Occupational Fatalities and the Labor Supply: Evidence from the Wars in Iraq and Afghanistan

Garret Christensen*

August 10, 2015

Abstract

Using data of all applicants to the enlisted US military during the wars in Iraq and Afghanistan, I find that the recruiting response to deaths of US soldiers is more complicated than full-information utility-maximization models predict. Deaths had a small but significant deterrent effect on recruiting in the soldiers' home counties. The deterrent is larger for deaths from the same county than for deaths from out of county. This is not driven by media coverage; I find that recruits are over-emphasizing very local information in enlistment decisions. The effect exhibits significant heterogeneity: deaths in Iraq decrease recruiting, while deaths in Afghanistan increase recruiting, and the deterrent is more negative in less populous and more racially diverse counties; it is smaller or even positive in counties that voted for George W. Bush.

1 Introduction

Standard full-information utility-maximization models predict that, all else equal, an increase in the risk of death in a profession would decrease an individual's desire to seek employment in that profession. I present evidence that this may not be the best model to explain behavior, using what is generally the most dangerous job held by the largest number of people: enlistment in the United States military. I show that enlistees are responding differently to deaths from their county than to deaths from further away, a finding that cannot be explained by easier access to news of local events. I also show that job-related deaths can sometimes lead to increases in employment in an industry.

The purpose of this paper is to empirically test whether deaths of employees in a given occupation affect selection into that same occupation by other potential employees in the way that simple

*CEGA, UC Berkeley, 207 Giannini Hall, Berkeley CA, 94720-3310. E-mail: garret@berkeley.edu. Many thanks to Dan Acland, John Warner, Alex Gelber and the personnel of the Defense Manpower Data Center for data and assistance. Thanks to Ted Miguel, Justin McCrary, David Card, Mark Borgschulte, Justin Gallagher, Willa Friedman and UC Berkeley seminar participants for suggestions. Data and replication files are available at https://github.com/garretchristensen/military and https://dataverse.harvard.edu/dataverse/garretchristensen.

models predict. Economic models since Adam Smith have used compensating differentials to explain wages in occupations entailing varying levels of risk or unpleasantness [Smith, 1776/2003]. Empirical studies have frequently estimated the value of a life using risk of death in different occupations.[1] Researchers have estimated how compensating differentials vary based on individual characteristics (e.g. age, gender, or being a single parent), but all these models either assume that safety is a normal good or estimate it as such.[2] To examine this question empirically I use new data from US soldiers in the wars in Iraq and Afghanistan and analyze how deaths affected the enlistment decisions of young Americans, but the results should generalize to many other occupations.

One possibility is that when someone dies in an occupation the brothers and friends of the deceased, and the population in general, would come to disapprove of the occupation (perhaps due to an increased assessment of their own risk) and become less likely to join. Since military pay is set at the same base rate across the country, I essentially hold compensation constant and look at the labor supply response to changes in perception of risk in my analysis. A standard model of compensating differentials would imply that if the wage were constant but assessment of risk increased, fewer would apply. However, if one was personally convinced of the virtue or necessity of the occupation in which the death occurred, then a sense of duty, patriotism, or pride might lead one to become more likely to join the occupation after an employee from the local area has been killed.

For example, it is the explicit policy of the New York City Fire Department to give a 10-point bonus on the employment exam to any applicant who is the child of a firefighter who was killed on 9/11.[3] The legacy points led to a minor uproar when they were initially refused to 13 applicants whose parent had died due to 9/11-related illnesses, but not actually on 9/11.[4] Dan Barta joined the Binghamton, NY police force after his father was killed in the line of duty, saying "it has been my dream since that day [the day my father was killed] to be a Binghamton Police Officer." [5] The "sandhogs" who do the dangerous work of boring the tunnels under New York City often follow in (fallen) friends or family members' footsteps.[6]

This possible incentive effect is clearly not unique to a single instance, and not unique to the military, though at least one example from the military received media attention: 61-year-old orthopedic surgeon Bill Krissoff acquired an age waiver and enlisted in the Navy Medical Corps

[1] See for example Thaler and Rosen [1976]. Rosen [1986] summarizes the extensive use of compensating differentials as a theory that explains supply of workers to jobs of different types in numerous occupations, including dangerous ones such as the military.

[2] See DeLeire and Levy [2004], Biddle and Zarkin [1988] and Garen [1988]. Thaler and Rosen [1976] build a model involving insurance that indicates that job safety is not necessarily normal with respect to property income, since property income is not at risk in the labor market and reduces the need for insurance, acting as a substitution effect.

[3] See http://www.nyc.gov/html/fdny/html/community/ff_faq_080106.shtm#legacy

[4] See http://www.nydailynews.com/new-york/gov-cuomo-13-fdny-sons-brave-future-article-1.1585065

[5] See http://www.wbng.com/home/Serving-the-community-A-family-legacy-230269421.html

[6] See http://www.villagevoice.com/2012-04-11/news/sandhogs-tunneling-second-avenue-subway/full/ or http://www.nydailynews.com/archives/news/brave-sandhogs-pause-reflect-article-1.569895

after his son Nathan was killed in the Marines in Iraq. [7] Since some of the Marine Corps' support operations are provided by the Navy, serving in the Navy Medical Corps enabled Krissoff to give medical care to those with whom his son had fought and died. This paper is an empirical test of the size of the deterrent or incentive effect in the military, and an analysis of when the effect may be larger or smaller.

My analysis draws on a valuable new dataset obtained through Freedom of Information Act requests consisting of the complete set of active duty enlisted applicants to the military from 2001 to 2006, matched with detailed data on every death of a US soldier that occurred in Operation Iraqi Freedom and Operation Enduring Freedom (i.e., the war in Afghanistan) during the same period. I have made these datasets publicly available on the Internet using Harvard's Dataverse.[8]

With detailed geographic and date information, I am able to analyze recruiting at the county-month level, a significant improvement upon much of the literature. I use data on the home locations of recently killed troops and correlate the deaths of soldiers from the local area with the local rates of recruiting while flexibly controlling for the underlying characteristics of counties as well as nation-wide changes over time using county and monthly fixed effects and state time trends. After controlling for these underlying characteristics, the hometown of the casualty is arguably exogenous, and I use this source of variation to analyze the causal effects of local deaths on local military recruiting.

Using natural log-based estimates of semi-elasticities, I find that when a soldier died in Iraq or Afghanistan, that soldier's home county saw a decrease in recruiting of almost one percent. This effect is similar for recruits in both of the stages of the recruiting process that I test. I also obtain very similar semi-elasticity estimates using either Poisson or negative binomial regression, and the estimates are very stable across different sets of fixed effects. I find that the effect is very localized—deaths in neighboring counties and deaths in counties in the same Nielsen media market produce no deterrent effect.

However, there is considerable heterogeneity in the deterrent effect of local deaths. Deaths of soldiers in Iraq lead to a larger reduction in recruiting, while deaths of soldiers in Afghanistan actually lead to a small increase in recruiting. The deterrent effect is also significantly larger in counties with higher than average African-American populations and is significantly smaller (and sometimes even positive) in more populous counties, counties with higher unemployment, and counties that voted for George W. Bush in 2000 or 2004. I also find that the effect is different for different types of recruits. It is significantly higher for recruits of the highest quality as measured by Armed Forces Qualification Test (AFQT) score and educational attainment. This evidence suggests that outside employment options and political opinions matter greatly in determining potential applicants' reactions to an on-the-job death, and is similar to what is found in Kahn [1987] concerning education and higher compensating differentials for risk.

My findings on local deaths provide evidence that people are not behaving in the way that a simple full-information utility-maximization model would predict. I show that one's hometown when enlisting has little to do with the likelihood of death given enlistment. Thus if a potential

[7] See http://www.npr.org/templates/story/story.php?storyId=17013597

[8] Please see https://dataverse.harvard.edu/dataverse/garretchristensen for data. All analysis files necessary to replicate this paper are also available online at https://github.com/garretchristensen/military.

recruit were to learn that a soldier from his or her county had been killed in a war, that soldier's death has no more bearing on his or her own risk from joining the military than the death of a soldier from halfway across the country. If a potential recruit were basing his enlistment decision on standard factors such as monetary compensation and the risk of death, a county death would have the same effect as a state death. The data shows that this is clearly not the case. Thus individuals must either be updating their priors with incomplete information and misperceiving the actual risk or basing the non-pecuniary benefits they receive from military service on the proximity of deaths, and not just the number. Unfortunately I am unable to distinguish between a purely information-based explanation and a more behavioral explanation based on saliency, though information on media markets provides suggestive evidence in favor of a behavioral explanation.

In addition to being of interest to labor economists who want to understand information processing in employment decisions, these findings may also be of interest to the military and policy makers who determine its funding. By analyzing the characteristics of a county, the military could produce a detailed estimate of the effect of deaths on recruiting in that county. If the military desires a wide geographic recruiting base, or if they desire to minimize costs, they could use the findings in this paper to help in their decision to reallocate recruiting funding and manpower.

The rest of the paper is as follows: section 2 describes the military recruitment process and places my work in the literature. Section 3 presents a very simple model of occupational choice that helps to frame the empirical results, section 4 describes the data used for my analysis, section 5 presents the analysis, and section 6 concludes.

2 Background

The military plays a very large role in the United States economy. In 2010, President Obama signed a bill authorizing $680 billion in military spending, making up nearly 20% of total federal expenditures.[9] Of this, $130 billion was for the wars in Iraq and Afghanistan, which have so far claimed the lives of over 8,000 US and coalition soldiers.[10] [11] Another $177.5 billion of this was to be spent on direct compensation to military personnel and family.[12] Through 2010, this money was used to pay and support over 1.4 million active duty men and women in uniform, and another 1.4 million National Guard and Reserve troops.

Recruiting this many troops costs a great deal. Most of the soldiers in the military serve for only a few years, so the military needs to recruit approximately 200,000 new troops every year. A 2003 GAO report lists the Defense Department annual recruiting budget as $4 billion, roughly $20,000 per recruit with over $1900 per recruit spent on advertising alone.[13] Part of this recruiting budget is spent on the salaries of production recruiters, active-duty men and women whose job it is to find new recruits. As of 2010, the Army employed over 8,000 soldiers as recruiters, and the

[9] http://www.nytimes.com/2009/10/29/business/29defense.html

[10] http://www.gpoaccess.gov/usbudget/fy10/pdf/fy10-newera.pdf

[11] http://www.cnn.com/SPECIALS/war.casualties/index.html

[12] http://www.defenselink.mil/news/2010%20Budget%20Proposal.pdf

[13] http://www.gao.gov/new.items/d031005.pdf

Navy 4,897.[14]

All recruiting of enlisted members of the military is handled by military recruiters. Being a recruiter is similar to other military occupational specialties—recruiters are mostly enlisted men and women who are assigned to a specific location for a three year stint, without absolute control over where they are assigned. Recruiters work out of offices spread all over the country, often in shopping malls or heavily trafficked areas. Whenever anyone enlists in the military, it is through such a recruiting office.

Potential recruits in the first stage of the process are referred to as "applicants." When a potential recruit first calls on the telephone or walks in the door and expresses interest in joining the service, the recruiter will make sure the candidate meets certain medical and legal requirements, for instance, he or she can have no felonies, cannot be on probation, and cannot be a single parent. The recruiter will enter data on the potential recruit into the database system as soon as possible after the initial expression of interest. The interested party will typically take a short (30-minute) practice version of the Armed Services Vocational Aptitude Battery (ASVAB). If they don't perform very well, perhaps they'll be told to study for a bit before taking the actual 3-hour ASVAB, but those who seem prepared would soon travel to a regional processing center (at a location other than the storefront recruiting center they've been visiting) and take the ASVAB, in some cases as soon as the day after expressing initial interest. Four of the 11 sections of the ASVAB are used as the AFQT. Assuming that a potential soldier passes the examination (one needs a score of 31 or higher to enlist in the Army) the applicant will then return to the recruiting center and be shown by their recruiter what jobs are available and when. All recruits in the data have AFQT scores, so potential recruits are only entered into my data set as soon as they have taken the test.

Once a potential recruit has taken the exam, chosen a military career (the availability of which depends on their test score) and is assigned a departure and enrollment date, they can sign a contract and take the oath of military service. This is the point at which a potential recruit is recorded as a "contract" in the data. When a contracted recruit finally ships off to training, they are recorded as an "accession." These accessions are the most commonly reported figures in the media and in Defense Department press releases pertaining to the military having reached its recruiting goals, but it is common in the literature to use data on contracts, since the accession date is more under the influence of the needs of the military, and is thus more demand-constrained and exhibits very strong seasonal fluctuations.

Although a good deal of research has been conducted on the labor supply elasticity of the all-volunteer US military, little, if any, has analyzed the effect of war-time deaths on the labor supply. Most of the existing research has focused on the supply elasticity with respect to salaries or unemployment, starting with 1960's estimates of labor supply in the absence of a draft, such as Altman and Fechter [1967] and Altman [1969]. Dale and Gilroy [1985] showed that higher unemployment typically led to higher recruiting levels and established the importance of using applicants and contracts in analysis instead of accessions (the final stage in the recruiting process, defined as shipping off to boot camp, which is much more seasonal); I follow this convention. Attempts have been made to account for both the supply and demand side of recruiting (Dertouzos [1985], Hanssens and Levien [1983], Dertouzos and Polich [1989], Asch [1990]) though in this

[14] http://www.2k.army.mil/faqs.htm, http://www.cnrc.navy.mil/PAO/facts_stats.htm

paper I focus on the supply side only.

Some limited research has been done analyzing the effect of US casualties in Iraq and Afghanistan at the national level (seeAsch et al. [2010], Simon and Warner [2007]). Yet no previous work has used the spatial variation in US military combat deaths in Iraq and Afghanistan (or those from any other war, for that matter) to examine the effect on recruiting, though researchers have used spatial variation in deaths for other purposes. Karol and Miguel [2007] used the plausibly exogenous variation in the geography of US deaths in Iraq at the state level to examine the effect on changes in voteshare for George W. Bush between the presidential elections of 2000 and 2004. They find strong negative localized effects of deaths–without the deaths, Bush might have won an additional two percent of the national vote. Earlier work by Gartner and Segura [1998] and Gartner et al. [1997] use the geographic variation in casualties from the Vietnam War to show that local casualties have a very strong relation to public approval of the President and his handling of the war.

A few papers in political science have found contradictory evidence regarding the effects of recruiting on the flip side of the insurgency/counter-insurgency coin. Research by Kocher et al. [2011] finds that civilian casualties in Vietnam helped the Viet Cong gain control in that area. Lyall [2009] finds that Russian shelling in Chechnya led to a reduction in local insurgent attacks, and recent research by Condra et al. [2010] that uses civilian casualties resulting from the US military's presence in Afghanistan and Iraq shows that local civilian deaths lead to more incidence of local violent attacks in Afghanistan, but not in Iraq. These results are consistent with my findings that the effects of war on recruiting vary in direction and magnitude by situation.

