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

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Abstract

I find that full information utility maximization models are insufficient to explain the recruiting response to deaths of US soldiers in recent years. Using data of all applicants to the enlisted US military during the wars in Iraq and Afghanistan, 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 neighboring counties or for out of county but in state deaths. The effect exhibits significant heterogeneity: deaths in Iraq decrease recruiting, while deaths in Afghanistan may 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

In a standard full information utility maximization model, one would predict that, all else equal, an increase in a profession's risk of death would decrease the desirability of employment in that profession. I present evidence that this may not be the best model to explain behavior, based on what is generally the most dangerous job held by the largest number of people: 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. In contrast to standard predictions, 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

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models predict. Since the time of Adam Smith, economists have used models with 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 siblings 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.

Here are a few examples to illustrate the point. The New York City Fire Department implements a recruitment policy of giving 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 at the World Trade Center on September 11, 2001.[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] Similarly, 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

[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`

orthopedic surgeon Bill Krissoff acquired an age waiver and enlisted in the Navy Medical Corps 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.

Is there a model that can test whether these examples are evidence of a more general phenomenon? This paper is an empirical test of the size of the deterrent or incentive effect of deaths in the military on recruiting, 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, comprising 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. I flexibly control 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. 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 over 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.

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 may actually lead to a small increase in recruiting. There are also differences across ethnic demographic, economic, and political lines. The deterrent effect is significantly larger in counties with higher than average African-American populations and is significantly smaller (and sometimes even positive) in 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

[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.

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 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 strictly rational 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.

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] $130 billion of that 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.

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. Recruiting this many troops costs a great deal. 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]

Military recruiters handle all recruiting of enlisted members of the military. 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, with limited 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.

The military refers to potential recruits in the first stage of the enlistment process 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, as the final stage in the recruiting process, defined as shipping off to boot camp, is much more seasonal. I follow this convention and use applicants and contracts. Attempts have been made to account for both the supply and demand

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

side of recruiting (Dertouzos [1985], Hanssens and Levien [1983], Dertouzos and Polich [1989], Asch [1990]) though in this paper I focus on the supply side only.

There has been some limited research analyzing the effect of US casualties in Iraq and Afghanistan at the national level (seeAsch et al. [2010], Simon and Warner [2007]). However, 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. For example, 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] used 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

[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.

individuals are responding differently to local deaths than they 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 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 changed this, as the military made data on a large number of deaths available to the public. 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.

I obtained the recruiting data used in this paper through Freedom of Information Act requests to the office of the Secretary of Defense, which were 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

[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 deaths from outside the state (national deaths) cannot be estimated due to the monthly fixed effects in most models, however in (possibly misspecified) models without the fixed effects, local deaths are multiple orders of magnitude larger for local deaths than for national 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. Note that all active duty (both applicants and contracts) and reserve/guard applicants data appears complete, at least as far as any civilian can confirm data obtained through FOIA. To account for the missing reserve and guard contracts, 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 A10 using all recruits (active, reserve, and guard), which results in very similar, if not slightly larger, estimates.

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 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.

The data includes "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 biased 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 A9.

To summarize the data, 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 (i.e. the data used for the majority of this paper). One can see that at most in any year, less than 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 in the battle area 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 3,125 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

[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`.

Table 1:

Annual US Military Deaths and Summary Characteristics

Year	Miltary FTE	Deaths per 100K	Total Deaths	Hostile Action Deaths	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/Afghanistan 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.

Active 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.

