlist to continue serving on active duty. A soldier with an expiring contract must be in good standing with the military in order to be eligible for reenlistment.[32] For an eligible soldier, the reenlistment opportunity window (ROW) typically opens 15 months before the end date of the current contract and closes three months before the end date of that contract (as depicted in Figure 2.1). The soldier must make a retention decision in this 12 month window; if he decides not to reenlist, he leaves active duty 90 days later at the contract

[32] For the purpose of reenlistment eligibility, good standing with the military entails satisfactory job performance, meeting health and physical conditioning requirements, and avoiding major disciplinary infractions (such as general misconduct, drug use, or abuse of alcohol).

end date.[33] Later in the paper, we will rely on variation in the timing of ROWs relative to transfer provision implementation (August 2009) in order to estimate a policy-induced retention effect.

Officers are appointed as lieutenants upon commissioning from either a military academy, ROTC program, or Officer Candidate School (OCS). Depending on source of commission, officers have an initial active duty service obligation ranging from three to five years (normally, with some additional time in the reserves). After that time, they may remain on active duty but typically do not have contractual obligation to serve for a minimum amount of additional years. Nearly all officers have already finished college upon commissioning; those who have not must complete a bachelor's degree within three years in order to be competitive for promotion.

As mentioned in the introduction, the military pension has a large influence on the retention behavior of service members. Perhaps unsurprisingly, the effect is strongest for senior service members. The current system features an all-or-nothing defined benefit pension; service members become pension eligible after 20 years of active duty service.[34] Since GI Bill transfer requires a commitment to four more years on active duty, it is useful to consider service members' willingness to serve that extra time in the absence of the benefit. We plot in Figure 2.2 conditional four-year continuation rates for those on

[33] A service member attempting to reenlist after the ROW can submit an exception to policy request through the first Colonel in the chain-of-command; the Army's Human Resources Command must then approve the request. This process is rare and occurs for less than 2% of the soldiers considered in this study.

[34] Starting in 2016, the military is phasing in a new pension system with 401(k)-like contributions for more junior service members and a smaller defined benefit for those who serve until retirement. All officers and enlisted considered in this study were subject to the all-or-nothing pension scheme described in the body of the paper.

active duty in the Army in 2005.[35] We are interested in the probability that a service member is still on active duty in 2009, because a hypothetical benefits transfer in 2005 would have required continued active service until at least 2009. Figure 2.2 shows that conditional continuation rates increase steadily after the first contract ends, are greater than 80% after 10 years, and approach 100% as the service member nears 16 years, decreasing thereafter. The structure of the military pension system clearly influences this behavior, consistent with theories of deferred compensation and the research findings already cited. This suggests that we are unlikely to see a transfer-induced retention boost for service members with 10+ years of service, since their likelihood of continued service is already very high. We return to the discussion of retention behavior in Section VI.

III. Economic Model

In this section, we summarize the key dimensions of and predictions from our economic model of intergenerational benefit-labor tradeoff. Appendix 2A contains the complete details. The broad purpose of the model is to understand the dilemma facing people in hazardous professions who might take on additional labor in exchange for intrafamily benefits. We tailor the model to the specific case of GI Bill benefits transfer in order to make predictions about what types of military parents might transfer benefits to a child. Testing these predictions against observational data will allow us to understand the new benefit in terms of the socioeconomic populations that it appeals to.

Our model is in the spirit of multi-period household decision-making in Becker and Tomes (1986) and Acemoglu and Pischke (2001). The model contains one parent and one child in a unitary household. There are exactly three periods in the model, which

[35] We choose 2005 for this exploration because 2005 is the last year for which conditional 4-year continuation rates would be unaffected by the new GI Bill and associated benefits transfer provision.

begins with the service member parent eligible to transfer benefits (i.e., still on active duty, 6+ years of service, has a child). The parent dies at the end of period 2. The parent faces key decisions of whether to transfer benefits or to use the education package himself (period 1) and then whether to pay the child's tuition (period 2) in the case of no transfer. The parent incurs additional hazard – the cost of military service (CMS) – if he agrees to transfer. The decisions made by the parent directly influence the child's consumption (in period 3 of the model) through the wage earnings channel.

The key economic tradeoff in our model is that the parent incurs the cost of military service (CMS) – by agreeing to additional active-duty military service – if he transfers benefits to the child. However, by transferring benefits, he provides a college education for the child without having to pay tuition during period 2. A further complication arises for a parent who has not completed his education; he foregoes own use of the GI Bill by agreeing to transfer benefits.

Solving the model (see Appendix 2A) leads to propositions that: 1) more educated parents are more likely to transfer benefits, and 2) parents with a lower CMS are more likely to transfer benefits. We cannot fully characterize CMS because of unobserved factors such as personal taste for military service. However, we argue based on the structure of the military and the existing pension system that parents with lower CMS have, on average, higher years of service, higher military rank, and less-intense recent combat deployment history.

IV. Data

The principle data for this project comes from four sources. First, the enlisted and officer master files, provided by the US Army's Office of Economic and Manpower

Analysis, contain rich soldier-level demographic, financial, and occupational data from the point of entry into the service as well as through subsequent military assignment. Second, the Army pay file contains information on receipt of hazardous fire pay, which allows us to observe how many months each year the service member served on a combat tour. Third, we have information on military families from the Defense Enrollment Elibility Reporting System (DEERS). The DEERS data are annual snapshots and include the date of marriage to spouse and number of children by age range.[36] Fourth, the Veteran's Administration (VA) – which oversees the GI Bill program – has provided data on individual service member benefits transfer, including the date of initial benefits transfer. Combining these data sources at the level of service member by year, we have an annual panel that depicts the details and timing of military career events, family size, and GI Bill benefits transfer (if applicable) for more than 1 million active-duty Army service members.

In the analysis that follows, we classify all service members – both enlisted and officer – by cohort of initial eligibility to transfer benefits (i.e., 2009-2015). As depicted in Figure 2.3, many service members in the first eligibility cohort (2009) are either high-ranking officers or senior enlisted soldiers who had exceeded the six years of service required for eligibility on August 1, 2009. Subsequent cohorts are much smaller and also more junior in their military tenure. In these subsequent cohorts, midcareer and junior

[36] The data on family composition in DEERS are self-reported. However, incentives are aligned for ensuring data accuracy: the service member must provide supporting documentation (marriage or birth certificates) to enroll dependents and DEERS enrollment is the gateway to the military's generous health care benefits plan.

enlisted soldiers account for more than 75% of the service members gaining transfer eligibility. [37]

In Table 2.1, we compare eligibility cohort 2009 to the smaller cohorts that followed. We treat the former as standalone because of its size and uniqueness (relative to subsequent cohorts) and also focus on cohort 2012 because it is representative of the smaller and younger cohorts that followed 2009. Summary statistics in Table 2.1 show that the 2009 cohort is different both from the pooled 2010-2015 cohort group and 2012 as a standalone. Panel A reveals that those in the initial cohort are much more likely to have already served 10 years or more, have higher levels of education, and are more likely to have high-school-aged children. The initial eligibility group has also transferred benefits at much higher rates (Panel B); the marginal annual transfer rates for the 2009 cohort are nearly twice those of the 2012 cohort for every year of comparison. The marginal annual transfer rate is the percentage of eligible cohort members in that year who made an initial benefits transfer. To be eligible for initial transfer, the service member must still be on active duty and have not yet transferred benefits.

V. Descriptive Results

We test our economic model of benefits transfer by examining detailed summary statistics of transfers made by the 2009 and 2012 eligibility cohorts. [38] Descriptive analysis confirms many of the predictions from the model. Figure 2.4 shows that officers from the 2009 cohort have marginal and cumulative transfer rates that are strictly higher

[37] Throughout the analysis, we collapse military rank into five broad categories. Senior officers are in the rank of major (O-4) or above and have 10 or more years of service as commissioned officers. Junior officers are lieutenants (O-1/O-2) and captains (O-3). Senior enlisted are high-ranking sergeants (E-7 and above) with typically 15+ years of service. Middle enlisted are junior sergeants (E-5/E-6). Junior enlisted are soldiers in the rank of E-1 to E-4.

[38] The next several paragraphs and figures are based on eligibility cohort 2009; descriptive analysis of the transfer behavior of eligibility cohort 2012 shows similar patterns to cohort 2009. See Appendix 2B for more details.

than those of enlisted.[39] The cumulative transfer rate each year for a cohort is the percentage of eligible cohort members who have made an initial benefits transfer since gaining elibility. By the end of 2015, more than 33,000 officers out of 54,037 from cohort 2009 had transferred benefits (greater than 60%). Transfer rates for enlisted members are significantly lower: by the end of 2015, about 54,000 out of more than 140,000 initially eligible had transferred benefits (39%).

The decision to transfer benefits is strongly related to the education level and time in service of the parent. More educated parents – whether officer or enlisted – are more likely to transfer benefits, as shown in Panel A of Figure 2.5. By 2015, nearly 70% of college-educated individuals from the 2009 cohort had transferred benefits, whereas only 30% of those with only a high school education had transferred benefits. Panel B of Figure 2.5 shows that transfer likelihood increases with time in service. More than 50% of eligible service members with 10+ years of service upon gaining eligibility had transferred benefits by 2015; fewer than 30% of those with less than 10 years had transferred in that same time period. This pattern is nearly identical for transfer rates by level of military rank (results not shown).[40] Taking these results together, it is easy to see that there are clear differences in transfer behavior by socioeconomic status: those eligible parents who are higher SES more likely to transfer benefits. For instance, a representative senior officer is a lieutenant colonel with 19 years of service, a graduate

[39] We plot marginal transfer rates in Figures 2.4 and 2.5 rather than empirical survivor functions (of the option to transfer) because service members who leave active duty forfeit the ability to transfer GI Bill benefits to a family member. Many eligible individuals leave without transferring benefits; for example, more than half of the enlisted service members from the 2009 eligibility cohort with only a high school education left the service before 2015 without transferring benefits. We address this topic again in Section VIII.

[40] The “up-or-out” promotion system in the military influences the strong correlation between rank and time in service; those who continue to serve must be promoted at certain intervals which forces rank and tenure to move in near concurrence.

education, and wages in 2010 of nearly $8000 per month; his likelihood of transfer if eligible was 25% in 2010. In contrast, a typical middle enlisted soldier is a sergeant with 8 years of service, high school education, and wages in 2010 of about $2800 per month; his likelihood of transfer was about 6%.[41]

The noticeable kinks in marginal transfer rates in 2013 that appear in Figures 2.4 and 2.5 are due to a policy change enacted that year affecting the senior service members typical of the 2009 cohort. Prior to 2013, service members who were very close to or beyond 20 years (pension eligibility) could transfer GI Bill benefits without incurring the full four-year service requirement. The 2013 policy change mandated a four-year contract for every transfer, regardless of time in service, but the policy was well publicized[42] before the change date (August 1, 2013). Thus, there was a predictable surge during 2013 in "free" transfers by senior officers and enlisted who had not yet transferred benefits. We discuss the implications of this unusual spike in transfers in Section VIII.

There are some additional insights that emerge from the descriptive analysis. First, one prediction from our economic model is not supported by the data: we find only small differences in transfer behavior based on recent deployment history.[43] One plausible explanation for the non-finding here is that there are differences in (unobservable) taste for military service for individuals with repeated deployments relative to other soldiers and that these differences influence the decision to transfer

[41] The wages reported in this example are only military base pay; service members also receive a housing allowance, family health care plan, and other benefits that markedly increase total compensation.
[42] See for instance, "Change to Army Post-9/11 GI Bill transfer policy takes effect Aug 1," US Army Official Website, July 8, 2013, www.army.mil, or "Troops nearing retirement can't transfer GI Bill benefits without giving 4 more years," Stars and Stripes Newspaper, June 25, 2013, www.stripes.com.
[43] We measure recent deployment history by the number of months receiving hostile fire pay in the last 3 years. For the 2009 eligibility cohort, the mean value is 7.4 months (out of 36) upon gaining transfer eligibility.

benefits and incur additional service. Next, we find differences in transfer behavior related to observed family structure (recall that our model assumes a unitary household with only one parent and one child). There are actually some educational transfers – to a spouse – when no children are present. However, this occurrence is uncommon and we observe that transfer is much more likely to occur when there is even one child in the family. Transfer is more likely when the military parent has more than one child. Age of the child also appears to be important in the decision making process: transfer is far more likely when the parent has a child who is between the ages 14-17, where the higher educational expenses facing the family are likely to be more salient.

To complete the descriptive analysis, we run linear regressions that analyze transfer behavior for the 2009 and 2012 cohorts – these results appear in Table 2.2.[44] The binary outcome in the regressions is whether the service member made an initial benefits transfer within some specified time period. We see confirmation in Table 2.2 of many model predictions and trends revealed in the preceding graphical analysis. First, there is a strong association between transfer likelihood and being a senior service member. This relationship is most evident in column 1, which considers transfers made by the 2009 cohort within that group's first three years of eligibility.[45] Conditional on education, service characteristics and family structure, senior personnel – whether officer and enlisted – are 20 percentage points (pp) more likely to transfer benefits than junior enlisted personnel, whose baseline transfer rate is approximately 15 percent. This strong result holds across cohorts and time horizons for all regressions in Table 2.2. Having a

[44] Results are similar for survival model specifications, wherein the hazard event is the parent's initial transfer of benefits.

[45] Given the unprecedented nature of the transfer provision (and the potential information problems near implementation), it is practical to consider at least some transfer time horizons longer than one year. As such, we use 3-yr time horizons for the transfer regressions that appear in columns 1 and 4 of Table 2.2.

college education or graduate degree is also strongly associated with transfer: this is the main source of differential behavior for senior officers versus senior enlisted.[46] For instance, among the 2009 cohort, those with a graduate degree are 17 pp more likely to transfer within 3 years than soldiers with just a high school education. Tenure in the military is another prominent predictor of transfer, with transfer likelihood increasing by 0.5 to 1 pp for every additional year on active duty. Unsurprisingly, the coefficients on both senior enlisted and senior officer are large and statistically significant for transfers in the year 2013 (columns 3 and 5 in Table 2.2), when many high-ranking service members made "free" benefits transfers just ahead of the policy change already discussed. Finally, we observe that having a high-school-aged child increases the likelihood of benefits transfer. For cohort 2009 across the first 3 years (column 1), the magnitude of the increased transfer likelihood is approximately 10 pp. Having a high-school-aged child is likewise positive and significant in the other regressions in Table 2.2 (columns 2-5).

VI. Empirical Strategy for Retention Analysis

A. Initial Analysis

In the remainder of the paper, we consider whether the transfer provision had any retention effects for the active duty US Army. Identifying the causal impact of the transfer provision is challenging in the first order because of its universal rollout in August 2009. Moreover, many of the soldiers who became eligible for transfer at policy implementation would have chosen to stay in the Army anyways. This is particularly

[46] One surprising finding is the negative coefficient on junior officers in column 2, since nearly all of these individuals have a college degree. Given that this is year 2010 (for the initial eligibility cohort), we could be picking up information frictions in this coefficient. It could also be that the junior officers want to hold onto the benefit for own use – perhaps due to the newness of this benefit for officers.

true for the 2009 cohort – which accounts for nearly 75% of the total transfers made as of late 2015 and contains many senior service members who were very near or had already attained pension eligibility. As we show in Figure 2.2, senior service members with 10-16 years of service are highly likely to serve four or more years, presumably in order to qualify for the Army pension.

These points raise the question of which soldiers' retention decisions were likely to be affected by the introduction of the transfer provision. As noted, the existing all-or-nothing pension system leads senior service members to supply a nearly inelastic labor supply as they approach 20 years. At the other end of the career spectrum, first-term soldiers have the lowest retention rates – and so potentially could be influenced to stay by the right incentive – yet these soldiers are not even eligible for the transfer program until they have both started families <u>and</u> reached 6 years of service. It is unlikely that a single soldier would be influenced by benefits transfer given the hazard risk entailed by continued military service in this time period (repeated combat deployments to Afghanistan and Iraq). Furthermore, for a new soldier on a typical initial contract of 3 or 4 years, he must make a first reenlistment (usually 3 to 5 more years) just to remain on active duty through the 6 year mark. As this second term is expiring, he is at 6-9 years of service and potentially influenced by the transfer provision to reenlist again. Thus, it is precisely at this near-midcareer juncture where we expect to detect a transfer-related retention effect, if at all.[47]

B. Sample

[47] We focus on enlisted service members for this portion of the analysis since officers do not typically serve on contracts once they have fulfilled the commissioning obligation.

We mark eligible enlisted soldiers by the last month of their reenlistment opportunity window, or ROW end month (which is three months prior to the end of the current contract, as depicted in Figure 2.1). Based on established reenlistment procedures, the ROW end month is the deadline by which an eligible soldier must decide whether or not to reenlist. The years 2008-2011 are the focus of this analysis since the benefits transfer provision was implemented in the middle of this time period. The sample consists of 308,223 reenlistment-eligible Army soldiers in 48 ROW end months, from January 2008 thru December 2011.

Summary statistics for the reenlistment-eligible sample appear in Table 2.3. In Panel A, we present demographic and Army career characteristics; eligible soldiers who have children are slightly older and more senior both in rank and years of service than service members who do not. Panel B shows mean reenlistment rates by family type and years of service band. Eligible service members with 3-5 years of service and no dependents are 55% likely to reenlist. Contrastingly, those who are 10+ years of service and have a child are 95% likely to reenlist, also with no difference before and after the transfer policy implementation. In between these extreme values, we note that reenlistment likelihood increases monotonically both in family composition and years of service.

