**Peer Groups and Employment Outcomes:**
**Evidence Based on Conditional Random Assignment in the U.S. Army**

Pinar Karaca-Mandic
University of Minnesota School of Public Health

Nicole Maestas
RAND

David Powell
RAND

Preliminary
December 2013

## Abstract

In studies of employment outcomes, it is typical to relate outcomes to personal attributes, such as race and gender; less often do we consider the race and gender composition of the group in which the person works. Yet interactions between group members may have powerful effects on an individual's job performance. Although we might believe groups matter, it is difficult to credibly measure group effects because individuals usually self-select into groups or are assigned to them on the basis of unobservable characteristics. In fact, the dearth of evidence on this subject is likely explained by difficulties in isolating the impact of peer composition from the assignment mechanism. In this paper, we use confidential U.S. Army personnel records, and exploit the conditional random assignment of newly enlisted young adults by the Army to their first work units. Our dataset contains a panel of approximately 66,000 new enlistees during 2002, with 2 million person-month observations up to 2005. Our primary outcome variable is time to promotion and we observe the peer composition of each enlistee, providing us with a rare opportunity to estimate the effect of group composition on employment outcomes. Our estimates suggest that an increase in the percentage of female peers decreases the time to promotion of men relative to women, whereas an increase in the percentage of women among the leadership in a unit decreases the time to promotion of women relative to men. We find similar effects for race. An increase in own-race peers disproportionately increases time to promotion for blacks and Asians. Hispanics, on the other hand, experience reductions in promotion time when grouped with a higher fraction of Hispanics. All racial groups analyzed benefit from more own-race peers in leadership positions.

Corresponding author email: dpowell@rand.org

We gratefully acknowledge funding from NICHD under grant 1 R03 HD054417 01 A1, and from the RAND Population Research Center under a pilot grant. We are very grateful to LTC S. Jamie Gayton for much detailed information about the Army's assignment and promotion processes.

## 1. Introduction

A growing literature on peer effects has largely ignored the role of gender and racial group composition on individual labor outcomes. Yet group attributes may have important effects on individual outcomes through social interactions between group members. Individuals typically interact with both peers and superiors in the course of performing job duties, and the quality of these interactions may directly affect job performance. Peers and superiors transmit information about workplace norms, provide on-the-job training, and often act as mentors and role models.

In this paper, we investigate how race and gender affect social interactions in the workplace. If interactions between individuals of different racial and gender types vary in quality, and if interaction quality affects job performance, then the racial and gender composition of an individual's work group may affect performance outcomes. Furthermore, these effects may vary by the race and gender of the individual. Empirically, it is difficult to disentangle the effects of peer composition from the selection mechanism that determines one's peer composition. We investigate the performance of individuals based on the composition of their peers and the composition of those in leadership positions.

Despite the potential importance of social interactions in the workplace, few studies have surmounted two identification challenges: The first challenge is selection bias. It is difficult to find sources of exogenous variation in the composition of work groups since individuals either choose or are assigned to work groups on the basis of unobservable characteristics related to their performance potential. The second challenge is measurement of the relevant peer group itself. There exist no publicly available datasets that systematically track work units, job assignments, and performance outcomes for all individuals in a work unit. While peer effects in education settings have been rigorously analyzed in a number of studies (e.g., Sacerdote, 2001; Zimmerman, 2003; Lyle, 2007; Hoxby, 2000), only a handful of studies have offered credible research designs in workplace settings. Mas and Moretti (2009) exploit random variation in shift assignments to estimate the effect of average co-worker productivity on individual productivity of checkers at a large grocery chain. Duflo and Saez (2003; 2002) used an experimental design to estimate peer effects within university departments with respect to the decision to enroll in tax deferred retirement accounts. Sorenson (2006) used panel data to identify peer effects in university departments with respect to health plan enrollment. Guryan et al. (2009) study peer effects in professional golf, finding little evidence that being matched with higher quality peers improves ones own performance. Jackson and Bruegmann (2009) find evidence that teachers improve when surrounded by more effective colleagues. Finally, Waldinger (2012) finds no evidence of peer effects among university scientists in Germany from 1925 to 1938. None of these studies have investigated the role of race and gender interactions. Furthermore, the literature has studied measures of performance or behavior but has focused less on employment outcomes for the individual.

We use a unique and important laboratory to address many of these issues. The United States Army is an ideal setting to understand the effects of social interactions on employment outcomes for several reasons. First, conditional on a set of known and entirely observable assignment variables, newly enlisted young adults are randomly assigned to their first work units, which vary in race and gender composition. The Army has no information about an individual's potential performance beyond his or her assignment variables (predominantly occupational choice and AFQT scores), both of which are measured at the time of enlistment and prior to the initial unit assignment.  While we may worry that individuals are systematically assigned to units, we observe the entire set of variables on which this assignment can occur, reducing concerns of bias arising from individuals' selection of their own work unit or from assignment based on unobservable characteristics.

Second, all individuals in units are identifiable in confidential Army personnel records (to which we have obtained access), and units are identifiable down to a level at which one would plausibly expect possible peer and leader effects to operate (companies). Third, individuals in different work units all have the same employer; therefore, they all face the same benefit and compensation schedules, as well as policies governing assignments and promotions.  This lessens concerns about unit-specific external factors that may impact individual outcomes.  Finally, although the Army is just a single employer, it is also the largest employer in the United States, and a major employer of young adults.

Finally, we are able to disentangle the impacts of the composition of one's peer from the composition of one's leadership group.  We observe the composition of each individual's peer group as well as the composition of those with higher ranks.  To our knowledge, no study has studied the different effects that peer and leader composition can have on labor outcomes.

Using monthly personnel records, we construct a panel of two million person-month observations for approximately 66,000 new enlistees who joined the Army during fiscal year 2002 and whom we follow through the end of fiscal year 2005. Our outcome of interest is time to promotion to the level of Specialist/Corporal (E4).  For each new recruit, we observe the gender and racial composition of his or her peers and superiors each month, and relate group composition to time to promotion.

We leverage the conditional random assignment of peers by using an instrumental variable strategy which instruments the actual peer composition experienced by the individual (which may change due to unit transfers) with the initial assignment. We condition on the entire set of characteristics observed by the Army when making the initial assignment. Our outcome variable is censored because many individuals have not been promoted by the end of our sample period. We use a quantile regression framework to account nonparametrically for censoring concerns. In our analysis sample, we observe a nontrivial fraction of our sample leaving the Army before promotion. This attrition can create a non-random sample, even conditional on covariates, so we model and adjust for this selection issue. In the end, we employ a newly-developed instrumental variable quantile regression that has been extended to account for sample selection adjustments.

Our estimates suggest that an increase in the percentage of female peers increases the time to promotion for females relative to males, whereas an increase in the percentage of women among the leadership in a unit decreases the time to promotion of women relative to men. We find similar patterns based on race. We estimate that blacks and Asians experience negative peer effects – more own-race peers increases time to promotion. Hispanics, however, experience positive peer effects. Increases in the fraction of people in leadership of the same race are beneficial for all racial minority groups in our data.

One interpretation of these results is that minority groups with low promotion prospects disproportionately benefit from minority leaders, who may advocate for them in promotion deliberations. However, since minority leaders must appear fair to other groups, more junior minority members must implicitly compete for their backing. The presence of successful minority leaders may also motivate junior minority members to work harder to attain promotion. Our results indicate that gender and racial diversity among peers leads to individual performance gains; while this could be due to there being fewer competitors for the attention and backing of influential leaders, it could also reflect complementarities in information exchange across individuals of different race and gender types.

In the next section, we provide a conceptual framework based on social interaction theory for thinking about the mechanism through which peer and leader effects may operate. In section 3, we describe our data and discuss the institutional details of assignments and promotions in the Army. Section 4 describes our empirical methodology, and Section 5 presents estimation results. Section 6 concludes.

## 2. Conceptual Framework

According to Parsons (1963), an individual can be influenced when he or she is in need of information. Certainly, a young, inexperienced employee, such as a new Army recruit, must obtain information in order to make perform job tasks. Among other things, he or she must collect information about performance expectations, procedures for performing many new job tasks, and social norms of the workplace, including rules of conduct and interaction with coworkers and superiors. This need for information is the basis for interactions between individuals, and the mechanism by which individuals influence one another. But all sources of information are not equal. Individuals discriminate in their acceptance of information on the basis of trust, more readily accepting information that comes from "friends," who are generally deemed more trustworthy (Parsons, 1963; Hallinan and Williams, 1990). Crucially, individuals tend to make friends with others they judge to be more like them, often inferring similarity from external characteristics such as race and gender (Homans, 1974; Newcomb, 1961). Thus, one can think of interactions between individuals in a group as varying in quality. Interactions between friends are higher quality interactions in the sense that the information exchanged is judged to be of higher quality. Interaction quality can also capture the collegial quality or manner in which information is conveyed. For example, information (of any quality) can be conveyed in a friendly manner, a neutral manner, or a hostile manner.

Social interaction theory suggests the hypothesis that interaction quality is higher among friendly individuals, who are more likely to be of similar characteristics. As more people of an individual's "type" join a work group, the opportunities for friendly interactions and exchange of high quality information within the group increase. When there are relatively few of an individual's type, the marginal gain in total interaction quality of one additional person of that type is large. However, as the number of one's type rises, the marginal gain of one additional person of that type might decline, and past a certain threshold, the addition of another person of that type might have no effect on the total quality of the individual's interactions. As individuals interact with more people of their type, higher quality information is exchanged, which we assume positively affects individual (and group) performance. In addition, interpersonal communications are more collegial, which could lead to better cooperation among individuals, greater job satisfaction, and ultimately better individual and group performance. We are not the first to hypothesize that outcomes vary with group size; beginning with Kanter's (1983) theory of proportional representation, sociologists have found empirical evidence of such effects in the workplace (see e.g., Jackson et al., 1995; Izraeli, 1983; South et al., 1982).

This theoretical framework can be easily extended to accommodate leadership effects. In particular, we hypothesize that higher quality interactions are experienced by employees and superiors of the same type (Athey, Avery and Zemsky, 2000). Higher quality interactions imply transmission of higher quality information, which may include career advice, informal training, and even type-specific advice, such as "how to succeed in the Army as a woman" (Chung, 2000). Even in the absence of direct interactions with leaders, it is possible that new employees infer information about their career prospects from the mere existence of a leader of their type (via a "role model" effect) (Chung, 2000).

This framework has several interesting empirical implications. First, peer group and leadership composition affect performance through an interaction between group characteristics and an individual's own type. Second, the phenomenon of a declining marginal gain implies asymmetric effects for members of minority and majority groups. For example, an increase in the fraction black (women) in a work unit might improve total interaction quality for blacks (women) and hence performance outcomes when they are in the minority, but not when they are in the majority. Since in Army units blacks (women) are most often in the minority and whites (men) in the majority, we might find strong peer and leadership effects for blacks (women) but little or no effect for whites (men). Finally, our framework suggests that because of declining marginal quality gains, efforts to increase diversity in work units could enhance total group performance if increasing the number of blacks (women) raises the performance of blacks and does not reduce performance of whites (men). The literature offers some support for this framework. Antecol and Cobb-Clark (2001) find that military women in a male dominated group are more likely to experience sexual harassment than those in female-dominated groups. Similarly, ethnic group members report fewer incidences of racial harassment and discrimination in local communities in which their group is more heavily represented (Antecol and Cobb-Clark, 2005). A policy implication of such a finding would be that a more efficient allocation of staff possibly be achieved through the creation of special training opportunities and incentives which encourage women and minorities to enter occupations in which they are underrepresented.

The education literature has noted the importance of understanding the impact of race and gender composition on outcomes. Angrist and Lang (2004) study the impact of desegregation on education outcomes. Hoxby (2000) and Hoxby and Weingarth (2005) examine the impact of gender and racial composition on testing outcomes. However, we know of no study that estimates such effects in an employment setting.

## 3. Data Description and Institutional Setting

### *3.1 Army Personnel Data*

We use confidential Army personnel files entitled the Total Army Personnel Data Base—Active Enlisted file (TAPDB-AE) (formerly the Enlisted Master File) published by the U.S. Army Military Personnel Center, Personnel Information Systems Command, United States Army. The TAPDB-AE has monthly data on the universe of active duty soldiers as well as personnel who have separated during the past 120 days. Monthly data are available from 1995 to present. The TAPDB-AE contains detailed career-related information including unit assignment, pay grade, Armed Forces Qualification Test (AFQT) scores, military occupational specialty (PMOS), location of assignment, date of enlistment, and demographic characteristics such as gender, race/ethnicity, education, marital status, and number of dependents.