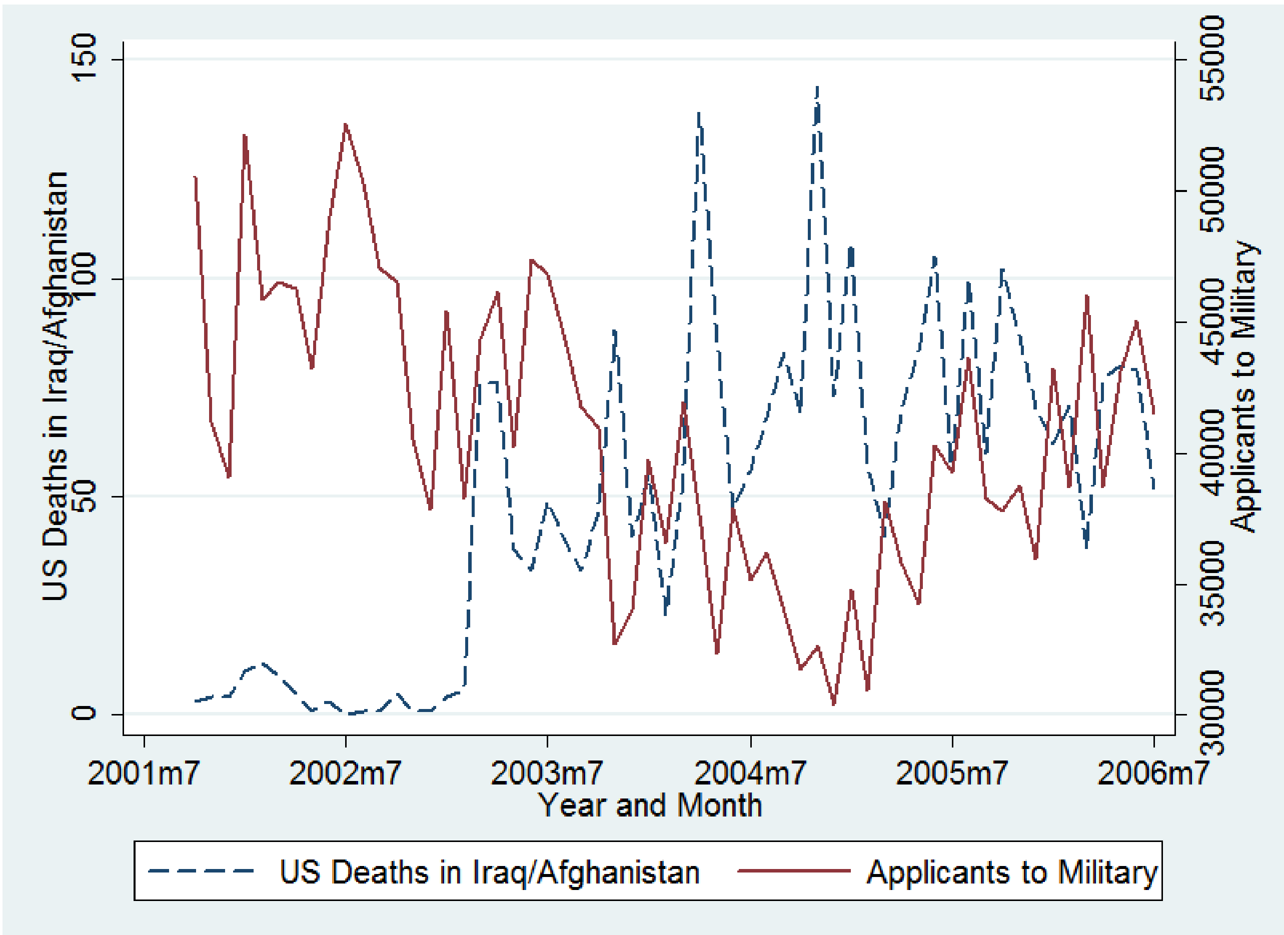

Figure 1: Graph of Monthly Recruits and Monthly Iraq/Afghanistan Combat Deaths

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 Location of Origin and Rates of Death

The specific military occupational specialty (MOS) for which the residents of certain counties or states are likely to sign up, and the corresponding likelihood of death faced by those in certain MOS affects the interpretation of my results. One could imagine that those in the infantry are more likely to be killed than those in ancillary support operations, and one could imagine that recruits from certain states are more likely than others to sign up for more dangerous occupations. However, I find that although counties do tend to send their recruits to different service branches, the rate of death faced by a recruit is statistically the same for all but a very small number of counties.

The first step in this analysis is conducted with a dataset separate from the deaths and recruits data, obtained after multiple FOIA requests, showing the total enlisted employment for each of the thousands of MOS by county and month. Using the midpoint month from my analysis (March 2004), I compare each county's distribution of employment across the four service branches to the national average distribution using Pearson's Chi-squared test. Using the observation in the dataset that I am able to match to a county, employment is split 35% Army, 26% Navy, 16% Marines, and 23% Air Force. The answer is clear: counties do not all send the same fraction of recruits to the four service branches, so the same applies to MOS. Without any correction for the multiplicity of hypothesis tests, as many as 1,225 of the 3,125 counties have ratios of employment that are different than that of the national average at the 95% confidence level. Using the Bonferroni, Benjamini Hochberg, and Benjamini Krieger Yekutieli corrections indicate that 304, 901, and 977 of the 3,125 have statistically different employment distributions at the 95% confidence level, respectively Yoav Benjamini [1995], Benjamini et al. [2006]. Results are very similar using other months of the data.

The second step is more consequential. Just because counties send different fractions of their enlistees to different service branches and MOS does not mean that an enlistee from a certain county was more likely to die in Iraq or Afghanistan. To examine this issue, I compare the number of recruits from a state (or county) to the number of deaths from the same state (or county). 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, and Figure 3 shows the same by county. The state 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. Looking at county figures shows that the majority

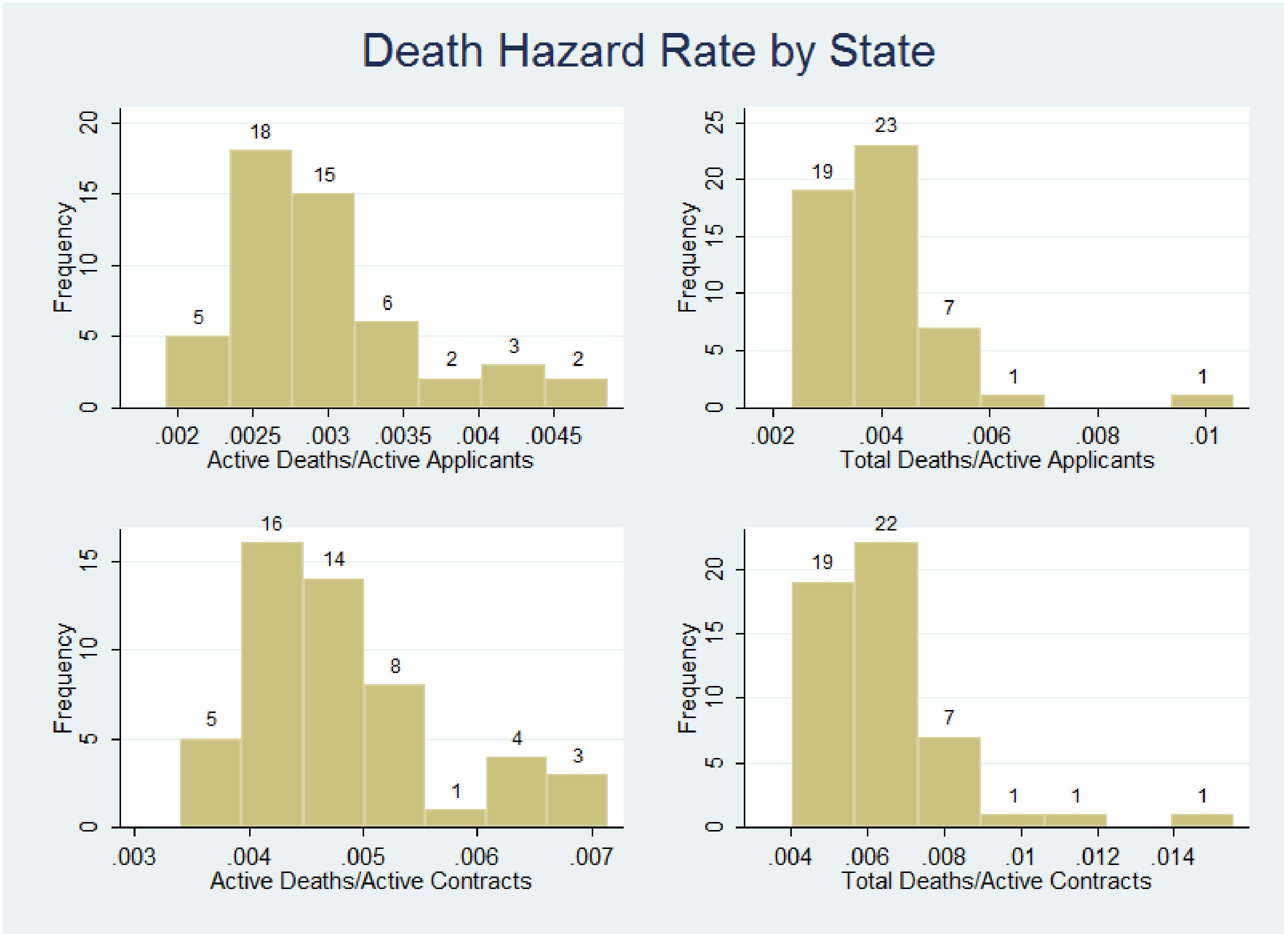

Figure 2: Death Hazard Rates by State: Active Duty/Total Deaths (2001-2010) and Active Duty Applicants/Contracts (1990-2006)

of counties have zero deaths. While some counties clearly exhibit higher rates, testing is required to determine whether the variation is significant.