C. Difference-in-Differences

To address the challenges articulated above and attempt to identify a causal retention effect, we adopt a difference-in-differences framework. We compare the change in retention behavior of service members with a child (treatment) between eligible and ineligible cohorts versus the concurrent changes for soldiers with no dependents (control) between eligible and ineligible cohorts in order to isolate the effects of the GI Bill transfer provision.

To estimate the impact of the transfer provision, we estimate the following difference-in-differences model:

$$R_{it} = \alpha + \varphi * post_t + \gamma * children_i + \gamma * post_t * children_i + X_{it} * \beta + \tau_t + \varepsilon_{it} \qquad (2.1)$$

In equation (2.1), R_{it} is a retention-related decision made by soldier i at time t. $post_t$ is an indicator variable for whether the service member faced a retention decision (whether to reenlist or not) after August 1, 2009, and $children_i$ is an indicator variable for whether the service member had a child (or multiple children) at the time of the retention decision. X_{it} is a vector of control variables with information on the service member and τ_t are calendar month fixed effects that account for cyclicality in retention. γ is the DD parameter that measures the change in retention for service members with at least one child who faced a retention decision after GI Bill transfer became an option. The identifying assumptions in this model are: 1) that the implementation date of the GI Bill transfer provision is unrelated to the timing of the service member's retention decision, and 2) that service members without dependents capture what the trends in retention would have been for service members with a child over the time period of our analysis, in the absence of the transfer provision (parallel trends). In all regression specifications, we compute robust standard errors.

To address the first DD assumption, we examine the timing of the policy implementation relative to densities by family type (single soldier versus soldier with dependents) to see whether individuals might have manipulated the timing of their contract end dates in response to the policy implementation date. We see no discernible shift in these densities around the time of GI Bill transfer implementation (see Figure

2B.1 in the Appendix), indicating that soldiers did not manipulate their contract end dates to be on the other side of program implementation

The second DD assumption requires that single soldiers are an appropriate comparison control group for soldiers with a child. In Figure 2.6, we see that the reenlistment rates for the two groups move together over time prior to the policy implementation, with the reenlistment rate for those with a child always higher but following parallel trends.

Finally, consistent with the reasoning at the beginning of this section, we compare DD estimates for groups of soldiers at different points in their careers – expecting to observe results for midcareer soldiers, if at all. Accordingly, we differentiate among subgroups of reenlistment-eligible service members with 3-5 years of service (no effect expected), 6-9 years of service (potentially an effect), and 10+ years of service (no effect expected).[48]

VII. Results for Retention Analysis

A. Main Results

In Panel A of Figure 2.6, which pools all soldiers by years of service, we observe parallel reenlistment trends for soldiers with a child versus single soldiers but no visible change in that trend difference after policy implementation. However, for the subset of soldiers in the 6-9 years of service range (Panel B), we see graphical evidence that the introduction of the transfer provision may have stabilized retention.[49]

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[48] This approach is suggestive of a triple-difference (DDD) methodology. For ease of exposition and to enable comparisons by career point, we present our model and the associated results as difference-in-differences (DD) – as in equation (1) – but we run separate regressions by years of service band. See Table 2.3.

[49] In both plots that appear in Figure 2.6, we adjust the monthly reenlistment rates for seasonality by controlling for calendar month fixed effects. In the raw plots, the seasonality is most pronounced for eligible cohorts with ROW end month in July, which is 90 days prior to the start of the new fiscal year and

Specifically, the retention rates for single soldiers dipped in the years 2010-2011 while there was no such decline for soldiers with a child. The transfer provision appears to have incentivized midcareer soldiers with children to remain in the service during this time when those without children were more likely to get out.

Table 2.4 presents regression estimates of equation (2.1) that confirm the graphical trends observed in Figure 2.6. As expected, we see no retention effect for the 3-5 years or 10+ years of service groups; the coefficient estimates for these populations are practically zero (columns 2 and 4). However, a midcareer military parent facing a retention decision after transfer provision implementation is 1.80 percentage points more likely to reenlist (column 3). These results are robust to the inclusion of controls for demographics, military career, education, and calendar month fixed effects that account for cyclicality in reenlistment. This regression result matches what we observe in the reenlistment rates graph in Figure 2.6 and in comparisons of group reenlistment means in Panel B of Table 2.3. Thus, we see evidence of a stabilizing effect on retention for midcareer enlisted with at least one child. Since more than 70 percent of the eligible soldiers in the 6-9 years group choose to reenlist, this 2 pp retention increase is a modest result - approximately a 3 percent increase relative to baseline. Nonetheless, this finding provides evidence that the deferred compensation inherent in the benefits transfer provision has the expected effect of reducing personnel turnover.

B. Robustness Checks

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the associated release of funding for retention. Importantly, that seasonality impact both the treatment and control groups both before and after policy implementation. The calendar month fixed effects also appear in the regression analysis that follows. We gratefully acknowledge author conversations with Deputy Chief of Staff of the Army, G-1 (Personnel), especially MAJ Brian Miller, for assistance in understanding the cause of the reenlistment trends.

The decision in equation (2.1) to compare service members with a child against those with no dependents excludes service members who have a spouse but no children at the time of the reenlistment decision. As a robustness exercise, we re-estimate equation (2.1) for the 6-9 years group but using the full reenlistment-eligible sample, so that we now include the soldiers with a spouse but no children. There is a question, however, of how to classify this soldier-family type with respect to treatment status. Since a service member can transfer benefits to a spouse, we reframe the specification in (2.1) so that the treatment condition is having any *dependent* at all (spouse or child); accordingly, the spouse-only soldiers are in the treatment group.[50] In this case, the difference-in-differences parameter is very close to the original estimate: 1.70 pp. This regression result appears in column 3 of Table 2.5.

Another possible concern with our DD specification lies in how we define the indicator variable $post_t$, which we define based on the timing of the soldier's reenlistment opportunity window (ROW) relative to program implementation (for $post_t = 1$, the ROW ends after August 1, 2009). As shown in Figure 2.1, a soldier who does not reenlist during the 12-month ROW stays on active duty for 90 days before the contract ends. In our study, soldiers whose ROW ends in the summer of 2009 comprise a margin of interest because their ROW expires just prior to program implementation yet they remain on active duty through program implementation. As mentioned in Section II, there is an administrative process for such a soldier to request an exception to policy and reenlist during the final 90 days of the current contract, but this occurrence is rare. We find that

[50] When we use the DD model exactly as specified in (2.1), the spouse-only soldiers are in the *control group* (because the treatment condition is having a child). The results from adding these soldiers to the control group are as expected: the DD coefficient is smaller (0.8 pp) and only marginally significant. See column 2 of Table 2.5.

about 1.5% of our sample from the summer 2009 population reenlist “late” in this manner; these individuals cross over from *before* status to *after* status. In the 6-9 years eligible population, there are 88 such individuals out of more than 5600 soldiers across ROW end cohorts June 2009, July 2009, and August 2009. Our main retention results are robust to excluding these 88 service members from the analysis (1.77 pp, result not shown).

Next, to explore more rigorously that separating timeframe, we consider cutoffs other than August 1, 2009, that might define before-and-after timeframes for the DD estimation. Even though service members could not transfer benefits prior to August 2009, it could be that *anticipation* of program implementation also affected behavior, like service member retention. To explore this possibility, we present in Figure 2.7 Google search trends by month for the phrase “GI Bill transfer.” The vertical axis measures search intensity and shows that the top value, indexed to 100, occurs in July 2013, just before the policy change affecting senior members who had not yet transferred benefits. August 2009 – the implementation date for benefits transfer – shows the next highest index value at 88. However, there is also a noticeable spike in the early summer leading up to August 2009 (seen by index 62 in May 2009). Thus, we consider May 2009 as a potential treatment cutoff date. When we re-estimate equation (2.1) with May 2009 as the cutoff date, the transfer-induced retention effect is 1.27 pp, as seen in column 4 of Table 2.5. This result is similar to that with August 2009 as the cutoff date but smaller, suggesting that anticipation of program implementation did not play a large role in retention decisions.

As a final robustness check, we add monthly data on two important macroeconomic factors – the U.S. unemployment rate and the total number of US troops deployed in Iraq and Afghanistan – that might have affected the individual soldier's retention decision. During the time period of study, the unemployment rate ranged from 4.9% to 10% while the total troop deployment number spanned 95,000 to 182,000. Although these factors are presumably unrelated to the timing of transfer provision implementation, we add these data as a robustness check because they are potentially relevant to the individual's stay-or-leave calculus. Our estimate for the retention effect is robust to inclusion of these controls: the DD retention effect is 1.99 pp, as shown in column 5 of Table 2.5. While the troop deployment number is not a significant predictor in the regression, the unemployment rate is statistically significant and shows a sensible effect: reenlistment for soldiers with 6-9 years of service is 1.3 pp more likely for each percentage point increase in the unemployment rate. Thus, our preferred specification uses August 2009 as the treatment boundary date and provides the 2 pp retention effect when the full covariate set is included.

VIII. Discussion

In this paper, we examine a provision of the post-9/11 GI Bill that allows service members to transfer generous education benefits to a family member in exchange for continued service on active duty. GI Bill transfer is both a complex economic decision for the service member as well as a potentially influential means of deferred compensation that encourages employees with firm-specific experience and skills to provide ongoing labor.

Our analysis reveals clear socioeconomic differences in likelihood of benefit usage, with takeup rates highest among senior service members who earn higher wages, are near or beyond pension eligibility, and have already completed their education. These descriptive findings align with predictions from our economic model of benefits transfer. We also find that the transfer provision had a modest stabilizing effect on Army retention in the years immediately following program implementation, in spite of generally low takeup and possible information frictions that could have limited visibility of the transfer provision.

At the heart of this paper is the question of how individuals resolve the tradeoff between securing intrafamily education benefits and providing continued labor in a hazardous profession. We see that higher-earning, more-educated parents are more likely to transfer benefits, even though the program has the potential to change intergenerational trajectories for other families in which one or both parents have only basic education and lower earnings potential. This outcome resonates with findings from other studies (Bertrand, Mullainathan, and Shafir, 2004; Currie, 2006) in which those who might most benefit from a program are least likely to participate.

Even for the higher-earning populations that are most likely to transfer benefits, there is still evidence of a real dilemma. The spike in "free" benefits transfer in 2013 bears out this point. Recall that senior service members who had not yet transferred benefits rushed to make use of the provision before August 2013 in order to avoid incurring the extra four-year service obligation. This result shows that while the education benefits package is undoubtedly valuable, it does not provide unlimited utility to the household (otherwise senior personnel would have been indifferent about taking it up in 2012 or 2014). Second, the mass transfers in 2013 are a tangible reminder of the significant costs of military service, particularly as experienced soldiers considered the prospect of four more years on active duty when there were still regular deployments to the wars in Afghanistan and Iraq.

There are several topics for future research that emerge from our analysis. First, another potential source of differential transfer behavior by socioeconomic status – left unexplored in the current paper – could relate to information problems. Researchers have noted that a lack of visibility of opportunities likely constrains participation both in higher education (Castleman, 2015; Hoxby and Turner, 2015) and in social benefits programs (Bhargava and Manoli, 2015). In the current setting, some service members might not appreciate the benefits (and costs) of college and so might not be making optimal intergenerational decisions; at the extreme, some might not even know about the option to transfer benefits. It could be that the most junior and lowest-educated service members – who transfer benefits at the lowest rates – are disproportionately affected by informational barriers, although it could also be that these soldiers are simply retaining the educational benefits for their own use and/or are not willing to take on the additional workplace hazard.

Second, the transfer provision could have measureable impacts on educational attainment for military children and even intergenerational mobility within military families. A meaningful number of benefits transfers were made by midcareer or senior enlisted with only high school educational attainment (and that educational demographic is increasingly more represented in the newer eligibility cohorts). Such service members are transferring a generous education benefits package that should make college completion more likely for their dependents. These dependents might thereby attain an educational level that at least one parent never did. As such, GI Bill transferability could significantly impact intergenerational educational mobility. Moreover, given the classroom and behavioral challenges faced by military children due to parental absence (Lyle, 2006) and frequent military moves (Chandra et al, 2010), transferrable education benefits could have an equalizing effect for these children while providing an important compensating wage differential for their military parents.

Finally, it remains an open question whether and to what extent the findings from this paper might generalize to civilian settings. For instance, similar to the military, professions like emergency response invest heavily in firm-specific training and unavoidably subject their employees to frequent hazard. It is reasonable to expect that these professions may at times experience retention challenges. Transferrable educational benefits like those from the GI Bill might be a fruitful form of deferred compensation that results in decreased personnel turnover overall or more selective retention targeting to personnel most likely to respond to these benefits. This is another topic worthy of future research.

Appendix 2A: Economic Model of GI Bill Benefits Transfer

In this Appendix, we provide full details on our economic model of intergenerational benefit-labor tradeoff. The broad purpose of the model is to understand the dilemma facing people in hazardous professions who might take on additional labor in exchange for the benefits transfer. We tailor the model to the specific case of GI Bill benefits transfer in order to make predictions about what types of military parents might transfer benefits to a child. Testing these predictions against observational data will allow us to understand the new benefit in terms of the socioeconomic populations that it appeals to.

A. The Basic Model

Our approach is in the spirit of models of multi-period household decision-making in Becker and Tomes (1986) and Acemoglu and Pischke (2001). The model contains one parent and one child; the household model is unitary and utility is log(consumption). In our model, there is only one level of schooling that differentiates individuals in the labor force: workers with a college degree earn the high wage while those without earn the low wage. There are exactly three periods in the model, which starts with the service member parent eligible to transfer benefits (still on active duty, 6+ years of service, has a child). In period 1, the parent decides whether to transfer benefits or not and then either continues an Army career or starts a civilian career. In period 2, the parent works in the civilian sector and the child completes her education, which may or may not include college, based on the decisions of the parent. The parent dies at the end of period 2. The household consumes c_1 and c_2 in periods 1 and 2, respectively, based on the education and therefore wage earnings of the parent. In period 3, the child receives utility from consumption$(\widehat{c})$ that is a function of her wage based on education. Thus, with the δ terms representing appropriate discount factors across time, household utility is:

$$u(c) = \ln(c_1) + \delta_1 * \ln(c_2) + \delta_2 * \ln(\widehat{c}) \tag{2A.1}$$

The child receives utility $\ln(w_l)$ if she does not attend or does not complete college and $\ln(w_h)$ if she attends and completes college. The present value difference in utility from these earnings is the time-discounted college premium: $\beta_2 * prem$. Importantly, the household faces uncertainty as to whether the child will complete college; the relevant uncertainty parameter, γ_{ea}, takes on values between 0 and 1 and depends upon the education level of the parent, the age of the child, and the judgment of the parent. Thus, we can re-write (2A.1) as the *expected* utility of the household in terms of wages, the college premium, and appropriate discounting parameters:

$$E(U) = E[\ln(w_1) + \delta_1 * \ln(w_2) + \beta_2 * \ln(w_l) + \delta_2 * \gamma_{ea} * prem] \tag{2A.2}$$

B. Choice Structure

The household faces several binary choices. First, the parent must decide in the first period whether to transfer benefits or not: this choice is x=0 or x=1. For x=1, the parent commits to staying in the Army through the end of period 1 and incurs the cost of military service (CMS). The vector c(**Z**) that defines CMS includes years of service, career field, rank, recent deployment history, and the (unobserved) personal taste for military service. Second, a parent who does not transfer benefits must decide whether to pay tuition for the child in period 2; this binary choice is t=0 or t=1. The tuition amount is T for choice t=1. Third, the uneducated parent faces an additional choice of whether or not to use the GI Bill benefit himself; this is e=0 or e=1. For e=1, the parent earns 0 in period 1 (while himself attending school) but then earns the high wage in period 2. The key economic tradeoff in our model is that the parent incurs the cost of military service (CMS) – by agreeing to additional active-duty military service – if he transfers benefits to the child. However, by transferring benefits, he also provides a college education for the child without having to pay tuition (T) during period 2. We treat college-educated versus non-college-educated parents as separate cases in the model, since the uneducated parent must also decide whether or not to use the GI Bill educational benefit himself.

Our model introduces uncertainty through γ_{ea} and unobserved heterogeneity in c(**Z**); however, we nonetheless simplify some of the complexity of the transfer decision. Namely, we allow for only two levels of education and corresponding wage levels and ignore the possibility of transfer to a spouse or to multiple children. We also assume that the uneducated parent will not pursue college himself in period 2, the final period of his life, since there would be no subsequent earnings payoff. Finally, by employing a unitary household structure, we dismiss potential intrafamily moral hazard problems addressed in Becker (1974), Burstyzn and Coffman (2012), and others.

C. Educated versus Uneducated Parents

The educated parent (ed) has already completed college and therefore earns the high wage; there is no higher level of education in our model that he can pursue and so his decision process is simpler than that of the uneducated parent. Accordingly, the educated parent first decides whether or not to transfer benefits (incurring extra time in the service) and then whether or not to pay tuition in the case of no benefits transfer. For binary choices x and t, this parent faces:

$$\max_{\substack{x=0,1\\t=0,1|x=0}} E_{ed} \begin{Bmatrix} \ln(w_h) + \delta_1 * \ln(w_h) + \delta_2 * \ln(w_l)\,, \\ \ln(w_h) + \delta_1 * \ln(w_h - T) + \delta_2 * \ln(w_l) + \delta_2 * \gamma_{ea} * prem, \\ \ln(w_h) - c(\boldsymbol{Z}) + \delta_1 * \ln(w_h) + \delta_2 * \ln(w_l) + \delta_2 * \gamma_{ea} * prem \end{Bmatrix} \tag{2A.3}$$

which simplifies to,

$$\max_{\substack{x=0,1\\t=0,1|x=0}} E_{ed} \begin{Bmatrix} \delta_1 * \ln(w_h)\,, \\ \delta_1 * \ln(w_h - T) + \delta_2 * \gamma_{ea} * prem, \\ -c(\boldsymbol{Z}) + \delta_1 * \ln(w_h) + \delta_2 * \gamma_{ea} * prem \end{Bmatrix} \tag{2A.3a}$$

Equation (2A.3a) presents the basic dilemma inherent in the benefit transfer provision. The college-educated military parent must decide whether to provide the child with the opportunity to earn the college premium: this is the $\delta_2 * \gamma_{ea} * prem$ term. If yes, the parent chooses to finance that opportunity either by reducing his own period 2 consumption by the tuition amount – this is cost T – or through own increased hazardous labor – at utility cost c(**Z**).