Our sample consists of 66,116 individuals who enlisted in the Army on or between October 1, 2001 and September 30, 2002, who were assigned to approximately 1,300 unique Army units, called companies. We observe each individual in every month through

September 30, 2005. Our resulting data file contains 2,092,197 person-month records. This observation window of three to four years is designed to follow new enlistees through the end of their first term enlistment contract. Enlistment contracts are for either 3 years (39%), 4 years (40%), 5 years (11%), or 6 years (10%).

Table 1A presents descriptive statistics for our sample of new recruits, measured in their seventh month in the Army, which for most, represents the beginning of their first real assignment after completion of all training (basic combat training and occupational training). The mean age is 21.[1] Males are the dominant gender group, representing 83 percent of the sample. About three-quarters are high school graduates, with just 15 percent having completed less education, and 10 percent having completed more.[2] Whites are the dominant racial group, representing 66 percent of the sample, followed by blacks (18 percent), Hispanics (13 percent), and Asians (4 percent). Aptitude is measured by the Armed Forces Qualification Test (AFQT), which is derived from the Armed Services Vocational Aptitude Battery (ASVAB). The Army groups AFQT scores into categories, where AFQT I is the highest category and AFQT V is the lowest. Just 6 percent of our sample scored in the highest AFQT category, 36 percent scored in the next highest range AFQT II, 29 percent scored in AFQT IIIA, 28 percent at AFQT IIIB, and just 2 percent scored in the lowest category, AFQT IV. No one scored in the AFQT V category, consistent with federal law

---

[1] The minimum allowable enlistment age is 17 and the maximum is 35 years. Those above age 35 have prior experience in the Army and enter at higher pay grades.

[2] Individuals who do not have a high school diploma at enlistment are required to score at the 31st percentile or above (AFQT IIIB or higher) on the Armed Forces Qualification Test (AFQT).

deeming individuals in this range ineligible to serve.[3] Our reported sample means are similar to published numbers for accessions in fiscal year 2002 (Department of Defense, 2002).[4]

Because we observe personnel records for all enlisted personnel, we can construct additional variables that summarize the peer and leadership composition of the individual's unit in every month. In our data, units are identified down to the level of the company.[5] Figure 1 shows the structure and hierarchy of Army units. At the top are Corps, which are each composed of two to five Divisions (10,000-18,000 soldiers); each Division is made up of three Brigades (3,000-5,000 soldiers); each Brigade is composed of three or more Battalions (500-600 soldiers); each Battalion has three to five Companies (100-200 soldiers); each Company has three to four Platoons (16-40 soldiers); and each Platoon has three to four Squads (4-10 soldiers). According to the Army, a company is a cohesive unit that can perform a battlefield function on its own. It is commanded by a Captain, whose principal non-commissioned (i.e., enlisted) assistant is a First Sergeant, and has a small headquarters component. Companies are typed by function, and individuals within companies hold complementary occupations which require them to interact frequently with one another in the course of carrying out the company's mission. For example, a typical Armor Tank Company might have has five officers and 57 enlisted soldiers who command 14 tanks and several wheeled vehicles.

*3.2 Defining Peers and Leaders*

---

[3] The thresholds between categories are based on percentiles of the score distribution of a civilian comparison group.

[4] One differences between our sample and the published numbers is that we report sample characteristics after the initial training period has finished for most soldiers (month 7), whereas the DOD numbers are for all accessions prior to the start initial training.

[5] Companies are identified in the data by a Unit Identification Code (UIC). It is not possible to use UICs to identify smaller units within companies such as platoons.

We define an individual's peer group to be all other enlisted soldiers within his or her company who hold his rank or lower. An individual's leaders are defined as all other soldiers within his or her company of higher rank. In our data Table 2 maps pay grades to ranks and job descriptions. At the lower ranks, pay grade and rank are virtually synonymous. For an individual who holds the rank of Private First Class (E3), his peers are all other E1's, E2's, and E3's within his company; whereas his leaders are soldiers at E4 or higher within his company. This distinction between leaders and peers represents functional distinctions in subordinate and supervisory relationships at this level; soldiers who hold E4 or higher are allowed to manage more junior soldiers, whereas those at ranks below E4 do not manage others and are primarily expected to carry out orders. Notably, we do not include commissioned officers in the unit among the set of leaders. Enlisted soldiers of low rank have very little interaction with commissioned officers; rather, higher ranking enlisted soldiers (non-commissioned officers) serve as both leaders and role models. In addition, it is unusual for enlisted soldiers to apply to officer's candidate school.

Table 1B shows the size and rank structure of the units to which the individuals in our data were assigned in their seventh month. The average company has 159 members. Over three-quarters of the unit are in the lowest ranks, E1 through E4, with approximately equal percentages in E2, E3 and E4. The leadership structure of the units has a declining share at each successively higher rank. In terms of numbers of individuals, the table shows that on average the peers (E1 to E3) constitute a group of about 96 individuals, whereas the leaders represent 64 individuals on average.

Table 3 shows summary statistics for the peers and leaders in the companies to which our focal recruits were assigned in their seventh month. For each peer and leader type, the table shows the percent of peers and leaders in the company measured three different ways—averaged over the preceding three months, the preceding six months, and since the initial month. The average percentages do not change much across measurement methods. For example, about 85 percent of peers are male, 63 percent are white, 19 percent are black, and 12 percent are Hispanic in almost all cases. The variation in the peer variables is shown in three ways; the overall standard deviation, the standard deviation between units, and the standard deviation within units over time. First, the implied coefficients of variation (the overall standard deviation divided by the mean) are sizeable, especially for groups other than non-white males. Second, there exists variation across units and within units over time, and in virtually all cases, the variation across units is larger. Third, the variation changes depending on the measurement method. Averaging peer and leader exposure over a small period of time (three months) uses relatively more variation over time than averaging over a longer period of time (since month 7).

### *3.3 Conditional Random Assignment to Units*

Our research design capitalizes on a unique feature of work assignments in the Army. Conditional upon a set of known and observed assignment variables, assignment of lower-ranking enlisted personnel to units is essentially random. More precisely, individuals are not assigned to units of different race and gender compositions according to their latent propensity to succeed in that unit. This occurs for three reasons: First, individual soldiers have no ability to affect their unit assignment. While they are permitted to express a geographical preference; this information is not necessarily taken into account, as the "needs of the Army" always trump individual preferences. Even to the extent geographical preferences are accommodated, an individual soldier has no control over the assignment of peers and leaders to a particular installation, let alone their allocation to different companies. Second, the Army has a limited set of information about soldiers upon which to make assignment decisions, and that information set is entirely observable in the Army personnel data we have obtained. Importantly, that information set includes aptitude, as measured by the AFQT at the time of enlistment; but it does not include any other information about an individual's latent potential for success in the Army, such as motivation, suitability to Army life, or ability to lead others. Information of this type is unknown to Army leadership at the time of initial assignment in the seventh month, which follows completion of basic combat training and specialized occupational training. Training occurs in centralized occupational training centers around the country, and there is no rating by instructors other than pass/fail that enters a recruit's personnel file. Third, the assignment process is a top-down process, driven by aggregate requirements for personnel of different grades in particular occupations at different installations. The Department of the Army authorizes numbers of personnel and equipment to the different installations Army-wide, and battalions at the installations report back where their shortages lie. The Senior Personnelist at the Department of the Army then assigns personnel to brigades at the different installations to fill shortages. At this point, soldiers are mere numbers on a page, categorized only by their assignment variables.

The single most important variable determining assignment is occupation, referred to as the primary military occupational specialty (PMOS). There are approximately 190 PMOS categories, each of which represents a different job title. Related PMOS' are grouped into broader Career Management Fields (CMF). AFQT is also an important assignment variable, affecting assignment both directly and indirectly. The indirect effect operates through the initial occupation choice made at the time of enlistment; each PMOS has a minimum AFQT threshold associated with it; for example, to enter the occupation of Aircraft Electrician, one must score at least 105 on the ASVAB sections forming the Mechanical Maintenance composite. Education level is used in conjunction with the AFQT score to identify so-called "high quality" recruits.

Owing to restrictions on the direct participation of women in combat operations, gender is also an important assignment variable. It influences occupational selection at the time of enlistment (certain PMOS' are closed to women) and may also affect subsequent unit assignment, since women may not be assigned to units that are likely to participate in direct combat operations upon deployment.

Race/ethnicity is not an explicit assignment variable; however, since it is readily observable by appearance or inferable from an individual's name, it must be considered an implicit assignment variable. In addition, the process of allocating personnel assigned to the brigade down to battalions and companies occurs *after* the assignees are physically present at the installation. The same is true for age, physical fitness (proxied by BMI), marital status, and having dependents. Although not explicit assignment variables, they are also observable by sight (e.g., new assignees will often arrive at the installation with their families), and family status is taken into account on the margin when considering who to assign to deployable companies.[6]

Given that we observe the full set of variables that are observed at the time of unit assignment, the initial peer composition variables should be conditionally random. Unfortunately, we do not observe additional variables that were unknown at the time of assignment to use as falsification tests. Because the TAPDB-AE is a personnel database, all

[6] For example, if all else is equal an unmarried soldier may be assigned to a deployable company whereas a married soldier with children may be assigned to a non-deployable company.

values of variables at the time of initial assignment are known and potentially used either explicitly or implicitly by the Army. Therefore, it is difficult to find a non-assignment variable with which to test whether the assumption of conditional random assignment holds. Our assumption is justified on the basis of detailed knowledge of the assignment process itself. A new recruit's latent performance potential is simply unobserved at the time of assignment; and therefore orthogonal to the race and gender composition of peers and leaders in their unit. Even if it hypothetically were observable, it is not obvious how this information would be used, since the Army seeks to maintain an optimal level of readiness of all its units. We will test this conditional random assignment by testing whether our peer composition variables are predictive of interactions between some of our control variables. This test is designed to see if interactions that we do not condition on for our main specifications are potentially omitted variables that cannot be explained by other covariates.

### *3.4 Promotion Process*

Our primary outcome of interest is time to promotion from E3 (Private First Class) to E4 (Specialist or Corporal).[7] Williamson (1999) provides a detailed description of the Army's promotion process for enlisted personnel. Promotions within the first four pay grades, E1 to E4, are handled on a decentralized basis, which means the company decides who gets promoted and who does not among those who meet standardized requirements for time spent in the current pay grade (time-in-grade) and tenure in the Army (time-in-service). There are no set limits as to how many soldiers can be promoted through E4. Promotions to

[7] The vast majority of E4's are Specialists; however, a small percentage of Specialists are given lateral appointments to Corporal (the lowest ranking non-commissioned officer) when they hold leadership positions that require them to have rank authority as a non-commissioned officer over lower ranking soldiers. This typically occurs when due to a shortage of E5's, an E4 is placed in a position usually occupied by an E5. The lateral appointment is not viewed as a promotion.

pay grades E5 through E6 are done through a semi-centralized process in which the company recommends individual soldiers for promotion, but the Department of the Army sets promotion criteria and decides who actually gets promoted.[8] The number who may hold the ranks of E5 and E6 at any given time is limited, according to the current staffing needs of the Army. Promotions to E7 through E9 are conducted in a centralized promotion process.

Eligibility for promotion from E3 to E4 requires six months spent in E3, and 26 months spent in Army service. However, at the discretion of the commander, and based on the soldier's performance, up to three months of the required time spent in E3, and up to 12 months of the required time spent in service may be waived.[9] Promotion determinations are made monthly. On the 1st of every month, each battalion headquarters receives from the Human Resource Command (the Department of the Army personnel section) a list of all E3 soldiers in the battalion. The list indicates name, grade, time in service, and time in grade. Each battalion also receives a monthly allocation of waivers. The allocation of waivers is set by the Human Resource Command in response to staffing shortages and excesses among E4's in different occupations and may vary from battalion to battalion. The battalion Command Sergeant Major (E9) gives the list to his First Sergeants (E8), who handle promotion matters on behalf of the company commanders. The First Sergeants meet with their platoon Sergeants (E7's), and together they decide who in the company merits promotion (with and without waiver) that month and who does not. The First Sergeants then brief and justify their choices to the battalion Command Sergeant Major. Once the list is finalized, the battalion

[8] At this level, promotion criteria formally extend beyond time-in-grade and time-in-service to also include promotion "points," which soldiers accumulate in a variety of ways, including through their commander's discretion, through awards and decorations, education and training, and from special promotion boards who judge soldiers on criteria such as appearance, self-confidence, oral expression, knowledge of world and Army affairs, leadership and future potential in the Army.

[9] We do not focus on transition from E1 to E2 since it is automatic after six months spent in E1. Similarly, we do not focus on the transition from E2 to E3 since the best soldier can be promoted at most six months earlier than the lowest performing soldier, and for most, promotion to E3 is routine after one year of service.

commander signs off and forwards the promotion list to the Human Resource Command. In sum, higher-ranking enlisted personnel are directly involved in the promotion process; that is, they not only may indirectly affect promotion as mentors and role models but also they may directly affect promotion by advocating for or against particular soldiers.