3 A Simple Model

In order to better frame the empirical analysis in economic terms, I will briefly discuss a model of occupational choice, adapted from standard models in Roy [1951] and Rosen [1986], which have previously been used to discuss the military in Warner and Asch [1995] and Fisher [1969]. Additional insights are adapted from behavioral models as discussed in DellaVigna [2009].

Assume that individuals are choosing between two occupation types, military (M) and civilian (C), and utility depends on wages (w) as well as a taste parameter (τ). Thus,

$$u^C = w^C + \tau^C \tag{1}$$

and

$$u^M = w^M + \tau^M. \tag{2}$$

Individuals will choose to enlist if $u^M > u^C$, or

$$(w^M - w^C) > \tau = (\tau^C - \tau^M) \tag{3}$$

that is, if the pay differential is greater than their relative preference for civilian life. Taste for military employment is a function of both the perceived risk of death an individual would face when employed by the military and an innate desire to serve in the military for cultural, patriotic, or other psychological reasons, which is itself a function of perceived risk of death. I write:

$$\tau^M = \tau^M(p(\hat{r}), \hat{r}) \tag{4}$$

where $p(\hat{r})$ is the level of patriotism or innate desire for a given individual and $\hat{r} \in (0,1)$ is the perceived risk of death in the military. I assume that p and τ^M are differentiable functions that vary across individuals in the population, creating the potential for different outcomes for different individuals. The empirical analysis in section 5.4 provides strong evidence that counties (and presumably, the individuals within those counties) have heterogeneous responses to risk and death depending on characteristics such as racial demographics and political preferences.

If I were to assume that patriotism were fixed for each individual instead of being a function of risk, that is, $\tau^M(p, \hat{r})$, then theory would predict that $\frac{\partial \tau^M}{\partial \hat{r}} < 0$, i.e., that more relative risk would make an occupation type less desirable, since higher risk of death or injury would lower expected future earnings. But by allowing patriotism to be a function of perceived risk, and by allowing for the possibility that $\frac{dp}{d\hat{r}} > 0$, it thus becomes a possibility that $\frac{\partial \tau^M}{\partial \hat{r}} > 0$, that the military becomes more attractive as it becomes more dangerous. As with the anecdotal example of Bill Krisoff mentioned earlier, additional deaths, which are signals of potential for future danger, may increase an individual's sense of duty, revenge, patriotism, or honor and make military employment more preferred. There is also anecdotal evidence that recruiting stations were overwhelmed with potential recruits after 9/11, but it is a goal of this paper to empirically determine whether increased risk actually led to more or fewer recruits.[15] To estimate $\frac{\partial \tau^M}{\partial \hat{r}}$, I assume the other terms in (3)—the preference for civilian employment, and the military and civilian wages—are all constant with respect to risk of death in the military. These and other identifying assumptions are discussed further in section 5.

In addition to empirically determining the sign and magnitude of the partial derivative mentioned above, the central economic question analyzed in this paper is whether individuals accurately perceive the increased risk they would face by enlisting in the military. Observing that the nation is at war and that soldiers are dying, potential recruits are assumed to infer some likelihood of their own death several months out into the future if they were to enlist. But information acquisition may be costly. Media coverage may be biased towards local events, so individuals with limited resources available for information acquisition may not be as well informed about deaths of soldiers from more distant locales. Or even if equally well informed, distant deaths may somehow seem less emotionally salient than deaths of soldiers from the local area. Thus I write $\hat{r} = r(d^{local} + (1-\theta)d^{distant})$, where $\theta \in (0,1)$ is the degree of inattention paid to distant deaths, a function of salience and competing stimuli. If in actuality deaths from distant locales contain no more information than local deaths on the true risk of death to a new enlistee, a standard model of full information would assume $\theta = 0$. A major purpose of this paper is to see if, for whatever reason, $\theta > 0$ in the observed data, and individuals are responding differently to local deaths than they

[15] Compare http://www.nytimes.com/2001/11/12/us/nation-challenged-recruit-self-described-slacker-decides-h html, which describes an individual motivated to enlist to http://www.nytimes.com/2001/09/16/us/after-attacks-military-despite-national-rush-emotion-recruiting-centers-aren-t.html, in which recruiters claim not to have seen a significant increase in qualified recruits.

are to distant deaths. The empirical results in section 5 consistently show that potential recruits are responding far more strongly to local deaths than to distant deaths. [16]

4 Data

The data used in this paper is a rich new set with valuable information. The military has typically not released or maintained publicly available datasets of the deaths of its soldiers in the last two decades, which were numerous even in times of peace. The onset of the wars in Iraq and Afghanistan has changed this, making data on a large number of deaths available to the public with relative ease. The recruiting data used in the literature has also typically been analyzed at the quarterly or yearly level, often at the state level, while my data contains the exact dates of applications and the ZIP code for each applicant, which I have aggregated to the monthly-county level.

The recruiting data used in this paper was obtained through Freedom of Information Act requests to the office of the Secretary of Defense and handled by the Defense Manpower Data Center. It consists of three distinct sets of individuals: "applicants," "contracts," and "accessions" (explained above) and contains the date on which these individuals were recorded as starting one of the three specific parts of the recruitment process, ZIP code, AFQT score, educational attainment, and branch and component of the military to which the potential recruit was applying. The same data is available for applicants and contracts, but the data are stored separately for each step in the recruiting process and are unfortunately not linked by individuals across datasets. Age of recruit is also unfortunately not included.

I have recruiting data for fiscal years 1990-2006. (The military operates on an October 1-September 30 fiscal year.) The applicants data set contains 6.4 million active duty observations, the contracts data set has 3.6 million active duty observations, and the accessions data set has 3.0 million active duty observations. [17] I am able to match roughly 96% of the applicant observations by ZIP code to a US county.

The main casualty data come from a public list compiled by the Statistical Information Analysis Division at the Defense Manpower Data Center and freely obtained from their website. [18] Starting October 7, 2001, every fatality in Operation Iraqi Freedom and Operation Enduring Freedom is

[16] I find that the recruiting response is always significantly different for local deaths (deaths in the same county) than for deaths from more distant locales (deaths from outside the county but in the same state, and deaths from outside the state). Coefficients on local deaths are typically on the order of five times larger for local deaths than for distant deaths. See Chetty et al. [2009] for actual estimation of a structural parameter very similar to θ, or the companion Chetty et al. [2007], which develops a structural interpretation for θ using bounded rationality.

[17] There are nearly 50% more recruits when one includes reserve and guard recruits (I observe roughly 9 million total applicants), however it appears that much of the contracts data for Reservists and Army and Air National Guard are missing (the data contain only 375 Army Reservist contracts, an implausibly low number over a 17-year period). To account for this, all of the analysis is run using only the applicants or contracts to the active duty components of the military. The main regression specification is repeated in the Appendix Table A7 using all recruits (active, reserve, and guard), which results in very similar estimates.

[18] This data was obtained from `http://siadapp.dmdc.osd.mil/personnel/CASUALTY/castop.htm` in 2010, but that site no longer operates. Similar data was available in 2014 from `https://www.dmdc.osd.mil/dcas/pages/casualties.xhtml`.

listed, and includes the service branch, component (active/reserve/guard), name, rank, pay grade, date of death, hostile status of death, age, gender, home of record city, home of record county, home of record state, home of record country, unit, incident geographic code, casualty geographic code, casualty county, city of loss, and race/ethnicity of the deceased.

An important point to note here is that the data include "home of record" which is where the soldier lived on the day they joined the service, and generally does not change over the course of military service, no matter how long. This is important with regards to my claim of plausible random assignment of death with respect to county after controlling for military population levels—the data is not tainted by service-men and women with very dangerous military professions buying homes near their duty-base and changing their legal residence to the county in which the base sits.

Since the focus of this paper is recent combat deaths, the main 2001-2006 fatality data used in the majority of this paper does not include the fairly common deaths of military members unrelated to combat abroad, or unrelated to the military at all (heart attacks, car accidents). After earlier drafts of this paper were completed, a FOIA request for detailed death data for all deaths in the military (not just those in the wars) for the entire period for which I had recruiting data (1990-2006) was granted. I use these deaths as placebo tests of my analysis and find that, as expected, there is no significant recruiting effect of local non-combat deaths. This is discussed in the appendix and shown in Table A10.

Table 1 shows total annual military deaths and the subsets of those recorded as hostile action from the FOIA data and those considered part of the Iraqi/Enduring Freedom operations as reported publicly by the DMDC. One can see that at most in any year, under 50% of the deaths of active duty US military members during the relevant time period (2001-2006) are classified as part of the Iraq/Afghanistan wars. Also, the Iraq/Afghanistan deaths outnumber the hostile deaths, so friendly fire or accidental deaths can be considered part of the war data. During the entire period for which I have data, 1999, two years prior to the beginning of my analysis, experienced the lowest number of deaths, with 796, of which zero were classified as hostile.

During the 2001-2006 period there were 2886 deaths in the combat death database, 2725 of which (94%) I have been able to link to the home county of record of the deceased soldier. I thus have data for both deaths and recruits for 58 months, for all the roughly 3,150 U.S. counties or county-equivalents. The number of deaths in a county-month range from 0 (98.7% of county-month observations) to a high of 8 in Los Angeles County in November, 2004. These and other summary statistics are presented in Table 1. Figure 1 shows monthly total national combat deaths and monthly total applicants to the military from October 2001 through July 2006.

Although my analysis primarily rests on the panel nature of the data and the inclusion of area and time fixed effects to identify the effect of local deaths, I have also included time varying characteristics of counties to the extent that they are available. These include unemployment at the state and county level as reported by the Bureau of Labor Statistics, and mortality for young males age 18-24 from the Multiple Cause of Death files at the National Center for Health Statistics National Vital Statistics System. Statewide numbers of recruiters by service branch have also been included in certain specifications.

5 Analysis

5.1 County Origin and Rates of Death

A characteristic that effects the interpretation of my results is the specific type of military career for which the residents of certain counties or states are likely to sign up. It seems likely that those in the infantry are more likely to be killed than those in ancillary support operations. And it is possible that recruits from certain states are more likely than others to sign up for more dangerous occupations. However, data on military occupational specialties by region of origin is not publicly available. Instead I make a comparison of the likelihood of death for a recruit from each of the states. (In the appendix, I establish the perhaps unsurprising fact that recruits and deaths are not uniformly distributed across the population. Here I restrict my attention to the likelihood of death *given* enlistment.)

Since I lack data on military occupational specialties, I can compare the number of recruits from a state to the number of deaths from the same state. Figure 2 shows histograms of the ratio of active duty deaths to total active duty applicants for each state over the whole period for which I have data. The ratios are centered around 0.3%, but are clearly not all identical. I have repeated this exercise including both active duty and reserve and guard deaths (since service and death in the reserve and guard duty is clearly correlated with where one lives, including them might lead to complications) for both applicants and contracts, using both unweighted and population-weighted means. The coefficients of variation for each of these eight methods of calculating the risk of death by state are relatively small, ranging from 0.143 to 0.319. Simply put, recruits have about the same likelihood of dying, regardless of where they are from.

Another way to analyze this is to look at each individual observation, and check the likelihood that it came from a binomial distribution with the hazard rate equal to that of the overall national hazard rate. (The number of active-duty deaths divided by the total number of active duty applicants was .003.) I then tested the likelihood that each observation came from a binomial distribution with this hazard rate of p=.003. Figure 3 displays two histograms of the p-value for each state, one using active-duty deaths and active duty applicants, the other using active-duty deaths and active-duty contracts. The histogram displays the p-values as calculated, but to interpret, one should use an adjustment for multiple testing such as Bonferroni or Sidak corrected p-values (i.e., divide the cutoff for significance by the number of tests, 51, thus replacing a cutoff of .05 with 0.05/51=0.0009). Only two of the state observations (Florida and Massachusetts) reject the null hypothesis that their true probability is in fact .003 using applicant data, and only one, Massachusetts, rejects using contracts data. So it is possible that recruits from certain states are more likely to enter dangerous military occupations, but according to my evidence, the idea that the risk of death is the same across all states can only be rejected for one or two states. Repeating this analysis with the 3,100 counties shows that rates of death given enlistment by county are also very rarely significantly different.

This is not necessarily a reason for concern regarding omitted variable bias, since fixed effects for each county will still be able to control for this underlying characteristic of the state, however, it does give a slightly different meaning to the estimates I will develop in the next few pages. If deaths in Iraq and Afghanistan were truly uniformly distributed amongst all the troops, regardless of where they came from, then the fact that a soldier from a given county, say Fairfax County, Virginia, had died would provide no more information regarding the risk of death to a potential recruit from Fairfax County upon enlisting than would the death of a soldier from Maricopa County, Arizona. Any extra deterrent to enlisting because this death happened to a local soldier would thus be an emotional or behavioral response and not an accurate updating of preferences based on risk. However, if a recruit from Fairfax County were more likely to sign up for front-line occupations, and those are the soldiers who were dying, then this death might actually contain a useful signal as to the risk of death, and an extra deterrent effect might be warranted for those reasons. Looking at the above histograms of the rates of death by state, it seems that soldiers from different states have only slightly different hazard rates, and it is not the case that one state or another with a supposed reputation for strong military support or lack thereof has a vastly different rate of death of its soldiers, and the behavioral explanation is still reasonable.

5.2 County-Level Analysis

The primary analysis is at the county level, the smallest region at which there is close to a one-to-one relationship from death data geographic unit to recruit data geographic unit.

Since data on recruits is in count form, the Poisson model is a more natural one to fit to the data, and provides the results on which I place primary emphasis.[19] Poisson regression fits a generalized linear model of the form $log(\mu_i) = x_i'\beta$, so $\mu_i = exp(x_i'\beta)$ and a one unit increase in x_j multiplies μ_j by $exp(\beta_j)$. However, as I am modeling an underlying rate of enlistment, $\mu_i = e^{x_i'\beta}$, the observed number of recruits is the rate times the exposure, which in my case is the population of young males. If R_i is the expected number of recruits, then $R_i = Population_i \cdot e^{x_i'\beta} = e^{ln(Population_i)+x_i'\beta}$. Thus all the Poisson models have been fitted with a coefficient constrained to 1 for the county's log young male population.[20]

The detailed specification I estimate follows the equation:

$$Recruits_{it} = Population_i \cdot e^{\beta_0 Deaths_{i,t}+\beta_1 Deaths_{i,t-1}+\beta_2 Unemployment_{it}+x_{it}'\eta+\alpha_i+\gamma_t+u_{it}}$$

where Deaths implies deaths from the given county, Unemployment county unemployment, and x includes in-state (but out of county) deaths as well as state unemployment. α_i is a set of fixed effects for each county, which flexibly control for any county characteristics such as the presence of a military base or political support for the military. γ_t is a set of fixed effects for every month, so national characteristics that are the same across counties in any given time period such as the total national number of deaths, national unemployment rate, or the military wage rate are also flexibly controlled for and cannot be separately estimated.