The uneducated parent (un) is the more difficult case because he faces three binary choices. The transfer decision is x=0 or x=1. Conditional on x=0, the parent faces e=0 versus e=1 (his use of the benefits) and then t=0 or t=1 for whether to pay his child's tuition. A reasonable simplifying assumption is that the parent will not pay out of pocket for his own college, because arguably he would have done so earlier in life instead of joining the Army or would use the GI Bill benefits himself to pay for college. For binary choices x, e, and t, the uneducated parent thus faces:

$$\max_{\substack{x=0,1\\e=0,1|x=0\\t=0,1|x=0}} E_{un} \begin{Bmatrix} \ln(w_l) + \delta_1 * \ln(w_l) + \delta_2 * \ln(w_l)\,, \\ \ln(w_l) + \delta_1 * \ln(w_l - T) + \delta_2 * \ln(w_l) + \delta_2 * \gamma_{ea} * prem, \\ 0 + \delta_1 * \ln(w_h) + \delta_2 * \ln(w_l)\,, \\ 0 + \delta_1 * \ln(w_h - T) + \delta_2 * \ln(w_l) + \delta_2 * \gamma_{ea} * prem, \\ \ln(\mathrm{w_l}) - c(\boldsymbol{Z}) + \delta_1 * \ln(w_l) + \delta_2 * \ln(w_l) + \delta_2 * \gamma_{ea} * prem \end{Bmatrix} \tag{2A.4}$$

which reduces to

$$\max_{\substack{x=0,1 \\ e=0,1|x=0 \\ t=0,1|x=0}} E_{un} \left\{ \begin{array}{c} \ln(w_l) + \delta_1 * \ln(w_l)\,, \\ \ln(w_l) + \delta_1 * \ln(w_l - T) + \delta_2 * \gamma_{ea} * prem, \\ 0 + \delta_1 * \ln(w_h)\,, \\ 0 + \delta_1 * \ln(w_h - T) + \delta_2 * \gamma_{ea} * prem, \\ \ln(\mathrm{w_l}) - c(\boldsymbol{Z}) + \delta_1 * \ln(w_l) + \delta_2 * \gamma_{ea} * prem \end{array} \right\} \tag{2A.4a}$$

Equation (2A.4a) shows that the dilemma for the uneducated parent is similar to that of the educated parent, but that the possibility of own-use of the benefits adds extra complexity.

D. Solving the Model

Case 1: The Educated Parent

The educated parent must first decide whether or not to transfer benefits (incurring extra time in the service) and then whether or not to pay tuition in the case of no benefits transfer. In order for the parent to transfer benefits, the third option from (2.A3) must be more desirable than each of the others. This requires the following two conditions:

$$-c(\boldsymbol{Z}) + \delta_2 * \gamma_{ea} * prem > \ 0 \tag{2A.3.1}$$

$$-c(\boldsymbol{Z}) + \delta_1 * ln(w_h) > \ \delta_1 * ln(w_h - T) \tag{2A.3.2}$$

These conditions require first that the discounted present value of the college premium for the child is higher than the cost of military service (from 2A.3.1) and then second that the educated parent prefers to pay for the child's education with continued military service rather than out-of-pocket tuition (from 2A.3.2).

Case 2: Uneducated Parent

This is the more difficult case because the uneducated parent faces three binary choices. The transfer decision is x=0 or x=1. Conditional on x=0, the parent faces e=0 versus e=1 (his use of the benefits) and then t=0 or t=1 for whether to pay his child's tuition. A reasonable simplifying assumption is that the parent will not pay out of pocket for his own college, because arguably he would have done so in the first place instead of joining the Army. In order for the parent to transfer benefits, the fifth option from (2A.4) must be more desirable than each of the others. This requires the four following conditions:

$$-c(\boldsymbol{Z}) + \delta_2 * \gamma_{ea} * prem > 0 \tag{2A.4.1}$$

$$-c(\boldsymbol{Z}) + \delta_1 * \ln(w_l) > \delta_1 * \ln(w_l - T) \tag{2A.4.2}$$

$$(1 + \delta_1) * \ln(w_l) - c(\boldsymbol{Z}) + \delta_2 * \gamma_{ea} * prem > \delta_1 * \ln(w_h) \tag{2A.4.3}$$

$$(1 + \delta_1) * \ln(w_l) - c(\boldsymbol{Z}) > \delta_1 * \ln(w_h - T) \tag{2A.4.4}$$

Condition (2A.4.1) requires that the discounted value of the college premium for the child is greater than the cost of military service. (2A.4.2) requires that the value of not paying tuition in period 2 is greater than the cost of military service. These first two conditions are similar to what the educated parent faces. Condition (2A.4.3) requires the parent to be better off enduring the cost of service and giving the child a chance at the college premium than using his own benefits to earn higher wages in period 2. Finally, (2A.4.4) requires that the difference between working at the low wage for two periods less working at the high and paying tuition is greater than the cost of military service. Thus, upon comparing conditions (2A.3.1) and (2A.3.2) to (2A.4.1) thru (2A.4.4), it is apparent that the benefits transfer decision is more complicated for the uneducated parent.

Measuring the Cost of Military Service

The vector **Z** consists of at least the following arguments:

*years of service (yos). A big factor in military careers is reaching pension eligibility (20 yos); those serving after 20 years are compensated well and typically serve in prestigious leadership positions. Thus, c(**Z**) is decreasing in yos both before and after 20 years of service.

*military rank. Typically, the military is more labor intensive and more dangerous at lower ranks, yet compensation increases with rank. Thus, c(**Z**) is decreasing in rank, similar to c(**Z**) and years of service.

*recent deployment history (within last 3 years). The intensity of recent deployment history increases the cost of military service because of the frequency of family separation (we assume that the disutility from family separation is convex in time).

*taste for military service. This personal characteristic is, of course, unobserved. c(**Z**) decreases as taste for military service increases. This unobservable characteristic could interact with years of service and recent deployment history.

Predictions for Aggregate Transfer Behavior

Based on analysis of and comparisons between the cases above, we make the following predictions about what types of parents are more likely to transfer benefits:

1. More educated parents are more likely to transfer benefits than less educated parents. First, comparison of Cases 1 and 2 above suggests that the transfer decision is more complicated for parents who are not college educated and that there are plausible reasons why transfer will not occur. Second, we assume γ_{ea} to be increasing in the education of the parent, meaning that a college-educated parent can predict success in college for his child more confidently than the non-educated parent. Thus, the expected value of the college premium is higher for the educated parent, *ceteris parabus*, which is the second factor making transfer more likely by the college-educated parent.

2. Parents with a lower cost of military service are more likely to transfer benefits, regardless of education level. Even though we cannot fully characterize the vector c(**Z**), we predict on average that benefits transfer is more likely for eligible parents with: higher rank; higher years of service; and less-intense recent deployment history.

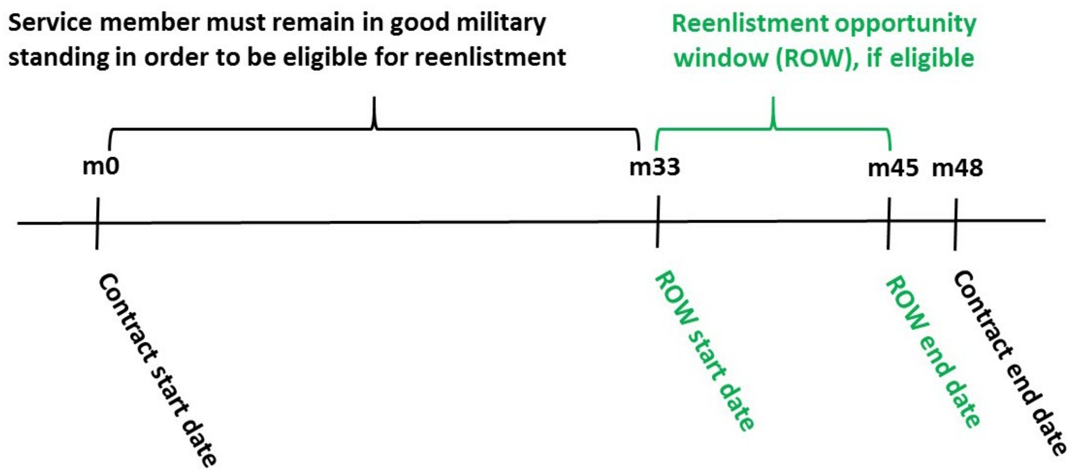
Appendix 2B: Descriptive Analysis of Transfer Behavior for Cohort 2012

This appendix offers a brief descriptive analysis of transfer behavior made by the 2012 cohort, which shows similar patterns to the 2009 cohort. Officers in this newer cohort are more likely than enlisted to transfer GI Bill benefits, as are parents who are more educated, higher in military rank, and longer tenured in the military. For brevity, we present only the overview of transfer behavior for 2012 - see Figure 2B.1. Even though this later cohort has patterns of cumulative and marginal transfer that are similar to those of the earlier cohort, the overall levels of transfer are lower at every comparable point. One key difference is that the 2012 cohort by percentage shows more transfers by midcareer and junior enlisted soldiers who have attained only a high school education. This result, of course, is mechanical because there are more such individuals in these later cohorts (as shown in Figure 2.3). This distinction is important because future cohorts will look much more like the 2012 group than the 2009 group. There is also an important opportunity in this high-school educated subpopulation in general because the transfer recipient – usually a child – has received a valuable education benefits package that encourages her to pursue an education level (college) that at least one parent never has. This finding suggests that the transfer provision could affect college enrollments and perhaps intergenerational educational attainment, as we discuss at the end of the main body of the paper.

Appendix 2C: Densities of Soldiers by Family Type at Policy Implementation

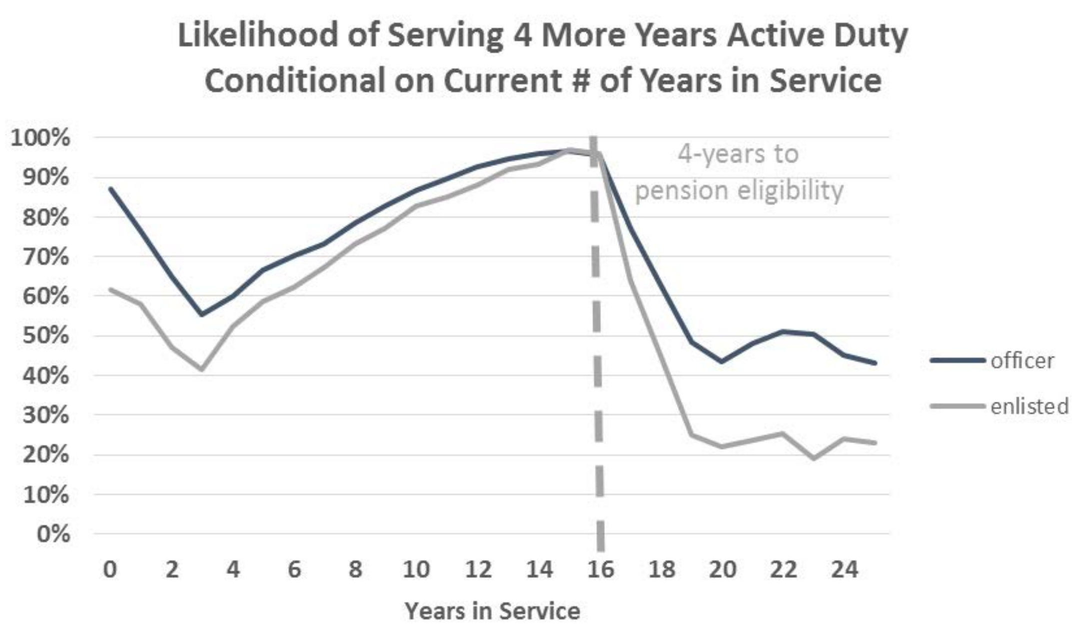
In order to address the first DD assumption of exogenous policy timing, we plot densities by ROW end date of soldiers with children versus those with no dependents. We see no discernible shift in these densities around the time of GI Bill transfer implementation, as shown in Figure 2C.1. This result is important but unsurprising given that reenlistment window and end of contract timing for 2009 were determined by enlistment and reenlistment decisions made back in 2005 (for a typical 4-year contract). In contrast, the earliest Congressional discussion of a new GI Bill with a benefits transfer provision did not occur until January 2008.

Figure 2.1: Sample Timeline for Military Enlistment Contract



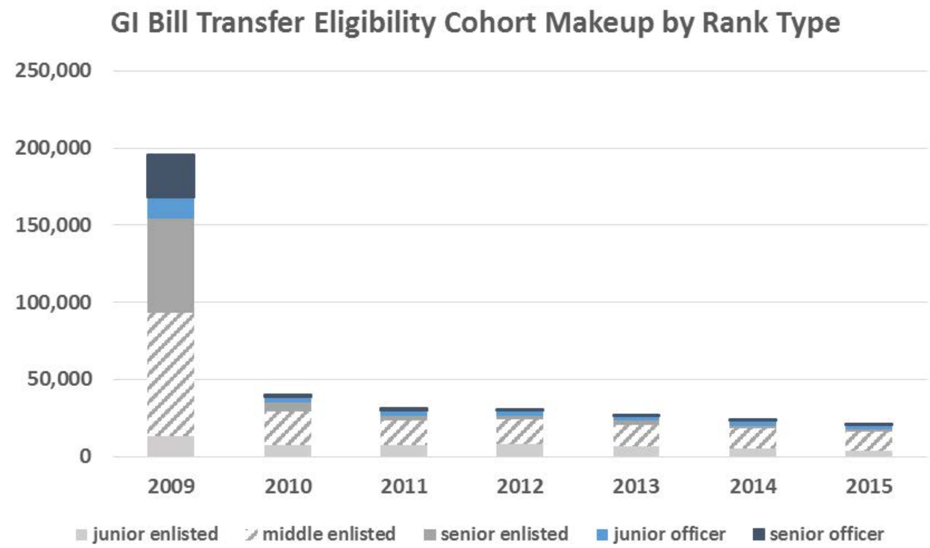
Note: Time is measured in months (m). Timeline is for a typical 4-year enlistment contract.

Figure 2.2: Conditional Continuation in the Active Duty US Army



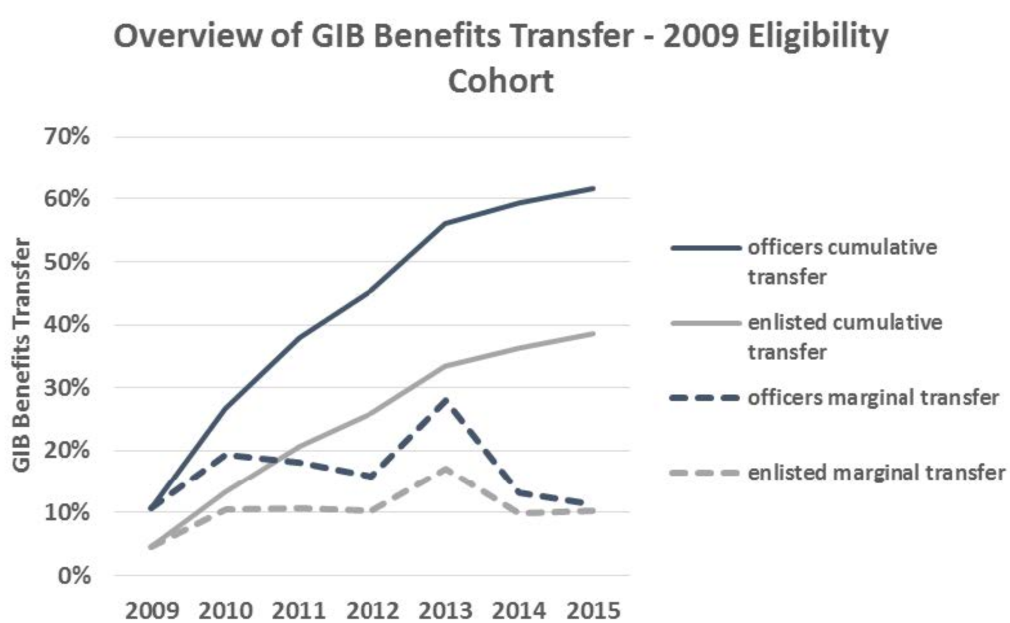
Note: Authors' calculations, data provided by Office of Economic and Manpower Analysis. We measure the probability of serving on active duty thru 2009 conditional on having served x number years by 2005. Results show that individuals near pension eligibility (i.e. – 12 to 19 years of service) are likely to serve four more years. We exclude officers and soldiers who left active duty between 2005-2008 due to death or disability. Sample includes all active duty US Army with 0-25 years of service as of 2005, n=532,934.