The average time to promotion to E4 is 15.7 months, with a standard deviation of 5.2 months. The implied coefficient of variation is 0.33, implying substantial variation in our outcome of interest. The top and bottom panels of Figure 2 show the (smoothed) non-parametric promotion hazards to E4 by gender and race, respectively. Time zero corresponds to the first month after the completion of training (i.e., month 7). For both men and women, the hazard rate rises sharply prior to about month 17, after which it rapidly declines. Notably, in all months, the hazard rate is higher for men than for women. The promotion hazard also varies by race. All race/ethnic groups have similar promotion rates in the early months, but around month 10, promotion of Hispanics and Asians accelerates relative to whites, and promotion of blacks lags relative to whites. While these non-parametric hazards do not account for occupational differences in promotion opportunities, we show in Section 5 that these gender and racial differences in promotion persist holding occupation and other characteristics constant.

### *3.5 Attrition*

Attrition is a significant issue for the Army, and an important consideration for our empirical strategy. Because individuals enter the Army under contract, the vast majority of attritors leave the army after their first term enlistment contract ends. That is, they simply opt not to re-enlist. This occurs well past the promotion window for E4. Attrition before this point requires breaking the enlistment contract, which entails being deemed unsuitable for the

Army usually on account of conduct problems or by officially stating that one is homosexual. Despite the contractual constraint, 37 percent break their first term contract (Buddin, 2005). The bulk of these separations occur in the first six months, during the initial training phase and *before* the first real assignment.

Conditional on successfully completing training—defined as being assigned to a unit in the seventh month—approximately 16 percent of our sample attrit prior to achieving promotion to E4, and conditional on attaining E3, eight percent attrit prior to achieving promotion to E4. A complicating factor is that while the initial unit assignment is random, subsequent attrition is nonrandom, almost certainly depending on unobservable characteristics. Indeed, the same peers and leaders that influence promotion are also likely to affect the probability of attrition; thus, we expect peer and leader effects on the probability of attrition as well as promotion. We explicitly model attrition and account for possible selection bias through a selection adjustment.

The top panel of Figure 3 shows the (smoothed) non-parametric attrition hazard. The hazard is low in the early months, rising slowly until about month 19 when it increases sharply, rising to its peak in about month 30. Since month zero represents the seventh month in the Army, month 30 coincides with the end of all three-year contracts. For comparison, the bottom panel reproduces the overall promotion hazard. Juxtaposed against one another we see that the period of highest attrition occurs after the peak promotion period, notably just beginning its steep rise in month 19 when the promotion hazard is at its peak; this suggests that many individuals wait until their promotion prospects are revealed before they leave the Army. If so, this helps mitigate any attrition bias in our estimates.

The top and bottom panels of Figure 4 show the attrition hazards by gender and race. The hazard takes a similar shape for men and women, but is higher for women than for men in all periods up until month 37. Similarly, the attrition hazard for blacks is highest in all months until month 34, followed by whites, Hispanics, and Asians.

*3.6 Unit changes*

The new recruits in our data change companies an average of once during the course of their first term contract. The dominant reason for unit changes are individual replacement tours in locations such as Korea and Saudi Arabia. Individual replacement tours involve sending individual soldiers abroad to replace others whose tours are ending, as opposed to the typical tour whereby an entire company is deployed as a group (examples of the latter are tours in Iraq and Afghanistan). A soldier sent on an individual replacement tour changes companies once when he or she starts the tour and again at the end upon return to the United States. Soldiers are also occasionally moved within a battalion to fill vacancies arising in adjacent companies; typically these vacancies are filled with new assignees to the installation, but in low-density occupations it is often not likely that a replacement will be forthcoming and a reallocation is made across companies within the battalion to preserve readiness. A final and relatively uncommon reason is so-called “re-starts.” Soldiers with disciplinary problems will occasionally be reassigned to an adjacent company (contingent upon space) in order to give the individual a fresh start. Although such individuals are poor performers the demographic composition of the receiving unit is usually not a factor influencing its selection—rather, the Army must have a need for an individual of that occupation, skill level, and grade in that company. However, we cannot be sure that subsequent peer groups are randomly-assigned, even conditional on observables. Consequently, while our endogenous treatment variables are the peer groups experienced throughout the individual's time before promotion, we instrument with the initial peer group composition. Thus, our variation originates only from the initial assignment.

## 4. Empirical Strategy

We focus on new enlistees in their seventh month, most of whom hold the ranks of Private (E2) or Private First Class (E3). We measure the time (in months) until promotion to E4. This time-to-promotion is our outcome variable. In defining the race and gender composition of the unit, we differentiate between peers and leaders. Specifically, all E1's, E2's, and E3's in the company are considered peers, while enlistees in E4 and above (up to E9) are considered leaders. We have two benchmark models. In the first model, we relate time to promotion to peer composition variables based on gender. In the second model, we use peer composition variables based on race. We consider the peer composition variables as our "treatment variables."

We separate our composition variables based on peers and leaders. The variable "Female Peers" is the fraction of peers who are female averaged over each month for the individual. We construct a similar variable "Female Leaders" for the fraction of leaders who are female. We will also interact these variables with a dummy variable equal to 1 if the individual is female. These interactions allow us to test for asymmetries in peer and leadership effects according to the extent to which an individual is similar to one's peers and leaders. We create similar variables for "Black," "Hispanic," and "Asian."

We drop all individuals in small occupations, defined as occupations with less than 50 people in our sample. Our estimation strategy requires us to estimate the relationship between all of our control variables on both attrition and time to promotion. Identification is difficult for these small occupations. Dropping these occupations should have little impact on our results given that we are selecting on an exogenous variable and these observations compose a small fraction of our sample.

Our empirical strategy is motivated by the details of our data and identification mechanism. We are interested in understanding how peer effects impact promotion time. We do not observe time to promotion, however, for individuals that have not been promoted by the end of the sample period. We consider the promotion time for these individuals as "censored." Quantile models are appropriate in this context given that they are typically robust to censoring concerns. The utility of quantile models in analyzing duration data has been made before (Koenker and Bilias, 2002; Koenker and Xiao, 2002; Chernozhukov and Fernandez-Val, 2005; Fitzenberger and Wilke, 2006) and is especially powerful when the full duration is not observed for all observations. Consequently, we use a quantile framework in our analysis.

It is rare to find conditional random assignment in the context of employment peers. Our initial peer variables have conditional random assignment, but changes in these variables due to unit changes are potentially not random. When individuals change units, it is possible that unobservable information is used in the reassignment. We are hesitant to use such variation. At the same time, we believe that it is important to model outcomes as a function of an individual's true peer group, which may be different than their initial peer group assignment. Therefore, we model individual outcomes as a function of the peer composition experienced throughout the entire pre-promotion period. We use the initial peer group as instruments. The initial assignment is conditionally random and should be correlated with the actual peer composition experienced by the individuals. As a result, we use an instrumental variable quantile regression framework.

Finally, a nontrivial fraction of our sample attrits before we can observe their time to promotion. This attrition may bias our estimates if our peer composition variables also affect the probability of attrition. Under such circumstances, the observed distribution of time to promotion is not random. We can only estimate the impact of peer composition on time to promotion for the sample that includes information on time to promotion. This includes individuals that are promoted during our sample period and individuals that we know are not promoted by the end of the sample period. Those that leave the Army also have censored promotion times, but the censoring variable is potentially related to the peer composition variables (unlike the fixed censoring that occurs at month 48). We model attrition as a form of sample selection.

We model promotion time as a function of our peer composition variables:

$$y = D'\beta(U^*), \quad U^* \sim U(0,1), \tag{1}$$

$$y^* = \min(y, C) * h \tag{2}$$

where *y* is the time to promotion in months and *D* represents our treatment variables - the peer composition variables, discussed above. $U^*$ is the individuals underlying “proneness” for promotion time, normalized to be uniform. This nonseparable disturbance term can be interpreted as a rank variable. Individuals with large $U^*$ are those that – holding peer composition constant – would be promoted later. Individuals with small $U^*$ are those that would be promoted sooner. We can interpret smaller $U^*$ as a measure of high “ability” in this context. We use the quantile framework primarily due to censoring concerns so we focus on the median, but we will also consider other parts of the distribution as well.

Because of censoring, we do not observe *y*. Instead, we observe the minimum of *y* and *C*. In our data, *C* is equal to 48 months. We also only observe the minimum of *y* and *C* for individuals that do not attrit. Remaining in our sample (not attriting) is denoted by *h=1*,

$$P(h = 1|W) = F(W'\delta). \tag{3}$$

We model remaining in our sample as an unknown function of *W*, which includes *Z*, *X*, and a "selection instrument," which we describe below. In many contexts, it is typical to assume that *F()* is the CDF of the normal distribution. We relax this assumption and do not specify this function.

To implement the instrumental variable estimator, we also must assume that the instruments (*Z)* affect *D*:

$$D = \varphi(Z, W, V) \tag{4}$$

where we do not specify $\varphi()$ and *V* is a disturbance term. We require very little structure on the relationship between the instruments and the treatment variables. Our final assumption is

$$U^*|Z, X, W'\widehat{\delta} \sim U^*|X, W'\widehat{\delta} \tag{5}$$

This assumptions states that the distribution of $U^*$ is unaffected by conditioning on the instruments once we condition on our covariates *X* and adjust for selection. This assumption is our exogeneity assumption and reflects the conditional random assignment in our data. Our peer composition instruments are unpredictive of individuals' underlying proneness for promotion once we condition on observable characteristics and an index function that predicts remaining in the Army during our sample period.

We are interested in estimating the Structural Quantile Function

$$Q_y(\tau|D) = D'\beta(\tau) \tag{6}$$

The function describes how the distribution of promotion (for the observed sample) changes for different values of the treatment variables. We focus on quantiles unaffected by censoring.

*Selection Mechanism*

We model selection semi-parametrically in equation (3). Typically in applied work, identification of the selection mechanism originates from one of two sources. First, it is most common to follow Heckman (1979) and assume a functional form of the selection mechanism. The nonlinearities in the assumed *F()* function (usually the normal distribution) allow for separate identification of the impact of the treatment variables on the outcome variables and the impact of selection on the observed distribution of the outcome.

Second, it is possible to use an excluded variable that affects selection without independently impacting the outcome variable. We refer to this variable as a "selection instrument." Newey (2009) discusses identification of two-step sample selection models using an excluded instrument. In practice, such excluded instruments are difficult to find. In our case, this assumption would require that we observe a variable that impacts attrition but not promotion. While it is possible that one or more of the variables in our data are unrelated to promotion, we find this argument difficult to make *a priori*. At the same time, given that we do not know *F()*, we will not impose any assumptions on this functional form.

Recent work, however, has shown that while distributional assumptions or excluded instruments are possible routes to identification, they are not necessary. Chen and Zhou (2005) introduce a matching estimator which matches observations with similar probabilities of selection and uses the within-match differences in the covariates to identify their effect. More recently, Escanciano, Jacho-Chavez, and Lewbel (2012) discuss identification of two-step semi-parametric models similar in spirit to the model that we will estimate. They show that nonlinearities in the selection mechanism can separately identify the impact of selection from the independent effects of the covariates. This identification does not require parameterizing the selection equation. The intuition is that the binary nature of the selection equation implies that it is, in fact, nonlinear with respect to the arguments. Without assuming a specific distribution, it is possible to estimate these nonlinearities and these use these nonlinearites to separately identify the impact of the variables from the effect of selection on the observed distribution of the outcome variable.

The intuition behind Escanciano, Jacho-Chavez, and Lewbel (2012) has been used previously in applied work. Mulligan and Rubenstein (2008) estimate a selection equation and use only observations with very large estimated index functions. This analysis sample is likely free of selection bias since the probability of remaining in the sample is close to 1. This estimator is similar to the Escanciano, Jacho-Chavez, and Lewbel (2012) argument – the nonlinear nature of the selection equation implies that changes in the covariates are separately identified. Escanciano, Jacho-Chavez, and Lewbel (2012) extend this argument, however, to avoid complete reliance on identification-at-infinity and show that identification is not restricted to the tails of the selection index.