To do this, I look at each individual county, 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 county observation came from a binomial distribution with this hazard rate of p=.003.

Figure 4 displays histograms of the p-value for each state and county, one set using active-duty deaths and active duty applicants, the other using active-duty deaths and active-duty contracts. If counties exhibit statistically indistinguishable rates of death, then p-values should be high. The histogram displays the p-values as calculated, but to interpret, one should, as above, use an adjustment for the high degree of multiple testing present such as Bonferroni (i.e., for states 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

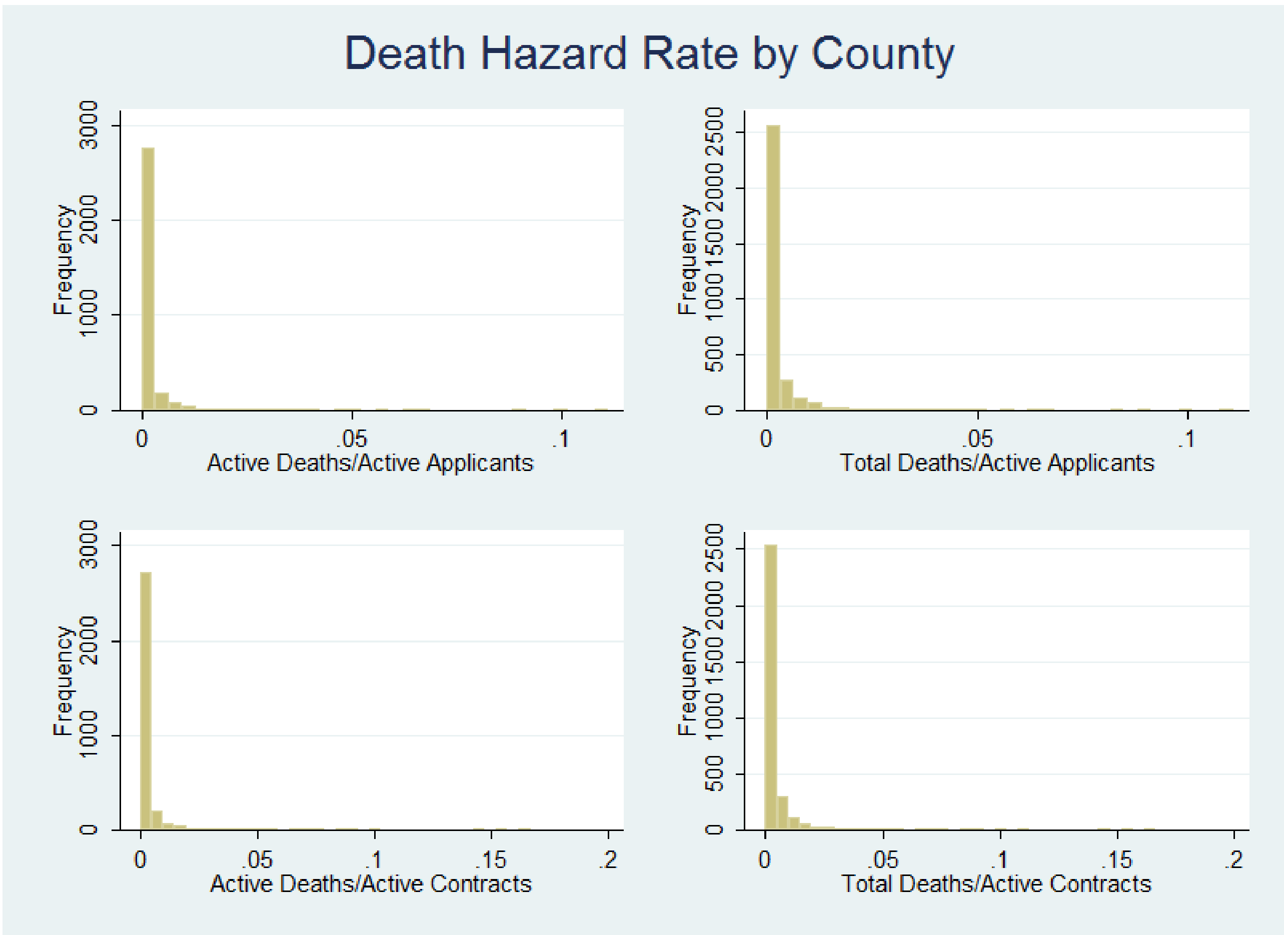

Figure 3: Death Hazard Rates by County: Active Duty/Total Deaths (2001-2010) and Active Duty Applicants/Contracts (1990-2006)