Figure 2.3: GI Bill Eligibility Cohort Makeup by Rank Type



Note: DoD data. We assign individuals to year cohorts based on when they first gained eligibility to transfer GI Bill benefits (6+ years active duty, has a dependent who can be the recipient). The large size of the 2009 cohort is due to policy implementation that year and the grandfathering in of senior personnel who were easily eligible for benefit.

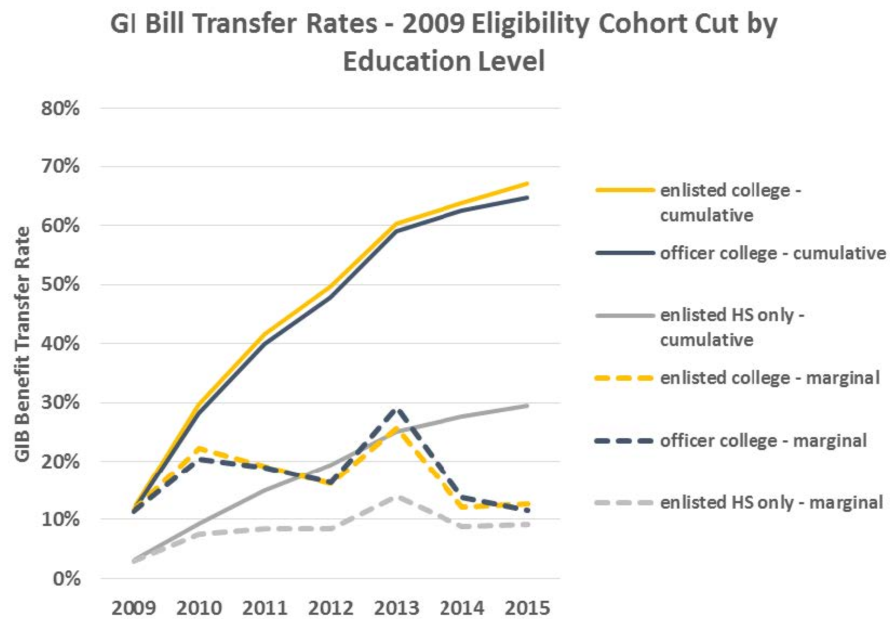
Figure 2.4: Overview of GI Bill Benefits Transfer – 2009 Eligibility Cohort



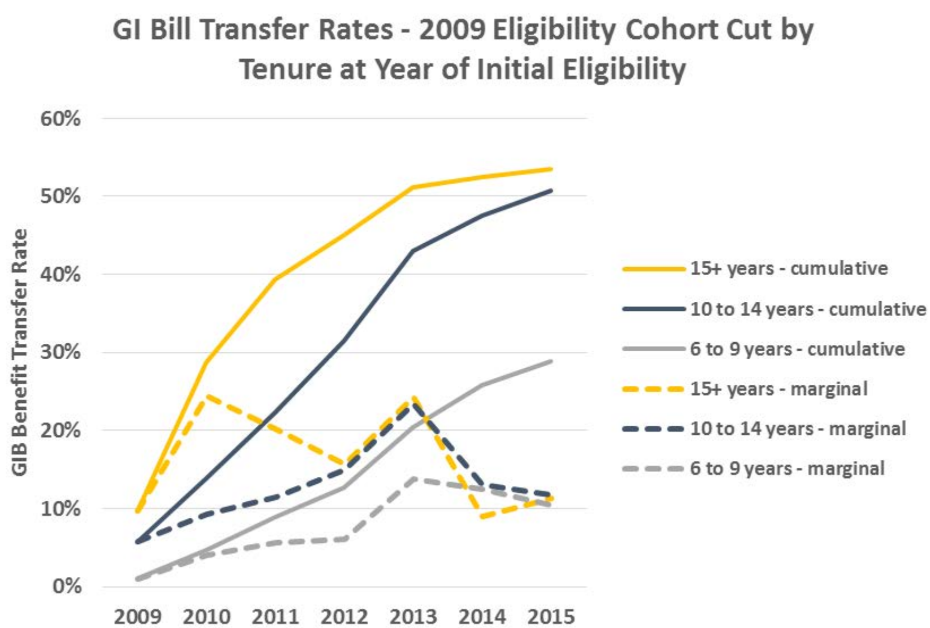
Note: DoD data. Graph tracks initial transfer of benefit by year. Cumulative rates are based on the whole eligibility cohort; marginal rates are based on cohort members who were eligible and had not yet transferred as of that year.

Figure 2.5: GI Bill Transfer Rates – 2009 Eligibility Cohort

A. Education Level



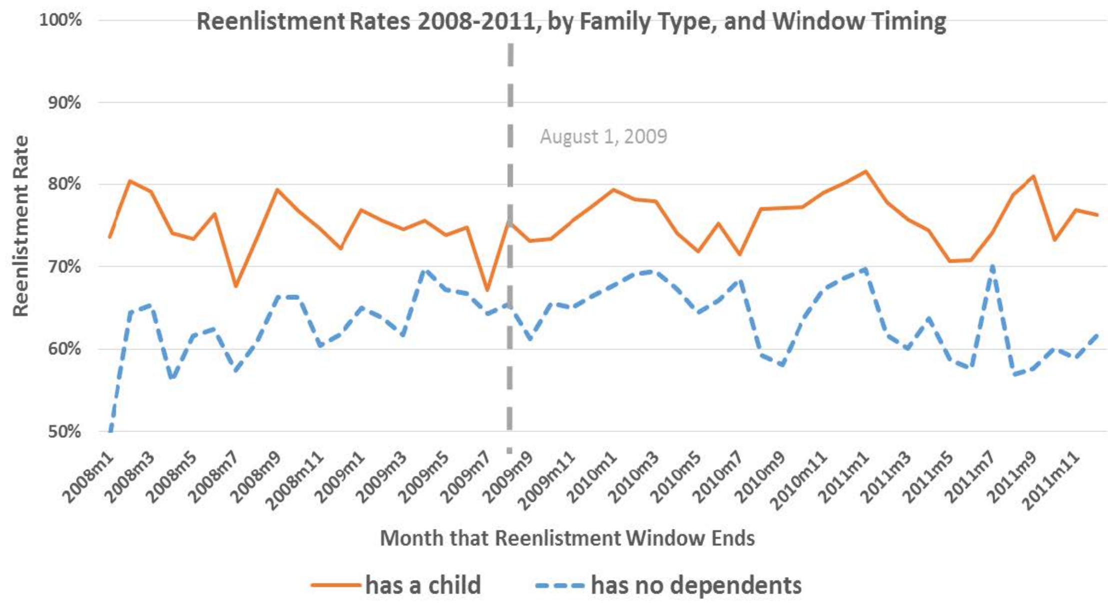
B. Tenure in the Military



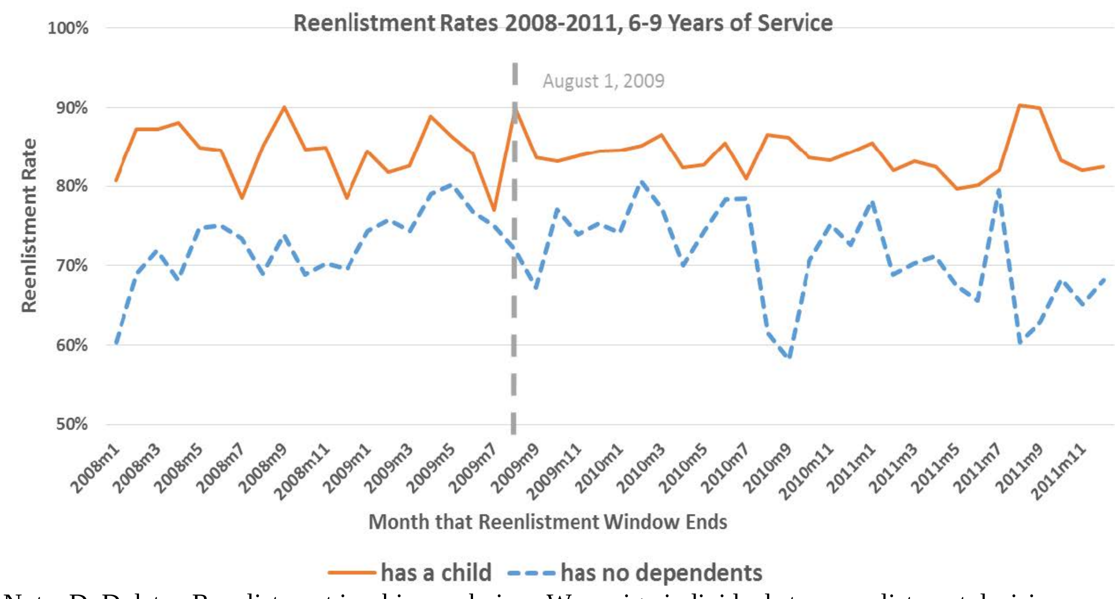
Note: DoD data. Graphs track initial transfer of benefit. Cumulative rates are based on the whole eligibility cohort; marginal rates are based on cohort members who were eligible and had not yet transferred as of that year. In Panel B, tenure in the military is measured at year of initial eligibility (2009).

Figure 2.6: Reenlistment Rates by Family Type for Eligible US Army Enlisted, 2008-2011

A. All Personnel, Grouped by End of Reenlistment Opportunity Window (ROW)

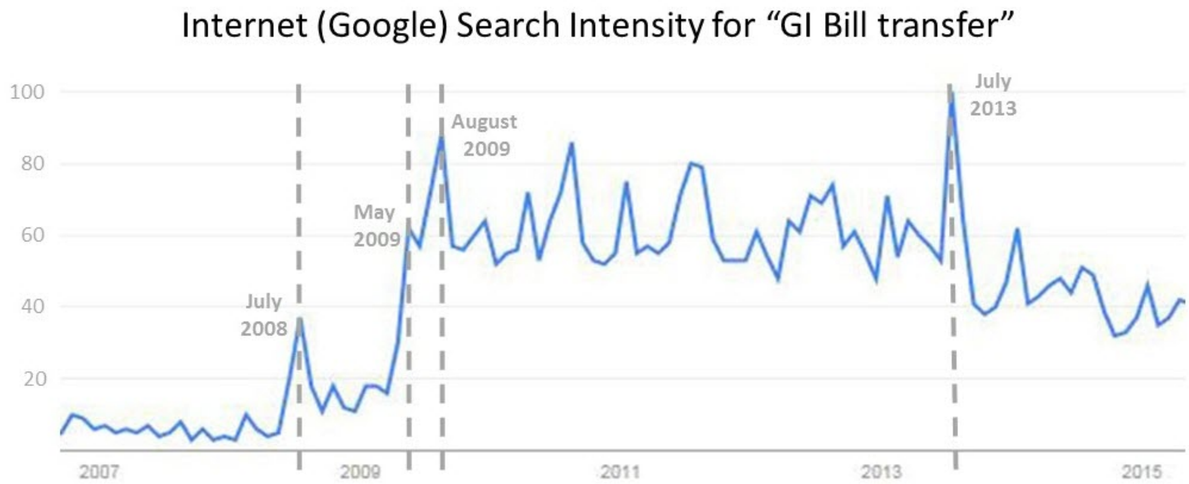


B. Eligible Personnel with 6-9 Years of Service, Grouped by Timing of ROW



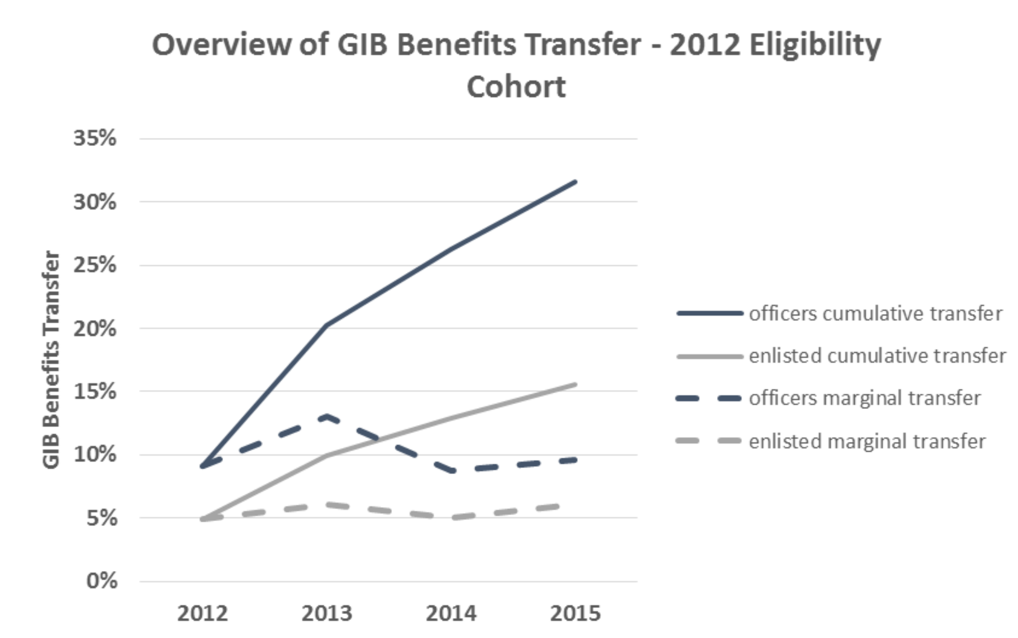
Note: DoD data. Reenlistment is a binary choice. We assign individuals to a reenlistment decision month – the horizontal axis – based on the final month of the reenlistment opportunity window (ROW). The dashed gray line marks transfer policy implementation. Panel A documents more than 240,000 reenlistment decisions made by soldiers across different career points (i.e. – years of service); Panel B more than 79,000 such decisions made by midcareer soldiers. Monthly reenlistment rates are adjusted for seasonality, as described in the text.

Figure 2.7: Search Intensity by Month for Transfer Provision of the GI Bill



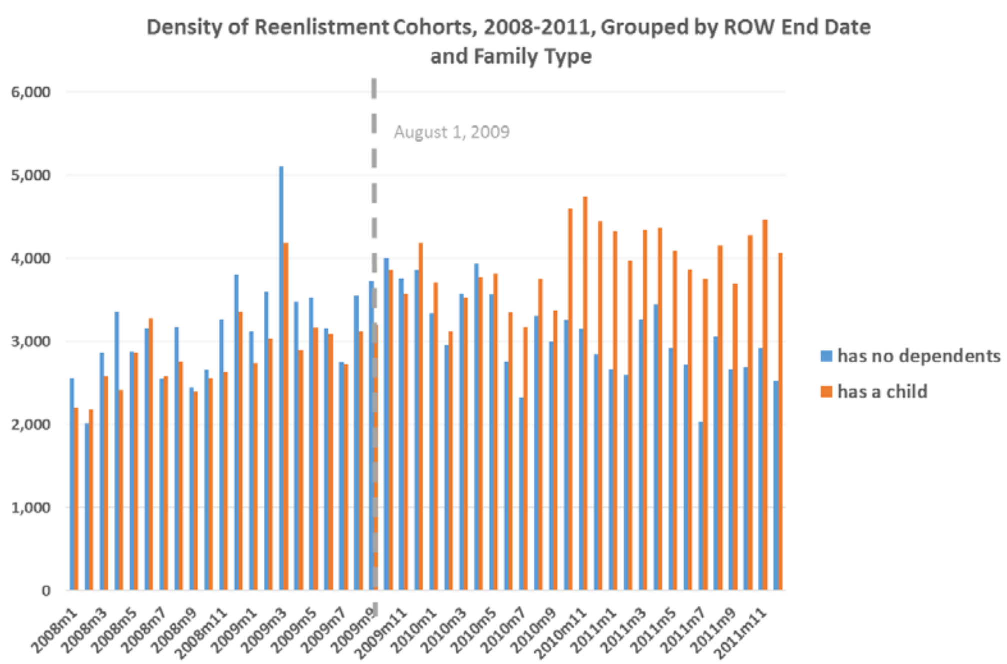
Note: Figure reports Internet search intensity on google.com for the phrase "GI Bill transfer" by month from 2007-2015. Intensity is measured by an index appearing on the vertical axis, where the maximum intensity (indexed to 100) occurred in July 2013, just before the policy change affecting benefit transfer by senior service members. Values for all other months are relative to the intensity recorded in July 2013. For instance, in August 2009, when transfer implementation occurred, the search intensity index was 88. This value is nearly 90% of the July 2013 value. Source: www.google.com/trends.

Figure 2B.1: Overview of GI Bill Benefits Transfer – 2012 Eligibility Cohort



Note: DoD data. Graph tracks initial transfer of benefit. Cumulative rates are based on the whole eligibility cohort; marginal rates are based on cohort members who were eligible and had not yet transferred as of that year.

Figure 2C.1: Active Duty US Army Personnel Eligible for Reenlistment, 2008-2011



Note: DoD data. Individuals are assigned to a reenlistment decision month based on the final month of the reenlistment opportunity window (ROW). The dashed gray line marks transfer policy implementation.