[19] Linear models of course ignore the restriction of the dependent variable of recruits to non-negative integers. See Cameron and Trivedi [2013] for a complete discussion. For the sake of robustness and transparency, I have also tested linear and log-linear specifications, which are shown in the Appendix. The results are qualitavely very similar, showing that a death leads to slightly larger decreases in percentage terms when estimated with log-linear OLS regressions than in the Poisson regressions. The appendix also includes a square root specification, as well as negative binomial. Again, the results are very similar.

[20] Regressions without the offset give qualitatively similar results.

Table 2 shows the results when Poisson regression is used to analyze the data at the county-month level. The left half of these regressions show the analysis done for applicants, the right hand side for contracts, one step further in the recruiting process. The first specification, for applicants in column one and contracts in column five, is the 'horse race' specification, comparing in-county deaths, out-of-county but in-state deaths, and out-of-state deaths. Of course this precludes the inclusion of monthly fixed effects, so this model is mis-specified to the extent that there is temporal heterogeneity in the recruiting response to deaths over the course of the wars, nevertheless, I find it illustrative that the coefficient for lagged in-county deaths is nearly five times that of the coefficient for an out-of-state death (1% compared to 0.2%). (A more detailed analysis of deaths at the national level is presented in the appendix.)

Fixed effects for each county and for each month are included for the remaining specifications, and state specific linear time trends in specifications 4 and 8. Observations are weighted by county population, and standard errors are clustered by county. The results indicate that one additional in-county death is followed in the next month by a 0.79% to 0.90% decrease in applicants and a 0.77% to 0.84% reduction in contracts. [21] Deaths from in-state but out-of-county appear to have a small positive effect, from 0.1% to 0.2%, which leads to some concern about the possible behavioral interpretation of my results—perhaps recruiters avoid an area after a death and instead spend their time recruiting from neighboring areas. This alternative mechanism, however, is complicated by the estimates below showing that deaths in contiguous counties do not lead to an increase in recruiting.

Unemployment at the state level has a negative effect: a one percentage point increase leads to a small but not always significant decrease in recruiting, while a one percentage point increase in county unemployment leads to a 1.6% increase in recruiting.[22] A simple comparison of the coefficients on lagged county deaths and county unemployment indicates that one fewer county death would cause the same increase in recruiting as a 4 to 5 point increase in county unemployment.

The idea that potential recruits are responding to county and state unemployment above and beyond the national unemployment level is in accordance with rational utility-maximizing individuals, assuming that moving across county or state lines (or finding employment across county or state lines) is costly, as county and state unemployment levels directly affect one's likelihood of employment, and thus income and utility. Deaths of active duty soldiers from one's own county or state are unrelated to one's own likelihood of dying in the service, since the Army operates at a national level and recruits are put into military careers irrespective of their state or county of origin (at least to the extent discussed above). Clearly this is not quite the case with Reserve and National Guard troops, as Reservists simply report to the nearest base for one weekend a month and two weeks a year of training, but their recruiting numbers are not included in this analysis.

This analysis has been done using all of active duty, reserve, and guard duty deaths. I do this

[21] Note that all death figures have been divided by 100 to make more useful digits of the coefficients visible, and thus all coefficients for deaths should be interpreted as percents and not fractions (i.e. 0.4 is 0.4 percent, not 40 percent).

[22] It should not be surprising that specifications including both county and state unemployment show one positive and one negative coefficient: hold state unemployment constant and increasing county unemployment means the county in question is relatively unlucky within the state, so recruits in that county have fewer other options and are more likely to enlist. Conversely, hold county unemployment constant and increase state unemployment, and the county is relatively lucky employment-wise, leading to fewer recruits.

because the main emphasis of my analysis is to determine the magnitude of the observed reaction to deaths. It may be true that the response to deaths of local soldiers from reserve and guards units is a rational response based on an updated assessment of the risk of death, but still, the magnitude of the observed deterrence effect, rational or not, would be what is of interest to policy makers. As a robustness check, however, I have run the analysis using only the active-duty deaths, and under this specification, in-county deaths are followed by a 1.0 to 1.1% reduction in recruits in the next month. The coefficients for out-of-county deaths and unemployment remain very similar. These results are shown in Appendix Table A8.

Additional Controls Despite the inclusion of fixed effects, the potential for omitted variable bias still exists. One of the most obvious ways this might occur is through the action of the military's production recruiters. It seems likely that the number of production recruiters is positively correlated with the number of recruits, and at the extreme this is clearly true mechanically. If the number of recruiters (or their level of effort) were also correlated with the number of deaths, my estimates would be biased. Given that recruiters serve for three years in one place, I find it highly unlikely that the military is relocating them in a way that is correlated with monthly deaths. Without being relocated, however, recruiters may change their level of effort. FOIA requests for data on recruiter quotas unfortunately have not been granted, so I am only able to use the number of recruiters by state and quarter until halfway through 2004, which I have included this extra control variable for that portion of the sample. I also have detailed mortality data, through 2004. It is conceivable that deaths unrelated to the military would play a role in determining recruiting (for example, young men in a crime-ridden community may be anxious to join the military as a means of escape) thus I include monthly male 18-24 year-old mortality figures as well. Table 3 shows these results. The analysis is done for both applicants and contracts, with the observations limited to those from October 2001 to June 2004. County and monthly fixed effects as well as state trends are included. One can see that the estimates of the effect of a death do not change very much (from -0.980 to -0.993 for applicants and -0.415 to -0.468 for contracts) when I add the extra controls.

Another interesting test of these results is shown in Table 4. Here I have included the number of deaths that occurred in contiguous counties and the number of deaths that occurred in counties that share the same media market as the main county of interest. County contiguity is defined using the 1991 ICPSR contiguous county file.[23] Media markets are defined using the Nielsen Media Research's Designated Market Area (DMA). In the year 2000, Nielsen divided the country into 208 DMAs based on a preponderence of residents having access to the same broadcast television and radio stations. (See Ansolabehere et al. [2006] and Ansolabehere et al. [1999] for more details.) The regressions show that deaths in nearby areas, whether defined using county borders or media market, do not affect recruiting in a given county. The deterrent effect of deaths appears to be very localized. This is also suggestive evidence that the county response to deaths is due to something more than information, since media markets are intended to share major news sources.

[23] U.S. Dept. of Commerce, Bureau of the Census. CONTIGUOUS COUNTY FILE, 1991: [UNITED STATES] [Computer file]. Washington, DC: U.S. Dept. of Commerce, Bureau of the Census [producer], 1992. Ann Arbor, MI: Inter- university Consortium for Political and Social Research [distributor], 1992. doi:10.3886/ICPSR09835

5.3 Lags and Leads of Deaths and Unemployment

My main empirical method thus far has been to compare county recruits in a given calendar month to county-wide and state-wide deaths in the previous month. It is possible that potential recruits initially deterred from enlisting by a death eventually "forget" about local deaths and join the military. Table 5 shows Poisson regressions with cumulative death and unemployment lags of two, four, six, and twelve months–that is, the sum of current deaths plus all the deaths that occurred in the previous number of months. The results indicate that deaths from previous months have, on average, a significantly smaller deterrent effect on recruiting than more recent deaths. Earlier regressions have shown a deterrent effect of nearly one percent for deaths in the previous month; these regressions show a much smaller average deterrent effect, decreasing to one-half a percent, down to one-third or even a statistically insignificant one-sixth of a percent deterrent effect for twelve months of lagged deaths. Weighted least squares regressions produce very similar semi-elasticity estimates.

As a robustness check on my main specification, I have included a one period lead of deaths. As expected, a death from the county one month into the future has no significant relationship with recruits in the preferred specifications. These regressions are shown in Appendix Table A9.

5.4 Heterogeneity of the Deterrent Effect

The analysis in the previous two subsections makes it clear that in-county deaths result in a significant decrease in county recruiting. An important corollary question concerns the heterogeneity of this effect. All counties are unlikely to observe the same deterrent effect of death. Here I investigate the recruiting response to deaths based on a county's demographic and cultural makeup, specifically, its population, unemployment, racial makeup, rural/urban status, and political alignment. Table 6 displays these regressions. They all include monthly and county fixed effects, out of county but in-state deaths, as well as unemployment, and I have added county characteristics interacted with lagged in-county deaths. All variables to be interacted have had the population weighted mean subtracted.[24] Note that the county characteristics, which are fixed over time and thus perfectly collinear with fixed effects, cannot also be included.

I have interacted lagged county deaths with inverse county population to estimate the effect in terms of deaths per population. Also included are interactions with the monthly county unemployment figure (the only county characteristic I have that changes over time and thus is not collinear with the fixed effects and can be included in the regression by itself), percent African-American population as measured in 2005, racial fractionalization using percent white, black, Native American, Asian, and Pacific Islander, a binary measure of rurality using the USDA's Economic Research Service classification, and the percent of the county that voted for George Bush in 2004. The regressions are run for applicants and contracts, the first column with percent black, and the second

[24] In a standard OLS regression this de-meaning would mean we could expect the main coefficient on lagged county deaths to remain essentially constant, but the weighting scheme used in Poisson regressions does not give the same sort of results. I have tested this and found that the main coefficient does stay very stable in least squares regressions regardless of what sort of weighted de-meaned interaction variables are included. I have also run these regressions using least squares and the results are qualitatively similar.

with racial fractionalization. I have also run regressions including interactions of all these same variables, but interacted with all four counts of deaths (in and out of county, lagged and current) the coefficients on the original interaction are very similar, and the coefficients for the interactions with out-of-county deaths and current in-county deaths all either go in the same direction as the ones shown in Table 6 or are statistically not different than zero.

Deaths per Male 18-24 year-old County Population has a rather large and negative coefficient, which is actually quite reasonable. The coefficient implies that there is a level effect of deaths, and then an additional effect of deaths per capita, from -2086 to -2215 for applicants and a statistically insignificant -1510 to -1704 for contracts. This means that an increase of one death for every one young male (obviously improbably high) would result in a decrease of recruits by 1500 to 2000 percent (also improbably high). Simpler to imagine is that for every additional 1500 to 2000 young males in a county, the deterrent effect of deaths is one percent less negative. More-populated counties have a smaller percentage recruiting response to deaths than less-populated counties. With more people, perhaps other young men are less likely to hear the news of the death of a soldier, and if they hear it, perhaps they are less likely to have known the soldier who was killed and thus be relatively undeterred by his death. It is slightly puzzling, however, why this differential effect would be so strongly significant for applicants and not significant for contracts.

Death * County Unemployment yields positive but insignificant estimates for applicants and significant estimates from 0.779 to 0.842 for contracts, indicating that deaths in counties with higher unemployment are not as large a deterrent effect, and can even make the recruiting response to deaths positive. Under the first specification for contracts, a county with the weighted average level of county unemployment (5.5% in the sample) would have a 0.5% reduction in recruits for every death. A county with 6.5% unemployment would actually see a 0.5+ (6.5-5.5)*0.8=1.3% increase in recruiting with every death (not to mention the 1.6% increase in recruiting thanks to the level effect of county unemployment) .

The percentage of county population that is African-American increases the size of the effect of a death. A county with the weighted average proportion of the population (13%) African-American would see a 0.5% reduction in recruits for every death, a county one standard deviation (13%) higher African-American population would see a -0.5+(13%*-0.06)=1.28% reduction in recruits for each death. The estimates are of the same order of magnitude for both applicants and contracts. I have also done the analysis using racial fractionalization, a more detailed description of the racial makeup of counties instead of simply percent African-American, but these estimates are not significant.

Rural is a binary measure of whether the county is rural using USDA's Rural-Urban continuum, which is partly a measure of population and partly distance from a metropolitan area. The estimate is insignificant, but the sign does seem to go in the same direction as population, however, indicating that rural counties (with lower populations not neighboring metropolitan areas) would have larger negative recruiting responses to deaths. Running the regressions without the rural interaction does not change the coefficient on the population interaction significantly.

Finally, I have interacted the county percent of the vote that went to George Bush in 2004 with deaths. The coefficient estimates range from 0.08% for applicants to 0.166% for contracts. This indicates that a county with the weighted mean Bush voteshare would see a decrease in recruiting of 0.5 to 0.7% for every death, but a county with one percentage point higher vote for Bush would see a 0.09% smaller (closer to zero) decrease in recruiting. This indicates that a county with roughly 6 to 8 percentage point higher than the weighted average Bush vote would see increases in recruiting after deaths. The average Bush vote share is 50.6%, and the standard deviation is nearly 14 percentage points. Well over half the counties had a Bush vote share over 57%. As shown in Karol and Miguel [2007], at least at the state level, war deaths led to poorer Bush election performance in 2004. As a robustness check I have replaced the Bush '04 vote share with Bush '00 county vote-share, which was obviously unaffected by Iraq and Afghanistan combat deaths. The estimates are nearly identical.

These estimates all show that county characteristics are very important in determining the response of a county's potential recruits to the news of a death. More heavily populated counties appear to have a smaller proportional response, as do counties with higher unemployment. Counties with higher fractions of African-American population have a larger response to deaths, as did counties that voted against George W. Bush (in either 2000 or 2004).

5.5 Recruiting Response for Different Types of Recruits

The military, like any other organization, has a strong interest in recruiting high quality employees. The services have generally held "high quality" to mean a person in possession of a high school degree and a score of 50 or higher on the AFQT. The services have often had separate quotas for high and low quality enlistees, and they have generally required that a high percentage of their recruits fall into the high category, although these requirements have changed over time with the needs of the services.