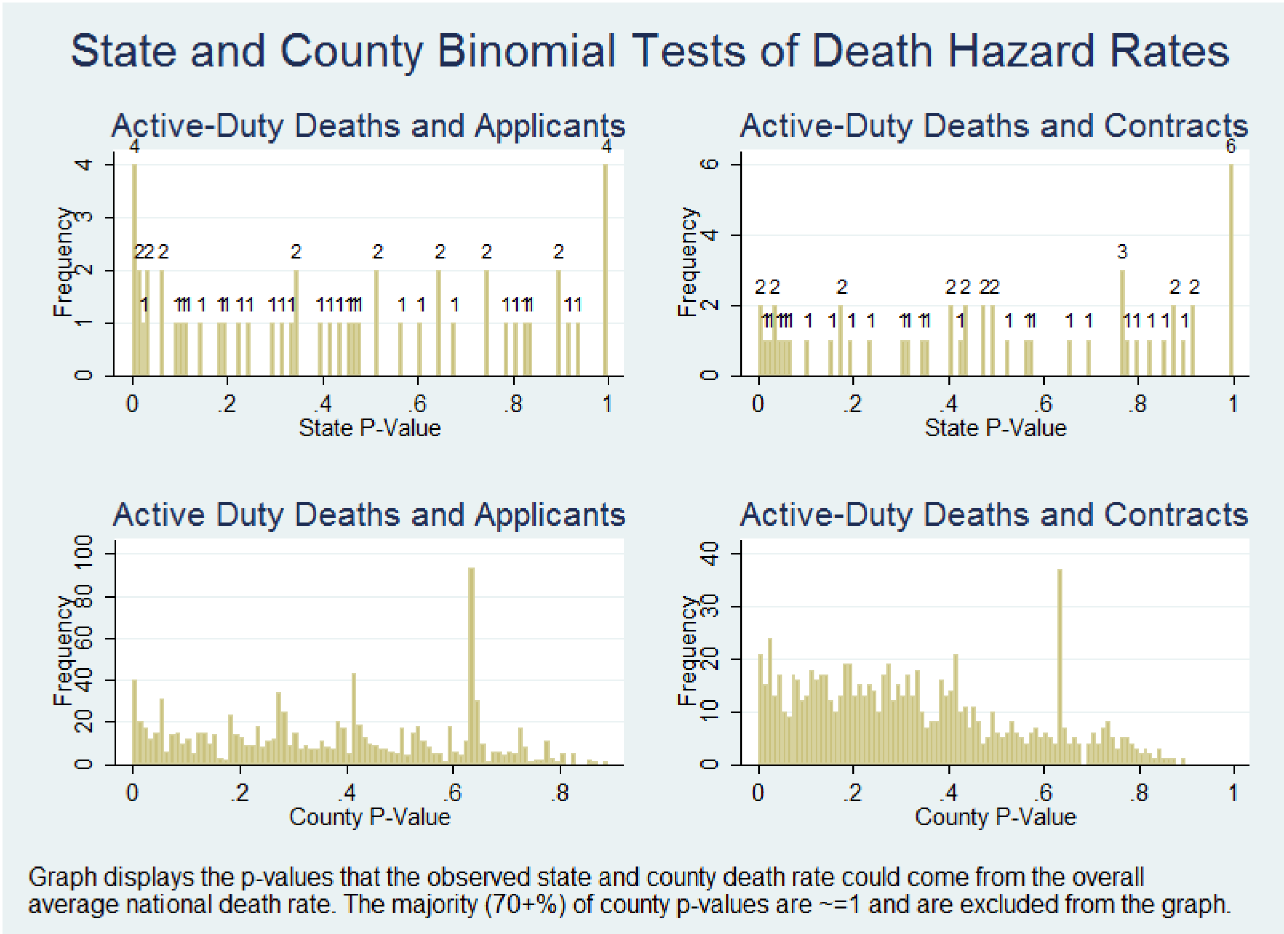

Figure 4: Histogram of P-Values Testing Whether Deaths Come from the Same Binomial Distribution

true probability is in fact .003 using applicant data, and only one, Massachusetts, rejects using contracts data.

Repeating this analysis with the 3,125 counties shows that rates of death given enlistment by county are also very rarely significantly different (eight times for applicants and zero for contracts).[19] So while it is the case that recruits from certain counties are more likely to enter dangerous military occupations, according to the data, the idea that the risk of death is the same across all states can only be rejected very infrequently.

[19]The Bonferroni correction is often considered to be quite conservative. Even using much more modern methods to adjust the False Discovery Rate (FDR), I obtain similar results. Both the Benjamini Hochberg q-values and Benjamini Krieger Yekutieli sharpened q-values indicate that 16 out of the more than 3,100 counties have significantly different death rates for applicants, and zero for contracts. See Yoav Benjamini [1995], Benjamini et al. [2006], Anderson [2008] for details on estimating FDR.

This is not necessarily a cause for concern regarding omitted variable bias and my estimates of the deterrent effect of deaths, since fixed effects for each county will still be able to control for this underlying characteristic of the state and county to the extent it is constant over time. However, it does give a slightly different meaning to the estimates I develop in the next few pages. If deaths in Iraq and Afghanistan were truly uniformly distributed amongst all the troops, regardless of county of origin, 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 locations have insignificantly different hazard rates, and it is not the case that one state or another 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. Main results are estimated using ordinary leasts squares and a log-linear model.[20] The regression generally follows the model:

$$Recruits_{it} = \beta_0 Deaths_{i,t} + \beta_1 Deaths_{i,t-1} + \beta_2 Unemployment_{it} + x'_{it}\eta + \alpha_i + \gamma_t + u_{it}$$

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 fixed over time 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.

Table 2 shows the results when linear 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. Fixed effects for each county and for each month are included in all specifications, as well as state-year fixed effects in specifications 3 and

[20]Log-linear estimates are calculated using Sergio Correia's reghdfe package in Stata 12 [Correia, 2015]. Since data on recruits is in count form, the Poisson model may also be appropriate for the data, as 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 Poisson regressions, which are shown in the Appendix. The results are qualitatively 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 negative binomial specification. Again, the results are very similar.

Table 2:
Log County Applicants vs Deaths and Unemployment

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
Current In-County Deaths/100	-0.352	-0.446	-0.569**	-0.368	-0.443	-0.588**
	[0.381]	[0.378]	[0.279]	[0.365]	[0.355]	[0.233]
Lag In-County Deaths/100	-1.031***	-1.106***	-1.188***	-1.147***	-1.184***	-1.270***
	[0.184]	[0.195]	[0.239]	[0.233]	[0.238]	[0.284]
Current Out-of-County Deaths/100		0.164***	0.124**		0.163**	0.127*
		[0.062]	[0.057]		[0.067]	[0.070]
Lag Out-of-County Deaths/100		0.099	0.049		0.017	-0.036
		[0.068]	[0.058]		[0.084]	[0.068]
County Unemployment		0.013**	0.011**		0.015**	0.013**
		[0.005]	[0.005]		[0.006]	[0.005]
State Unemployment		0.005	-0.035***		0.000	-0.031***
		[0.007]	[0.008]		[0.007]	[0.011]
Observations	178,809	178,739	178,739	178,809	178,739	178,739
R-squared	0.964	0.965	0.965	0.956	0.957	0.958
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	YES	NO	NO	YES

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: Table shows linear regression estimates of log (national active duty recruits +1) on deaths.
Fixed effects are included separately by county and month, and for each state-year, as indiciated,
The first three columns show applicants and the last three show contracts.
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6. 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 1.1% decrease in applicants and a similar 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 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% increase in recruiting.[22] A simple comparison of the coefficients on lagged county deaths and county unemployment indicates that one fewer death of a soldier from the county would lead to the same increase in recruiting as a one percentage point increase in county unemployment.