Table 2.1: Summary Statistics for Transfer-Eligible Cohorts

	2009 elig cohort		2010-2015 cohorts		2012 elig cohort	
Panel A. Demographics and Career Information Upon Gaining Transfer Eligibility						
	mean	SD	mean	SD	mean	SD
n	195,365	n/a	173,979	n/a	30,586	n/a
senior officer	0.140	(0.346)	0.029	(0.169)	0.026	(0.160)
junior officer	0.073	(0.260)	0.120	(0.325)	0.113	(0.317)
senior enlisted	0.310	(0.462)	0.098	(0.297)	0.076	(0.266)
middle enlisted	0.412	(0.492)	0.533	(0.499)	0.520	(0.500)
junior enlisted	0.066	(0.248)	0.220	(0.414)	0.264	(0.441)
graduate degree	0.129	(0.335)	0.051	(0.220)	0.044	(0.205)
college degree	0.145	(0.352)	0.135	(0.342)	0.122	(0.327)
some college	0.234	(0.423)	0.174	(0.379)	0.160	(0.366)
high school only	0.479	(0.500)	0.631	(0.483)	0.667	(0.471)
20+ years service	0.159	(0.366)	0.024	(0.154)	0.016	(0.127)
15-19 years service	0.222	(0.416)	0.042	(0.202)	0.032	(0.176)
10-14 years service	0.274	(0.446)	0.089	(0.285)	0.070	(0.256)
6-9 years service	0.344	(0.475)	0.841	(0.366)	0.880	(0.325)
age	35.7	(6.76)	30.2	(5.47)	29.8	(5.23)
3+ children	0.254	(0.435)	0.159	(0.366)	0.156	(0.363)
2 children	0.312	(0.463)	0.237	(0.425)	0.237	(0.425)
1 child	0.238	(0.426)	0.279	(0.448)	0.283	(0.451)
no children	0.195	(0.396)	0.325	(0.468)	0.324	(0.468)
oldest child 14-17 yo	0.249	(0.433)	0.083	(0.276)	0.073	(0.260)
combat specialty	0.234	(0.423)	0.233	(0.423)	0.256	(0.436)
logistics specialty	0.429	(0.495)	0.479	(0.500)	0.457	(0.498)
other specialty	0.337	(0.473)	0.288	(0.453)	0.287	(0.452)
# mos depl last 3 years	7.40	(6.51)	6.87	(5.89)	7.98	(5.96)
Panel B. Annual Transfer Behavior						
	# xfer	xfer rate	# xfer	xfer rate	# xfer	xfer rate
year 1	12,203	0.062	7,305	0.043	913	0.031
year 2	21,092	0.129	7,364	0.058	1,695	0.066
year 3	16,412	0.127	5,595	0.067	1,020	0.055
year 4	11,849	0.116	4,416	0.086	907	0.064
year 5	15,908	0.198	2,454	0.086	n/a	n/a
year 6	5,858	0.011	1,212	0.094	n/a	n/a
year 7	4,429	0.105	n/a	n/a	n/a	n/a

Source: DOD Data. This table provides summary statistics by cohort of officers and soldiers that gained eligibility to transfer GI Bill benefits. The 2009 cohort is the first such cohort; the middle columns pool the remaining cohorts that gained eligibility. 2012 is representative of the smaller more junior cohorts. that subsequently gained eligibility.

Table 2.2: Descriptive Regressions for Benefits Transfer, Cohorts 2009 and 2012

Dependent variable is indicator variable for initial benefits transfer in specified time period.
Explanatory variables are characteristics of the transfer-eligible service member.

	(1)	(2)	(3)	(4)	(5)
eligibility cohort	2009	2009	2009	2012	2012
transfer time period	w/in 3 yrs	in 2010	in 2013	w/in 3 yrs	in 2013
# eligible to transfer	195,274	163,947	64,458	30,557	25,562
share who transfer	0.320	0.129	0.247	0.185	0.073
senior officer	0.238***	0.016***	0.113***	0.146***	0.055***
	(0.007)	(0.006)	(0.010)	(0.025)	(0.021)
junior officer	0.097***	-0.040***	0.041***	0.108***	0.014
	(0.006)	(0.005)	(0.011)	(0.014)	(0.011)
senior enlisted	0.185***	0.039***	0.105***	0.195***	0.075***
	(0.004)	(0.003)	(0.006)	(0.014)	(0.011)
middle enlisted	0.072***	0.004**	0.042***	0.072***	0.019***
	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)
graduate degree	0.172***	0.139***	0.146***	0.175***	0.102***
	(0.006)	(0.006)	(0.009)	(0.020)	(0.016)
college degree	0.080***	0.061***	0.071***	0.053***	0.036***
	(0.004)	(0.004)	(0.006)	(0.012)	(0.010)
some college	0.050***	0.021***	0.050***	0.043***	0.019***
	(0.003)	(0.002)	(0.004)	(0.007)	(0.005)
years of service	0.011***	0.010***	0.006***	0.005***	0.005***
	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.001)
age	-0.002***	0.000	-0.001	0.005***	0.002***
	(0.0003)	(0.000)	(0.0003)	(0.001)	(0.001)
# children 14-17	0.098***	0.026***	0.036***	0.061***	0.017***
	(0.002)	(0.002)	(0.002)	(0.008)	(0.006)
other controls	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.08	0.05	0.08	0.04

Heteroskedasticity-robust standard errors in parentheses. Columns 1 and 4 consider whether a service member made any initial transfer within the first 3 years of eligibility. Columns 2,3, and 5 examine marginal transfer rates for the year specified. To be counted as eligible for marginal transfer, the service member must have not yet transferred benefits and still be on active duty. Other controls include race, gender, and number of non-HS-aged children by their age range. 91 individuals from cohort 2009 and 29 individuals from cohort 2012 are missing the years of service variable.
* p<0.10, ** p<0.05, *** p<0.01

Table 2.3: Summary Statistics for Retention Sample

Active duty Army, eligible to reenlist, years 2008-2011. Soldiers are grouped by family type.

	no dependents		**spouse only**		**has children**	
Panel A. Demographics and Career Information at Start of Reenlistment Eligibility						
	mean	SD	mean	SD	mean	SD
n	116,087	n/a	55,132	n/a	137,004	n/a
senior enlisted	0.033	(0.178)	0.029	(0.169)	0.074	(0.261)
middle enlisted	0.535	(0.499)	0.560	(0.496)	0.658	(0.475)
junior enlisted	0.432	(0.495)	0.410	(0.492)	0.269	(0.443)
college degree	0.046	(0.210)	0.045	(0.208)	0.041	(0.199)
some college	0.133	(0.339)	0.118	(0.323)	0.159	(0.366)
high school only	0.810	(0.393)	0.826	(0.379)	0.785	(0.411)
10+ years service	0.120	(0.325)	0.102	(0.303)	0.270	(0.444)
6-9 years service	0.274	(0.446)	0.304	(0.460)	0.383	(0.486)
3-5 years service	0.605	(0.489)	0.594	(0.491)	0.348	(0.476)
age	27.1	(4.67)	27.1	(4.59)	29.9	(5.07)
3+ children	0	n/a	0	n/a	0.263	(0.440)
2 children	0	n/a	0	n/a	0.357	(0.479)
1 child	0	n/a	0	n/a	0.381	(0.483)
no children	1	n/a	1	n/a	0	n/a
combat specialty	0.256	(0.437)	0.309	(0.462)	0.253	(0.435)
logistics specialty	0.504	(0.500)	0.444	(0.497)	0.481	(0.500)
other specialty	0.240	(0.427)	0.247	(0.431)	0.266	(0.442)
# mos depl last 3 years	8.9	(6.11)	9.22	(6.02)	8.270	(6.30)
Panel B. Mean Reenlistment Rates						
	mean	SD	mean	SD	mean	SD
all						
pre-Aug 1, 2009	0.643	(0.479)	0.716	(0.451)	0.851	(0.356)
post-Aug 1, 2009	0.650	(0.477)	0.715	(0.451)	0.849	(0.358)
3-5 years service						
pre-Aug 1, 2009	0.554	(0.497)	0.654	(0.476)	0.762	(0.426)
post-Aug 1, 2009	0.552	(0.497)	0.645	(0.479)	0.749	(0.434)
6-9 years service						
pre-Aug 1, 2009	0.760	(0.427)	0.791	(0.406)	0.876	(0.330)
post-Aug 1, 2009	0.730	(0.444)	0.774	(0.418)	0.861	(0.346)
10+ years service						
pre-Aug 1, 2009	0.902	(0.297)	0.926	(0.262)	0.951	(0.215)
post-Aug 1, 2009	0.904	(0.295)	0.917	(0.277)	0.952	(0.214)

Source: DOD Data. This table presents summary statistics on soldiers eligible to reenlist in years 2008-2011.

Table 2.4: Difference-in-Differences Estimates of Retention Effect Due to GI Bill Transfer Provision

Active duty enlisted Army, eligible to reenlist, years 2008-2011.
Sample includes soldiers who have at least one child or who have no dependents.
Dependent variable is indicator variable for reenlisting during opportunity window.

		Regressions by years of service (yos) bands		
	all	3-5 yos	6-9 yos	10+ yos
	(1)	(2)	(3)	(4)
Constant	0.345***	0.642***	0.699***	0.848***
	(0.006)	(0.011)	(0.012)	(0.011)
Post (Aug 2009 - Dec 2011)	0.021***	0.020***	-0.008	0.009*
	(0.003)	(0.004)	(0.005)	(0.005)
Children	0.177***	0.209***	0.117***	0.048***
	(0.003)	(0.005)	(0.005)	(0.005)
Post * Children	-0.004	-0.009	0.018***	0.003
	(0.004)	(0.006)	(0.006)	(0.006)
Demographics	Yes	Yes	Yes	Yes
Military career	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
ROW Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	241045	113021	79930	48094

Heteroskedasticity-robust standard errors in parentheses. Regression is the baseline difference-in-differences specification that tests for a retention effect from the transfer provision. Sample includes all reenlistment-eligible soldier who have at least one child (treatment) or who have no dependents (control). Post indicates that the reenlistment opportunity window (ROW) closes for that soldier after transfer provision implementation. Demographic controls include gender, race, and age. Military career controls include career field and recent deployment history. Education controls include AFQT and education level. ROW fixed effects are by calendar month and account for cyclicality in Army retention behavior.
* p<0.10, ** p<0.05, *** p<0.01

Table 2.5: Robustness Checks for DD Regression for 6-9 Years of Service Population

Active duty enlisted Army, eligible to reenlist, years 2008-2011, 6-9 years of service.
Dependent variable is indicator variable for reenlisting during opportunity window.

	(1)	(2)	(3)	(4)	(5)
are spouse-only families included?	no	yes	yes	no	no
treatment *trait*	has child	has child	has child or spouse	has child	has child
post boundary	Aug 2009	Aug 2009	Aug 2009	May 2009	Aug 2009
Constant	0.699***	0.711***	0.673***	0.695***	0.551***
	(0.012)	(0.011)	(0.011)	(0.012)	(0.026)
Post	-0.008	0.002	-0.008	-0.001	-0.029***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)
Trait	0.117***	0.107***	0.097***	0.120***	0.117***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
*Post * Trait*	0.018***	0.008	0.017***	0.013**	0.020***
	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)
Demographics	Yes	Yes	Yes	Yes	Yes
Military career	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes
ROW Month FE	Yes	Yes	Yes	Yes	Yes
Unempl Rate	No	No	No	No	Yes
Total Deployed	No	No	No	No	Yes
Observations	79930	95970	95970	79930	79930

Heteroskedasticity-robust standard errors in parentheses. Column 1 presents the original DD specification from Table 4. Columns 2 and 3 analyze the full reenlistment-eligible sample - which includes soldiers with a spouse but no children - but with a different treatment trait for each regression. Column 4 considers May 2009 as a boundary date for program implementation based on Google trends search results that appear in Figure 9. Column 5 adds monthly data on the US unemployment rate and on the total number of US troops deployed to Iraq and Afghanistan.
* p<0.10, ** p<0.05, *** p<0.01

CHAPTER 3

Estimating Adverse Peer Effects in the Workplace: Evidence from a Surge of Morality Waivers to Enlist in the US Army

Abstract

While a large body of research has investigated peer effects in education, relatively little is known about peer influence in the workplace. In particular, few studies have investigated how bad peers affect an individual's performance and longevity in the workforce. I address this gap in the literature by leveraging the conditional random assignment of US Army soldiers to work groups to investigate the impact of exposure to peers with differing levels of adverse characteristics. In the time period of study, the Army granted large numbers of morality waivers to new recruits who had prior felony or misdemeanor convictions that would normally preclude enlistment. I find that non-waivered soldiers exposed to a larger share of such peers with criminal backgrounds are more likely to commit major misconduct during their first term in the Army. Additionally, that misconduct is most likely to occur in the same month that a company member with a waivered criminal background commits misconduct. Taken together, these results indicate that the peer effect acts through multiple channels: not only exposure to peers with adverse characteristics but also the contemporaneous behavior of those same peers.

Introduction

Social scientists have long argued that peers may have an important influence on individual behavior in a wide variety of contexts, including educational investments, propensities to engage in criminal behavior, and workplace productivity. Over the last two decades there has been a dramatic expansion in research on peer effects in education. Studies have found positive effects on individual performance from stronger peers both in primary school and in higher education; peers also influence non-academic outcomes in college, such as the decision to join a fraternity or sorority. [51] However, individuals can also suffer adverse peer effects, such as from classroom peers who witness domestic violence at home (Carrell and Hoekstra, 2010) or neighborhood youth involved in criminality (Damm and Dustmann, 2014). “Bad apple” models of peer interaction suggest that exposure to just one such individual with adverse characteristics or negative behavioral tendencies can impact the actions of the peer group (Hoxby and Weingarth, 2005; Gino, Ayal, and Ariely, 2009).

Peers may be just as influential on individual behavior in the labor market as they are in the educational setting, yet there is much less research about peer effects in workplace settings. The relatively small existing literature on peer effects in the workplace has shown that one’s productivity is related to the productivity of peers, whether in a retail setting (Mas and Moretti, 2009) or in the laboratory (Ichino and Falk, 2006). Peers also influence personal decision-making in the workplace, such as for

[51] See, for instance, Hoxby (2000), Sacerdote (2001), Hanushek et al (2003), Stinebrickner and Stinebrickner (2006), and Kremer and Levy (2008). Epple and Romano (2011) and Sacerdote (2012) provide detailed surveys of the literature.

retirement investment and the decision to take paternity leave (Duflo and Saez, 2003; Dahl, Løken, and Mogstad, 2014).[52]

Estimating the causal effect of one's peers, regardless of setting, is inherently difficult. First, individuals often choose their environments and the peer groups with whom they interact, which introduces substantial selection bias if those individuals purposefully seek out peers of a certain type. Additionally, there are the well-known empirical challenges of reflection and unobserved correlated effects, confounding any estimation of peer effects based on contemporaneous social interaction (Manski, 1993; Lyle, 2007). As a result of these challenges, causal inference in social settings is very difficult, as is determining the extent to which different channels (i.e. - peer actions, peer characteristics) underlie any estimated peer effect.

In the current paper, I leverage a policy shock in military recruiting to investigate the impact of peers with adverse characteristics on individual workplace performance and longevity. Starting in 2005, when US armed forces were enmeshed in an intense and prolonged ground combat in Iraq and Afghanistan and against the backdrop of low domestic unemployment, the Army granted large numbers of morality waivers to individuals with criminal backgrounds, in order to meet recruiting goals. Prior to the policy change these individuals would have been far less likely to be eligible to enlist given their criminal background.

Of relevance given that the social setting is important to the study of peer effects, soldiers serving in the same military unit have nearly non-stop interaction, both during

[52] A few authors have studied workplace peer effects in professional sports in the United States: Guryan, Kroft, and Notowidigdo (2009) examines ability pairings in golf tournaments while Gould and Kaplan (2011) studies the diffusion of an unethical practice – the use of illegal, performance-enhancing substances – in baseball.

Army training and also during non-duty hours, when they reside by work group in dormitory-like military barracks. As such, I hypothesize that the presence of soldiers with criminal backgrounds might encourage other soldiers to engage in criminal activities themselves or at least participate in general misconduct. I additionally explore channels of peer influence in the paper: whether it is just the criminal backgrounds of the waivered soldiers or also their own misconduct that contributes to the adverse peer effect.

I identify the impact of exposure to peers with criminal backgrounds by capitalizing on the Army's conditional random assignment of soldiers to work groups. The Army arbitrarily assigns new soldiers to companies conditional on only a small set of known observable characteristics that does not include whether the recruit received a waiver. This assignment process has two important implications. First, the sampling variation associated with the process implies that some companies end up with more individuals with waivers than other companies. Second, it implies that, conditional on a few observable characteristics, the unobservables of one's peers are unrelated to one's own characteristics. Taken together, these propositions imply that one can estimate the effect of adverse peers by comparing the average outcomes of individuals who have more adverse peers to the outcomes of individuals who have fewer adverse peers (after taking into account differences in observable characteristics across individuals).

I find that soldiers assigned to companies where they are exposed to a greater share of peers with criminal backgrounds are more likely to commit major misconduct during their first term in the Army. A one standard deviation increase in exposure to morality waiver peers results in a 2.5% increase in the likelihood of major misconduct. The adverse peer effect is concentrated among young soldiers: those who are 17-21 years of age upon entry into military service. Moreover, that misconduct is most likely to occur in the same month that a company member with a waivered criminal background commits misconduct. These results indicate that the peer effect acts through multiple channels: exposure to peers with adverse characteristics as well as misconduct actions committed by those same peers.

The rest of the paper proceeds as follows. Section II provides background information on the Army and enlistment waivers. Section III describes the data. Section IV details the empirical strategy. I present and interpret the results in Section V. Finally, Section VI concludes.

II. Background

A. US Army Structure

The structure of the US Army provides an interesting and informative opportunity to study workplace peer effects. After completing initial training, or "boot camp," new soldiers are randomly assigned to semi-permanent work groups (more on this process in Section IV) and have nearly nonstop workday and off-duty social interaction with a pre-determined friend set. Figure 3.1 depicts the organizational structure of the Army. The hierarchical level of interest in this study is the company, which contains about 60 junior enlisted soldiers. Whereas the officers and sergeants in the company are leaders and managers responsible for day-to-day operations, the junior soldiers (new employees) fill out the rank-and-file. When the unit is on a mission exercise, these soldiers train together day and night, performing a variety of grueling collective tasks that might include 15-mile foot marches, digging foxholes, replacing the track on a tank, or engaging in ground combat.