Table 7 shows results for recruits of different quality levels. I have broken recruits into four groups, the first three of which attempt to use definitions explicitly used by the military. Low Quality recruits either scored below 50 on the AFQT or do not have a high school degree. High Quality have both a 50 or higher on the AFQT as well as a high school degree. High Quality-Alt scored 50 or higher on the AFQT but may still be in their senior year of high school (many recruits sign contracts while they are still in school, but join through the Delayed Entry Program, so they do not actually ship out until they graduate and are considered high quality recruits by the military.) Very High Quality recruits is not a specific distinction used by the military, but is meant to identify the most sought after recruits–those who have a 75 or higher on the AFQT and have taken at least some college courses. There are fewer observations in this specification since 666 counties never have a very high quality recruit and cannot be included. The results indicate that all but the Very High Quality recruits have roughly the same response to deaths: a slightly smaller than 1% reduction in recruits for every death. Amongst Very High Quality recruits, the effect is almost 2.5%.[25] Another interesting difference is the effect of unemployment on different

[25] It may be slightly surprising that higher-quality recruits are more deterred by local deaths if one interprets the response to a county death as an "over-response" compared to deaths from out of county or out of state, since higher quality recruits are better-educated and might be expected to read national newspapers or acquire information about distant deaths with lower cost. Indeed regressions not shown indicate that the response to out-of-county and out-of-state deaths is no larger for higher quality recruits than for lower quality recruits. However, the results are consistent with a story of the local-death-deterrent being due to personal knowledge of the soldier who was killed, since evidence

types of recruits. *A priori* it is unclear how unemployment would affect different types of recruits. Higher unemployment could raise low quality enlistment because low quality individuals have fewer outside options, or it could hurt low quality individuals, because high quality individuals have their outside options eliminated, then they join the military in greater numbers, and there isn't enough demand remaining for low quality individuals to enlist. (While High Quality can typically enlist in the military at any time with no cap on demand, low quality recruiting is frequently subject to both demand and supply constraints.) The table seems to indicate that county unemployment leads to a 2.5% increase in high quality recruiting and a 1.5% increase in low quality recruits. Again, I have tested whether the results are the same when done using weighted least squares analysis, and the results exhibit the same patterns for deaths—very high quality recruits are more deterred by deaths than other types of recruits.

The appendix includes a similar analysis in Table A11 with recruits broken out by military service branch.

5.6 Recruiting Response for Different Types of Deaths

In addition to responses for different types of recruits, I have run analysis comparing the response to deaths of different types, specifically, the service branch in which the death occurred, the gender of the casualty, the classification of the death by the military as hostile or non-hostile, the race of the casualty, and the war in which the deceased was killed (Iraq or Afghanistan). Casualties are found to have no significantly different deterrent effect based on gender, hostility-status, and race.[26] The appendix includes results in Tables A12 and A13 comparing deaths across military service branches, with no significant differences by branch. However, the war in which the death occurred has a significant effect of the recruiting response. Table 8 shows that county deaths from Iraq lead to a 1.6 to 1.7% decrease in recruiting in the following month, while county deaths from Afghanistan lead to an increase in recruiting of 2.3 to 2.9% in the following month. These effects are significant with high confidence, and tests of the equality of the coefficients are easily rejected. The same pattern holds, though slightly less pronounced, when one restricts the analysis to after March 2003 when both wars were occurring simultaneously. This seems to be further evidence that recruits are responding not only to the risk of death, but are also exhibiting a response based on a subjective valuation of the circumstances of the death, as well as how their politics affect that valuation. Perhaps the perception that the war in Afghanistan was 'just' while the war in Iraq was not is enough to completely change the direction of the effect. (Only Representative Barbara Lee of California voted against the Authorization for Use of Military Force in September 2001, while 133 Representatives and 23 Sentators voted against the war in Iraq War Resolution in October

indicates that those with more education are likely to have larger social networks. As written in Glaeser et al. [2002], "The connection between social capital and human capital is one of the most robust empirical regularities in the social capital literature."

[26]Although statistical tests cannot reject that the race of the death does not affect the size of the deterrent effect, I have also run regressions interacting the race of the death with county racial characteristics. The coefficient of interaction between black deaths and black population is twice the magnitude of the coefficient on the interaction of white deaths and black population, indicating that perhaps counties with more blacks are even more deterred by black soldier deaths, although the difference between these two interactions is again not significant.

2002.)

I have also tested specifications that separately interact Iraq and Afghanistan deaths with county characteristics. The coefficients on the interactions are not statistically different from one another, and go in the same direction for county population, percent African-American, and county unemployment—that is, both wars have positive interactions with unemployment, both negative for percent African-American, and both negative for population. However, the coefficients for the interaction of deaths with county percent George Bush vote share have different directions and are significantly different (p-values are between .05 and .10), with positive coefficients for Bush voteshare interacted with Iraq deaths, and negative coefficients for Bush voteshare interacted with Afghanistan deaths. This implies that the incentive effect of a death in Afghanistan is actually smaller in Bush voting counties than in non-Bush counties. That is, deaths in Afghanistan drew out more new recruits overall, and relatively more new recruits in non-Bush counties than in Bush counties. Deaths in Iraq led to an overall decrease in recruits, with an incentive effect in some Bush counties and a deterent effect in most non-Bush counties. This again seems to fit with the not uncommon perception that the country was united in response to 9/11 and the war in Afghanistan (the effects go in the same direction), but deeply divided over Iraq (the effects go in opposite directions in some counties).

6 Conclusion

A perfectly rational fully-informed individual conforming to a standard economic model would become less likely to start employment in a profession when they learned that the profession in question was more dangerous. This paper presents evidence that young men and women enlisting in the military are not behaving in this mannner. Individuals respond more to a local death than to a death from farther away, and the difference cannot be explained by media markets. In addition, the evidence suggests that opinions about the war matter affect these decisions as well, since counties with more Democratic voters have a more negative response to deaths, and the nation as a whole has a more negative response to deaths in Iraq compared to deaths in Afghanistan.

As far as policy is concerned, I have shown in this paper that military deaths make the difficult and expensive task of recruiting significantly more complicated. At the national level (as shown in the appendix), a one percent increase in the death rate is associated with a 1.5 to 2.5 percent decrease in national recruiting in the following month. This should not necessarily be given a causal interpretation, due to the potential for omitted variable bias. However, I make the case that panel data regression analysis at the county level warrants a causal interpretation, as I can flexibly control for county characteristics that are fixed across time, national trends that are constant across different counties, and even state-level time trends. Using both weighted least squares and Poisson regression shows remarkably similar and stable estimates of the effect of deaths of local soldiers on local recruiting. Each in-county death leads to a one percent decrease in that county's recruiting in the next month, and this finding is robust across several specifications. Thus a large fraction of the overall deterrent effect of deaths appears to be due to local deaths. I have also shown that the local effect is in fact quite concentrated—deaths in contiguous counties and deaths in counties in the same media market do not cause a decrease in recruiting.

A one percent reduction may be small in terms of practical significance, but this effect is equal in magnitude to the effect of a fairly large (4 to 5 percentage point) change in unemployment, and may be of use to the military, especially given that the localized deterrent effect also exhibits heterogeneity in interesting fashions. Counties with higher than average young male populations see smaller decreases in recruiting, as do counties with higher than average unemployment. Counties that voted for George W. Bush in 2000 or 2004 see very different, and even positive recruiting responses to local military deaths. Counties with higher than average African-American populations see significantly more negative responses to local deaths. The effect of a death leads to a larger decrease in recruiting for the Marines, and the Air Force sees smaller reactions. The military also sees the largest reduction in recruits of the highest quality (as measured by AFQT score and educational attainment) after a local death. However, it does not appear that recruits are responding significantly differently to deaths in their own service branch than to deaths from a different service branch.

Still, it is puzzling to the economist who assumes actors have full information and are completely rational why there would be any difference in the response to a local death than to a death from further away. I have documented that the likelihood of dying is not related to the location in which one enlists, so this paper provides evidence of a larger response to local matters than is justified based on calculation of risk alone. Models of non-standard decision making that include a salience parameter such as Chetty et al. [2009] or Hossain and Morgan [2006] may be able to better explain the observed recruiting phenomenon.

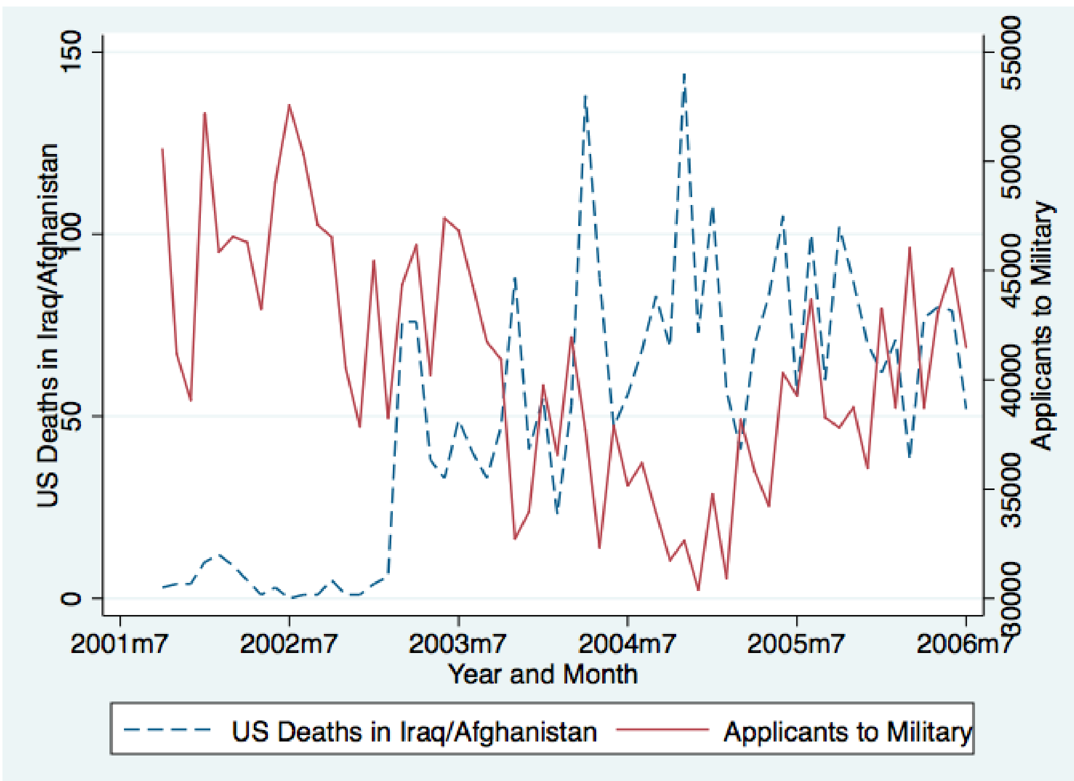

Figure 1: Graph of Monthly Recruits and Monthly Iraq/Afghanistan Combat Deaths

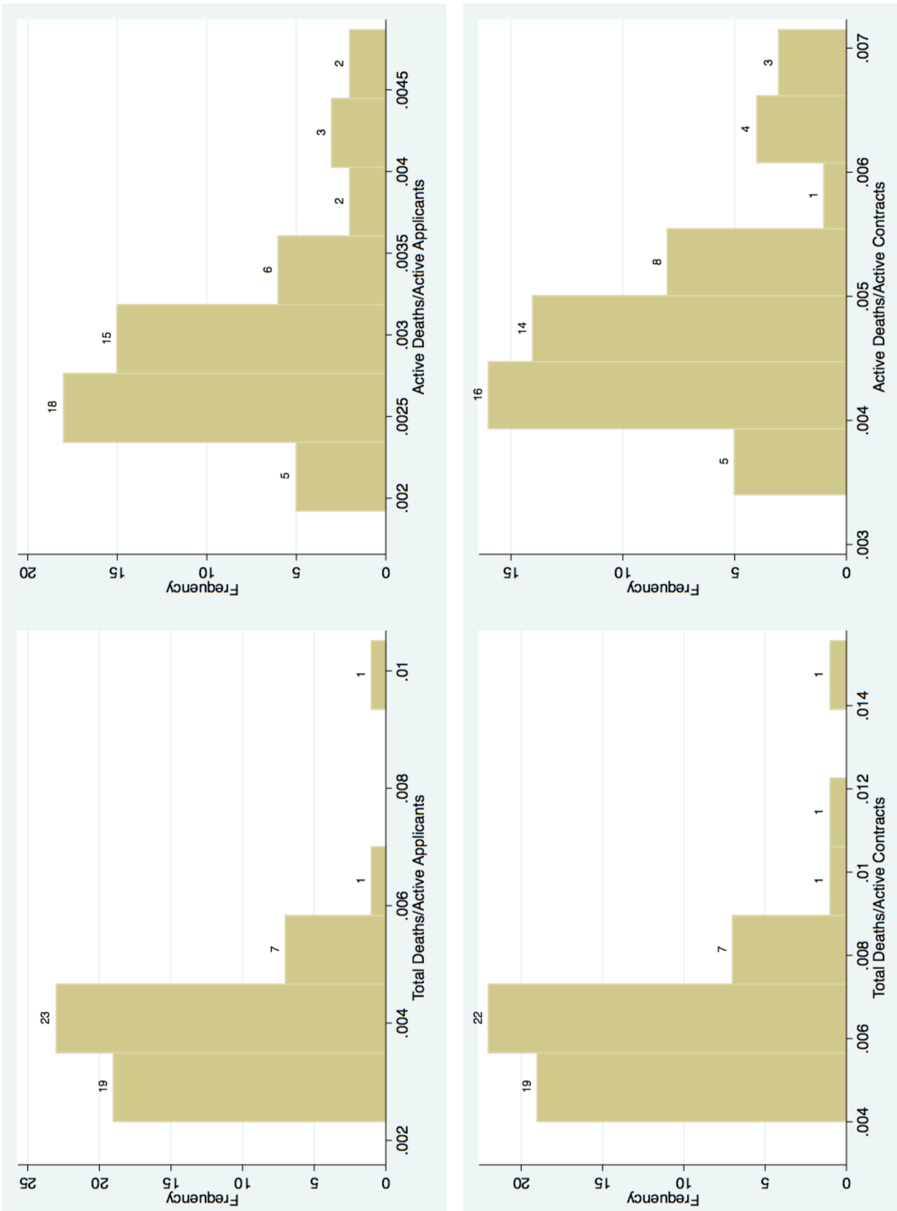

Figure 2: Active Duty/Total Deaths (2001-2010) and Active Duty Applicants/Contracts (1990-2006)