Assuming that moving across county or state lines (or finding employment across county or state lines) is costly, 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, as county and state unemployment levels directly affect one's likelihood of employment, and thus income and utility. As shown in section 5.1, 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.

I performed this analysis using all of active duty, reserve, and guard duty deaths, 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 (since those who enlist would serve in the same location-based reserve or guard unit) 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 similar or slightly larger reduction in recruits in the next month. The coefficients for out-of-county deaths and unemployment also remain similar. These results are shown in Appendix Table A5.

[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: holding 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.

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 in 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, it is 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[23], which I have included as an 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 October 2001 to June 2004. County and monthly fixed effects are included. The estimates are similar in this restricted time period to those from the full sample, and the effect of a death does not change significantly when I add the extra controls. (Comparing column 1 to 2 and 3 to 4.)

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.[24] 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 DMA and Ansolabehere et al. [1999] for more details.) The regressions show that deaths in nearby areas, whether defined using county borders or media market, have smaller effects on recruiting in a given county. The effect size is roughly half as large as that of a death from the county. While it seems that recruits do respond to information from outside the county, this is perhaps 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.

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 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 a

[23]I am grateful to John Warner for sharing this data.

[24]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

Table 3: Recruiter and Mortality Controls

VARIABLES	(1) Applicants	(2) Applicants	(3) Contracts	(4) Contracts
Current In-County Deaths/100	-0.740**	-0.634**	-0.406	-0.356
	[0.298]	[0.305]	[0.327]	[0.318]
Lag In-County Deaths/100	-1.096**	-1.077***	-0.732*	-0.731*
	[0.443]	[0.391]	[0.406]	[0.383]
Current Out-of-County Deaths/100	0.216**	0.293***	0.195**	0.239***
	[0.093]	[0.094]	[0.095]	[0.089]
Lag Out-of-County Deaths/100	0.230**	0.310***	0.083	0.141
	[0.101]	[0.102]	[0.100]	[0.099]
State Unemployment	-0.010	-0.009	-0.008	-0.008
	[0.009]	[0.009]	[0.009]	[0.009]
County Unemployment	0.019***	0.019***	0.017***	0.017***
	[0.002]	[0.002]	[0.002]	[0.002]
Military Recruiter by State		0.023**		0.020*
		[0.010]		[0.011]
Lag County Mortality Rate		0.001*		0.000
		[0.000]		[0.000]
Lag Out-of-County Mortality Rate		0.000		-0.000
		[0.000]		[0.000]
Observations	97,794	97,794	97,794	97,794
R-squared	0.968	0.968	0.962	0.962
County FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Stateyear FE	NO	NO	NO	NO

Robust standard errors in brackets

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

Notes: Table shows linear regression estimates of log (national active duty recruits +1) on deaths. Fixed effects are included separately by county and month, and for each state-year, as indiciated, The first four columns show applicants and the last three show contracts.

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Table 4: Deaths in Neighboring Counties and Same Media Market

	Media and Contiguous Deaths									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Applicants	Applicants	Applicants	Applicants	Applicants	Contracts	Contracts	Contracts	Contracts	Contracts
Current In-County Deaths/100		-0.541*		-0.533*	-0.540*		-0.514**		-0.509**	-0.528**
		[0.291]		[0.282]	[0.284]		[0.237]		[0.232]	[0.234]
Lag In-County Deaths/100		-1.005***		-1.123***	-1.134***		-1.015***		-1.183***	-1.183***
		[0.250]		[0.258]	[0.256]		[0.280]		[0.314]	[0.313]
Death in Neighbor County	-0.222	-0.141				-0.431**	-0.353			
	[0.144]	[0.163]				[0.200]	[0.222]			
Lag Death in Neighbor County	-0.587***	-0.505**				-0.720***	-0.636***			
	[0.212]	[0.212]				[0.227]	[0.223]			
State Unemployment	-0.036***	-0.037***	0.004	-0.036***	-0.035***	-0.032***	-0.033***	-0.001	-0.032***	-0.031***
	[0.008]	[0.008]	[0.011]	[0.008]	[0.008]	[0.011]	[0.011]	[0.011]	[0.011]	[0.011]
County Unemployment	0.011**	0.011**	0.012**	0.011**	0.011**	0.013**	0.013**	0.014**	0.013**	0.013**
	[0.005]	[0.005]	[0.006]	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]	[0.005]	[0.005]
Death in Media Market			-0.399	-0.078	-0.171			-0.800**	-0.355*	-0.485**
			[0.267]	[0.159]	[0.172]			[0.364]	[0.193]	[0.201]
Lag Death in Media Market			-0.802***	-0.457**	-0.537***			-1.150***	-0.692***	-0.728***
			[0.298]	[0.193]	[0.205]			[0.352]	[0.220]	[0.236]
Current Out-of-County Deaths/100					0.145**					0.193**
					[0.063]					[0.075]
Lag Out-of-County Deaths/100					0.128**					0.069
					[0.065]					[0.080]
Observations	178,568	178,568	178,739	178,739	178,739	178,568	178,568	178,739	178,739	178,739
R-squared	0.965	0.965	0.965	0.965	0.965	0.958	0.958	0.957	0.958	0.958
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
Notes: Table shows linear regression estimates of log (national active duty recruits +1) on deaths.
Fixed effects are included separately by county and month as indiciated,
The first five columns show applicants and the last five show contracts.
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significantly smaller deterrent effect on recruiting than more recent deaths. Earlier regressions have shown a deterrent effect of over one percent for deaths in the previous month; these regressions show a relative decline in the effect size the longer a time period included. The effect size decreases to one third a percent for applicants for twelve months of lagged deaths. The decline in effect size does not appear to be as steady for contracts. Poisson regressions produce very similar semi-elasticity estimates.

As a robustness check on my main specification, I have also run regressions including deaths one month into the future. In the main log-linear specification, deaths from the same county one month into the future appear to have small but statistically significant relationships with recruits. However, the Poisson models, as well as the log-linear model using only active duty deaths, show clearly that deaths in the future do not correlate signficantly with current recruiting levels. These regressions are shown in Appendix Table A7 and Table A8.

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. Note that most of the county characteristics are fixed over time and thus perfectly collinear with fixed effects and 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 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, a binary measure of rural status 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.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.

Death * County Unemployment yields positive but insignificant estimates for applicants and small but significant estimates for contracts, indicating that deaths in counties with higher unemployment are not as large a deterrent effect, and could potentially even make the recruiting response to deaths positive.