While at home station, the junior soldiers reside by company in Army-provided dormitories (or "barracks") that feature two- or three-person rooms, administrative offices, and indoor and outdoor leisure spaces. During off-duty hours at home station, soldiers have both free time and the financial means to leave the barracks area to "blow off steam," often in adjacent towns known for having large numbers of bars, dance clubs, tattoo parlors, pawn shops, and similar establishments. Soldiers assigned to the same company comprise a natural friend set, given the strong bonds forged while conducting the challenging military tasks described above. Based on this nearly non-stop interaction, it is reasonable to expect that these soldiers influence one another's conduct; peer influence could lead to negative outcomes for individuals if adverse peers induce misconduct or even criminal behavior.[53]

B. US Army Accessions and Morality Waivers

The Army must man its formations – such as the one pictured in Figure 3.1 – with the required mix of junior, midcareer, and senior personnel. Given that more than half of first-term soldiers do not serve beyond the initial contract end date,[54] one of the Army's most important administrative functions is the recruitment of new personnel. Since conscription practices ended service-wide in 1973, the Army has relied exclusively on volunteers, thereby competing for its workforce in the general labor market.[55] Historically, defense policymakers have leveraged various incentives – such as the level

[53] Numerous authors have studied peer influence on criminal behavior in other settings and for both youth and adult populations; see for instance Warr and Stafford (1991), Glaeser, Sacerdote, and Scheinkman (1996), Haynie (2001), and Haynie and Osgood (2005).
[54] Simon, Negrusa, and Warner (2010) analyzes more than 800,000 Army recruits who signed enlistment contracts in the years 1988-2001. About half stayed to the end of the initial enlistment contract, and of those who stayed, only 40% remained on active duty for another year or more beyond that first contract end date.
[55] Warner and Asch (2001) discusses some of economic aspects of the all-volunteer force in the United States.

of military pay, non-pecuniary benefits like health care and education programs, and enlistment bonuses – in order to entice new recruits to choose military service over other work opportunities.

In some exigent circumstances, policymakers might leverage other approaches in order to achieve required manning levels. The period 2005-2008 represents one such circumstance. During this timeframe, US involvement in the wars in Iraq and Afghanistan intensified: casualty figures regularly showed more than 500 US service members wounded or killed in action per month[56] - the large majority from the Army - and many soldiers served repeated combat tours within just a few years. At the same time, unemployment in the US was low and there were no immediate signs of the looming financial crisis, at least at the beginning of this time period. Against this backdrop, the Army struggled to meet its recruiting goals, falling short of stated goals for both quantity and quality of new recruits in 2005.[57] Thus, starting in 2005, the Army loosened its policy on granting enlistment waivers for health, aptitude, and criminal background conditions that would normally preclude enlistment. For instance, whereas in 2004, 12 percent of new recruits enlisted with some type of waiver; by 2008, more than 25 percent of recruits received a waiver (Korb and Segal, 2011). Of particular interest in this study is the latter category of so-called "morality" waivers, the number of which soared during this time period and resulted in the Army admitting thousands of new soldiers with major non-traffic criminal convictions, recent drug use, and even adult felonies. The Army abruptly stopped granting waivers for felons and recent drug abusers

[56] Defense Casualty Analysis System, Summary by Month and Service, from Defense Manpower and Data Center. Available at https://www.dmdc.osd.mil/dcas/pages/casualties.xhtml

[57] See Kapp (2006), which is a Congressional Research Service report on recruiting and retention in the Armed Forces for fiscal year 2005. Measures of quality are based on AFQT percentile and having graduated high school.

in early 2009.[58] I leverage this temporary rise in the granting of morality waivers because it led to an influx of "bad" peers. I identify the impact of those peers by exploiting randomness found in established assignment procedures in the military.

III. Data Description

A. Sources

I rely on data from two sources. First, I draw administrative military data on enlisted soldiers from the US Army's Office of Economic and Manpower Analysis (OEMA). These records contain rich soldier-level demographic, financial, and occupational data from the point of entry into the service as well as through subsequent military assignment. Importantly, these data include the specific dates when soldiers enter into and depart from the assigned company. These data also indicate military rank each month, so I can also determine whether and when a soldier has a reduction in rank, which is one disciplinary measure taken to punish misconduct. I additionally observe enlistment term (or contract period) outcomes for each soldier. A typical enlistment term is for either 3 or 4 years; term outcomes can include reenlistment (signing up for another term), voluntary separation at term end, or early dismissal from the Army for misconduct.

Second, for Army accessions in the years 2003-2007, I draw data on enlistment waivers for every soldier who joined active duty in those years. These data were provided to me by the US Army's Recruiting Command (USAREC), the headquarters which oversees Army recruiting.[59] For each new recruit in this time period, I observe whether or not he required a waiver to enlist and what type of waiver or waivers were

[58] "Army More Selective as Economy Lags," The Washington Post, April 19, 2009. Available at http://www.washingtonpost.com/wp-dyn/content/article/2009/04/18/AR2009041801992.html
[59] These data are separate from the standard enlisted military file (EMF) that is the primary data source. Unfortunately, I do not have access to waiver data for years outside the period 2003-2007.

needed – whether for age, education, health, or morality reasons. Morality waivers are necessary for those potential recruits with criminal records; the waiver codes in the data distinguish between misdemeanor and felony offenses. Figure 3.2 shows that the fraction of new entrants receiving a misdemeanor-based waiver more than doubled between 2003 and 2007. The increase is even starker for felony-based waivers, which nearly tripled over the same time period. Given that the Army hired 57,000 new recruits in 2007, those soldiers receiving a morality waiver accounted for about 14% of new recruits in that year.

B. Measuring Conduct Outcomes

The biggest data challenge in this project lies in the measurement of soldier misconduct, since I observe neither individual behavior nor incidents of arrest or misconduct, like which might appear in reports from law enforcement. In the absence of these primary data, I rely on three indicators of the nature of a soldier's conduct; these variables appear in the administrative personnel records to which I have access. First, soldiers may receive a reduction in military rank for serious disciplinary offenses, such as public intoxication, minor property damage, or disorderly conduct. These incidents are more severe than smaller offenses (such as being late for work call or improper uniform wear) that would be handled locally through assignment of extra duty or temporary confinement to the barracks. Second, for the most serious behavioral incidents – like aggravated assault or major theft – a soldier can be dismissed permanently from the military on misconduct grounds. In the analysis that follows, I define *major misconduct* by the occurrence of either (or both) reduction in rank or misconduct dismissal. Third, a general indicator of good conduct is whether the soldier finishes the first enlistment (or contract) term. To finish the term, the soldier must maintain favorable standing with the military: satisfactory job performance, meeting health and physical conditioning requirements, and avoiding major disciplinary infractions (like what would lead to a misconduct dismissal).[60]

C. Sample

The full analytical sample for this project consists of new soldiers who joined companies in any US Army active-duty combat brigade across the years 2004-2009. These brigades contain 1352 different companies and more than 175,000 new soldiers that joined those units during the time period.[61]

Since I observe company assignment by month as well as waiver status for soldiers joining in 2003-2007, I estimate morality waiver rates by company by month for the years 2004-2009. For each individual joining a company, I calculate the company rate excluding him – the "leave-out" mean – by dividing the number of company peers requiring a waiver by the total number of company peers. I aggregate the monthly rates across the first year in the Army for each soldier; the resulting average first-year exposure is the treatment variable in this study. Figure 3.3 plots the distribution of the treatment variable for soldiers who joined companies in 2007, after the waiver-heavy cohort from 2006 had completed boot camp and joined companies. In 2007, the average treatment

[60] I use these administrative disciplinary measures (reduction in rank, misconduct dismissal, finishing the term) to proxy for soldier misconduct or good conduct, which likely results in measurement error. Since soldier conduct is a left-hand side variable in subsequent regression analysis, I am not seriously concerned about possibly biased estimation of the causal effects of peer waiver exposure – as long as the measurement error is not systematically related to the peer waiver exposure. I provide suggestive evidence that any measurement error and treatment assignment are unrelated when I show morality waiver peer exposure to be randomly assigned (see Section IV).

[61] There are other units in the Army's force structure that I purposefully exclude from this study. First, training brigades are not appropriate for this analysis since most of their manning consists of transient soldiers who cycle in and out of the unit based on start and end dates of military training. The units that conduct boot camp for new enlistees are an example of this type of training brigade. Second, units smaller than brigades – such as those that staff Army hospitals or recruiting detachments – do not have the regimented structure conducive to peer effects analysis and may not even be assigned junior soldiers. I therefore also exclude such units from the analysis.

rate was 0.10. At this mean value, a new soldier is exposed in a given month to 6 peers with a prior criminal background out of the 59 total peers in the company. A new soldier at this mean exposure level therefore experiences 72 waiver-peer-months during the first year. Figure 3.3 shows that there is significant sampling variation around this mean, indicating that potential treatment realizations for new soldiers vary widely.

The preferred sample consists of the 76,616 new soldiers who joined companies in 2005-2007 and did not require a morality waiver.[62] This sample selection is shaped first by my interest in estimating the spillover effect from the waivered soldiers onto their higher-quality (non-waivered) peers. Next, I focus on the 2005-2007 subset of these new soldiers due to the limitations of the waiver data – entry cohorts 2003-2007 only – and the precision of the associated estimates of waiver peer rates in the company. For instance, I omit soldiers joining in 2004 because companies at that time contained numerous soldiers from entry cohorts 2000-2002 whose waiver status is unknown to me; therefore, I cannot precisely estimate the required exposure rates for 2004. Similarly, I omit soldiers joining in 2008 since those soldiers' own waiver status is also unknown. Appendix 3A provides more details on sample selection.

Descriptive statistics appear in Table 3.1, with the preferred sample in the leftmost columns. As shown in Panel A, these new soldiers are young (21 years) on average and about 90% have completed no college. Approximately 68% are white and more than 90% are male. Conduct-related outcomes appear in Panel B. New soldiers in the preferred sample are more likely to face a reduction in rank than conduct dismissal; 21% of the soldiers face either or both events and therefore qualify as committing major

[62] I exclude soldiers who died during the first term of service or were discharged from the service for disability or injury.

misconduct. Nearly 80% of the new soldiers complete the first enlistment term. The rightmost columns in Table 3.1 provide a comparison against more than 9,000 soldiers who joined in the same years as the preferred sample but required a morality waiver to enlist. There are some differences between these groups. First, the waivered soldiers are more likely to have a GED instead of a high school diploma, older on average, and more likely to be white. The waivered soldiers are also more likely to enter the Army with a combat career field, such as infantry or artillery, as opposed to a logistics field. As one might expect, the soldiers with prior criminal backgrounds are also more likely to commit major misconduct while in the Army than are their peers: nearly 30% of soldiers who received misdemeanor or felony waivers commit major misconduct during the first term, whereas rates are significantly lower (21%) for the non-waivered soldiers. [63] I return to misconduct committed by waivered soldiers at the end of Section V.

IV. Empirical Strategy

A. Conditional Random Assignment

To estimate the causal effect of workplace exposure to peers with criminal backgrounds, I rely on Army conditional random assignment (CRA) of new soldiers to companies. The Army arbitrarily assigns its junior enlisted members to companies based on established personnel processes that prioritize the "needs of the Army,"[64] not based on the preferences of the soldier and without regards to the enlistment waiver status of the soldiers already assigned to the destination company. For example, the Army may assign

[63] Gallaway et al (2013) finds a similar descriptive finding: waivered soldiers are more likely to be separated from the Army for misconduct and to be screened for alcohol/substance abuse and test positive for illicit substances.

[64] Department of Defense Directive 1315.07 and Army Regulation 600-14 provide the regulatory basis for CRA. Other researchers have used versions of this identification strategy, including Angrist and Johnson (2000), Carrell and Zinman (2014), and Carter and Skimmyhorn (2016). Army Regulation 600-13 provides the further stipulation that female soldiers cannot be assigned to units that have a routine mission to engage in direct combat, or to units which collocate with units assigned a direct combat mission.

two soldiers with motorized vehicle repair specialty to two different companies, one with several morality waiver peers and the other none. Those assignments are conditional on the soldiers' specialties (vehicle repair) and the companies' needs (vehicle mechanics), but otherwise arbitrary and therefore unrelated to anything else about either soldier.

In addition to the established personnel processes that underlie CRA, there are three further reasons to expect randomness in the assignment of new soldiers to morality waiver peers. First, new soldiers have no influence over the assignment process, unlike sergeants and officers who submit "dream sheets" and can directly contact career managers; thus, a new soldier has no means to communicate preferences related to unit assignment or associated peer composition. Second, soldiers in boot camp do not receive individual performance reports and do not interview for their next job, so these are not factors that an assignment manager could consider when placing new soldiers into companies. Finally, enlistment waiver status is not part of the military personnel records jacket of any soldier, which is precisely why I had to obtain the variable separately from the recruiting headquarters and for only a few select cohorts (as described in Section III). As such, morality waiver status could not be an assignment criterion for personnel managers. Thus, it is reasonable to expect random assignment of soldiers to companies with varying levels of peers who required morality waivers to enlist in the Army.

I confirm that a natural experiment results from CRA by comparing, in Table 3.2, the baseline characteristics of soldiers assigned to different rates of morality waiver peer treatment. Column 1 presents a regression of the average first-year morality waiver exposure on the assignment controls: rank, career field, time and their interactions along with gender. In column 2, I add a vector of entry characteristics – including AFQT, education level, age, and race – to the assignment controls. These are other observable characteristics of the new soldier that the assignment manager could theoretically consider when placing individuals into companies. The regression in column 2 has an explanatory power nearly identical to that seen in column 1 and none of the entry characteristics added in column 2 is significant. This result indicates that the assignment manager is <u>not</u> relying on these other characteristics when placing new soldiers into companies. In columns 3 and 4, I rerun these regressions for the preferred sample – soldiers who enlisted in the years 2005-2007 and did not require a morality waiver – and results are nearly identical. Importantly, these analyses confirm that new soldiers—conditional on rank, career field, Army requirements, and gender—are randomly assigned to companies and therefore levels of exposure to morality waiver peers.[65]

B. Estimation of Peer Effects

Given the plausible exogeneity resulting from Army CRA, I estimate the causal effect of assignment to waivered peers with the following linear probability model:

$$Conduct_{ijt} = \pi_0 + \pi_1 * morwa_{ijt} + \pi_2 * X_{ij} + \pi_3 * A_{ij} + Z_j + \mu_{ijt} \qquad (3.1)$$

In equation (3.1), $Conduct_{ijt}$ is a binary outcome for major misconduct during the initial enlistment term for soldier *i* assigned to company *j* at time *t*. π_0 is the regression intercept. $morwa_{ijt}$ is the explanatory variable of interest, measuring the soldier's exposure to peers in the company who required a morality waiver to enlist. X_{ij} is a vector of individual covariates (such as AFQT, education level, and race) not considered

[65] As mentioned in Section III, I exclude the waivered soldiers from the preferred sample to focus the analysis on spillover effects onto the non-waivered soldiers. In supplementary analysis, I find that waivered soldiers have slightly higher exposure rates to waivered peers: about 1/20 of a standard deviation of exposure, which is 1/10 of a waivered peer per month in a company of 60 junior soldiers. This difference is statistically significant due to the large sample size, but not of practical importance. I separately test for peer effects on the waivered soldiers in Section V.

in the assignment process. A_{ij} contains the assignment controls: career field, military rank, and time of assignment along with gender. Z_j are Army location and military unit fixed effects, which control for observed and unobserved differences in local opportunities for and attitudes towards committing misconduct. Factors in Z_j could impact both the individual and the peer group, and so are often called "common shocks." μ_{ijt} is the disturbance term. Crucially, Army CRA provides for an unbiased estimate for π_1 by satisfying the conditional independence assumption:

$$E[\mu_{ijt}|A_{ij}] = 0 \tag{3.2}$$

The estimation in (3.1) is in the reduced form, meaning that each estimated coefficient, such as π_1, must be interpreted as a combination of structural parameters representing the potential channels (peer actions, peer characteristics) through which the peer group might influence the individual, or vice versa. Appendix 3B provides full details on the simultaneous equations that lead to the derivation of (1). Even though the reduced-form peer effect that I estimate is causal, very strong assumptions are necessary in order to interpret the estimate for π_1 as measuring purely a peer action effect, or, alternatively, purely a peer characteristic effect. Without such assumptions, the reduced-form coefficient measures an effect that acts through both channels of peer actions and peer characteristics. I explore these channels in the next section of the paper after first presenting the main peer effects results.

V. Results

A. Main Peer Effects Results

Using least squares estimation of equation (3.1), I find that new soldiers are more likely to commit major misconduct when randomly assigned to a higher percentage of peers who received morality waivers. When the treatment variable $morwa_{ijt}$ is a rate of exposure, the point estimate for the causal parameter is 0.111, as reported in column 3 of Table 3.3. [66] Since one standard deviation of peer treatment is 0.046, the effect size of peer exposure on own misconduct is 0.111 x 0.046 = 0.005, which marks a 0.5 pp increase in misconduct likelihood. Given that the mean major misconduct in the preferred sample is roughly 0.21, the economic magnitude of the adverse peer effect is about 2.5%.