We employ a similar strategy. While we will make no parametric assumptions on the $F()$ function of the selection equation, our first step is to "naively" guess that the differences between the selection index and the selection probabilities are related to the nonlinearities determined by a normal distribution. We use a probit regression to create predict probabilities as a function of $Z$ and $X$. We use these predicted probabilities as our selection instrument, the excluded instrument that does not independently impact the outcome variable (conditional on all other variables). Next, we use a semi-parametric method to estimate δ in our selection equation. We relate selection into our sample to *Z*, *X*, and our predicted probability. This predicted probability varies independently of *Z* and *X* due *only* to the nonlinearities determined by the normal distribution. Note, however, that we are not imposing that *F()* is the CDF of the normal distribution. If these nonlinearities are not predictive of actual selection, then we will observe no empirical relationship between the selection instrument and selection conditional on all other variables. Put differently, we guess that the normal distribution is in some way related to the true distribution and hope that it maps out the nonlinearities. To the extent that it does not, we are less likely to find an empirical relationship between our selection instrument and selection. This relationship is testable and our strategy relies on finding this empirical relationship.

We see this method as a simple means of implementing an identification strategy similar to the one introduced by Escanciano, Jacho-Chavez, and Lewbel (2012). While they suggest a two-step semi-parametric strategy which estimates the nonlinearities in the selection mechanism, we implement this strategy differently but the motivation is similar.

Using our selection instrument, we estimate the selection equation semi-parametrically using the monotone rank (MR) estimator of Cavanagh and Sherman (1998). This estimator maximizes the correlation between the index $(W'\delta)$ and the outcome variable (*h*). The parameters are identified up to scale. This estimated index allows us to compare individuals with similar predicted indices in the main equation. The MR estimator makes no parametric distributional assumptions. This step will provide information about whether our predicted probability of selection, in fact, predicts selection. If it does, then we have a shock to selection that operates independent of time to promotion.

*Instrumental Variable Quantile Regression with Sample Selection*

We discussed earlier the merits of using an instrumental variable quantile regression approach in our context. We use the instrumental variables generalized quantile regression (IV-GQR) estimator first introduced in Powell (2013a) which was extended to account for sample selection in Powell (2013b). To our knowledge, this estimator is the only instrumental variable quantile regression estimator that accounts for sample selection. The IV-GQR estimator is a "generalization" of traditional quantile methods because quantile regression (QR) and instrumental variable quantile regression (IV-QR) are special cases of IV-GQR.

Buchinsky (2002) introduced a sample selection version of quantile regression, paralleling the mean regression selection framework of Newey (2009). Huber and Melly (2011) point out that the Buchinsky (2002) framework assumes a constant effect throughout the distribution and cannot reveal heterogeneous effects.

Let $U^* = f(X, U, S)$ where *X* are the control variables, *U* represents "unobserved proneness", and *S* is the disturbance term related to sample selection. We place no restrictions on *f()*. A conditional quantile framework would separate this disturbance term and, by controlling for *X* and the determinants of *S* (through an estimated selection index), would allow the variables to vary based only on unobserved proneness.

For comparative purposes, ignore selection and let us consider the differences between IV-GQR and IV-QR (Chernozhukov and Hansen, 2006). These differences are the same when comparing GQR and QR (Koenker and Bassett, 1978). IV-QR includes all variables in the structural model and the parameters vary based only on *U*. This alters the interpretation of the parameters. The parameters in a conditional quantile framework vary based on unobserved proneness. As one adds more control variable, some of this unobserved proneness becomes observed. An individual at the bottom of the promotion time distribution given her education, AFQT scores, and occupation may be at the top of the unconditional (on education, AQFT, and occupation) distribution. IV-QR assumes that the treatment variables have the same effect at the same part of the conditional distribution even though some of these observations are at the bottom of the unconditional (on control variables) distribution and some are at the top.

IV-GQR conditions on the control variables for identification purposes but the parameters still vary based on $U^*$. This property is especially important in the context of sample selection to allow for heterogeneous effects. There is little justification for separating the disturbance term based on whether that part of the disturbance is predicted by the selection adjustment. IV-GQR separates the variables into "treatment variables" (our peer composition variables) and "control variables" (the assignment variables). While traditional quantile models require that all variable enter the structural model, IV-GQR models outcomes as a function of the treatment variables only and uses the control variables for identification purposes.

IV-GQR uses two sets of moment condition. The first set are extended to account for sample selection as we include the predicted selection adjustment as an additional control variable.

$$E\{Z_i'[1(y_i \leq D_i'\beta(\tau)) - \tau_{X,W'\hat{\delta}}]\} = 0 \tag{7}$$

$\tau_{X,W'\hat{\delta}}$ is equal to $P(y_i \leq D_i'\beta(\tau)|X_i, W_i'\hat{\delta})$. Note that replacing $\tau_{X,W'\hat{\delta}}$ with $\tau$ (i.e., no control variables), IV-GQR reduces to an instrumental variables quantile regression estimator. The intuition behind the above condition is that the probability that an individual will have an outcome variable below the quantile function is not uniform across individuals. Instead, control variables are predictive of this probability. Furthermore, sample selection changes the observed probability. Controlling for the selection index accounts for these probability changes as well. IV-GQR also requires another moment condition:

$$P\big(y_i \leq D_i{}'\beta(\tau)\big) = \tau \qquad (8)$$

This condition states the unconditional probability is equal to $\tau$. In this paper, our analysis sample consists of individuals that do not leave the Army before they are promoted (*h=1*). Powell (2013b) uses an identification-at-infinity condition to ensure that equation (8) holds for the entire sample (*h=0* or *h=1*) but also discusses that this condition is not necessary. Our quantiles in this paper refer to the observed distribution – the median estimates refer to the median of the selected sample. If our treatment variables also affect attrition, then the median of the selected sample is not equal to the median of the total sample (including attriters). However, the estimated $\beta(\tau)$'s are still consistent.[10] We are less interested in understanding how the quantiles of the distribution would shift given less attrition and are instead primarily interested in understanding how peer composition affects promotion time of those that do not attrit in the sample that we observe. Thus, our estimates are consistent in the presence of sample selection, but they refer to the impact of the treatment variables on the distribution of the observed selected sample.

IV-GQR requires simultaneous estimation of $P\big(y_i \leq D_i{}'\beta(\tau) | X_i, W_i{}'\hat{\delta}\big)$. Powell (2013a) recommends a probit regression for computational reasons and shows that the distributions assumptions required for a probit regression need not be true to generate consistent estimates. Instead, the estimated probabilities may not be the true probabilities, but

[10] For example, if no one attrited, then the median quantile of our analysis sample might refer to the 60$^{th}$ quantile of the total sample. The estimates are still consistent, however.

the estimator only requires that the difference between the estimated and true probabilities are not systematically related to the instruments. This assumption seems reasonable in most empirical contexts.

A final benefit of IV-GQR in our context is that it is computationally easier to use than alternative IV quantile methods.

*Estimation Strategy Summary*

Our empirical strategy leverages the conditional random assignment of the peer composition of each individual in our data. We implement an instrumental variable quantile regression to account for censoring. We adjust for selection since a nontrivial fraction of our sample leaves the Army before we can observe their time to promotion. We implement a strategy to control for this selection which uses the nonlinearities in the selection equation to separately identify the effect of selection independent of the effects of the peer composition variables. Our strategy can be summarized in the following steps.

1) We estimate a probit regression for selection:

$$P(h_i = 1|Z_i, X_i) = \Phi(Z_i'\gamma + X_i'\theta)$$

2) We create predicted probabilities to use as our selection instrument:

$$s_i = \Phi(Z_i'\hat{\gamma} + X_i'\hat{\theta})$$

3) We model selection as an unknown function of *Z*, X, s and estimate the parameters using MR estimator. We make no assumptions on *F()*.

$$P(h_i = 1|Z, X_i, s_i) = F(Z_i'\alpha + X_i'\psi + s_i\rho)$$

4) Using parameter estimates found in (3), we predict the selection index for each observation. We use a series approximation as recommended in Newey (2009) to control for selection in the main equation relating the treatment variables to promotion

time. In practice, we use a 3-piece spline in the selection index to control for selection.

5) Conditioning on all control variables (*X*) and the 3-piece spline of the selection index, we implement IV-GQR to estimate the relationship between the peer composition variables and the distribution of time to promotion. We estimate these effects at the median, quantile 25, and quantile 75.

We use Markov Chain Monte Carlo (MCMC) to implement both the MR estimator and the IV-GQR estimation. The usefulness of MCMC is described in Chernozhukov and Hong (2003). For inference, we use subsampling (Politis and Romano, 1994). Because we are using a two-step process, we subsample the entire process

## 5. Results

Table 4 shows the results of a probit regression to model attrition as a function of our initial peer composition variables (our instruments) and our control variables. This step predicts the probability of attrition for each person and we use this variable as our selection instrument. Attrition is the inverse of selection in our context so we show the results for attrition, though there is no difference between controlling for attrition or selection. We show the effect of our instruments on attrition in Table 4. The results suggest that a higher fraction of women in leadership positions increases the rate of attrition for everyone but does so disproportionately for women. We find less evidence of such interactive effects based on race.

The next step is to use the MR estimator to estimate the relationship between our selection instrument and selection into the sample. The parameters are identified only up to scale so we are primarily concerned with the direction and the significance of the estimates. We report these in Table 5. We find strong relationships between our selection instrument and actual selection for both the specification with gender composition variables and the specification with race composition variables. Given that we have an excluded instrument for selection, we are able to adjust for selection in our main results.

Our identification strategy also relies on a first stage relationship between our instruments and our peer composition variables. We believe that only the initial assignment is conditionally random. It should not be surprising, however, to find a relationship with the endogenous variables since this relationship is partially mechanical. Table 6a provides the first stage estimates for the gender variables. We report partial F-Statistics in the final row and find very strong relationships. Table 6b includes the same results for the race variables. Again, we find very strong relationships. Our instruments appear to be strong enough that we should not have problems detecting peer effects if they exist.

Table 7a presents our main results using the gender peer composition variables. We report results for quantiles75, 50, and 25. We interpret quantile 75 as corresponding to "slow promoters" (proneness for long times to promotion) while quantile 25 provides information about the effects on "fast promoters." We find evidence that an increase in the fraction of peers that are female reduces time to promotion for men, with the largest effects at the lower end of the promotion time distribution. Women, however, experience an increase in time to promotion, with an especially large effect for the fast promoters. Given a higher fraction of female leaders, women are promoted much faster. The estimates suggest that an increase in the fraction of leaders who are female by 0.01 decreases promotion time for the fast promoters by over 0.02 months.

Table 7b presents the same results using the race composition variables. Here, we see that an increase in black peers reduces promotion time generally, but we find consistent evidence that a higher fraction of black peers lengthens the time to promotion for blacks. Increases in the fraction of Hispanic peers reduce time to promotion with a disproportionate effect on Hispanics. The fraction of peers in a unit who are Asian increases promotion time. We also estimate consistent positive effects of own-race peers on the promotion time of Asians.

We again find that the composition of peers and leaders have differential effects. Interestingly, an increase in the fraction of black leaders reduces promotion time for the median and low quantile, while increase promotion time for the high quantile. These estimates suggest that a higher fraction of black leaders is beneficial to the fast promoters but detrimental to the slow promoters.

For Hispanics and Asians, we find consistent evidence that more own-race leaders improve promotion outcomes. Overall, with some exceptions, we find that own-race peers lengthen the time to promotion but own-race leaders reduce it. Our results also show that accounting for heterogeneity is important as the impact changes throughout the promotion time distribution.

Our main conclusion is that peer composition matters. Peer composition as defined by the race and gender makeup of one's unit impacts employment outcomes. Furthermore, this effect is not uniform across peer and leadership groups, and we even find evidence of heterogeneity within the distribution of time to promotion.

*Conditional Random Assignment*

As discussed above, it is difficult to test conditional random assignment in our context. A primary concern is that though we observe the entire set of assignment variables, we cannot condition on them in a completely non-parametric manner due to the curse of dimensionality. In Table 8, we test whether some of the interactions that we excluded are potentially related to our peer composition variables. We select a few variables to ensure independence across tests (eg., We have three education dummies which saturate the space. Testing significance for one of these dummies is not independent of testing significance for either of the others.) We regress the interactions on all of our control variables and our peer composition instruments. We argue that our vast array of control variables likely accounts for many of these interactions due to the richness of our data even f we do not explicitly include such interactions. Table 8 suggests that this point is true. We present p-values for the joint significance tests. We do these separately by race and gender. Our peer composition variables are not statistically significant at the 5% level for any of the interactions.