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 0.7% reduction in applicants for every death, a county with one standard deviation

Table 5: Cumulative Lags

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Applicants	(5) Contracts	(6) Contracts	(7) Contracts	(8) Contracts
Cum. 2 Lags Out-of-County Deaths	0.087**				0.052			
	[0.042]				[0.049]			
Cum. 2 Lags In-County Deaths	-0.775***				-0.685***			
	[0.186]				[0.218]			
Cum. 2 Lags State Unemployment	0.323				0.178			
	[0.226]				[0.256]			
Cum. 2 Lags County Unemployment	0.321*				0.431**			
	[0.194]				[0.215]			
Cum. 4 Lags Out-of-County Deaths		0.061				0.046		
		[0.037]				[0.044]		
Cum. 4 Lags In-County Deaths		-0.627***				-0.629***		
		[0.148]				[0.193]		
Cum. 4 Lags State Unemployment		0.465**				0.229		
		[0.187]				[0.211]		
Cum. 4 Lags County Unemployment		0.060				0.234		
		[0.170]				[0.192]		
Cum. 6 Lags Out-of-County Deaths			0.063**				0.062*	
			[0.031]				[0.036]	
Cum. 6 Lags In-County Deaths			-0.539***				-0.667***	
			[0.111]				[0.140]	
Cum. 6 Lags State Unemployment			0.467***				0.218	
			[0.137]				[0.157]	
Cum. 6 Lags County Unemployment			-0.032				0.116	
			[0.133]				[0.153]	
Cum. 12 Lags Out-of-County Deaths				0.041*				0.060**
				[0.024]				[0.026]
Cum. 12 Lags In-County Deaths				-0.354***				-0.589***
				[0.096]				[0.107]
Cum. 12 Lags State Unemployment				0.090				-0.035
				[0.093]				[0.108]
Cum. 12 Lags County Unemployment				0.167*				0.227*
				[0.098]				[0.118]
Observations	175,595	169,321	163,047	144,225	175,595	169,321	163,047	144,225
R-squared	0.965	0.965	0.965	0.964	0.957	0.957	0.957	0.957
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	NO	NO	NO	NO	NO	NO

Robust standard errors in brackets

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

Notes: Table shows linear regression estimates of log (national active duty recruits +1) on cumulative lagged deaths. Fixed effects are included separately by county and month as indiciated, The first five columns show applicants and the last five show contracts.

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Table 6: Linear Interactions

VARIABLES	(1) Applicants	(2) Contracts
Current In-County Deaths/100	-0.501	-0.534
	[0.381]	[0.357]
Lag In-County Deaths/100	-0.686	-0.207
	[0.480]	[0.491]
Current Out-of-County Deaths/100	0.165***	0.160**
	[0.061]	[0.067]
Lag Out-of-County Deaths/100	0.083	-0.016
	[0.069]	[0.087]
Lag County Death*County Unemployment	0.007	0.012***
	[0.004]	[0.004]
Lag County Death/County Population	2.698	3.211*
	[1.984]	[1.826]
Lag County Death*%Black Population	-0.065**	-0.117***
	[0.033]	[0.041]
Lag County Death*%George Bush Vote	0.092***	0.154***
	[0.030]	[0.027]
Lag County Death*Rural	-0.029	-0.019
	[0.034]	[0.033]
State Unemployment	0.005	-0.000
	[0.007]	[0.007]
County Unemployment	0.012**	0.014**
	[0.006]	[0.006]
Observations	177,371	177,371
R-squared	0.965	0.957
County FE	YES	YES
Month FE	YES	YES
Stateyear FE	NO	NO

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Table shows linear regression estimates of log (national active duty recruits +1) on deaths. Fixed effects are included separately by county and month, and for each state-year, as indiciated, The first three columns show applicants and the last three show contracts.
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(13%) higher African-American population would see a -0.7+(13%*-0.065)=1.55% reduction in recruits for each death. The estimates are slightly large for contracts than for applicants.

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. Deaths per Male 18-24 year-old County Population has a positive but only marginally significant coefficient. This indicates that perhaps the size of the county does not strongly affect how its population responds to a death.

Finally, I have interacted the county percent of the vote that went to George Bush in 2004 with deaths. The coefficient estimates are 0.09% for applicants to 0.15% for contracts. This indicates that a county with the weighted mean Bush voteshare would see a decrease in applicants of 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%, which indicates that the prospect of an increase in recruiting due to deaths is not at all unlikely.

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. High unemployment may dampen the deterrent effect of deaths slightly. 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

Table 7: Recruits by Quality

VARIABLES	(1) LQ Applicants	(2) HQ50 Applicants	(3) HQ50-Alt. Applicants	(4) HQ75 Applicants	(5) LQ Contracts	(6) HQ50 Contracts	(7) HQ50-Alt. Contracts	(8) HQ75 Contracts
In-County Deaths/100	-0.439	-0.828*	-0.463	-1.123	-0.802**	-0.468	-0.269	0.870
	[0.364]	[0.444]	[0.438]	[0.868]	[0.362]	[0.340]	[0.355]	[1.207]
Lag In-County Deaths/100	-1.249***	-1.309***	-1.217***	-3.687***	-1.549***	-1.113***	-1.371***	-4.115***
	[0.242]	[0.391]	[0.285]	[0.481]	[0.327]	[0.288]	[0.272]	[1.151]
Out-of-County Deaths/100	0.175**	0.114	0.204***	0.093	0.148*	0.092	0.139*	-0.029
	[0.076]	[0.087]	[0.069]	[0.204]	[0.083]	[0.087]	[0.079]	[0.187]
Lag Out-of-County Deaths/100	0.025	0.111	0.193**	0.015	-0.077	0.035	0.052	-0.063
	[0.079]	[0.088]	[0.080]	[0.194]	[0.103]	[0.100]	[0.094]	[0.241]
State Unemployment	-0.002	0.024***	0.022***	0.031***	-0.011	0.021**	0.018**	0.027***
	[0.007]	[0.008]	[0.007]	[0.010]	[0.008]	[0.008]	[0.008]	[0.011]
County Unemployment	0.011**	0.017***	0.011*	0.004	0.012**	0.019***	0.014**	0.010**
	[0.005]	[0.006]	[0.006]	[0.004]	[0.006]	[0.006]	[0.006]	[0.004]
Observations	178,739	178,739	178,739	178,739	178,739	178,739	178,739	178,739
R-squared	0.952	0.940	0.951	0.788	0.937	0.930	0.943	0.720
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	NO	NO	NO	NO	NO	NO

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
Notes: Table shows linear regression estimates of log (national active duty recruits +1) on cumulative lagged deaths. Fixed effects are included separately by county and month as indiciated,
The first four columns show applicants and the last four show contracts.
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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. The results indicate that all but the Very High Quality recruits have roughly the same response to deaths: a 1% reduction in recruits for every death. Amongst Very High Quality recruits, the effect is almost 4%.[25]

Again, I have tested whether the results are the same when done using Poisson regression, and the results exhibit the same patterns for deaths—very high quality recruits are more deterred by deaths than other types of recruits.