The regressions in Table 3.3 reveal that the point estimate for the morality waiver peer effect is robust to including a variety of individual characteristics as well as the series of fixed effects meant to address common shocks. In column 2, I add variables on the educational and demographic characteristics of the new soldier. While there are differences in misconduct rates by age and race/ethnicity, the topline coefficient on the waiver peer rate moves only slightly – bolstering the case for the conditional exogeneity discussed in Section IV. Column 3 adds battalion controls (Z_j from the regression equation), which are more than 300 separate fixed effects meant to capture any number of relevant differences across Army headquarters: how leaders handle disciplinary violations; military deployment experiences; day-to-day operations, etc. The battalion controls also subsume fixed effects for Army location, thereby controlling for possible differences in criminal activity, behavioral cultures, and law enforcement across Army posts. Importantly, the estimate for the adverse peer effect is robust to the full set of these controls, indicating that common factors such as the Army location or the actions of local leadership are not driving the observed peer effect.

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[66] Probit marginal effects, evaluated at mean values of the explanatory variables, are nearly identical to the coefficients estimated with the linear probability model.

I also fit a simple nonlinear model to examine where the linear-in-means peer effect is driven within the distribution of peer exposure. These regressions reveal that the adverse peer effect is mostly concentrated in the top half of the distribution (i.e. – soldiers who are treated with exposure rate greater than 0.09). Please see Appendix 3C for details. The linear-in-means model discussed above remains my preferred specification.

B. Heterogeneous Treatment Effects

Researchers across a variety of disciplines have found that the extent of peer influence varies across subpopulations. [67] Accordingly, I explore possible peer effect heterogeneity by expanding equation (3.1) to include interaction terms. These regression results appear in Table 3.4. Column 1 presents the original specification from the main analysis. In column 2, I add an interaction term for age, designating *older* soldiers as those who are at least 22 years old at entry into the Army (this is 30% of the preferred sample). I observe significant treatment heterogeneity based on age: the magnitude of the peer effect is 50% larger for the younger soldiers and null for those older than 22 years old at entry.

Next, columns 3 and 4 of Table 3.4 consider heterogeneity by gender and race/ethnicity. I add separate interactions terms for female, black, and Hispanic soldiers to test whether any of these subgroups exhibits differential response to exposure to morality waiver peers. The point estimates for these interaction terms are insignificant at conventional statistical levels, but the coefficient on *black * exposure* (0.163) in column

[67] For instance, Warr (1993), Gardner and Steinberg (2005), and Steinberg and Monahan (2007) find differences in peer effects by age of the individual; Cross and Madson (1997) and Han and Li (2009) by gender; Brooks-Gunn et al. (1993) and Graham, Taylor, and Ho (2009) by race/ethnicity.

4 suggests that the adverse peer effect could be significantly larger for new black soldiers (p-value 0.12).[68]

C. Other Outcomes

In this section, I explore other individual outcomes that could be influenced by exposure to morality waiver peers. Results appear in Table 3.5. Column 1 contains the main result for major misconduct from Table 3.3. Columns 2 and 3 consider the event indicators of major misconduct separately, revealing that most of the peer effect occurs in the serious but not severe offenses that are punished by reduction in rank (column 2). This result suggests that peers exert a stronger influence for "basic" misconduct than for more serious misconduct, consistent with model predictions and findings in Glaeser, Sacerdote, and Scheinkman (1996).

Column 4 of Table 3.5 considers how morality waiver peer exposure affects the binary outcome of finishing the first enlistment (or contract) term – a general indicator of good conduct and an important outcome for the military. To finish the term, the soldier must maintain favorable standing with the military: satisfactory job performance, meeting health and physical conditioning requirements, and avoiding major disciplinary infractions (like what would lead to a misconduct dismissal). In other words, receiving a misconduct dismissal is only one way out of many in which a soldier might not finish the first term. The regression in column 4 reveals that morality waiver exposure has no overall impact on the binary outcome of finishing the first term: the null effect is a

[68] I also calculate exposure rates by company within gender and race/ethnic groups and then estimate equation (3.1) with a set of exposure rates by group. I find no statistically significant differences in how individuals respond to own gender or own race exposure versus that from the other gender or other races. Estimates here are generally imprecise and not shown. One reason for the imprecision is the predominantly white male population that I study; each company features only a small number of (or no) soldiers from the minority demographic sub-groups.

precise zero (effect size -0.0003, p-value 0.89). Therefore, I find that exposure to some morality waiver peers slightly impacts the likelihood of conduct dismissal without having an overall effect on contract completion rates. I discuss the implications of this finding in Section VI.

Finally, I separately consider new soldiers from 2005-2007 who required a morality waiver to enlist. There are about 9300 such soldiers. As already shown in Table 3.1, these waivered soldiers are nearly 10 percentage points more likely to commit major misconduct than are their non-waivered peers. Estimation of equation (3.1) for this group shows no evidence of peer effects: the conduct outcomes of the waivered soldiers appear to be unaffected, on average, by the criminal backgrounds of their company peers (results not shown).

A related question is whether there is evidence of within-study rehabilitation effects, *per se*, for the waivered soldiers – like from serving with a very high percentage of non-waivered peers. It could be that serving with such "good apples" might positively affect a soldier who entered with a criminal background. The regression discussed above indicates that such rehabilitation is not occurring; the waivered soldiers are unaffected, on average, by the criminal backgrounds of their peers. I bolster this non-finding for the waivered soldiers (i.e. – no evidence of rehabilitation) by estimating a simple nonlinear model similar to that discussed earlier and in Appendix 3C. I find that waivered soldiers who are assigned to a lowest quartile morality waiver company (peer waiver rate below 0.06) are no less likely to commit major misconduct than are other waivered soldiers assigned to higher levels of exposure.[69]

D. Network Analysis

[69] Results available from the author on request.

In this section, I examine the relationship between misconduct committed by waivered and non-waivered soldiers assigned to the same company. This non-parametric analysis is exploratory only because of the simultaneity of contemporaneous outcomes (the reflection problem), but it sheds some light on potential channels underlying the observed peer effect.

This simple network analysis investigates 15,876 incidents of major misconduct committed by the preferred sample (non-waivered soldiers) alongside 2,677 incidents of major misconduct committed by their waivered peers assigned to the same company. Consistent with data limitations discussed in Section III, I can pinpoint an act of misconduct only to the first day of the month that punishment was handed down. Accordingly, the network analysis is "granular" only to the level of *month* of disciplinary resolution: for instance, within company C, even if soldiers A and B received disciplinary action in the same month, I do not know if they acted together, if soldier A's misconduct action preceded soldier B's, etc. Nonetheless, the results that follow provide suggestive evidence of contemporaneous peer influence in misconduct.

I proceed with the network analysis by first arraying the misconduct by waivered soldiers across 2,525 unique company*months; for instance, a waivered soldier from company C being reduced in rank in November 2007 qualifies as one such event occurring in a company*month. I then assign the misconduct incidents by the *non-waivered* soldiers to months based on timing relative to misconduct events by their same-company waivered peers. For instance, a misconduct event by a non-waivered soldier that is coded "3" occurred three months after a waivered soldier in the same company committed major misconduct, while misconduct occurring in the same month is coded

“0.” As shown in Figure 3.4, the largest concentration of non-waivered soldier misconduct occurs at month 0, or in the same month that the waivered soldier also commits misconduct. In other words, the new soldiers appear most likely to commit misconduct not only when assigned to a company with waivered peers, but also in the same month that one of those same waivered peers commits misconduct. This result suggests that waivered soldiers may be inducing non-waivered soldiers to be partners in misconduct events (or perhaps to do a copycat offense days later), so that the peer effect acts not only through background characteristics – the morality waiver – but also through same-period behavior. This result indicates multiple channels of the peer effect and is therefore complementary to the reduced-form interpretation of the main regression results discussed earlier.

VI. Discussion

In this paper, I study new soldiers who are randomly assigned to varying levels of exposure to peers who required morality waivers to join the US Army. I find that soldiers assigned to higher rates of such peers with criminal backgrounds are more likely to commit major misconduct during their first term in the Army. The adverse peer effect is concentrated among young soldiers: those who are 17-21 years of age upon entry into military service. Non-waivered soldiers are most likely to commit misconduct in the same month that a company peer with criminal background commits misconduct, suggesting that the peer effect acts through multiple channels.

This paper provides some of the first empirical evidence that adverse peers affect outcomes in the workplace, not just in traditionally-studied settings like education and neighborhoods. Perhaps unsurprisingly, my estimates are smaller in magnitude than those in the earlier studies of youth populations. For instance, results in Carrell and Hoekstra (2010) indicate that a one standard deviation increase in peers who witness domestic violence increases the likelihood of behavioral disruption by 11% in an elementary classroom setting,[70] while Damm and Dustmann (2014) finds a 5% effect for immigrant youths growing up in neighborhoods in Denmark. Even though each of these settings and populations differs from that examined here, there is a consistent pattern suggesting that older subjects are less vulnerable to adverse peer effects. This pattern is similar to findings in the sociology literature (Warr, 1993; Gardner and Steinberg, 2005) and actually holds within my study alone, given the finding that older soldiers are not, on average, significantly affected by exposure to morality waiver peers.

There is also evidence in this study of the real dilemma faced by firms or organizations that must modify or lower, even if temporarily, hiring standards in order to achieve targeted manning levels. In the current context, I identify a negative spillover effect onto higher-quality, traditional recruits from serving in the company of waivered peers. Namely, the personal cost to a soldier who commits misconduct – sometimes under influence from his waivered peers – is a smaller paycheck (since pay is tied to military rank) as well as some reputational damage at work. There are also associated costs borne by the organization, not only direct costs from the "bad apples," but also indirect costs such as from administrative processing, decreased mission readiness, etc. However, the null result for enlistment term completion, shown in Table 3.5, puts an important bound on the cost of the morality waiver soldiers to the organization. It is important to interpret this bound with caution, since the expansion in waivers in 2005-2008 was actually small relative to the overall size of the active duty Army.

[70] I calculate the 11% magnitude based on results presented in Tables 1 and 2 of their paper.

Accordingly, much larger expansions in morality waivers – either in the Army at large or among a few select career fields or units – could fundamentally change the makeup and social norms of the organization and lead to drastically different outcomes.

Finally, and of broader interest, the question of hiring standards may generalize to other settings where firms or organizations face personnel shortages. Two prominent examples are in the labor markets for teachers and nurses. In each case, the organizations did not hire peers with adverse characteristics, *per se*, but rather modified existing entry requirements (related to preparation) in order to meet staffing needs. Observers have studied some of the hiring consequences in each of these labor markets. For instance, Boyd et al. (2006) studies the impacts on student achievement in New York City from new hires who enter through new routes that allow reduced coursework prior to teaching. The authors find that teachers with reduced coursework prior to entry often provide smaller test score gains for students, but that those differences disappear as the cohort matures. Similarly, Bevill et al. (2007) examines how having fewer nurses with college degrees in North Carolina creates future challenges in filling the faculty ranks in nursing schools.

These spillover effects – whether to individual employees, the organization, or both – are an important dimension of hiring practices, particularly when the organization faces challenges in hiring fully-qualified employees. The cases discussed here – military enlistees, teachers, nurses – show significant differences in the impacts of the externalities across different stakeholders but these are noteworthy consequences in each case. Accordingly, estimating such spillovers and examining organizational decision-making in these labor markets and others remains a worthwhile topic for future research.

Appendix 3A – Sample Selection

In this appendix, I provide more details on the decision to focus on non-waivered soldiers who joined the Army in 2005-2007 as my preferred sample. This sample selection stems from an important data limitation, namely that the waiver data (from US Army Recruiting Command) cover only soldiers who enlisted in the years 2003-2007. This data limitation affects how precisely I can estimate the morality waiver peer rate in companies for different years; I measure that precision by the associated “coverage rate.” At any given time, the junior enlisted peer group in an Army company consists of enlistees from the preceding 3-5 cohort years. Soldiers from beyond this time horizon either have either left the Army or promoted to the rank of sergeant, thereby leaving the peer group. Given the limits of my data, estimating the morality waiver peer rate for a year like 2004 could be troubling. While I observe the waiver status of the newest group members (enlistees from 2003 and 2004), there are also junior soldiers in that company from cohorts 2001 and 2002 whose waiver status I do not observe. Similarly, for a year like 2008, even though I may precisely estimate the overall morality waiver peer rate (i.e. – high coverage rate) because of the high percentage of 2003-2007 enlistees in that company, the waiver status of the new soldier joining that company is unobservable to me.

I apply this coverage rate methodology to the entire analytical sample (n=175,805). The unit of observation is the soldier and I calculate a coverage fraction for each soldier based on his first month in the company. I then average the coverage rate across all soldiers in the sample who enlisted in that year. Figure 3A.1 shows that coverage rates are low, as expected, for 2004 (median rate is only 0.33) and also that the soldier's own waiver status is unknown for years 2008-2009. However, for years 2005-2007, median coverage is above 0.75 and the new soldier's own waiver status is known. Thus, these three years comprise the preferred sample.

Appendix 3B – Simultaneous Equations Modeling for Peer Effects

In this appendix, I describe the canonical linear-in-means peer effects equation and some associated algebra that lead to the derivation of equation (3.1), the main specification for peer effects estimated in the paper.

The traditional linear-in-means peer effects model stems from Manski's (1993) framework for understanding why individuals who belong to the same social group might behave in the same way or make similar choices. The mechanisms he considers are peer actions, peer characteristics, and correlated effects (also called "common shocks"). The linear-in-means specification in this setting is:

$$Conduct_{ijt} = \alpha + \beta * \overline{Conduct}_{-jt} + \gamma * X_{ij} + \sigma * A_{ij} + \delta * morwa_{ijt} + Z_j + \varepsilon_{ijt} \qquad \text{(3B.1)}$$

In equation (3.B1), $Conduct_{ijt}$ is a binary outcome for major misconduct during the initial enlistment term for soldier *i* assigned to company *j* at time *t*. $\overline{Conduct}_{-jt}$ measures *contemporaneous* peer misconduct: the average misconduct incidence among soldier i's peers in the company at time t, excluding individual i. X_{ij} is a vector of individual covariates (such as AFQT, education level, and race) not considered in the assignment process. A_{ij} contains the assignment controls: career field, military rank, and time of assignment along with gender. $morwa_{ijt}$ measures the soldier's exposure to peers in the company who required a morality waiver to enlist; this is the peer characteristic of interest. Z_j are Army location and unit fixed effects, the common shocks that could impact both the individual and the peer group. ε_{ijt} is the error term.

There are well-known empirical challenges in the estimation of (3B.1), even in settings with random assignment, as detailed in Manski (1993), Lyle (2007), and others. The most prominent challenge lies in the simultaneity of the variables $Conduct_{ijt}$ and $\overline{Conduct}_{-jt}$, often referred to as the "reflection problem." Following Sacerdote (2001) and others, I consider a second equation that captures the potential influence of the individual on the group outcome:

$$\overline{Conduct}_{-jt} = \tilde{\alpha} + \tilde{\beta} * Conduct_{ijt} + \tilde{\gamma} * X_{ij} + \tilde{\sigma} * \mathrm{A_{ij}} + \tilde{\delta} * \mathrm{morwa_{ijt}} + Z_j + \tilde{\varepsilon}_{ijt} \qquad \text{(3B.2)}$$

Combining (3.B1) and (3.B2) gives the following reduced-form equation:

$$Conduct_{ijt} = \pi_0 + \pi_1 * morwa_{ijt} + \pi_2 * X_{ij} + \pi_3 * A_{ij} + Z_j + \mu_{ijt} \qquad \text{(3B.3)}$$

Equation (3B.3) still includes measures of peer *characteristics* through the variable $morwa_{ijt}$ but excludes the simultaneous term, $\overline{Conduct}_{-jt}$, that is a measure of contemporary peer action. This step mechanically removes the reflection problem and concerns about simultaneity. The reduced-form coefficients in (B3), such as π_1, are composite of parameters from (3B.1) and (3B.2). More precisely,

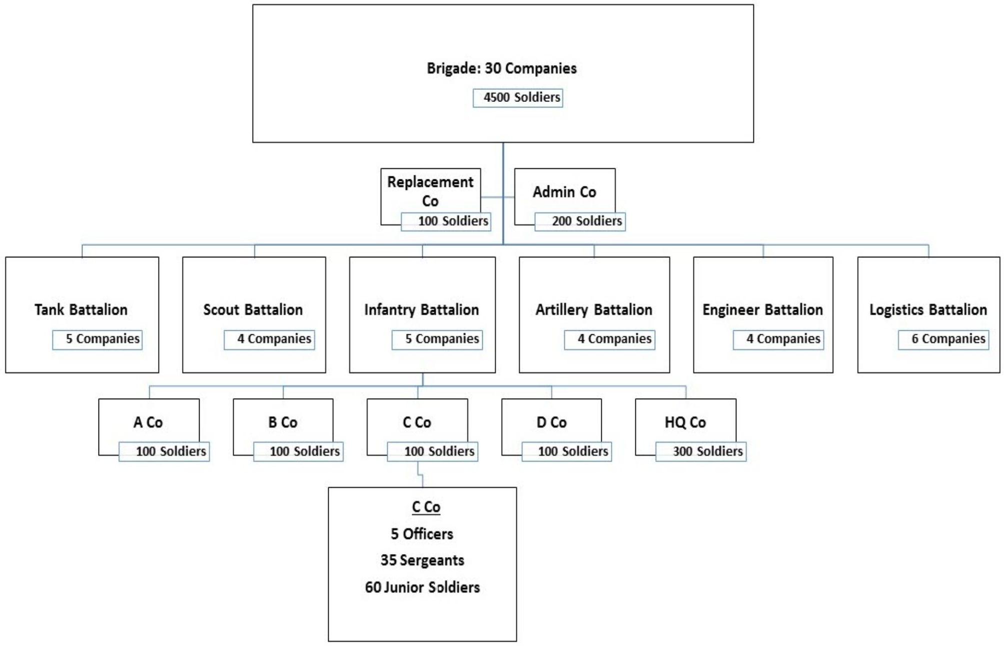
$$\pi_1 = \frac{\beta\tilde{\delta}+\delta}{1-\beta\tilde{\beta}} \qquad \text{(3B.4)}$$

after inserting (3B.2) into (3B.1) and collecting terms. The β terms measure the peer actions channel while the δ terms are from the peer characteristics channel. Based on the complexity of the relationship in equation (3B.4), the researcher would need to make very strong assumptions about several parameters to identify any one structural parameter of interest, say δ, even after first obtaining an estimate for π_1 from equation (3B.3). Nonetheless, the estimate for π_1 gives well-identified evidence of peer effects (i.e. – free of simultaneity bias) in the reduced form, even though it does not untangle the mechanisms of peer influence that the estimation of equations (3B.1) and (3B.2) would attempt to address.