## 6. Discussion and Conclusions

Our results point to the importance of race and gender interactions in the workplace. For a cohort of recruits who enlisted in the U.S. Army in 2002, we find that a rise in the percentage of female peers in a unit decreases the time to promotion for men relative to women, whereas a rise in the percentage of female leaders decreases the time to promotion for women relative to men. Interestingly, the magnitude of the leader effect is much greater than the relative peer effect, suggesting the greater importance of like superiors compared to like peers in promotion outcomes. One interpretation of this pattern is as follows. Since women have lower promotion probabilities in general, they may disproportionately benefit from the presence of women in leadership positions who may be more likely to advocate for them during promotion deliberations. A female leader, however, must appear to her colleagues fair, and thus can only reasonably advocate for certain women, not all women. This might create an environment of implicit competition among junior women for the backing of the female leader. Even if female leaders have no direct effect on promotions, they could still have an indirect effect if they allocate time to mentoring junior women; because time is a fixed resource, they may not be able to devote attention to all women, and thus junior women implicitly compete for the time and attention of more senior women. A related interpretation of the leadership effect is that women, who otherwise face worse promotion prospects than men, may be motivated to work harder by the presence of female role models.

We observe a similar pattern of negative peer and positive leadership effects for blacks, with an important exception that blacks at the high end of the promotion time distribution are actually harmed by more blacks in leadership positions. Like women, blacks also have lower promotion probabilities than whites, Hispanics and Asians. Relatively more blacks in leadership positions may, on the margin, benefit more junior blacks, but since black leaders must appear fair to those of other races, an increase in the number of black peers means that any given black soldier is less likely to be the one selected for backing during promotion deliberations. In addition, it may also be that the presence of successful black leaders motivates junior blacks to work harder in order to attain promotion. These effects may disproportionately affect the high ability blacks.

Another related interpretation of our results is that women and blacks benefit from greater diversity among their peers. This is contrary to the hypotheses implied by social interaction theory (described in Section 2), which in relating higher interaction quality with race and gender similarity, imply that group homogeneity creates performance gains. A diversity effect could arise in at least two ways. If individuals of different race and gender types possess complementary types of information (perhaps from different sources), communication across types may enhance performance. Effects of this type have been noted with respect to peer differences in productivity (see Mas and Moretti, 2009; Hamilton et al., 2003). A second possibility is that as the percentage of minority individuals in a group rises, they might tend to segregate themselves in small groups, both limiting their possibilities for exchange of potentially complementary information with others, and perhaps even engendering resentment among members of the dominant group.

In contrast to females and blacks, we observe the opposite pattern for Hispanics. Hispanics are a minority group in the Army (like women and blacks), but as a group they are most likely to be promoted at any point in time (along with Asians). In other words, this is a group with very good promotion prospects in the Army despite their minority status. As the percentage of Hispanic peers rises, the time to promotion for Hispanics decreases rather dramatically. Furthermore, for Hispanics, peer effects dominate leadership effects. One interpretation of this pattern is that because of their excellent promotion prospects, Hispanics need not rely on the presence of Hispanic leaders to move ahead. It may also be the case that Hispanics are just as likely to receive mentoring from more senior whites and blacks as from more senior Hispanics, and/or that senior whites and blacks are just as likely as senior Hispanics to be viewed as role models. A related interpretation of this pattern is that Hispanics benefit from homogeneity in their peer group, consistent with social interaction theory; however, it is not clear why Hispanics would benefit from homogeneity among their peers, when blacks and females do not, unless their differential promotion prospects mean that different peer and leader mechanisms necessarily operate in different ways. This complexity suggests that interventions seeking to improve outcomes for minority groups must differentiate between groups that are disadvantaged and advantaged in a given setting.

Overall, we find strong evidence of important peer composition effects. Peers and leaders matter and their racial and peer composition affect promotion outcomes. These are some of the first estimates in the economics literature about the importance of such margins on employment outcomes.

## References


Antecol, Heather and Deborah Cobb-Clark. (2001) "The Sexual Harassment of Female Active-Duty Personnel: Effects on Job Satisfaction and Intentions to Remain in the Military." Claremont-McKenna College Working Paper.

Antecol, Heather and Deborah Cobb-Clark. (2005) "Racial and Ethnic Harassment in Local Communities." Claremont-McKenna College Working Paper.

Athey, Susan; Christopher Avery, and Peter Zemsky, (2000). "Mentoring and Diversity." The American Economic Review, Vol. 90, No. 4, pp. 765-786.

Buchinsky, M. (2002). Quantile regression with sample selection: Estimating women's return to education in the US. In Economic Applications of Quantile Regression (pp. 87-113). Physica-Verlag HD.

Buddin, Richard J., 2005. "Success of First-Term Soldiers: The Effects of Recruiting Practices and Recruit Characteristics." Santa Monica, CA: RAND Corporation.

Carrell, Scott E., Richard L. Fullerton, James E. West, 2008. "Estimating Academic Peer Effects: The Importance of Knowing the Relevant Peer Group." mimeo, UC Davis.

Cavanagh, C., & Sherman, R. P. (1998). "Rank estimators for monotonic index models." Journal of Econometrics, 84(2), 351-381.

Chen, Songnian and Zhou, Yahong, (2005). "A Simple Matching Method for Estimating Sample Selection Models Using Experimental Data." Annals of Economics and Finance, 6, issue 1, p. 155-167.

Chernozhukov, V., & Fernández-Val, I. (2005). "Subsampling inference on quantile regression processes." Sankhyā: The Indian Journal of Statistics, 253-276.

Chernozhukov, V., & Hansen, C. (2006). "Instrumental quantile regression inference for structural and treatment effect models." Journal of Econometrics, 132(2), 491-525.

Chernozhukov, V., & Hong, H. (2003). "An MCMC approach to classical estimation." Journal of Econometrics, 115(2), 293-346.

Chung, Kim-Sau, (2000). "Role Models and Arguments for Affirmative Action." The American Economic Review, Vol. 90, No. 3, pp. 640-648.

Department of Defense, "Population Representation in the Military Services Fiscal Year 2002," Department of Defense, 2002. http://www.pentagon.mil/prhome/poprep2002/index.htm .

Duflo, Esther and Emmanuel Saez (2003). The Role of Information and Social Interactions in Retirement Plans Decisions: Evidence from a Randomized Experiment," Quarterly Journal of Economics, 118 (3), 815–842.

Duflo, Esther and Emmanuel Saez (2002). "Participation and Investment Decisions in a Retirement Plan: The Influence of Colleagues Choices," Journal of Public Economics, 85, 121–148.

Escanciano, J. C., Jacho-Chávez, D., & Lewbel, A. (2012). "Identification and estimation of semiparametric two step models." Unpublished manuscript.

Fitzenberger, B., & Wilke, R. A. (2006). "Using quantile regression for duration analysis." Allgemeines Statistisches Archiv, 90(1), 105-120.

Guryan, J., Kroft, K., & Notowidigdo, M. J. (2009). "Peer Effects in the Workplace: Evidence from Random Groupings in Professional Golf Tournaments." American Economic Journal: Applied Economics, 1(4), 34-68.

Hallinan, Maureen T. and Richard A. Williams (1990). "Students' Characteristics and the Peer-Influence Process", Sociology of Education, Vol. 63, No. 2, pp. 122-132.

Hamilton, Barton H., Jack A. Nickerson, and Hideo Owan (2003). Journal of Political Economy, vol. 111, no. 3.

Heckman, J. J. (1979). Sample selection bias as a specification error. Econometrica, v.47(1): 153-161.

Homans, G. C. (1974). "Social Behavior: Its Elementary Forms." New York: Harcourt, Brace & Co.

Hoxby, Caroline M. (2000). "Peer Effects in the Classroom: Learning from Gender and Race Variation." NBER Working Paper No. W7867.

Hoxby, C. M., & Weingarth, G. (2005). "Taking race out of the equation: School reassignment and the structure of peer effects." Working paper.

Huber, M., & Melly, B. (2011). "Quantile regression in the presence of sample selection." School of Economics and Political Science, Department of Economics, University of St. Gallen.

Izraeli, Dafna N., (1983). "Sex Effects or Structural Effects? An Empirical Test of Kanter's Theory of Proportions." Social Forces, Vol.62, pp.153-165.

Jackson, C. K., & Bruegmann, E. (2009). "Teaching students and teaching each other: The importance of peer learning for teachers." American Economic Journal: Applied Economics, 1(4), 85-108.

Jackson P. B., Thoits P. A., Taylor H. F., (1995). "Composition of the Workplace and Psychological Well-Being: The Effects of Tokenism on America's Black Elite." Social Forces, Vol.74, pp.543-557.

Koenker, R., & Bassett Jr, G. (1978). "Regression quantiles". Econometrica, v.46(1), 33-50.

Koenker, R., & Bilias, Y. (2002). "Quantile regression for duration data: a reappraisal of the Pennsylvania reemployment bonus experiments." In Economic Applications of Quantile Regression (pp. 199-220). Physica-Verlag HD.

Koenker, R., & Xiao, Z. (2002). "Inference on the quantile regression process." Econometrica, 70(4), 1583-1612.

Lyle, David S., Estimating and Interpreting Peer and Role Model Effects from Randomly Assigned Social Groups at West Point, The Review of Economics and Statistics, May 2007, 89(2): 289–299.

Mas, A., & Moretti, E. (2009). "Peers at Work." The American Economic Review, 99(1), 112-145.

Newcomb, T. M., (1961). "The Acquaintance Process." New York: Holt, Rinehart & Winston.

Newey, W. K. (2009). "Two-step series estimation of sample selection models." The Econometrics Journal, 12(s1), S217-S229.

Parsons, Talcott, (1963). "On the Concept of Influence." The Public Opinion Quarterly, Vol. 27, pp. 37-62.

Politis, D. N., & Romano, J. P. (1994). "Large sample confidence regions based on subsamples under minimal assumptions." The Annals of Statistics, 22(4), 2031-2050.

Powell, D. (2013a). "A New Framework for Estimation of Quantile Treatment Effects." RAND Working Paper.

Powell, D. (2013b). "Quantile regression with sample selection estimates of the gender wage gap." RAND Working Paper.

Sacerdote, Bruce, (2001). "Peer Effects with Random Assignment: Results for Dartmouth Roommates," Quarterly Journal of Economics, CXVI, 681–704.

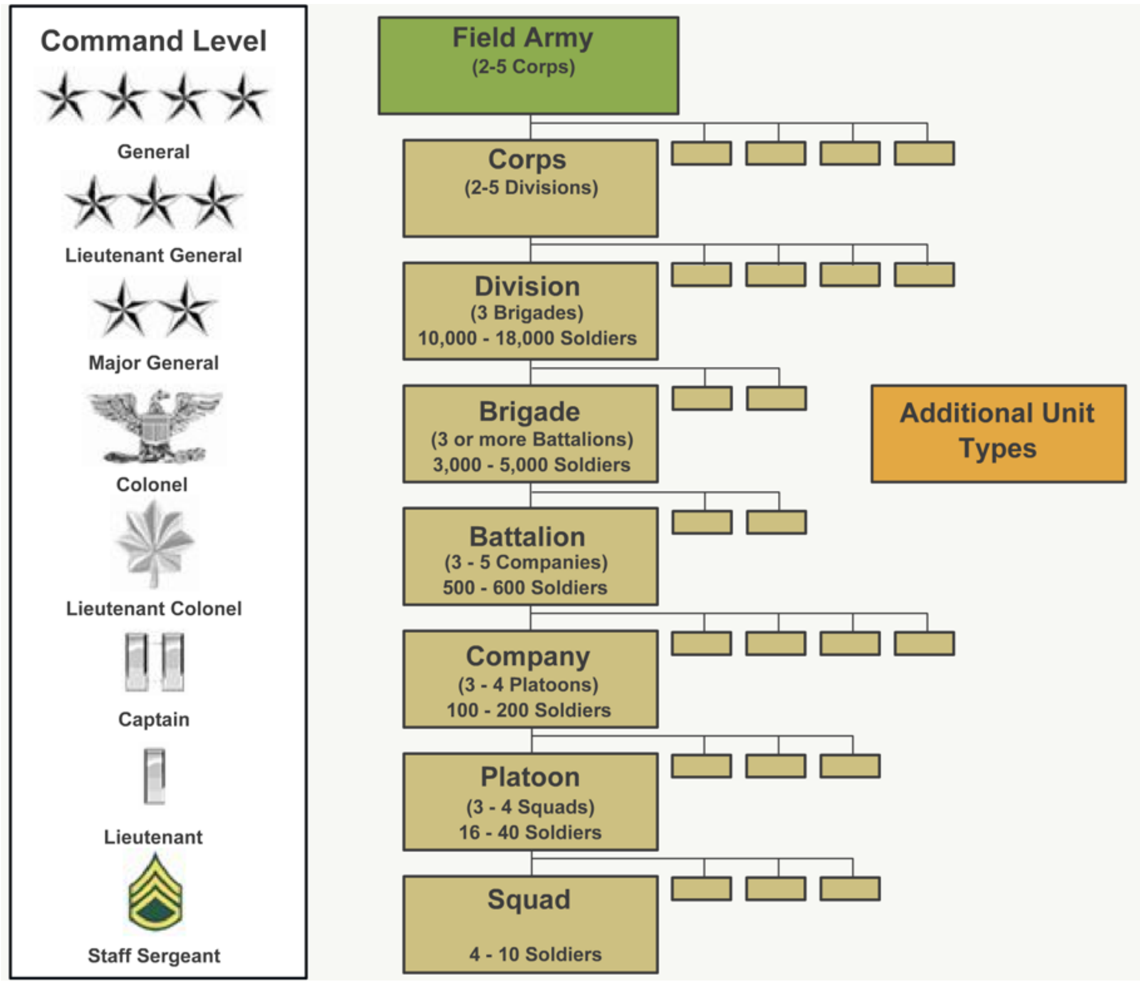
Sorensen, A. T. (2006). "Social learning and health plan choice." The Rand Journal of Economics, 37(4), 929-945.