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]

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 2.1% decrease in recruiting in the following month, while county deaths from Afghanistan lead to a statistically instignificant increase in recruiting of 1.4% in the following month. The same pattern holds, though slightly less pronounced, when one restricts the analysis to after March 2003 when both wars were occurring simultaneously, and for Poisson regression specifications, which are shown in Appendix Table A11.

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 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

[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 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]I have also compared deaths across military service branches, finding no significant differences by branch.

Table 8: Deaths in Different Wars

VARIABLES	(1) Applicants	(2) Applicants	(3) Contracts	(4) Contracts
In-County Deaths/100	-0.625	-0.626	-1.416**	-1.418**
	[0.568]	[0.568]	[0.575]	[0.575]
Iraq Lag In-County Deaths/100	-2.143***	-2.147***	-2.331***	-2.343***
	[0.635]	[0.635]	[0.633]	[0.633]
Afghanistan Lag In-County Deaths/100	1.433	1.440	-0.639	-0.627
	[1.853]	[1.853]	[1.959]	[1.959]
Out-of-County Deaths/100	-0.089	-0.087	0.048	0.050
	[0.074]	[0.074]	[0.069]	[0.069]
Iraq Lag Out-of-County Deaths/100		-0.041		0.009
		[0.073]		[0.073]
Afghanistan Lag Out-of-County Deaths/100		-0.251		-0.291
		[0.279]		[0.277]
State Unemployment	-0.028***	-0.028***	-0.021***	-0.021***
	[0.005]	[0.005]	[0.005]	[0.005]
County Unemployment	0.008***	0.008***	0.009***	0.009***
	[0.002]	[0.002]	[0.002]	[0.002]
Lag Out-of-County Deaths/100	-0.045		-0.029	
	[0.072]		[0.073]	
Observations	178,910	178,910	178,910	178,910
R-squared	0.859	0.859	0.836	0.836
County FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Stateyear FE	YES	YES	YES	YES
Test In-County	0.0658	0.0650	0.404	0.398
Test Out-of-County		0.451		0.286

Robust standard errors in brackets

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

Notes: Table shows linear regression estimates of log (national active duty recruits +1) on cumulative lagged deaths by war. Fixed effects are included separately by county and month as indiciated, The first four columns show applicants and the last four show contracts.

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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 but are not significantly different, 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 may actually be 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. 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.

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 lead to smaller decreases 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 one percentage point decrease in unemployment, and may be of use to the military, especially given that the localized deterrent effect also exhibits heterogeneity in interesting fashions. 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 military also sees the largest reduction in recruits of the highest quality (as measured by AFQT score and educational attainment) after a local death.

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.

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

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
Current National Deaths/100	-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 National Deaths/100		-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(monthly national recruits) on deaths.
The first three columns show applicants and the last three show contracts.
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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 0.15 to 0.2 percent decrease in applicants and a similar 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. However, it is interesting to note that the correlation between national deaths is much smaller than the county effect (.15 compared to 1.1 percent).

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

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
Current National Deaths/100	-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 National Deaths/100		-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 national monthly recruits on deaths. The first three columns show applicants and the last three show contracts.
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A.2 Additional Robustness Checks

Other functional forms Economists often favor linear models in applied work, and these are shown in the main body of the paper, but some would consider Poisson regressions to be the most natural fit for count data with a large number of zeros that have no log, so I have exhaustively tested other models and find generally similar results across all specifications. I present these results here.

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.[27]

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.

Appendix Table A3 shows the Poisson semi-elasticity estimates for both applicants and contracts. The dependent variable is 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 0.9% reduction in both applicants and recruits, very similar to the log-linear regressions in the main body of the paper. Out-of-county deaths lead to small increases in recruiting.

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

Table A3: Poisson Regressions of County Recruits on Deaths and Unemployment

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
Current In-County Deaths/100	-0.045	-0.180	-0.089	0.027	-0.146	-0.086
	[0.436]	[0.433]	[0.320]	[0.448]	[0.431]	[0.310]
Lag In-County Deaths/100	-0.756***	-0.898***	-0.793***	-0.646**	-0.836***	-0.774***
	[0.184]	[0.195]	[0.244]	[0.279]	[0.273]	[0.259]
Current Out-of-County Deaths/100		0.218***	0.183***		0.230***	0.139**
		[0.064]	[0.062]		[0.070]	[0.071]
Lag Out-of-County Deaths/100		0.179***	0.155***		0.202***	0.103
		[0.066]	[0.058]		[0.078]	[0.064]
State Unemployment		-0.003	-0.025***		-0.010	-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]
Observations	178,239	178,169	178,169	178,182	178,112	178,112
Number of fips	3,127	3,127	3,127	3,126	3,126	3,126
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
State Trends	NO	NO	YES	NO	NO	YES
Likelihood	-332831	-331962	-331200	-278656	-278173	-277676

Robust standard errors in brackets

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

Notes: Table shows Poisson regression of national active duty recruits on deaths.
Fixed effects are included separately by county and month, and linear state trends, as indiciated,
The first four columns show applicants and the last three show contracts.
Filename:redefPbasic.tex

Additional specifications include modeling with a negative binomial conditional fixed effects regression, with results shown in Table A4. 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 and show that results are robust.

Tests of Additional Data In additionally to exhaustively testing functional forms and getting similarly robust results, I also obtain extremely similar results when I test only subsets on the data. For instance 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 Appendix Table A5 appear slightly *stronger*, in that deterrent effects of in-county deaths are estimated to be slightly larger than one percent. Appendix Table A6 shows Poisson regressions using only active duty deaths and again, the results are robust

Tests of lead periods, i.e. testing the regression specification by testing for implausable effects of deaths in the future on current recruiting, are show in tables A7 and A8. The Poisson specification, as well as specifications using only active duty deaths, seem to pass this test.