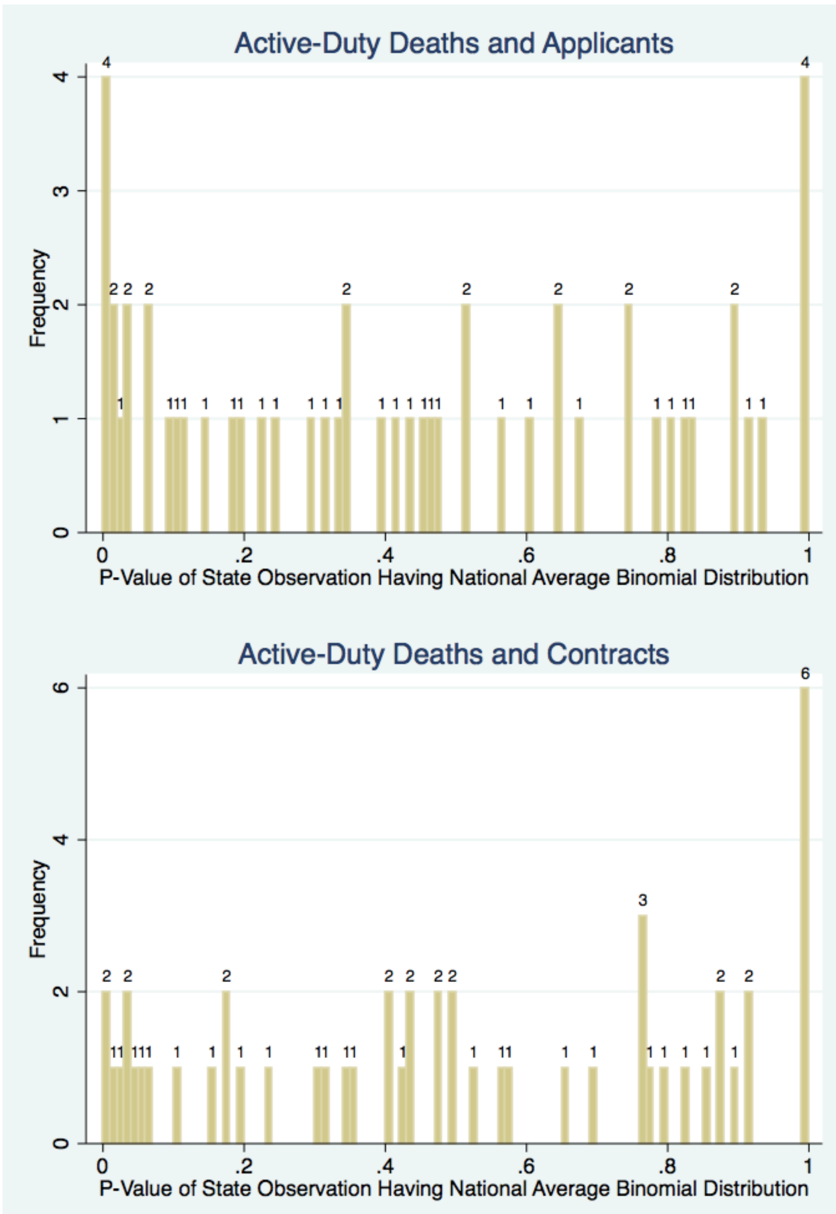

Figure 3: Histogram of P-Values Testing Whether State Deaths All Came from the Same Binomial Distribution

Table 1:

Annual US Military Deaths and Summary Characteristics

Year	Miltary FTE	Deaths per 100K	Total Deaths	Hostile Action Deaths in Iraq/Afghanistan in Data
1990	2,258,324	67	1507	1	
1991	2,198,189	81	1787	147	
1992	1,953,337	66	1293	1	
1993	1,849,537	66	1213	29	
1994	1,746,482	62	1075	0	
1995	1,661,928	63	1040	7	
1996	1,613,675	60	974	20	
1997	1,578,382	52	817	0	
1998	1,538,570	54	827	3	
1999	1,525,942	52	796	0	
2000	1,530,430	55	841	17	
2001	1,552,096	61	951	62	11
2002	1,627,142	65	1064	18	49
2003	1,732,632	85	1465	336	531
2004	1,711,916	109	1874	738	897
2005	1,664,014	117	1943	739	939
2006	1,611,533	117	1882	769	915
2007	1,608,226	121	1953	847	1019
2008	1,683,144	86	1441	353	467
2009	1,640,751	92	1516	347	457

Notes: FTE numbers and Iraq/Afhganistan death data from http://siadapp.dmdc.osd.mil/personnel/CASUALTY/castop.htm, total death numbers from FOIA requests.

Data from 2001-2006 Study Period

Deaths (Requires DOD classification as part of OIF/OEF and successful matching to home of record county)

Total Deaths: 2725

Total Deaths/County:
- Mean:0.87 (s.d. 2.5)
- Max:73 (Los Angeles, CA)
- 35% of Counties see at least one death over the study period.

Total Deaths/County/Month:
- Mean: 0.015 (s.d. 0.13)
- Max: 8 (Los Angeles, CA, November 2004)
- 1.4% of County-Months see at least one death.

Recruits (Applicants) (Requires successful matching of FOIA-reported ZIP to county)

Total Applicants: 2,253,105

Total Applicants/County:
- Mean: 719.8 (s.d. 1948.6)
- Max: 50,787 (Los Angeles, CA)
- 100% of counties have at least one applicant.

Total Applicants/County/Month:
- Mean: 12.4 (s.d. 34.3)
- Max: 1274 (Los Angeles, CA, October 2001)
- 84.4% of County-Months have at least one applicant

Active Duty Applicants:1,565,744

Active Applicants/County:
- Mean: 500.2 (s.d. 1456.6)
- Max: 39,917 (Los Angeles, CA)
- 100% of counties have at least one active duty applicant.

Activel Applicants/County/Month:
- Mean: 8.6 (s.d. 25.8)
- Max: 1033 (Los Angeles, CA, July 2002)
- 77.2% of County-Months have at least one active duty applicant.

Table 2:

Poisson Regression of County Recruits on Deaths and Unemployment

	Applicants				Contracts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Horse Race	Basic	w/State	w/State Trend	Horse Race	Basic	w/State	w/State Trend
In-County Deaths/100	-0.516	-0.045	-0.18	-0.089	-0.695	0.027	-0.146	-0.086
	[0.509]	[0.436]	[0.433]	[0.320]	[0.558]	[0.448]	[0.431]	[0.310]
Lag In-County Deaths/100	-1.035***	-0.756***	-0.898***	-0.793***	-1.195***	-0.646**	-0.836***	-0.774***
	[0.367]	[0.184]	[0.195]	[0.244]	[0.383]	[0.279]	[0.273]	[0.259]
Out-of-County Deaths/100	0.184***		0.218***	0.183***	0.167**		0.230***	0.139**
	[0.066]		[0.064]	[0.062]	[0.075]		[0.070]	[0.071]
Lag Out-of-County Deaths/100	-0.129*		0.179***	0.155***	-0.108		0.202***	0.103
	[0.072]		[0.066]	[0.058]	[0.084]		[0.078]	[0.064]
Out-of-State Deaths/100	-0.125***				-0.163***			
	[0.005]				[0.006]			
Lag Out-of-State Deaths/100	-0.202***				-0.162***			
	[0.006]				[0.006]			
State Unemployment			-0.003	-0.025***			-0.01	-0.025***
			[0.006]	[0.006]			[0.007]	[0.006]
County Unemployment			0.016***	0.016***			0.016***	0.016***
			[0.005]	[0.004]			[0.005]	[0.004]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	NO	YES	YES	YES	NO	YES	YES	YES
State Time Trend	NO	NO	NO	YES	NO	NO	NO	YES
Observations	178,239	178,239	178,169	178,169	178,182	178,182	178,112	178,112
Number of Counties	3,127	3,127	3,127	3,127	3,126	3,126	3,126	3,126
Likelihood	-342459	-332831	-331962	-331200	-286140	-278656	-278173	-277676

Notes: Dependent variable is the number of recruits in a county-month. The right hand side variables represent deaths in a month divided by 100, so coefficients are interpretable as semi-elasticities, and .8 refers to 0.8 percent. Out of county deaths refers only to in-state but out-of-county deaths. Robust standard errors in brackets, which allow for clustering by county. All regressions include an offset of county young male population (using Stata's exposure option). Fixed effects included are for every county and separately for calendar month. State-specific linear time trends are also included in specifications 4 and 8.

*** p<0.01, ** p<0.05, * p<0.1 redfPbasic.xlsx

Table 3:

Poisson Regression with Recruiter and Mortality Controls

	Applicants		**Contracts**	
	(1)	(2)	(3)	(4)
VARIABLES	Basic	w/ Controls	Basic	w/ Controls
In-County Deaths/100	-0.494*	-0.484	-0.012	-0.075
	[0.297]	[0.314]	[0.308]	[0.315]
Lag In-County Deaths/100	-0.980***	-0.993***	-0.415	-0.468
	[0.373]	[0.362]	[0.410]	[0.400]
Out-of-County Deaths/100	0.088	0.156	0.034	0.103
	[0.095]	[0.099]	[0.091]	[0.091]
Lag Out-of-County Deaths/100	0.175*	0.207**	0.096	0.142
	[0.103]	[0.104]	[0.102]	[0.101]
State Unemployment	-0.038***	-0.038***	-0.026**	-0.025**
	[0.010]	[0.010]	[0.012]	[0.012]
County Unemployment	0.021***	0.021***	0.019***	0.019***
	[0.002]	[0.002]	[0.003]	[0.003]
Recruiters/100		0.033***		0.043***
		[0.011]		[0.012]
Lag State Mortality/100		0.037		-0.007
		[0.039]		[0.037]
Lag County Mortality/100		0.031**		0.021*
		[0.013]		[0.013]
Population Offset	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES
State Time Trend	YES	YES	YES	YES
Observations	97,353	97,353	97,274	97,274
Number of Counties	3,122	3,122	3,119	3,119
Likelihood	-180856	-180838	-151557	-151543

Notes: Dependent variable is the number of recruits in a county-month. The right hand side variables represent deaths in a month divided by 100, so coefficients are interpretable as semi-elasticities, and .8 refers to 0.8 percent. Out of county deaths refers only to in-state but out-of-state deaths. Robust standard errors in brackets, which allow for clustering by county. All regressions include an offset of county young male population (using the exposure option). Fixed effects included are for every county and month. State-specific time trends are also included in all specifications.
*** p<0.01, ** p<0.05, * p<0.1

Table 4:

Poisson Regression of Media-Market and Contiguous County Deaths

	Applicants				Contracts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Neighboring		Media		Neighboring		Media	
In-County Deaths/100		-0.107		-0.039		-0.085		-0.029
		[0.342]		[0.323]		[0.322]		[0.307]
Lag In-County Deaths/100		-0.691***		-0.720***		-0.644***		-0.693***
		[0.222]		[0.247]		[0.241]		[0.267]
Contiguous County Deaths/100	0.191	0.227			0.085	0.118		
	[0.165]	[0.183]			[0.189]	[0.207]		
Lag Contiguous County Deaths/100	-0.154	-0.096			-0.207	-0.154		
	[0.216]	[0.220]			[0.212]	[0.212]		
Media Market Deaths/100			0.135	0.148			-0.014	-0.002
			[0.164]	[0.166]			[0.183]	[0.185]
Lag Media Market Deaths/100			-0.164	-0.137			-0.318	-0.292
			[0.183]	[0.183]			[0.206]	[0.204]
State Unemployment	-0.025***	-0.025***	-0.024***	-0.024***	-0.025***	-0.025***	-0.025***	-0.025***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
County Unemployment	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
State Time Trend	YES	YES	YES	YES	YES	YES	YES	YES
Observations	178,055	178,055	178,169	178,169	177,998	177,998	178,112	178,112
Number of Counties	3,125	3,125	3,127	3,127	3,124	3,124	3,126	3,126

Notes: Robust standard errors in brackets, clustered by county. Neighboring counties are defined using the ICPSR contiguous county file. Media Market deaths are defined using Nielsen Media Research's DMA, data courtesy of James Snyder. All regressions include an offset of county young male population (using Stata's exposure option). Fixed effects included are for every county and month. State-specific time trends are also included.

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

Table 5:

Poisson Regressions of Recruits on Cumulative Lags of Deaths and Unemployment

	Applicants				**Contracts**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Two Lags	Four Lags	Six Lags	Twelve Lags	Two Lags	Four Lags	Six Lags	Twelve Lags
In-County Deaths/100	-0.490***	-0.423***	-0.377***	-0.163*	-0.368*	-0.362**	-0.403***	-0.373***
	[0.177]	[0.161]	[0.126]	[0.097]	[0.206]	[0.167]	[0.127]	[0.092]
Out-of-County Deaths/100	0.122***	0.089**	0.102***	0.087***	0.073*	0.068*	0.096***	0.100***
	[0.038]	[0.038]	[0.032]	[0.025]	[0.041]	[0.038]	[0.032]	[0.027]
State Unemployment	-0.007***	-0.002	0.001	-0.001	-0.007***	-0.005**	-0.002	-0.002**
	[0.002]	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]
County Unemployment	0.004***	0.001	0	0.002*	0.005***	0.002*	0.001	0.002**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
State Time Trends	YES	YES	YES	YES	YES	YES	YES	YES
Observations	175,035	168,727	162,475	143,581	174,979	168,727	162,423	143,489
Number of Counties	3,127	3,126	3,126	3,123	3,126	3,126	3,125	3,121

Notes: Dependent variable is the number of recruits in a county month. Right hand side is the number of deaths (divided by 100) in the current month plus previous two, four, six, or twelve months. State and county unemployment are also cumulative in the same manner. Robust standard errors in brackets which allow for clustering by county. All regressions include an offset of county population (using the exposure option).
*** p<0.01, ** p<0.05, * p<0.1

Table 6:

Poisson Regression with Multiple Interactions

VARIABLES	**Applicants** (1) w/ %Black	(2) w/ Racial Fractionalization	**Contracts** (3) w/ %Black	(4) w/ Racial Fractionalization
County Deaths/100	-0.227	-0.206	-0.205	-0.169
	[0.422]	[0.423]	[0.419]	[0.423]
Lag County Deaths/100	-0.739	-0.525	-0.509	-0.222
	[0.462]	[0.497]	[0.519]	[0.559]
Out of County Deaths/100	0.221***	0.221***	0.226***	0.225***
	[0.063]	[0.063]	[0.069]	[0.069]
Lag Out of County Deaths/100	0.172***	0.177***	0.184**	0.189**
	[0.066]	[0.066]	[0.079]	[0.078]
State Unemployment	-0.003	-0.003	-0.01	-0.01
	[0.006]	[0.006]	[0.006]	[0.006]
County Unemployment	0.016***	0.016***	0.015***	0.015***
	[0.005]	[0.005]	[0.005]	[0.005]
Death * County Unemployment	0.42	0.377	0.842**	0.779**
	[0.417]	[0.419]	[0.380]	[0.388]
Death / County Population	-2,085.880***	-2,215.198***	-1,509.78	-1,703.94
	[511.203]	[601.024]	[1,088.919]	[1,148.970]
Death * %Population Black	-0.061**		-0.100***	
	[0.030]		[0.038]	
Death * Racial Fractionalization		-2.306		-0.957
		[3.215]		[3.524]
Death * %Bush Vote '04	0.088***	0.088***	0.151***	0.166***
	[0.027]	[0.033]	[0.025]	[0.034]
Death * Rural	-4.139	-4.419	-5.998	-6.081
	[3.851]	[3.847]	[4.205]	[4.204]
Population Offset	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Observations	176,801	176,801	176,744	176,744
Number of Counties	3,103	3,103	3,102	3,102
Likelihood	-330331	-330334	-276845	-276850

Notes: Dependent variable is the number of recruits in a county-month. The right hand side variables represent deaths in a month divided by 100, so coefficients are interpretable as semi-elasticities, and .8 refers to 0.8 percent. Percent Bush vote and percent population Black are on 0-100 scale. Out of county deaths refers only to in-state but out-of-state deaths. Robust standard errors in brackets, which allow for clustering by county. All regressions include an offset of county population (using the exposure option). Fixed effects included are for every county and month.