South, Bonjean, Markham, Corder, (1982). "Social Structure and Intergroup Interaction: Men and Women of the Federal Bureaucracy." American Sociological Review, Vol. 47, pp. 587-599.

Waldinger, F. (2012). “Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany.” The Review of Economic Studies, 79(2), 838-861.

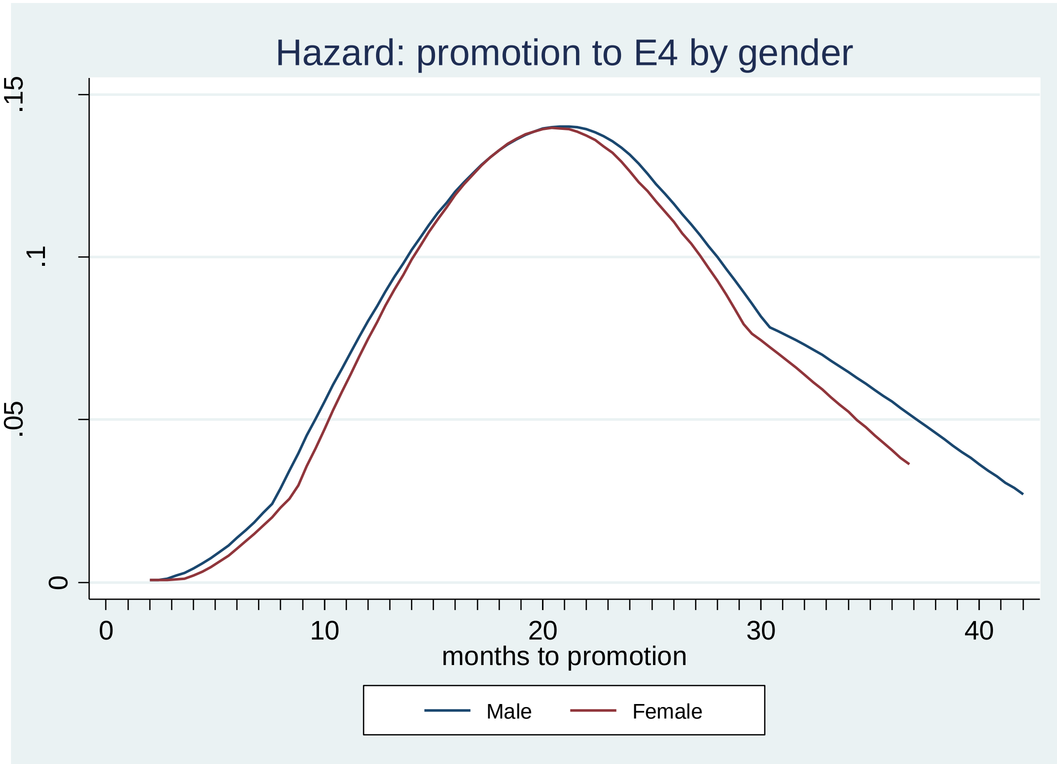
Zimmerman, D. J. (2003). “Peer effects in academic outcomes: Evidence from a natural experiment.” Review of Economics and Statistics, 85(1), 9-23.

Figure 1. Structure of Units in the U.S. Army




Source: http://www.army.mil/institution/organization/unitsandcommands/oud/

Figure 2. Promotion Hazard by Gender and Race



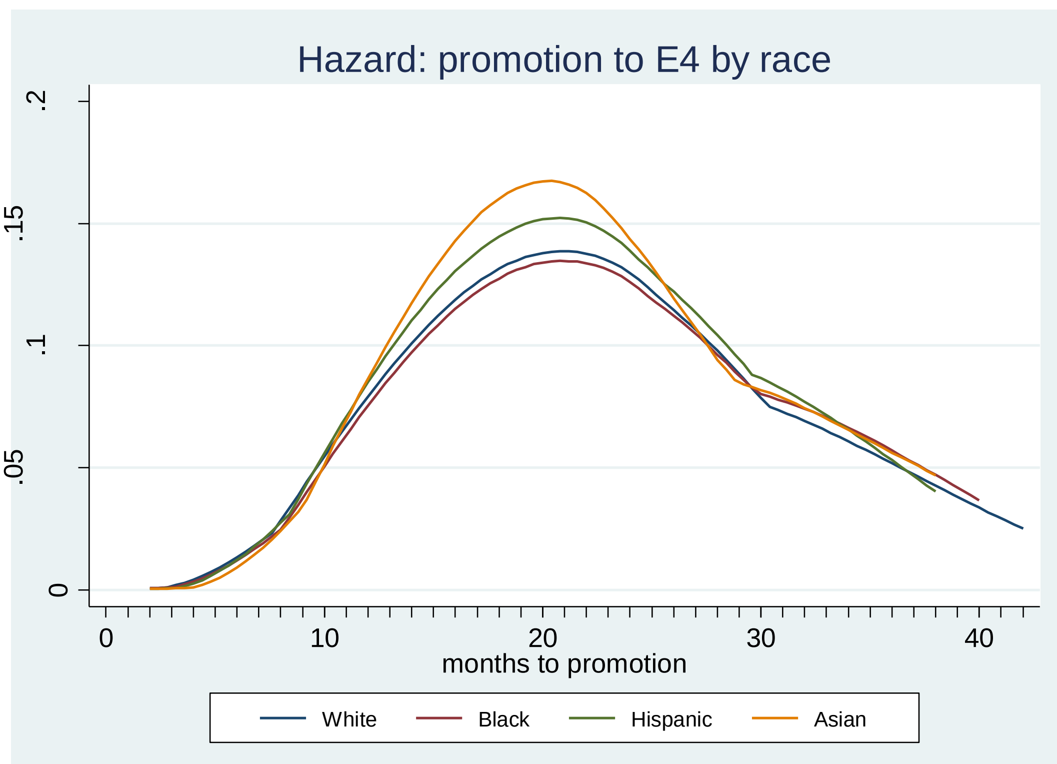
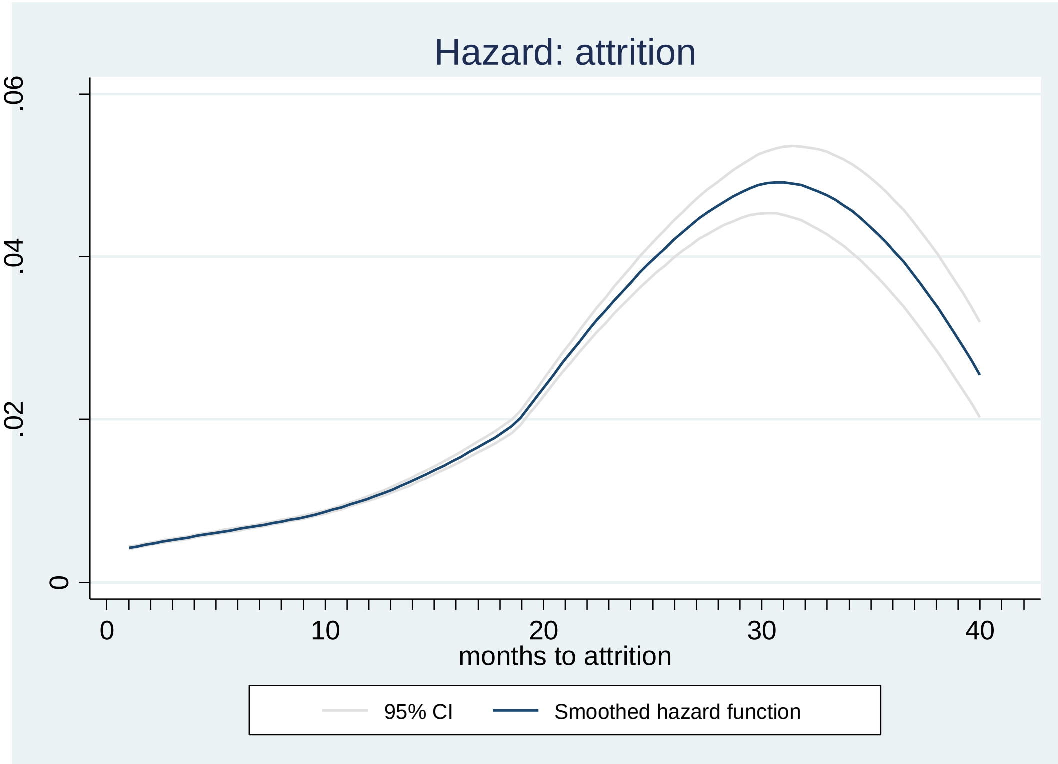