Appendix 3C – Nonlinear Peer Effects Model

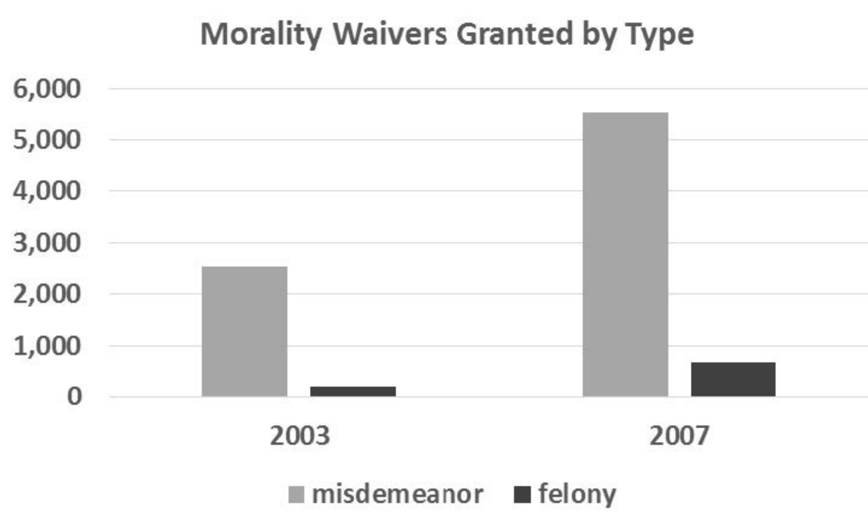
In this appendix, I estimate a simple nonlinear peer effects model in order to explore the linear-in-means result in the main body of the paper. The model is very similar to that in equation (3.1). The outcome of interest is still whether or not the new soldier commits major misconduct in the first term. The explanatory variables of interest are indicators for quartile of assignment to morality waiver peer exposure. As suggested by the histogram in Figure 3.3, a soldier with top quartile exposure has fraction 0.12 or greater of peers with waivered criminal backgrounds. In a third quartile company, that same rate is 0.09 greater. The regression results in Table 3C.1 show that the peer effect is concentrated in the top two quartiles – or upper half – of the distribution. New soldiers assigned to this level of waiver peer exposure are about 1 percentage point more likely to commit major misconduct than are new soldiers assigned to a bottom quartile rate (0.06) of criminal background peers. Given a baseline misconduct rate of about 0.21, assignment to a higher than average rate of morality waiver peer exposure increases the likelihood of major misconduct by 5%. This result is not drastically different from the linear-in-means model discussed in the main body, which remains my preferred specification.

Figure 3.1: Organization of a US Army Brigade



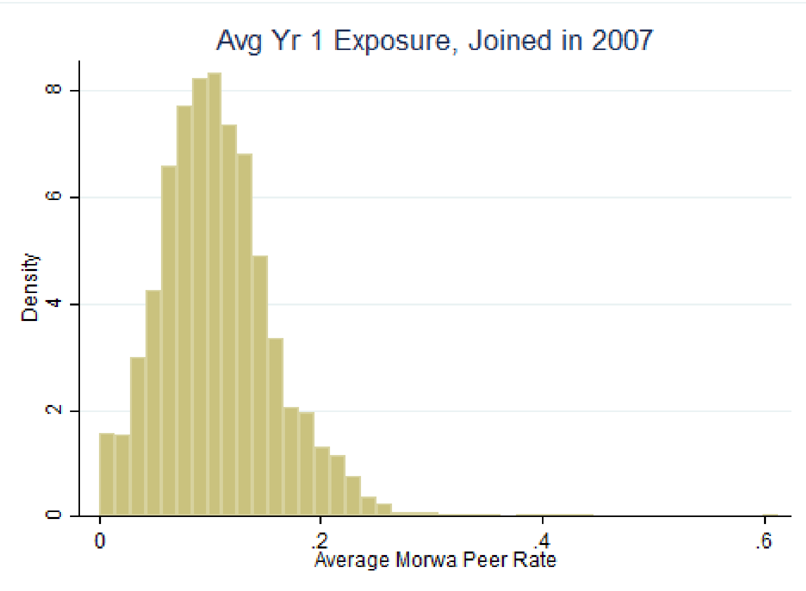
Note: Figure depicts the organizational structure of a typical brigade in the US Army. The hierarchical level of interest in this study is the company, which contains the junior soldier peer group (about 60 individuals).

Figure 3.2: Expansion of Morality Waivers to Enlist in the US Army, 2003-2007



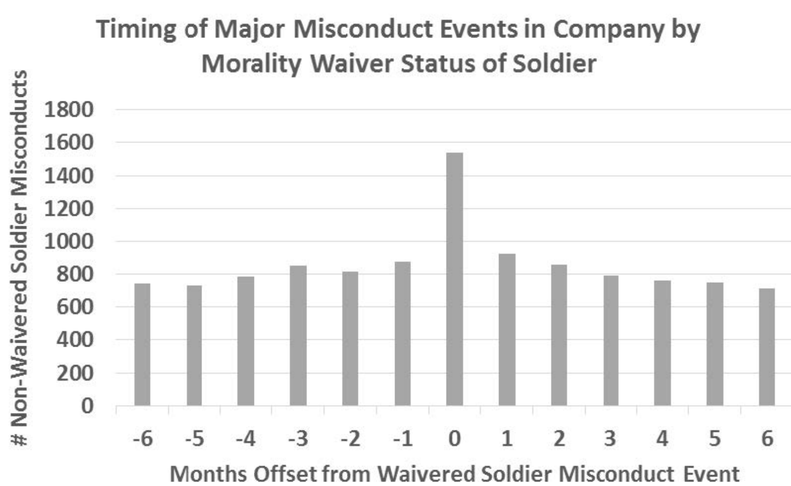
Note: DoD Data. Total number of active duty Army recruits was about 76,000 in 2003 and 56,000 in 2007. The expansion of morality waivers first occurred in 2005, when the Army missed its annual recruiting goals. In 2007, 14% of all new recruits required a morality a morality waiver in order to enlist.

Figure 3.3: Potential Peer Morality Waiver Exposure, 2007



Note: DoD Data. Analysis is for new US Army soldiers who joined companies in 2007. Horizontal axis measures fraction of assigned peer group that required a morality waiver to enlist. At mean, a soldier is treated with 0.10 exposure, meaning 6 peers out of 59 in his company required a waiver. Histogram contains 44 bins, width 0.012.

Figure 3.4: Network Analysis of Major Misconduct Events



Note: DoD Data. Analysis is based on 15,876 misconduct incidents by non-waivered soldiers from the preferred sample and 2,677 misconduct incidents by their waivered peers. The bars plot the timing of non-waivered soldier misconduct relative to misconduct events committed by waivered soldiers assigned to the same company.

Figure 3A.1: Peer Coverage Rate and Preferred Sample

Join Year	Peer Waiver Status Coverage at Median	Own Waiver Status Known?
2004	0.33	yes
2005	0.76	yes
2006	0.88	yes
2007	0.93	yes
2008	0.87	no
2009	0.59	no

Note: DoD Data. Enlistment waiver status is observed for enlistees in the years 2003-2007 only. Coverage fraction is calculated for each soldier's first month in the company and then averaged across all soldiers in the sample who enlisted in that year. 25th and 75th percentile coverage rates are denoted by whiskers. Join years 2005, 2006, and 2007 comprise the preferred sample.

Table 3.1: Summary Statistics

	preferred sample joined 2005-2007 no waiver needed		waivered sample joined 2005-2007 waiver required	
Panel A: Entry Characteristics				
	Mean	SD	Mean	SD
AFQT	57	(20)	59	(18)
GED only	0.21	(0.41)	0.30	(0.46)
high school only	0.70	(0.46)	0.59	(0.49)
some college only	0.06	(0.24)	0.09	(0.29)
college degree	0.02	(0.15)	0.02	(0.14)
age at entry	21	(3.4)	23	(3.8)
white	0.68	(0.47)	0.78	(0.42)
black	0.14	(0.03)	0.09	(0.28)
Hispanic	0.12	(0.33)	0.10	(0.29)
other race	0.06	(0.23)	0.04	0.20
female	0.11	(0.31)	0.05	(0.21)
combat career field	0.48	(0.50)	0.56	0.50
logistics career field	0.36	(0.48)	0.26	(0.44)
Panel B: Conduct Outcomes				
	Mean	SD	Mean	SD
reduction in rank	0.18	(0.38)	0.24	(0.43)
misconduct dismissal	0.08	(0.28)	0.14	(0.34)
any major misconduct	0.21	(0.41)	0.29	(0.45)
finish enlistment term	0.79	(0.41)	0.75	(0.43)
sample size	76616		9337	

Sources: Office of Economic and Manpower Analysis and US Army Recruiting Command. Standard deviations appear in parentheses. Preferred sample and waivered sample contain new soldiers assigned to an Army brigade and who spent at least 3 months in a company. Preferred sample includes enlistees from 2005-2007 who did not require a morality waiver to enlist. Waivered sample includes new recruits from 2005-2007 who required a morality waiver to enlist.

Table 3.2: Conditional Random Assignment Tests

Dependent variable is average rate of first-year exposure to conduct-waiver peers
Explanatory variables are characteristics of the newly assigned soldier

	new recruits, 2004-2009 full sample		new recruits, 2005-2007 did not need waiver	
mean yr 1 exposure	0.091		0.089	
	(1)	(2)	(3)	(4)
AFQT		-0.000		-0.000
		(0.000)		(0.000)
GED only		-0.000		0.003
		(0.002)		(0.005)
high school only		-0.001		0.002
		(0.002)		(0.005)
some college		-0.001		0.002
		(0.002)		(0.005)
college degree		-0.001		0.003
		(0.002)		(0.005)
age at entry		0.000		0.000
		(0.000)		(0.000)
black		-0.000		-0.001
		(0.000)		(0.000)
Hispanic		0.001		0.001
		(0.000)		(0.000)
other race		0.001		0.000
		(0.001)		(0.001)
assignment controls (rank, career field, time and inter-actions; gender)	Yes	Yes	Yes	Yes
R^2	0.216	0.217	0.244	0.245
Observations	175805	175805	76616	76616

Standard errors in parentheses. The dependent variable is the average exposure to peers who required a conduct waiver to enlist. Assignment controls are based on applicable regulations for general assignment of service members (AR 600-14) and for females to a unit with a direct combat mission (AR 600-13). Soldiers in columns 3-4 are the subset who did not require a conduct waiver to enlist and who enlisted in years (2005-2007) in which unit waiver rate coverage is highest based on data availability for this study.

Table 3.3: New Soldier Misconduct and Exposure to Peers Who Required a Conduct Waiver to Enlist in the US Army

Sample consists of enlistees in 2005-2007 who did not require a conduct waiver
Dependent variable is an indicator for whether soldier committed major misconduct in first term
Each column estimates a linear-in-means peer effects model

Mean major misconduct		0.207	
	(1)	(2)	(3)
Average exposure to waiver peers	0.095**	0.113**	0.111**
during first year in company	(0.046)	(0.046)	(0.044)
AFQT		-0.001***	-0.001***
		(0.000)	(0.000)
college degree		0.012	0.015
		(0.009)	(0.009)
some college		-0.014***	-0.014***
		(0.006)	(0.006)
age at entry		-0.010***	-0.010***
		(0.000)	(0.000)
black		0.069***	0.069***
		(0.005)	(0.005)
Hispanic		-0.031***	-0.031***
		(0.004)	(0.004)
other race		-0.024***	-0.022***
		(0.006)	(0.006)
assignment controls	Yes	Yes	Yes
battalion controls	No	No	Yes
Observations	76616	76616	76616

Standard errors are clustered at the company level in all regressions. Major misconduct is measured by either dismissal from the Army for misconduct or reduction in rank due to misconduct. The explanatory variable of interest measures the average exposure during the new soldier's first year to peers who required a morality-conduct waiver to enlist. Assignment controls are military occupation, year of enlistment, military rank, and gender - per standard regulations governing military assignment. Battalion controls fixed effects based on higher headquarters to which the company is assigned; the battalion controls subsume fixed effects for Army location.
* p<0.10, ** p<0.05, *** p<0.01

Table 3.4: Heterogeneity in Peer Effects Result for Preferred Sample

Sample consists of enlistees in 2005-2007
Dependent variable is an indicator for major misconduct in first term
Each regression estimates a linear-in-means peer effects model

mean major misconduct	0.207			
	(1)	(2)	(3)	(4)
Exposure to waiver peers in first year	0.111** (0.044)	0.165*** (0.051)	0.112** (0.046)	0.095* (0.049)
Older * Exposure		-0.184*** (0.064)		
Female * Exposure			-0.011 (0.118)	
Black * Exposure				0.158 (0.102)
Hispanic * Exposure				-0.035 (0.095)
Demographics	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Assignment controls	Yes	Yes	Yes	Yes
Battalion controls	Yes	Yes	Yes	Yes
Observations	76616	76616	76616	76616

Standard errors are clustered at the company level in all regressions. Major misconduct is measured by either dismissal from the Army for misconduct or reduction in rank due to misconduct. Column 1 contains the original specification from Table 3. Column 2 allows the response to waiver peer exposure to vary by age; older soldiers are those 22 years old or more at entry into the Army. Column 3 allows the response to differ by gender; column 4 race or ethnic group. Demographic variables include age at entry and race. Education measures are AFQT and level of civilian education at entry. Assignment controls and battalion controls are as in Table 3.3.
* p<0.10, ** p<0.05, *** p<0.01

Table 3.5: Other Outcomes for Preferred Sample

Sample consists of enlistees in 2005-2007
Dependent variable is an indicator variable for specified outcome
Each regression estimates a linear-in-means peer effects model

	(1)	(2)	(3)	(4)
outcome	any major misconduct	reduction in rank	misconduct dismissal	reenlistment eligibility
mean of outcome	0.207	0.178	0.084	0.207
Exposure to waiver peers in first year	0.111**	0.106**	0.042	-0.006
	(0.044)	(0.042)	(0.028)	(0.042)
Demographics	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes
Assignment controls	Yes	Yes	Yes	Yes
Battalion controls	Yes	Yes	Yes	Yes
Observations	76616	76616	76616	76616

Standard errors are clustered at the company level in all regressions. Major misconduct is measured by either dismissal from the Army for misconduct or reduction in rank due to misconduct. Column 1 contains the original specification from Table 3. Columns 2 and 3 consider the event indicators of major misconduct separately. Column 4 uses completion of the initial enlistment term as the outcome. Demographic variables include age at entry to the military and race. Education measures are AFQT and level of civilian education at entry. Assignment controls and battalion controls are as in Tables 3.3 and 3.4.
* p<0.10, ** p<0.05, *** p<0.01

Table 3C.1: New Soldier Misconduct and Exposure to Peers Who Required a Conduct Waiver to Enlist in the US Army (Nonlinear Specification)

Sample consists of enlistees in 2005-2007 who did not require a conduct waiver
Dependent variable is an indicator for whether soldier committed major misconduct in first term

Mean major misconduct		0.207	
	(1)	(2)	(3)
4th qtile (top) morwa exposure	0.008	0.010*	0.008
	(0.006)	(0.006)	(0.006)
3rd qtile morwa exposure	0.006	0.007	0.009*
	(0.005)	(0.005)	(0.005)
2nd qtile morwa exposure	0.003	0.003	0.004
	(0.005)	(0.005)	(0.005)
AFQT		-0.001***	-0.001***
		(0.000)	(0.000)
college degree		0.012	0.014
		(0.009)	(0.009)
some college		-0.014**	-0.014**
		(0.006)	(0.006)
age at entry		-0.010***	-0.010***
		(0.000)	(0.000)
black		0.069***	0.069***
		(0.005)	(0.005)
Hispanic		-0.031***	-0.031***
		(0.004)	(0.004)
other race		-0.024***	-0.022***
		(0.006)	(0.006)
assignment controls	Yes	Yes	Yes
battalion controls	No	No	Yes
Observations	76616	76616	76616

Standard errors are clustered at the company level in all regressions. Major misconduct is measured by either dismissal from the Army for misconduct or reduction in rank due to misconduct. The explanatory variables of interest are indicators for quartile of exposure during the new soldier's first year to peers who required a morality-conduct waiver to enlist. Top quartile rate is 0.12 or greater, 3rd quartile is 0.09 or greater, 2nd quartile is 0.06 or greater. Assignment controls are military occupation, year of enlistment, military rank, and gender - per standard regulations governing military assignment. Battalion controls are fixed effects based on higher headquarters to which the company is assigned; the battalion controls subsume fixed effects for Army location.
* p<0.10, ** p<0.05, *** p<0.01

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