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

Table 7:

Poisson Regressions of Recruits by Quality Level

	Applicants				**Contracts**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Low	High	High-Alt	Very High	Low	High	High-Alt	Very High
In-County Deaths/100	-0.03	-0.161	0.065	-0.341	-0.287	0.185	0.285	2.405*
	[0.318]	[0.480]	[0.432]	[0.983]	[0.313]	[0.406]	[0.365]	[1.347]
Lag In-County Deaths/100	-0.839***	-0.687*	-0.793***	-2.465***	-1.020***	-0.44	-0.867***	-2.491
	[0.289]	[0.370]	[0.277]	[0.834]	[0.359]	[0.289]	[0.278]	[1.615]
Out-of-County Deaths/100	0.238***	0.083	0.184**	0.323	0.171**	0.092	0.149*	0.412
	[0.077]	[0.092]	[0.077]	[0.295]	[0.087]	[0.103]	[0.089]	[0.372]
Lag Out-of-County Deaths/100	0.165**	0.136	0.285***	0.011	0.084	0.124	0.190**	0.024
	[0.074]	[0.084]	[0.073]	[0.260]	[0.094]	[0.095]	[0.080]	[0.360]
State Unemployment	-0.033***	-0.013	-0.007	-0.029	-0.033***	-0.017*	-0.013*	-0.045
	[0.006]	[0.008]	[0.007]	[0.022]	[0.007]	[0.009]	[0.007]	[0.028]
County Unemployment	0.012***	0.025***	0.014***	0.013	0.011***	0.025***	0.016***	0.023**
	[0.004]	[0.005]	[0.004]	[0.009]	[0.004]	[0.005]	[0.004]	[0.011]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
State Time Trend	YES	YES	YES	YES	YES	YES	YES	YES
Observations	178,055	176,573	177,884	140,207	177,713	175,889	177,998	131,999
Number of Counties	3,125	3,099	3,122	2,461	3,119	3,087	3,124	2,317

Notes: Dependent variable is the number of active duty recruits of the quality-level indicated at the top. Regression is Poisson, and deaths have been divided by 100, so coefficients can be interpreted as semi-elasticities. All regressions include county young male population as an offset (using exposure option). Low quality is a recruit who scored below 50 on the AFQT or does not have a high school diploma. High Quality have both a 50 or higher and a high school degree. High Quality-Alt have a 50+ and have either finished high school or are in their senior year. Very High is a 75+ AFQT and at least some college. Robust standard errors which allow for clustering by county are in brackets. Monthly and county fixed effects as well as state time trends are included in all specifications.

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

Table 8:

Poisson Regression of County Recruits with Deaths by Specific War

	Applicants		**Contracts**	
	(1)	(2)	(3)	(4)
VARIABLES	County	State	County	State
In-County Deaths/100	-0.345	-0.334	-0.683**	-0.664**
	[0.292]	[0.291]	[0.331]	[0.335]
Iraq Lag In-County Deaths/100	-1.633***	-1.589***	-1.709***	-1.626***
	[0.406]	[0.389]	[0.451]	[0.433]
Afghanistan Lag In-County Deaths/100	2.416*	2.298*	2.926**	2.699**
	[1.370]	[1.394]	[1.205]	[1.184]
Out-of-County Deaths/100	-0.043	-0.026	-0.285***	-0.253***
	[0.065]	[0.065]	[0.071]	[0.072]
Lag Out-of-County Deaths/100	-0.489***		-0.485***	
	[0.056]		[0.064]	
Iraq Lag Out-of-County Deaths/100		-0.527***		-0.564***
		[0.058]		[0.066]
Afghanistan Lag Out-of-County Deaths/100		0.421*		1.115***
		[0.232]		[0.254]
State Unemployment	-0.075***	-0.075***	-0.073***	-0.073***
	[0.006]	[0.006]	[0.006]	[0.006]
County Unemployment	0.018***	0.018***	0.018***	0.019***
	[0.004]	[0.004]	[0.004]	[0.004]
Population Offset	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES
State Time Trends	YES	YES	YES	YES
Observations	178,169	178,169	178,112	178,112
Number of fips	3,127	3,127	3,126	3,126
Likelihood	-334757	-334742	-281121	-281091
Test Lag County Deaths	0.003	0.006	0.001	0.001
Test Lag State Deaths		0.000		0.000

Notes: Dependent variable is the number of active duty recruits in a county-month. Robust standard errors in brackets, clustered by county. Regressions include county young male population as an offset (using exposure option). County and monthly fixed effects are included, as well as state time trends. Beneath the regression are the p-values from tests of equality of the coefficients for the deaths of each of the two wars, separately by state and county.

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

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A Supplementary Appendix

A.1 National Level Analysis

Although this paper focuses on the effects of local deaths on local recruiting, it is worthwhile to briefly discuss the effects of total national deaths on national recruiting. Table A1 shows a simple linear regression analysis of the the national time series of monthly combat deaths and log monthly total applicants from October 2001 through July 2006. Table A2 shows the same specifications using Poisson regression. Graphically, spikes in deaths after the initial invasion of Iraq and the first and second battles for Fallujah (the obvious high points in the figure) are very clearly followed by decreases in recruits. With one observation for every month nation-wide, there are only 58 observations, but there is still a strong and consistent negative correlation between deaths in the current and/or previous month and recruits. In terms of semi-elasticities, as shown in the table, one deaths is associated with a 1.5 to 2 percent decrease in applicants and a 2.0 to 2.7 percent reduction in contracts. (Standard non-logged OLS regressions show that deaths are associated with 60-90 fewer applicants and 27 to 43 fewer contracted recruits.) So it would seem that deaths in the military are followed by an overall decrease in the national number of recruits. This should not necessarily be given a causal interpretation, as a simple linear time trend is not nearly enough to control for all the unobserved changes that occurred in the country over this nearly five-year period, all of which could be biasing the estimate up or down.

The same potential problem does not exist once I narrow the analysis to a finer geographic level and use repeated observations from multiple states or counties over time, where I can use fixed effects to flexibly control for unobserved characteristics. It seems prima facie obvious that there are significant differences between states and counties that might be correlated with both the number of deaths and the number of recruits. County population jumps to mind. A naive regression of counties' recruits on death without accounting for population would have an upward-biased estimate due to omitted variable bias, since with equal recruiting rates, the higher a county's population, the more recruits from that county, and mechanically, the more deaths from that county. With an obvious measure like population, it is possible to get rough estimates of the population that change over time, but with many more subtle county characteristics, such as abstract support for the military, it is not possible to get even one estimate for the county, let alone multiple measurements over time, thus the need for fixed effects to flexibly control for all immeasurable county characteristics fixed over time and reduce or eliminate omitted variable bias.

A.2 Distribution of Recruits Across States

Figure A1 shows that, as one would expect, there are clearly differences in state populations. The horizontal axis is a state's percentage of the nation's male 18-24 year-old population, and the vertical axis shows a state's percentage of the applicants over the entire 16-year period for which I have data. With one observation for each state, a constant national propensity to enlist would yield a population weighted OLS regression coefficient of 1, which can be easily rejected statistically. Figure A2 shows a state's percentage of the young male population and its percentage of the deaths in Iraq and Afghanistan. This slope is also statistically different from 1, indicating that there is not one constant national likelihood of death in the military. This finding may be unsurprising, and is shown only since it may be interesting to know in and of itself which states have higher proportions of their young men enlist and die in the military.

A.3 Additional Robustness Checks

Other functional forms Although I consider the Poisson regressions to be the most natural fit for count data with a large number of zeros that have no log, I have exhaustively tested other models and find generally similar results across all specifications. I present all these results here. Ordinary least squares results for recruit levels (as opposed to logs) are shown in Appendix Table A3. All observations are weighted by county population. One can see that with a full set of fixed effects, in-county deaths in the previous month are associated with 15 fewer applicants and nearly 10 fewer contracts. In-state deaths are associated with 0.3 to 1.1 fewer applicants, and 0.2 to 0.7 contracted recruits fewer, although the estimate is sometimes positive and not always statistically different from zero. The coefficient on lagged in-county deaths is the main estimate of interest, and is remarkably stable across different sets of fixed effects after county-level fixed effects are included.

I have calculated, but do not show estimates of the elasticity of the recruiting response to death based on least squares regressions. They indicate that a one percent increase in the number of in-county deaths leads to a 2.7% reduction in in-county recruits in the next month. However, I put less emphasis on this result for two reasons. First, the vast majority of county-months do not observe a death, and thus one cannot take the natural log of the data for simple elasticity calculations. Second, since most county-months have zero deaths, when any number of deaths is observed, there has actually been an infinite percent increase in the number of deaths.

Semi-elasticity estimates, where the right-hand side variable is in levels and the left hand side is logged eliminates some of the problems with logs of zero, but a non-trivial 30% of county-months have zero active-duty recruits, so the log-linear OLS model is by no means ideal, even if it is more easily comparable to the Poisson estimates shown above. One advantage of these linear models, however, is that I can test inclusion of state-by-year fixed effects which improves my case for causal identification. Unfortunately I cannot include these state-by-year fixed effects in Poisson regression due to convergence issues, however, the extra fixed effects result in similar estimates as the other specification; in some cases they make the effect appear even larger.

Appendix Table A4 shows the semi-elasticity estimates for both applicants and contracts. The dependent variable is the log of active duty recruits. Observations have been weighted by county population. The semi-elasticity estimates show that an in-county death in the previous month leads to a 0.8 to 2% reduction in both applicants and recruits, very similar to the Poisson regressions in the main body of the paper. Out-of-county deaths lead to small increases in recruiting, although the effect is slightly more volatile than that for in-county deaths and becomes negative when state*year interacted fixed effects are added.

Additional specifications include modeling the left hand side variable as the square root of recruits, with results shown in Table A5, and a negative binomial conditional fixed effects regression, with results shown in Table A6. Again, results are very similar: by far the largest deterrant effect comes from in-county deaths. Problems exist with negative binomial fixed effects regression, as explained in Allison and Waterman [2002], so these results are presented only to exhaustively test other functional forms.

Tests of Additional Data The main Poisson regression specification from Table 2 is repeated in Appendix Table A7 using all recruits, including the reserve and guard contracts that appear to be underreported in the FOIA data. Results are very similar.

In addition to testing every recruit, I also test the model by using only deaths from active duty soldiers, as opposed to deaths of all soldiers (active, reserve, and guard) as in all other specification. Results, shown in Table A8 appear slightly stronger, in that deterrent effects of in-county deaths are estimated to be slightly larger than one percent.

Appendix Table A9 repeats the main specification but adds one lead period of deaths as a falsification test of the model. As expected, deaths in the future have no relation to current recruiting.

I also use additional data on deaths acquired through a FOIA request. This data consists of all deaths of anyone in the military from 1990-2006, regardless of circumstance or location. Thus it includes numerous deaths that are completely unrelated to the wars in Iraq or Afghanistan, and even unrelated to the military—heart attacks, car accidents, etc. As I expected given the comparatively banal circumstances of the majority of these deaths, all regressions indicate no significant recruiting response to in-county deaths, neither in the entire 1990-2006 period nor the 2001-2006 period used in the main regression tables. These results are shown in Appendix Table A10.

A.4 Recruits and Deaths Across Service Branches

In this section I examine how the individual services fare in their recruiting. There are clearly differences between the services in terms of their operations; perhaps stemming from this there are often assumed to be significant cultural differences between the branches, leading to a difference in the type of people who make up the potential applicant pool for each of the services, and the possibility for a difference in the potential applicants' response to a local death. Table A11 shows these estimates, again using Poisson regression analysis at the month-county level, with county and monthly fixed effects and state time trends. It appears that Marine recruiting decreases at a rate of over 2% for every death, while the Air Force reaction to death is a statistically insignificant 0.05% reduction in recruits. Deaths at the state level and state and county unemployment seem to have effects that are less clearly distinguishable across service branches. This makes sense given that very few of the deaths in Iraq and Afghanistan have come from the Air Force, while many have come from the Marines. But an even larger proportion have come from the Army, so if potential recruits were simply steering away from the branches of the military with the most deaths, the Army would be the branch with the largest recruiting response to deaths, which is not the case. I have repeated this exercise using weighted least squares regressions of the log of the recruits of each service branch, and the deterrent effects by service branch maintain the same ratios relative to one another, exhibiting further evidence that the recruiting deterrent is greatest for the Marine Corps.

Amongst the four branches of the military, the deaths in Iraq and Afghanistan have been highly concentrated amongst soldiers in the Army and the Marines. In the data used in this paper, roughly 2000 deaths are from the Army, 800 from the Marines, 85 from the Navy, and 50 from the Air Force. Since there have been 40 times more deaths in the Army than the Air Force, it is entirely possible that potential Army recruits have instead gone on to join the Air Force instead. To test this, I have rearranged the data into county-month-service branch observations and test the recruiting response to a specific service branch after deaths from the same service branch and from other service branches. Table A12 shows the results of these tests. Poisson regressions shows the percent response to a death in the same service branch as the recruit, and in any of the other three service branches. As before, I have controlled for monthly fixed effects, state trends, and state and county unemployment. In these regressions I have included interacted county*service branch fixed effects as well. The bottom of the table shows pair-wise comparisons of the corresponding same-service and other-service death coefficients. For example, for applicants, a lagged same-service in-county death leads to a 0.7% reduction in recruits in that service, while a lagged other-service in-county death leads to a 1.1% reduction in recruits for that service. In all of the specifications, tests fail to reject the hypothesis that the effect of a lagged same-service in-county death is statistically identical to that of a lagged other-service in-county death. The same can be said of lagged same-service out-of-county deaths and lagged other-service out-of-county deaths. However, for several of the current-month deaths, statistical tests reject equivalence. They indicate that same-service deaths have a larger (and positive effect) than do other-service deaths. *A priori* I would have assumed that if anything, same-service deaths would lead to a larger decrease in recruits, since recruits could either not sign up or substitute to a different service, but this does not seem to be the case. The results are further evidence that potential recruits are not using the information contained in a death (in this case, the service branch in which the death occurred) in a sophisticated or strictly risk-based manner.

A slightly different way to get at the question of deaths by service branch is to lump all the recruits together but show the specific response to deaths in a given service. These estimates are shown in Table A13. The coefficients are positive for Air Force and the Navy in-county deaths, however they are not statistically significant. I have also run specifications with the in-state but out-of-county deaths split by service branch, and I have run tests of equivalence of the coefficients for all the service branches. The hypotheses of equality cannot be rejected for county deaths, but can be for state deaths.