Figure 3. Comparison of Attrition and Promotion Hazards



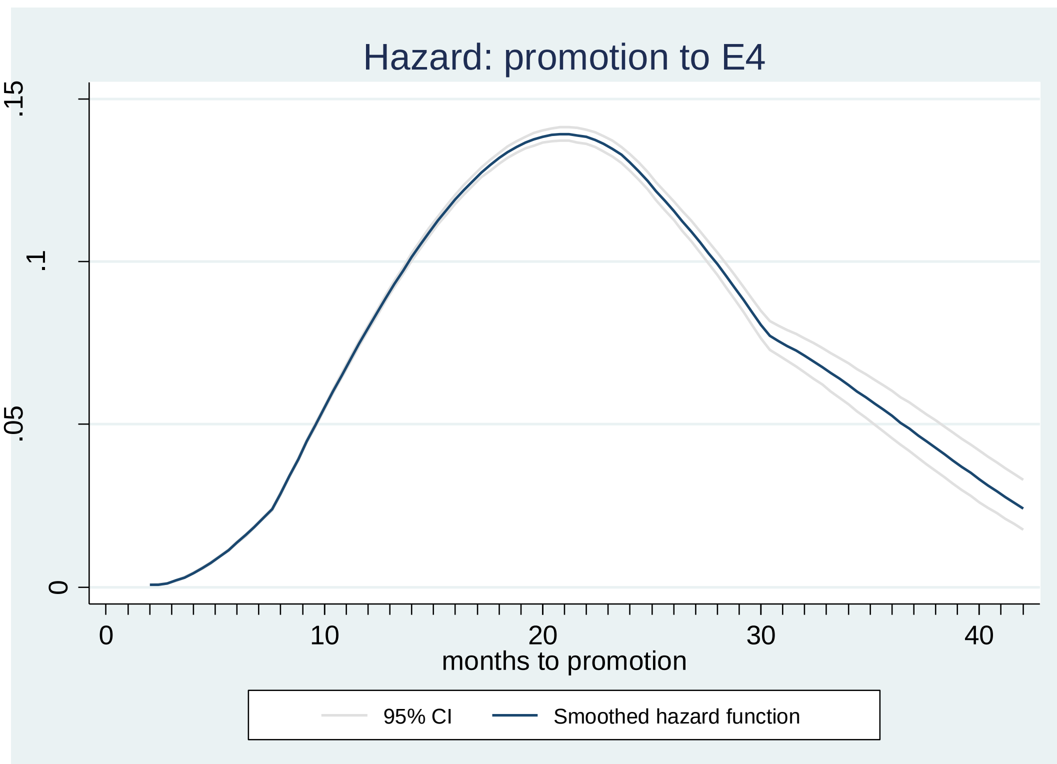
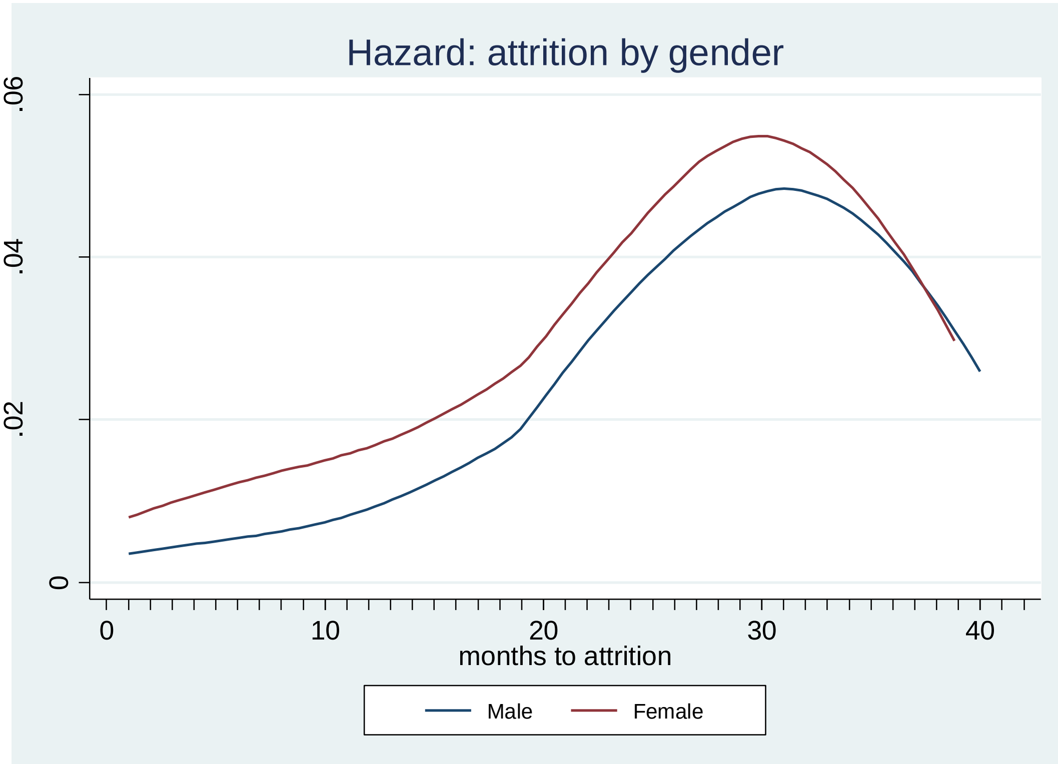
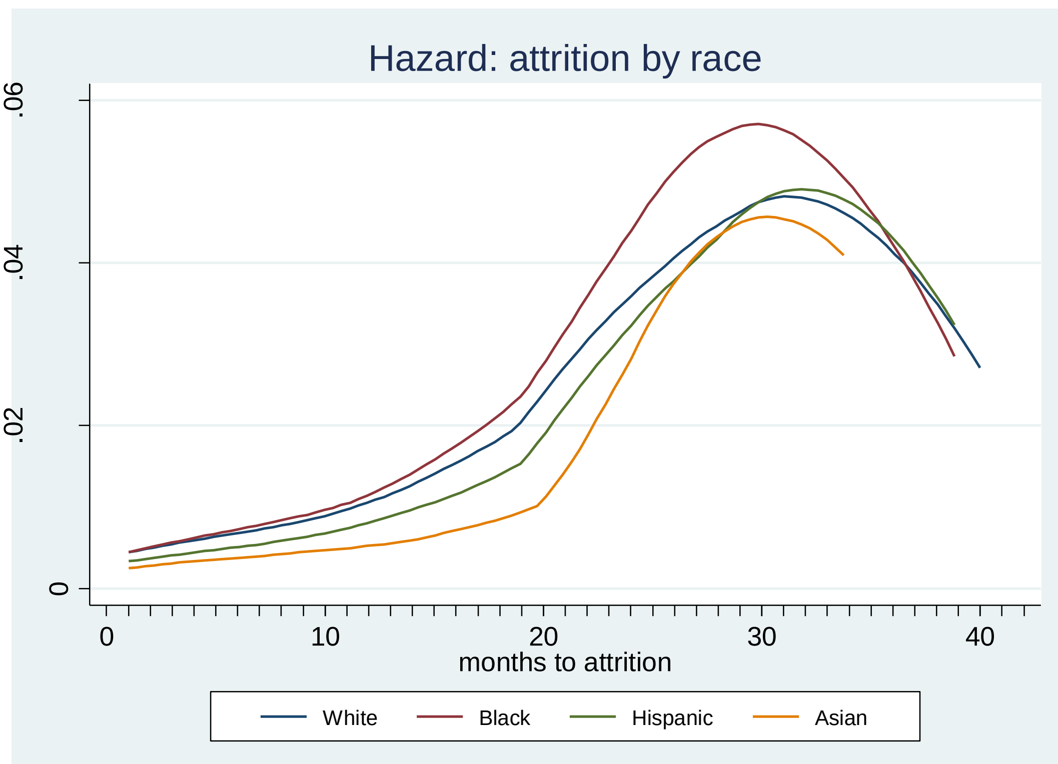



Figure 4. Attrition Hazard by Gender and Race



| Table 1A: Summary Statistics for Individual Enlistees | | | | |
|---|---|---|---|---|
| | Month 7 | | First month at E3 | |
| Variable | Mean | Std. Dev. | Mean | Std. Dev. |
| Age | 21.1 | 3.4 | 21.2 | 3.1 |
| Married (%) | 16 | 37 | 19 | 39 |
| Number of Dependents | 0.2 | 0.4 | 0.2 | 0.4 |
| Less than High School (%) | 15 | 36 | 15 | 36 |
| High School Graduate (%) | 74 | 44 | 78 | 41 |
| Some College (%) | 6 | 24 | 6 | 25 |
| College (%) | 4 | 21 | 0 | 5 |
| Male (%) | 83 | 38 | 84 | 37 |
| Female (%) | 17 | 38 | 16 | 37 |
| White (%) | 66 | 47 | 65 | 48 |
| Black (%) | 18 | 38 | 17 | 38 |
| Hispanic (%) | 13 | 34 | 13 | 34 |
| Asian (%) | 4 | 19 | 4 | 19 |
| AFQT I (%) | 6 | 23 | 5 | 21 |
| AFQT II (%) | 36 | 48 | 35 | 48 |
| AFQT IIIA (%) | 29 | 45 | 30 | 46 |
| AFQT IIIB (%) | 28 | 45 | 29 | 45 |
| AFQT IV (%) | 2 | 12 | 2 | 12 |
| AFQT V (%) | 0 | 0 | 0 | 0 |
| N | 55,370 | | 47,402 | |

Table 1B: Summary Statistics Describing Unit Size and Rank Structure

| Variable | Mean | Std. Dev. |
|---|---|---|
| Unit Size | 159 | 83 |
| *Mean % of Enlisted Rank in Unit* | | |
| E1 (%) | 11.7 | 15.7 |
| E2 (%) | 22.7 | 17.3 |
| E3 (%) | 20.3 | 8.9 |
| E4 (%) | 21.2 | 13.1 |
| E5 (%) | 12.3 | 10.0 |
| E6 (%) | 7.3 | 6.6 |
| E7 (%) | 3.3 | 4.3 |
| E8 (%) | 1.0 | 1.7 |
| E9 (%) | 0.3 | 0.9 |
| *Mean Number of Enlisted Rank in Unit* | | |
| E1 | 22.1 | 34.9 |
| E2 | 40.1 | 43.9 |
| E3 | 33.5 | 25.5 |
| E4 | 31.1 | 25.6 |
| E5 | 16.7 | 17.6 |
| E6 | 9.8 | 10.7 |
| E7 | 4.4 | 7.5 |
| E8 | 1.2 | 2.1 |
| E9 | 0.4 | 1.2 |

**Note:** Means computed over all units occupied by new recruits in 2002 at start of first assignment (month 7).

Table 2. Army Enlisted Personnel Rank and Pay Grade Structure

| Pay Grade | Rank | Job Description |
|---|---|---|
| E1 | Private (PVT) | Trainee starting Basic Combat Training. Primary role is to carry out orders. |
| E2 | Private (PV2) | |
| E3 | Private First Class (PFC) | Automatic promotion after one year, earlier by request of supervisor. Primary role is to carry out orders. |
| E4 | Specialist (SPC) | Can manage enlisted soldiers of lower rank. |
| | Corporal (CPL) | The lowest Non-Commissioned Officer (NCO). Serve as team leaders of the smallest Army units. Responsible for individual training, personal appearance of soldiers. |
| E5 | Sergeant (SGT) | Commands a squad of 9-10 soldiers. Considered to have the greatest impact on soldiers because sergeants oversee them in their daily tasks. Sergeants set an example and the standard for privates. |
| E6 | Staff Sergeant (SSG) | Also commands a squad of 9-10 soldiers. Often supervises one or more SGTs. |
| E7 | Sergeant First Class (SFC) | Key assistant and advisor to the platoon leader. Generally has 15 to 18 years of Army experience. |
| E8 | Master Sergeant (MSG) | Principal NCO at the battalion level, and often higher. Not charged with all the leadership responsibilities of a 1SG, but expected to dispatch duties with the same professionalism. |
| | First Sergeant (1SG) | Principal NCO of the company: "the provider, disciplinarian and wise counselor." Instructs other Sergeants, advises the Commander and helps train all enlisted soldiers. Assists officers at the company level (62 to 190 soldiers). |
| E9 | Sergeant Major (SGM) | SGMs' experience and abilities are equal to that of the CSM, but sphere of influence is generally limited to those directly under his charge. Assists officers at the battalion level (300 to 1,000 soldiers). |
| | Command Sergeant Major (CSM) | Functions without supervision. Supplies recommendations to the commander and staff, and carries out policies and standards on the performance, training, appearance and conduct of enlisted personnel. Assists officers at the brigade level (3,000 to 5,000 soldiers). |
| | Sergeant Major of the Army | There is only one Sergeant Major of the Army. Oversees all Non-Commissioned Officers. Serves as the senior enlisted advisor and consultant to the Chief of Staff of the Army (a four-star General). |

Sources: http://www.army.mil/symbols/Enlisteddescriptions.html and http://www.us-army-info.com/pages/ranks.html

| Table 3. Summary Statistics for Unit-Level Peer and Leader Variables | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 6 month avg | | 3 month avg | | Avg since month 7 | |
| Variable | | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| *Peers* | | | | | | | |
| Male (%) | Overall | 85 | 18 | 85 | 18 | 84 | 18 |
| | Between individual | | 17 | | 17 | | 18 |
| | Within individual | | 6 | | 7 | | 4 |
| Female (%) | Overall | 15 | 18 | 15 | 18 | 15 | 17 |
| | Between individual | | 17 | | 17 | | 17 |
| | Within individual | | 6 | | 7 | | 4 |
| White (%) | Overall | 63 | 15 | 63 | 15 | 63 | 14 |
| | Between individual | | 14 | | 14 | | 14 |
| | Within individual | | 6 | | 7 | | 4 |
| Black (%) | Overall | 19 | 13 | 19 | 13 | 19 | 12 |
| | Between individual | | 12 | | 12 | | 12 |
| | Within individual | | 5 | | 6 | | 3 |
| Hispanic (%) | Overall | 12 | 7 | 12 | 7 | 12 | 6 |
| | Between individual | | 6 | | 6 | | 6 |
| | Within individual | | 4 | | 5 | | 2 |
| Asian (%) | Overall | 4 | 4 | 4 | 4 | 3 | 3 |
| | Between individual | | 3 | | 3 | | 3 |
| | Within individual | | 2 | | 3 | | 1 |
| *Leaders* | | | | | | | |
| Male (%) | Overall | 88 | 13 | 89 | 13 | 88 | 14 |
| | Between individual | | 13 | | 13 | | 14 |
| | Within individual | | 5 | | 5 | | 4 |
| Female (%) | Overall | 12 | 13 | 11 | 13 | 12 | 13 |
| | Between individual | | 13 | | 13 | | 13 |
| | Within individual | | 5 | | 5 | | 3 |
| White (%) | Overall | 57 | 15 | 57 | 16 | 57 | 15 |
| | Between individual | | 15 | | 14 | | 15 |
| | Within individual | | 6 | | 7 | | 5 |
| Black (%) | Overall | 26 | 14 | 26 | 14 | 26 | 14 |
| | Between individual | | 13 | | 13 | | 14 |
| | Within individual | | 5 | | 6 | | 4 |
| Hispanic (%) | Overall | 11 | 6 | 11 | 6 | 10 | 6 |
| | Between individual | | 5 | | 5 | | 6 |
| | Within individual | | 4 | | 4 | | 3 |
| Asian (%) | Overall | 4 | 4 | 4 | 4 | 4 | 3 |
| | Between individual | | 3 | | 3 | | 3 |
| | Within individual | | 2 | | 2 | | 2 |
| N | | 803786 | | 810671 | | 813848 | |
| n | | 51665 | | 51747 | | 51781 | |
| T-bar | | 15.6 | | 15.7 | | 15.7 | |

Table 4: Probit Regression to Model Attrition as Function of Exogenous Variables

| Initial Peer Composition | P(Attrition) | Initial Peer Composition | P(Attrition) |
|---|---|---|---|
| Female Peers | 0.058 | Black Peers | 0.118 |
| | (0.082) | | (0.085) |
| Female Peers x Female | -0.14 | Black Peers x Black | -0.135 |
| | (0.124) | | (0.148) |
| Female Leaders | 0.263*** | Hispanic Peers | -0.021 |
| | (0.079) | | (0.120) |
| Female Leaders x Female | 0.265** | Hispanic Peers x Hispanic | 0.288 |
| | (0.131) | | (0.295) |
| | | Asian Peers | -0.156 |
| | | | (0.205) |
| | | Asian Peers x Asian | 0.421 |
| | | | (0.878) |
| | | Black Leaders | -0.147** |
| | | | (0.063) |
| | | Black Leaders x Black | -0.097 |
| | | | (0.119) |
| | | Hispanic Leaders | -0.202** |
| | | | (0.089) |
| | | Hispanic Leaders x Hispanic | 0.264 |
| | | | (0.195) |
| | | Asian Leaders | 0.437*** |
| | | | (0.115) |
| | | Asian Leaders x Asian | 0.531 |
| | | | (0.513) |
| N | 48447 | N | 48447 |

*10 % Significance, **5% Significance, ***1% Significance. Standard errors in parentheses. All variables listed refer to the initial assignment peer composition. Other controls included but not shown: year dummies, primary military occupational speciality (PMOS) dummies, entry paygrades, education dummies, age, number of dependents, AFQT category dummies, BMI, and indicators for: female, black, Hispanic, Asian.