Table A1:
Log Total Apps vs. Total Deaths: Semi-Elasticity

VARIABLES	(1) APP	(2) APP	(3) APP	(4) CON	(5) CON	(6) CON
Current Deaths	-0.206***	-0.084	-0.112*	-0.258***	-0.150**	-0.136*
	[0.041]	[0.051]	[0.056]	[0.048]	[0.062]	[0.070]
Lag Deaths		-0.170***	-0.203***		-0.161**	-0.145**
		[0.050]	[0.058]		[0.062]	[0.072]
Observations	58	57	57	58	57	57
R-squared	0.311	0.419	0.432	0.339	0.406	0.408
Linear Trend	NO	NO	YES	NO	NO	YES

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
Notes: Table shows linear regression estimates of log national monthly deaths on recruits.
The first three columns show applicants and the last three show contracts.
Filename:deathsvrecruitsSEMI.tex

Table A2:
Poisson Regression: Total Applicants vs. Total Deaths

VARIABLES	(1) APP	(2) APP	(3) APP	(4) CON	(5) CON	(6) CON
Current Deaths	-0.209***	-0.086***	-0.110***	-0.261***	-0.147***	-0.132***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.004]	[0.004]
Lag Deaths		-0.166***	-0.196***		-0.161***	-0.142***
		[0.002]	[0.003]		[0.004]	[0.004]
Observations	58	57	57	58	57	57
Linear Trend	NO	NO	YES	NO	NO	YES
Likelihood	-15147	-12409	-12202	-8909	-8001	-7967

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
Notes: Table shows Poisson regression estimates of total national monthly deaths on recruits.
The first three columns show applicants and the last three show contracts.
Filename:deathsvrecruitsP.tex

Figure A1: State Percentage of Recruits by State Percentage of Young Male Population

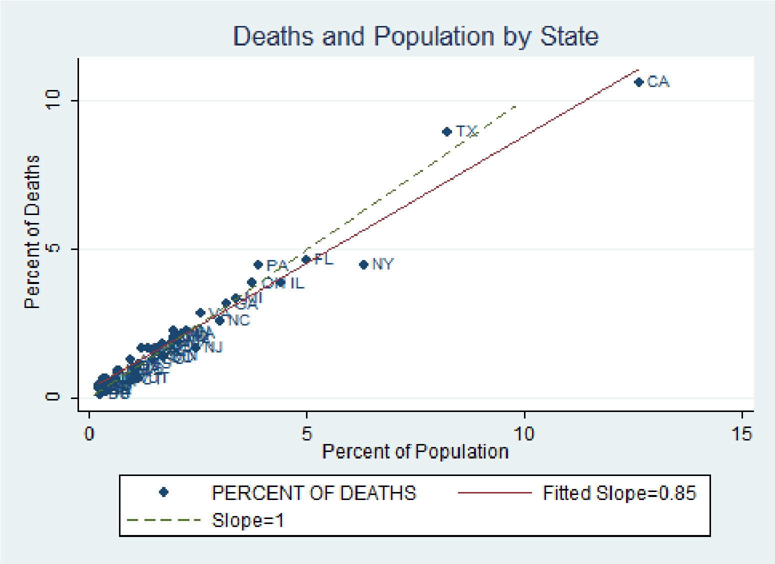

Figure A2: State Percentage of Population vs. State Percentage of Deaths

Table A3:

Basic County-Level Least Squares Analysis of Deaths and Unemployment

	Applicants				**Contracts**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Basic	w/State	w/State Trend	w/State*Year FE	Basic	w/State	w/State Trend	w/State*Year FE
In-County Deaths	-14.551***	-13.845***	-12.174***	-12.553***	-9.298***	-8.867***	-7.835***	-8.132***
	[4.710]	[4.515]	[3.177]	[3.360]	[3.307]	[3.174]	[2.339]	[2.453]
Lag In-County Deaths	-17.691***	-16.601***	-14.790***	-15.344***	-10.591***	-9.947***	-8.827***	-9.165***
	[4.193]	[3.724]	[2.521]	[2.758]	[2.930]	[2.632]	[1.815]	[2.014]
Out-of-County Deaths		-0.231**	0.541	0.836		-0.175**	0.228	0.384
		[0.105]	[0.392]	[0.527]		[0.070]	[0.247]	[0.345]
Lag Out-of-County Deaths		-1.139**	-0.298*	-0.399***		-0.667*	-0.233**	-0.147
		[0.562]	[0.170]	[0.119]		[0.355]	[0.108]	[0.091]
County Unemployment		2.550***	2.471***	4.100***		1.928***	1.860***	2.333***
		[0.890]	[0.792]	[1.205]		[0.607]	[0.549]	[0.680]
State Unemployment		5.665**	-1.934*	0.079		2.871**	-1.238*	0.669
		[2.268]	[1.135]	[1.248]		[1.397]	[0.677]	[0.894]
Constant	91.650***	46.975***	89.360***	65.840***	53.118***	27.096***	50.180***	34.593***
	[1.921]	[14.041]	[3.921]	[7.561]	[1.273]	[9.122]	[2.668]	[5.747]
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
State Time Trends	NO	NO	YES	NO	NO	NO	YES	NO
State*Year FE	NO	NO	NO	YES	NO	NO	NO	YES
Observations	178,809	178,739	178,739	178,739	178,809	178,739	178,739	178,739
R-squared	0.968	0.968	0.971	0.968	0.963	0.964	0.966	0.963

Notes: Dependent variable is the number of recruits in a county-month. Robust standard errors in brackets, clustered by county. Observations are weighted by county population. The left four columns are for applicants, the right are for recruits. Fixed effects are by county, monthly, linear state time trend, or interacted state*year.

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

Table A4:

Least Squares Deaths and Unemployment as Semi-Elasticities

	Applicants				**Contracts**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Basic	w/State	w/State Trend	w/State*Year FE	Basic	w/State	w/State Trend	w/State*Year FE
In-County Deaths/100	-0.182	-0.312	-0.18	-1.071**	-0.1	-0.236	-0.153	-1.374***
	[0.408]	[0.404]	[0.305]	[0.420]	[0.387]	[0.364]	[0.264]	[0.435]
Lag In-County Deaths/100	-0.821***	-0.940***	-0.795***	-2.017***	-0.887***	-0.970***	-0.877***	-2.084***
	[0.185]	[0.196]	[0.268]	[0.335]	[0.240]	[0.244]	[0.301]	[0.359]
Out-of-County Deaths/100		0.194***	0.193***	0.039		0.194**	0.139*	-0.195**
		[0.067]	[0.067]	[0.074]		[0.075]	[0.076]	[0.093]
Lag Out-of-County Deaths/100		0.141*	0.148**	-0.773***		0.075	0.015	-0.654***
		[0.073]	[0.064]	[0.064]		[0.091]	[0.075]	[0.075]
County Unemployment		0.014**	0.012**	0.037***		0.016***	0.015***	0.034***
		[0.006]	[0.006]	[0.006]		[0.006]	[0.005]	[0.005]
State Unemployment		0.002	-0.023***	-0.008		-0.003	-0.024***	0.011
		[0.007]	[0.007]	[0.011]		[0.008]	[0.009]	[0.016]
Constant	3.488***	3.402***	3.548***	3.298***	3.015***	2.945***	3.066***	2.745***
	[0.009]	[0.039]	[0.044]	[0.068]	[0.011]	[0.044]	[0.049]	[0.090]
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
State Time Trend	NO	NO	YES	NO	NO	NO	YES	NO
State*Year FE	NO	NO	NO	YES	NO	NO	NO	YES
Observations	137,595	137,541	137,541	137,541	124,334	124,281	124,281	124,281
R-squared	0.959	0.96	0.961	0.957	0.952	0.952	0.953	0.947

Notes: Dependent variable is the natural log of active duty recruits in a county month. Coefficients can be interpreted as semi-elasticities. Deaths on the right hand side have been divided by 100, so a -0.82 coefficient on the four death variables would imply a 0.82 percent (not 82 percent) decrease. Robust standard errors in brackets, clustered by county. Observations have been weighted by county populations.
*** p<0.01, ** p<0.05, * p<0.1

Table A5:

Least Squares Deaths and Unemployment and Square Root of Recruits

	Applicants				**Contracts**			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-County Deaths	-0.258***	-0.244***	-0.212***	-0.218***	-0.209***	-0.198***	-0.174***	-0.179***
	[0.068]	[0.065]	[0.044]	[0.046]	[0.063]	[0.060]	[0.043]	[0.044]
Lag In-County Deaths	-0.340***	-0.317***	-0.282***	-0.291***	-0.259***	-0.241***	-0.215***	-0.221***
	[0.050]	[0.043]	[0.030]	[0.033]	[0.048]	[0.042]	[0.027]	[0.032]
Out-of-County Deaths		-0.002	0.012*	0.017**		-0.003	0.005	0.01
		[0.003]	[0.007]	[0.008]		[0.003]	[0.006]	[0.007]
Lag Out-of-County Deaths		-0.023**	-0.007*	-0.003		-0.017**	-0.009***	-0.005
		[0.010]	[0.004]	[0.003]		[0.008]	[0.003]	[0.003]
County Unemployment		0.143***	-0.066**	-0.084**		0.084**	-0.060**	-0.077**
		[0.050]	[0.031]	[0.036]		[0.042]	[0.027]	[0.036]
State Unemployment		0.084***	0.080***	0.079***		0.081***	0.077***	0.077***
		[0.025]	[0.022]	[0.022]		[0.022]	[0.019]	[0.019]
Constant	7.407***	6.176***	7.352***	7.442***	5.647***	4.754***	5.571***	5.655***
	[0.049]	[0.293]	[0.144]	[0.201]	[0.042]	[0.253]	[0.133]	[0.202]
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
State Time Trend	NO	NO	YES	NO	NO	NO	YES	NO
State*Year FE	NO	NO	NO	YES	NO	NO	NO	YES
Observations	178,809	178,739	178,739	178,739	178,809	178,739	178,739	178,739
R-squared	0.982	0.982	0.983	0.984	0.977	0.978	0.979	0.979

Notes: Dependent variable is the square root of active duty recruits in a county month. Robust standard errors in brackets, clustered by county. Observations have been weighted by county populations.
*** p<0.01, ** p<0.05, * p<0.1 sqrt.txt

Table A6:

Negative Binomial Regression of County Recruits on Deaths and Unemployment

	Applicants				Contracts			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-County Deaths/100	-0.656***	-0.091	-0.223	-0.111	-0.737***	0.019	-0.152	-0.09
	[0.226]	[0.217]	[0.218]	[0.220]	[0.273]	[0.265]	[0.266]	[0.268]
Lag In-County Deaths/100	-1.143***	-0.780***	-0.921***	-0.796***	-1.238***	-0.650**	-0.838***	-0.774***
	[0.230]	[0.221]	[0.223]	[0.225]	[0.276]	[0.269]	[0.271]	[0.273]
Out-of-County Deaths/100	0.168***		0.212***	0.186***	0.160***		0.228***	0.140**
	[0.051]		[0.051]	[0.054]	[0.060]		[0.061]	[0.064]
Lag Out-of-County Deaths/100	-0.142***		0.174***	0.159***	-0.116*		0.201***	0.104
	[0.051]		[0.052]	[0.055]	[0.060]		[0.062]	[0.065]
Out-of-State Deaths/100	-0.001***				-0.002***			
	[0.000]				[0.000]			
Lag Out-of-State Deaths/100	-0.002***				-0.002***			
	[0.000]				[0.000]			
State Unemployment			-0.003	-0.026***			-0.010***	-0.026***
			[0.003]	[0.004]			[0.003]	[0.004]
County Unemployment			0.015***	0.015***			0.016***	0.016***
			[0.001]	[0.001]			[0.002]	[0.002]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	NO	YES	YES	YES	NO	YES	YES	YES
State Time Trend	NO	NO	NO	YES	NO	NO	NO	YES
Observations	178,239	178,239	178,169	178,169	178,182	178,182	178,112	178,112
Number of Counties	3,127	3,127	3,127	3,127	3,126	3,126	3,126	3,126
Likelihood	-342459	-332831	-331962	-331200	-286140	-278656	-278173	-277676

Notes: Dependent variable is the number of recruits in a county-month. The right hand side variables represent deaths in a month divided by 100, so coefficients are interpretable as semi-elasticities, and .8 refers to 0.8 percent. Out of county deaths refers only to in-state but out-of-county deaths. Standard errors in brackets, which allow for clustering by county. All regressions include an offset of county young male population (using Stata's exposure option). Fixed effects included are for every county and separately for calendar month. State-specific linear time trends are also included in specifications 4 and 8.
*** p<0.01, ** p<0.05, * p<0.1 negbinom.xlsx

Table A7:

Poisson Regression of County Recruits (Including Reserves and Guard) on Deaths and Unemployment

	Applicants			Contracts		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Basic	w/State	w/State Trend	Basic	w/State	w/State Trend
In-County Deaths/100	-0.306	-0.385	-0.141	0.025	-0.144	-0.091
	[0.344]	[0.345]	[0.224]	[0.442]	[0.424]	[0.304]
Lag In-County Deaths/100	-1.115***	-1.152***	-0.887***	-0.638**	-0.823***	-0.770***
	[0.224]	[0.232]	[0.222]	[0.275]	[0.268]	[0.257]
Out-of-County Deaths/100		0.222***	0.308***		0.228***	0.139*
		[0.055]	[0.053]		[0.070]	[0.071]
Lag Out-of-County Deaths/100		0.066	0.165***		0.201***	0.103
		[0.059]	[0.053]		[0.077]	[0.064]
State Unemployment		0.001	-0.034***		-0.01	-0.027***
		[0.006]	[0.005]		[0.006]	[0.006]
County Unemployment		0.020***	0.019***		0.017***	0.017***
		[0.005]	[0.004]		[0.005]	[0.004]
Population Offset	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES
State Time Trend	NO	NO	YES	NO	NO	YES
Observations	178,239	178,169	178,169	178,182	178,112	178,112
Number of Counties	3,127	3,127	3,127	3,126	3,126	3,126
Likelihood	-379511	-378163	-377054	-279019	-278532	-278043

Notes: Dependent variable is the number of recruits of any type (including Guard and Reserves, which are very likely under-reported in the data) in a county-month. The right hand side variables represent deaths in a month divided by 100, so coefficients are interpretable as semi-elasticities, and .8 refers to 0.8 percent. Out of county deaths refers only to in-state but out-of-state deaths. Robust standard errors in brackets, which allow for clustering by county. All regressions include an offset of county young male population (using Stata's exposure option). Fixed effects included are for every county and month. State-specific time trends are also included.
*** p<0.01, ** p<0.05, * p<0.1 allrecPbasic.xls›