Table 5: Impact of Selection Instrument on Sample Selection

| | Selection | Selection |
|---|---|---|
| Selection Instrument | 0.184*** | 0.418*** |
| | (0.003) | (0.007) |
| Gender / Race | Gender | Race |

*10 % Significance, **5% Significance, ***1% Significance. Standard errors in parentheses generated from subsampling. Reported estimates are identified up to scale. Other variables included but not shown: peer composition variables, year dummies, primary military occupational speciality (PMOS) dummies, entry paygrades, education dummies, age, number of dependents, AFQT category dummies, BMI, and indicators for: female, black, Hispanic, Asian.

Table 6a: Relationship between Initial Peer Composition Variables and Actual Peer Composition Variables

| Initial Peer Assignment | %Female Peer | %Female Peer x Female | %Female Leader | %Female Leader x Female |
|---|---|---|---|---|
| Female Peers | 0.648*** | -0.010*** | 0.172*** | -0.007*** |
| | (0.004) | (0.002) | (0.003) | (0.002) |
| Female Peers x Female | -0.013* | 0.657*** | -0.096*** | 0.088*** |
| | (0.007) | (0.004) | (0.005) | (0.003) |
| Female Leaders | 0.016*** | -0.003 | 0.370*** | -0.008*** |
| | (0.004) | (0.002) | (0.003) | (0.002) |
| Female Leaders x Female | -0.012 | 0.033*** | 0.056*** | 0.473*** |
| | (0.008) | (0.004) | (0.006) | (0.003) |
| Partial F-Statistic | 12223.17 | 14325.19 | 10088.88 | 12003.55 |

*10 % Significance, **5% Significance, ***1% Significance. Standard errors in parentheses. All variables listed in first column refer to the initial assignment peer composition. Other controls included but not shown: year dummies, primary military occupational speciality (PMOS) dummies, entry paygrades, education dummies, age, number of dependents, AFQT category dummies, BMI, and indicators for: female, black, Hispanic, Asian.

Table 6b: Relationship between Initial Peer Composition Variables and Actual Peer Composition Variables

| Initial Peer Assignment | Black Peers | Black Peers x Black | Hispanic Peers | Hispanic Peers x Hispanic | Asian Peers | Asian Peers x Asian | Black Leaders | Black Leaders x Black | Hispanic Leader | Hispanic Leaders x Hispanic | Asian Leaders | Asian Leaders x Asian |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Black Peers | 0.608*** | -0.017*** | -0.000 | -0.002** | 0.001 | 0.000 | 0.122*** | -0.026*** | -0.006*** | -0.005*** | -0.000 | 0.000* |
| | (0.003) | (0.002) | (0.002) | (0.001) | (0.001) | (0.000) | (0.004) | (0.002) | (0.002) | (0.001) | (0.001) | (0.000) |
| Black Peers x Black | 0.012** | 0.677*** | -0.001 | 0.001 | -0.005** | 0.000 | -0.011 | 0.201*** | 0.009*** | 0.003** | -0.004** | -0.000 |
| | (0.006) | (0.003) | (0.004) | (0.002) | (0.002) | (0.001) | (0.007) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) |
| Hispanic Peers | -0.005 | -0.005** | 0.607*** | -0.002 | 0.000 | 0.001* | 0.002 | -0.008*** | 0.074*** | -0.003** | 0.010*** | 0.001** |
| | (0.005) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) | (0.005) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) |
| Hispanic Peers x Hispanic | 0.011 | 0.003 | -0.050*** | 0.561*** | 0.001 | -0.001 | -0.001 | 0.002 | -0.031*** | 0.058*** | 0.002 | -0.001 |
| | (0.012) | (0.006) | (0.008) | (0.003) | (0.004) | (0.001) | (0.013) | (0.007) | (0.006) | (0.003) | (0.004) | (0.001) |
| Asian Peers | 0.012 | -0.004 | 0.033*** | 0.011*** | 0.589*** | -0.000 | 0.024*** | 0.001 | 0.025*** | 0.004** | 0.075*** | -0.001 |
| | (0.008) | (0.004) | (0.005) | (0.002) | (0.003) | (0.001) | (0.009) | (0.005) | (0.004) | (0.002) | (0.003) | (0.001) |
| Asian Peers x Asian | 0.076** | -0.011 | 0.094*** | -0.013 | 0.013 | 0.612*** | 0.019 | -0.020 | 0.001 | -0.009 | -0.017 | 0.069*** |
| | (0.032) | (0.017) | (0.021) | (0.008) | (0.012) | (0.003) | (0.035) | (0.018) | (0.018) | (0.008) | (0.011) | (0.002) |
| Black Leaders | 0.029*** | -0.004*** | -0.000 | 0.001 | 0.002** | 0.001** | 0.481*** | -0.005 | -0.006*** | 0.001 | -0.003*** | -0.000** |
| | (0.003) | (0.001) | (0.002) | (0.001) | (0.001) | (0.000) | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) |
| Black Leaders x Black | 0.016*** | 0.070*** | -0.010*** | -0.002 | -0.002 | -0.001 | 0.025*** | 0.536*** | -0.006** | -0.002 | -0.001 | 0.001 |
| | (0.005) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) | (0.006) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) |
| Hispanic Leader | -0.002 | 0.002 | 0.008*** | -0.002** | 0.006*** | -0.001* | 0.027*** | 0.007*** | 0.363*** | -0.000 | 0.006*** | 0.000 |
| | (0.004) | (0.002) | (0.002) | (0.001) | (0.001) | (0.000) | (0.004) | (0.002) | (0.002) | (0.001) | (0.001) | (0.000) |
| Hispanic Leaders x Hispanic | -0.012* | -0.003 | -0.025*** | -0.014*** | -0.002 | 0.000 | -0.010 | -0.009** | 0.002 | 0.364*** | -0.005* | -0.000 |
| | (0.007) | (0.004) | (0.005) | (0.002) | (0.003) | (0.001) | (0.008) | (0.004) | (0.004) | (0.002) | (0.002) | (0.001) |
| Asian Leaders | -0.011** | -0.009*** | 0.001 | 0.001 | 0.010*** | 0.000 | 0.025*** | 0.001 | 0.013*** | 0.004*** | 0.331*** | -0.001 |
| | (0.005) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) | (0.006) | (0.003) | (0.003) | (0.001) | (0.002) | (0.000) |
| Asian Leaders x Asian | 0.009 | 0.005 | -0.012 | -0.003 | -0.007 | 0.001 | 0.010 | -0.003 | 0.014 | -0.005 | 0.008 | 0.349*** |
| | (0.023) | (0.012) | (0.015) | (0.006) | (0.009) | (0.002) | (0.026) | (0.013) | (0.013) | (0.006) | (0.008) | (0.002) |
| Partial F-Statistic | 4091.04 | 6715.46 | 3523.95 | 3357.67 | 3401.71 | 3886.00 | 4081.86 | 6353.72 | 3757.93 | 4746.74 | 3437.99 | 3449.40 |

*10 % Significance, **5% Significance, ***1% Significance. Standard errors in parentheses. All variables listed in first column refer to the initial assignment peer composition. Other controls included but not shown: year dummies, primary military occupational speciality (PMOS) dummies, entry paygrades, education dummies, age, number of dependents, AFQT category dummies, BMI, and indicators for: female, black, Hispanic, Asian.

Table 7a : IV Quantile Estimates of Impact of Peer Composition on Time to Promotion using Gender Peer Variables

| | Quantile 75 | Quantile 50 | Quantile 25 |
|---|---|---|---|
| Female Peers | -0.241** | -0.532** | -1.079*** |
| | (0.100) | (0.222) | (0.148) |
| Female Peers x Female | 0.290 | 2.126*** | 4.476*** |
| | (0.177) | (0.247) | (0.179) |
| Female Leaders | 1.003*** | 0.648*** | 0.592*** |
| | (0.123) | (0.195) | (0.171) |
| Female Leaders x Female | -1.407*** | -3.675*** | -2.728*** |
| | (0.183) | (0.219) | (0.225) |

*10% Significance, **5% Significance, ***1% Significance. Standard errors in parentheses generated from subsampling. Control variables include year dummies, primary military occupational speciality (PMOS) dummies, entry paygrades, education dummies, age, number of dependents, AFQT category dummies, BMI, and indicators for: female, black, Hispanic, Asian. Selection adjustment spline variables also included.

Table 7b : IV Quantile Estimates of Impact of Peer Composition on Time to Promotion using Race Peer Variables

| | Quantile 75 | Quantile 50 | Quantile 25 |
|---|---|---|---|
| Black Peers | 0.009 | -0.447** | -0.435*** |
| | (0.100) | (0.176) | (0.143) |
| Black Peers x Black | 1.027*** | 1.253*** | 1.196*** |
| | (0.133) | (0.195) | (0.157) |
| Hispanic Peers | -0.046 | -0.676*** | -0.572*** |
| | (0.140) | (0.188) | (0.166) |
| Hispanic Peers x Hispanic | -0.841*** | -1.838*** | -1.927*** |
| | (0.176) | (0.196) | (0.194) |
| Asian Peers | 1.297*** | 1.123*** | 1.340*** |
| | (0.171) | (0.195) | (0.152) |
| Asian Peers x Asian | 0.534*** | 1.749*** | 3.855*** |
| | (0.178) | (0.184) | (0.179) |
| Black Leaders | -0.021 | 0.038 | -0.030 |
| | (0.085) | (0.174) | (0.141) |
| Black Leaders x Black | 0.397*** | -0.940*** | -1.619*** |
| | (0.126) | (0.191) | (0.158) |
| Hispanic Leaders | -0.112 | -0.125 | -0.157 |
| | (0.126) | (0.200) | (0.188) |
| Hispanic Leaders x Hispanic | -0.064 | -1.172*** | -0.615*** |
| | (0.161) | (0.210) | (0.180) |
| Asian Leaders | -0.074 | 0.914*** | 0.587*** |
| | (0.162) | (0.199) | (0.151) |
| Asian Leaders x Asian | -1.725*** | -2.176*** | -0.785*** |
| | (0.158) | (0.173) | (0.187) |

*10% Significance, **5% Significance, ***1% Significance. Standard errors in parentheses generated from subsampling. Control variables include year dummies, primary military occupational speciality (PMOS) dummies, entry paygrades, education dummies, age, number of dependents, AFQT category dummies, BMI, and indicators for: female, black, Hispanic, Asian. Selection adjustment spline variables also included.

Table 8: Conditional Random Assignment Test

| Gender Composition Variables | | | | |
|---|---|---|---|---|
| | Age | Married | AFQT1 | BMI |
| College | 0.890 | 0.386 | 0.369 | 0.733 |
| Age | | 0.227 | 0.447 | 0.249 |
| Married | | | 0.937 | 0.295 |
| AFQT1 | | | | 0.879 |

| Race Composition Variables | | | | |
|---|---|---|---|---|
| | Age | Married | AFQT1 | BMI |
| College | 0.710 | 0.064 | 0.969 | 0.799 |
| Age | | 0.871 | 0.530 | 0.122 |
| Married | | | 0.862 | 0.217 |
| AFQT1 | | | | 0.847 |

All numbers refer to the p-value in joint significance test of the peer composition variables in predicting the interaction of the variable listed by column and the variable listed by row.