Table A8:

Poisson Regression of County Recruits on Only Active Duty Deaths and Unemployment

	Applicants				Contracts			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-County Deaths/100	-0.466	0.092	-0.072	0.032	-0.82	0.518	0.227	0.323
	[0.548]	[0.469]	[0.463]	[0.366]	[0.680]	[0.418]	[0.399]	[0.327]
Lag In-County Deaths/100	-1.382**	-0.993***	-1.164***	-1.051***	-1.603***	-0.593*	-0.864**	-0.770*
	[0.582]	[0.300]	[0.324]	[0.340]	[0.533]	[0.340]	[0.340]	[0.397]
Out-of-County Deaths/100	0.203**		0.214***	0.172**	0.208**		0.267***	0.167**
	[0.085]		[0.077]	[0.068]	[0.090]		[0.084]	[0.072]
Lag Out-of-County Deaths/100	-0.167*		0.239***	0.198***	-0.154		0.240**	0.122*
	[0.094]		[0.076]	[0.067]	[0.103]		[0.094]	[0.067]
Out-of-State Deaths/100	-0.002***				-0.002***			
	[0.000]				[0.000]			
Lag Out-of-State Deaths/100	-0.002***				-0.002***			
	[0.000]				[0.000]			
State Unemployment			-0.002	-0.025***			-0.009	-0.026***
			[0.006]	[0.006]			[0.007]	[0.006]
County Unemployment			0.016***	0.016***			0.016***	0.016***
			[0.005]	[0.004]			[0.005]	[0.004]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	NO	YES	YES	YES	NO	YES	YES	YES
State Time Trend	NO	NO	NO	YES	NO	NO	NO	YES
Observations	178,239	178,239	178,169	178,169	178,182	178,182	178,112	178,112
Number of Counties	3,127	3,127	3,127	3,127	3,126	3,126	3,126	3,126
Likelihood	-342726	-332832	-331963	-331202	-286056	-278657	-278172	-277677

Notes: Dependent variable is the number of recruits in a county-month. The right hand side variables represent active-duty deaths in a month divided by 100, so coefficients are interpretable as semi-elasticities, and .8 refers to 0.8 percent. Out of county deaths refers only to in-state but out-of-county deaths. Robust standard errors in brackets, which allow for clustering by county. All regressions include an offset of county young male population (using Stata's exposure option). Fixed effects included are for every county and separately for calendar month. State-specific linear time trends are also included in specifications 4 and 8.

*** p<0.01, ** p<0.05, * p<0.1 redfPbasicR.xlsx

Table A9:

Poisson Regression of County Recruits on Deaths and Unemployment, Leads included

	Applicants				Contracts			
VARIABLES	(1) Horse Race	(2) Basic	(3) w/State	(4) w/State Trend	(5) Horse Race	(6) Basic	(7) w/State	(8) w/State Trend
Future In-County Deaths/100	-0.466	-0.044	-0.174	-0.08	-0.354	-0.02	-0.172	-0.122
	[0.300]	[0.269]	[0.293]	[0.266]	[0.349]	[0.322]	[0.323]	[0.265]
In-County Deaths/100	-0.572	-0.12	-0.281	-0.181	-0.705	-0.009	-0.203	-0.143
	[0.517]	[0.410]	[0.412]	[0.310]	[0.581]	[0.437]	[0.426]	[0.317]
Lag In-County Deaths/100	-1.027***	-0.669***	-0.839***	-0.756***	-1.193***	-0.548**	-0.753***	-0.719***
	[0.366]	[0.174]	[0.190]	[0.246]	[0.385]	[0.248]	[0.251]	[0.277]
Future Out-of-County Deaths/100	0.002		0.132**	0.119*	0.023		0.125*	0.061
	[0.056]		[0.059]	[0.069]	[0.065]		[0.064]	[0.067]
Out-of-County Deaths/100	0.208***		0.188***	0.173***	0.188**		0.202***	0.131*
	[0.065]		[0.060]	[0.059]	[0.075]		[0.067]	[0.068]
Lag Out-of-County Deaths/100	-0.141**		0.182***	0.167***	-0.144*		0.192**	0.115*
	[0.071]		[0.063]	[0.058]	[0.083]		[0.075]	[0.064]
Future Out-of-State Deaths/100	-0.115***				-0.139***			
	[0.005]				[0.005]			
Out-of-State Deaths/100	-0.068***				-0.093***			
	[0.005]				[0.006]			
Lag Out-of-State Deaths/100	-0.173***				-0.128***			
	[0.005]				[0.006]			
State Unemployment			-0.004	-0.027***			-0.01	-0.027***
			[0.006]	[0.006]			[0.006]	[0.006]
County Unemployment			0.016***	0.016***			0.016***	0.016***
			[0.005]	[0.004]			[0.005]	[0.004]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	NO	YES	YES	YES	NO	YES	YES	YES
State Time Trend	NO	NO	NO	YES	NO	NO	NO	YES
Observations	175,056	175,224	174,986	174,986	175,056	175,224	174,986	174,986
Number of Counties	3,126	3,129	3,126	3,126	3,126	3,129	3,126	3,126
Likelihood	-335647	-326793	-325809	-325088	-280280	-273471	-272894	-272427

Notes: Dependent variable is the number of recruits in a county-month. The right hand side variables represent deaths in a month divided by 100, so coefficients are interpretable as semi-elasticities, and .8 refers to 0.8 percent. Out of county deaths refers only to in-state but out-of-county deaths. Robust standard errors are in brackets, which allow for clustering by county. All regressions include an offset of county young male population (using Stata's exposure option). Fixed effects included are for every county and separately for calendar month. State-specific linear time trends are also included in specifications 4 and 8.

*** p<0.01, ** p<0.05, * p<0.1 redfPF1.xlsx

Table A10:

Poisson Regressions of Recruiting on All Deaths (Including Non-Combat)

	Applicants				Contracts			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In-County Deaths/100	0.339	0.321	-0.112	-0.15	0.472	0.453	-0.043	-0.101
	[0.379]	[0.369]	[0.215]	[0.214]	[0.375]	[0.364]	[0.233]	[0.229]
Lag In-County Deaths/100	0.371	0.359	-0.105	-0.117	0.277	0.274	-0.111	-0.144
	[0.401]	[0.392]	[0.199]	[0.199]	[0.398]	[0.388]	[0.217]	[0.216]
Out-of-County Deaths/100		0.268***		0.098**		0.316***		0.144***
		[0.052]		[0.041]		[0.056]		[0.047]
Lag Out-of-County Deaths/100		0.247***		0.059		0.245***		0.052
		[0.047]		[0.044]		[0.046]		[0.053]
State Unemployment		0.006		-0.003		0.011***		-0.01
		[0.004]		[0.006]		[0.004]		[0.006]
County Unemployment		0.014***		0.016***		0.015***		0.016***
		[0.002]		[0.005]		[0.002]		[0.005]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
Years Used	1990-2006	1990-2006	2001-2006	2001-2006	1990-2006	1990-2006	2001-2006	2001-2006
Observations	619,146	619,029	181,366	181,296	619,146	619,029	181,308	181,238
Number of Counties	3,127	3,127	3,127	3,127	3,127	3,127	3,126	3,126
Likelihood	-1293000	-1291000	-339441	-338580	-1047000	-1045000	-284016	-283543

Notes: Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1. Columns 1-4 use applicants data. Columns 5-8 use contracts data. Regressions use either 1990-2006 or 2001-2006 deaths data that includes every military death including non-combat deaths, with years as indicated beneath columns.

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Table A11:

Poisson Regressions of Recruits by Service Branch

	Applicants				Contracts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Army	Air Force	Marines	Navy	Army	Air Force	Marines	Navy
In-County Deaths/100	0.549	-1.345**	-1.002	-0.382	0.79	-1.560**	-0.14	-0.712
	[0.405]	[0.649]	[0.616]	[0.609]	[0.514]	[0.755]	[0.516]	[0.582]
Lag In-County Deaths/100	-0.617*	-0.049	-2.528***	-0.637	-0.585	-0.936	-1.113*	-0.924
	[0.340]	[1.088]	[0.562]	[0.469]	[0.473]	[0.625]	[0.606]	[0.582]
Out-of-County Deaths/100	0.205**	0.181	0.026	0.230**	0.279*	0.011	0.025	0.12
	[0.104]	[0.135]	[0.124]	[0.108]	[0.143]	[0.146]	[0.140]	[0.120]
Lag Out-of-County Deaths/100	0.025	0.174	0.039	0.436***	0.055	0.224	-0.055	0.210*
	[0.094]	[0.142]	[0.127]	[0.121]	[0.110]	[0.166]	[0.122]	[0.119]
State Unemployment	-0.017*	-0.018	-0.026**	-0.039***	-0.033***	-0.003	-0.036***	-0.022**
	[0.009]	[0.011]	[0.011]	[0.010]	[0.011]	[0.012]	[0.011]	[0.011]
County Unemployment	0.014***	0.017***	0.020***	0.016***	0.019***	0.011*	0.020***	0.014***
	[0.004]	[0.006]	[0.005]	[0.006]	[0.005]	[0.006]	[0.005]	[0.005]
Population Offset	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES	YES	YES	YES	YES
State Time Trend	YES	YES	YES	YES	YES	YES	YES	YES
Observations	177,029	174,578	173,894	175,604	175,661	173,039	171,842	174,578
Number of Counties	3,107	3,064	3,052	3,082	3,083	3,037	3,016	3,064

Notes: Dependent variable is the number of active duty recruits to the service branch indicated at the top. Robust standard errors which allow for clustering by county are in brackets. All regressions include county young male population as offset (using exposure option). Monthly and county fixed effects as well as state time trends are included in all specifications.
*** p<0.01, ** p<0.05, * p<0.1

Table A12:

Poisson Regressions of County-Month-Service Branch Recruits on Same Service and Other Service Deaths

	Applicants		**Contracts**	
	(1)	(2)	(3)	(4)
VARIABLES	County*Unit FE	w/ Trend	County*Unit FE	w/Trend
Same Service In-County Deaths/100	0.412	0.484	1.888***	1.975***
	[0.683]	[0.691]	[0.683]	[0.712]
Other Service In-County Deaths/100	-0.165	-0.085	-0.613	-0.563
	[0.522]	[0.486]	[0.599]	[0.546]
Lag Same Service In-County Deaths/100	-0.741	-0.667	-0.479	-0.403
	[0.679]	[0.697]	[0.810]	[0.850]
Lag Other Service In-County Deaths/100	-1.155***	-1.063***	-1.265**	-1.220***
	[0.409]	[0.388]	[0.492]	[0.444]
Same Service Out-of-County Deaths/100	0.519***	0.463***	0.688***	0.572***
	[0.148]	[0.133]	[0.157]	[0.144]
Other Service Out-of-County Deaths/100	0.013	-0.026	0.066	-0.026
	[0.086]	[0.084]	[0.089]	[0.092]
Lag Same Service Out-of-County Deaths/100	0.196	0.139	0.233	0.096
	[0.162]	[0.158]	[0.203]	[0.182]
Lag Other Service Out-of-County Deaths/100	0.160*	0.121	0.156*	0.05
	[0.088]	[0.083]	[0.090]	[0.089]
Population Offset	YES	YES	YES	YES
County & State Unemployment	YES	YES	YES	YES
County*Service Branch FE	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES
State Time Trend	NO	YES	NO	YES
Observations	701,105	701,105	695,120	695,120
Number of County*Service Branch	12,305	12,305	12,200	12,200
Likelihood	-784693	-783929	-634157	-633660
In-County Test	0.465	0.451	0.0054	0.00378
Lag In-County Test	0.605	0.606	0.428	0.394
Out-of-County Test	0.00528	0.00434	0.00122	0.000942
Lag Out-of-County Test	0.855	0.924	0.74	0.834

Notes: Dependent variable is the number of recruits in a given county-month-service branch. Robust standard errors which allow for clustering at the county-service branch level are in brackets. All regressions include an offset of young male county population. County and State Unemployment, County*Service Branch fixed effects, monthly fixed effects, and in certain specifications, state time trends are all included. Beneath the regression are p-values of tests that the Same-Service coefficient is equal to the corresponding Other-Service coefficient.

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

Table A13:

Poisson Regression of County Recruits and Deaths by Service Branch

	Applicants		**Contracts**	
	(1)	(2)	(3)	(4)
VARIABLES	County	State	County	State
In-county Deaths/100	-0.086	-0.084	-0.091	-0.088
	[0.317]	[0.313]	[0.302]	[0.302]
Lag In-County Army Deaths/100	-0.926**	-0.983**	-1.094*	-1.130**
	[0.453]	[0.439]	[0.582]	[0.568]
Lag In-County Air Force Deaths/100	2.948	2.572	2.726	2.233
	[2.632]	[2.516]	[2.980]	[2.958]
Lag In-County Marine Corps Deaths/100	-1.140**	-1.337***	-0.922**	-1.096***
	[0.473]	[0.456]	[0.396]	[0.413]
Lag In-County Navy Deaths/100	0.692	0.623	0.281	0.211
	[1.173]	[1.185]	[1.783]	[1.815]
Out-of-County Deaths/100	0.186***	0.186***	0.142**	0.145**
	[0.062]	[0.062]	[0.070]	[0.071]
Lag Out-of-County Total Deaths/100	0.155***		0.102	
	[0.058]		[0.064]	
Lag Out-of-County Army Deaths/100		0.103		0.014
		[0.105]		[0.111]
Lag Out-of-County Air Force Deaths/100		-0.657		-0.892
		[0.620]		[0.638]
Lag Out-of-County Marine Corps Deaths/100		0.315***		0.229**
		[0.093]		[0.113]
Lag Out-of-County Navy Deaths/100		1.313***		1.378***
		[0.450]		[0.479]
State Unemployment	-0.024***	-0.025***	-0.025***	-0.025***
	[0.006]	[0.005]	[0.006]	[0.006]
County Unemployment	0.016***	0.016***	0.016***	0.016***
	[0.004]	[0.004]	[0.004]	[0.004]
Population Offset	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Monthly FE	YES	YES	YES	YES
State Time Trends	YES	YES	YES	YES
Observations	178,169	178,169	178,112	178,112
Number of Counties	3,127	3,127	3,126	3,126
Test Lag County Deaths	0.222	0.207	0.563	0.626
Test Lag State		0.0382		0.021

Notes: Dependent variable is the number of active duty recruits in a county-month. Robust standard errors in brackets, clustered by county. Regressions include county young male population as an offset (using exposure option). County and monthly fixed effects are included, as well as state time trends. Beneath the regression are the p-values from tests of equality of the coefficients for the deaths of all four service branches, separately by state and county.

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