Table A4:

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 A5: Active Duty Deaths Linear

Log County Applicants vs Active Duty Deaths and Unemployment

VARIABLES	(1) Basic	(2) State	(3) w/Stateyear	(4) Basic	(5) State	(6) w/Stateyear
In-County Active Duty Deaths/100	-0.169	-0.274	-0.456	-0.236	-0.337	-0.518
	[0.419]	[0.420]	[0.339]	[0.468]	[0.455]	[0.385]
Lag In-County Active Duty Deaths/100	-1.294***	-1.356***	-1.525***	-1.489***	-1.512***	-1.679***
	[0.314]	[0.326]	[0.307]	[0.382]	[0.417]	[0.462]
Out-of-County Active Duty Deaths		0.153**	0.125**		0.180**	0.169**
		[0.074]	[0.064]		[0.075]	[0.077]
Lag Out-of-County Active Duty Deaths		0.133*	0.064		0.034	-0.037
		[0.078]	[0.064]		[0.101]	[0.070]
County Unemployment		0.013**	0.011**		0.015**	0.013**
		[0.005]	[0.005]		[0.006]	[0.005]
State Unemployment		0.005	-0.035***		0.001	-0.030***
		[0.007]	[0.008]		[0.007]	[0.011]
Observations	178,809	178,739	178,739	178,809	178,739	178,739
R-squared	0.964	0.965	0.965	0.956	0.957	0.958
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	YES	NO	NO	YES

Robust standard errors in brackets

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

Notes: Table shows linear regression estimates of log (national active duty recruits +1) on *only* active duty deaths. Fixed effects are included separately by county and month, and for each state-year, as indiciated, The first three columns show applicants and the last three show contracts. Filename:LNLinearWR.tex

Appendix Tables A7 and **??** repeat the main specification but add lead periods of deaths as a falsification test of the model. As expected, deaths in the future have no relation to current recruiting.

Table A6: Active Duty Deaths Poisson

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
Active Duty In-County Deaths/100	0.241	0.045	0.159	0.224	-0.056	0.038
	[0.448]	[0.454]	[0.358]	[0.509]	[0.484]	[0.355]
Lag Active Duty In-County Deaths/100	-1.018***	-1.185***	-1.062***	-0.928***	-1.182***	-1.089***
	[0.315]	[0.337]	[0.345]	[0.332]	[0.331]	[0.408]
Active Duty Out-of-County Deaths/100		0.222***	0.184***		0.273***	0.168**
		[0.075]	[0.067]		[0.080]	[0.074]
Lag Active Duty Out-of-County Deaths/100		0.223***	0.185***		0.229**	0.107
		[0.077]	[0.065]		[0.092]	[0.066]
State Unemployment		-0.002	-0.025***		-0.009	-0.026***
		[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]
Observations	178,239	178,169	178,169	178,182	178,112	178,112
Number of fips	3,127	3,127	3,127	3,126	3,126	3,126
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
State Trends	NO	NO	YES	NO	NO	YES
Likelihood	-332832	-331963	-331201	-278655	-278171	-277676

Robust standard errors in brackets

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

Notes: Table shows Poisson regression of national active duty recruits on deaths.
Fixed effects are included separately by county and month, and linear state trends, as indiciated,
The first four columns show applicants and the last three show contracts.
Filename:redefPbasicR.tex

Table A7: Testing Effect of Leads: Linear

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
Lead In-County Deaths/100	-0.580**	-0.457*	-0.625***	-0.758***	-0.627**	-0.821***
	[0.228]	[0.269]	[0.234]	[0.259]	[0.292]	[0.265]
Current In-County Deaths/100	-0.533*	-0.525	-0.627**	-0.537**	-0.485	-0.622**
	[0.281]	[0.360]	[0.270]	[0.250]	[0.356]	[0.249]
Lag In-County Deaths/100	-1.092***	-1.065***	-1.199***	-1.180***	-1.114***	-1.248***
	[0.218]	[0.194]	[0.227]	[0.276]	[0.248]	[0.290]
Lead Out-of-County Deaths/100		0.097	0.042		0.074	0.048
		[0.059]	[0.061]		[0.062]	[0.072]
Current Out-of-County Deaths/100		0.149**	0.130**		0.162**	0.129*
		[0.059]	[0.055]		[0.066]	[0.068]
Lag Out-of-County Deaths/100		0.101	0.044		0.007	-0.049
		[0.066]	[0.058]		[0.082]	[0.069]
State Unemployment		0.003	-0.035***		-0.000	-0.031***
		[0.007]	[0.008]		[0.008]	[0.011]
County Unemployment		0.013**	0.011**		0.015**	0.013**
		[0.006]	[0.005]		[0.006]	[0.005]
Observations	175,672	175,602	175,602	175,672	175,602	175,602
R-squared	0.965	0.965	0.965	0.958	0.957	0.958
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	YES	NO	NO	YES

Robust standard errors in brackets

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

Notes: Table shows linear regression estimates of log (national active duty recruits +1) on deaths

As well as future 'lead' periods. Fixed effects are included separately by county and month, and for each state-year, as indiciated,

The first columns show applicants and the last show contracts.

Filename:forwardbasicWLN.txt

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 A9.

Tests of the entire set of recruits (active duty, guard, and reserve troops, not just active duty recruits as are used in most specifications) reveal similarly robust results–the deterrent effect appears even larger under this specification. Results are shown in Appendix Table A10.

Tests of the heterogeneity of the effect by which the war in which the death occur also appear significantly stronger using a Poisson regression. Results are shown in Appendix Table A11.

Table A8: Testing Effect of Leads: Poisson

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
Lead In-County Deaths/100	-0.047	-0.172	-0.084	-0.042	-0.170	-0.121
	[0.268]	[0.289]	[0.267]	[0.313]	[0.317]	[0.262]
Current In-County Deaths/100	-0.120	-0.287	-0.195	-0.034	-0.209	-0.156
	[0.402]	[0.417]	[0.328]	[0.425]	[0.431]	[0.335]
Lag In-County Deaths/100	-0.680***	-0.846***	-0.761***	-0.583**	-0.758***	-0.721**
	[0.175]	[0.190]	[0.258]	[0.238]	[0.250]	[0.283]
Lead Out-of-County Deaths/100		0.126**	0.097		0.120*	0.042
		[0.059]	[0.067]		[0.064]	[0.065]
Current Out-of-County Deaths/100		0.188***	0.188***		0.202***	0.143**
		[0.060]	[0.060]		[0.067]	[0.069]
Lag Out-of-County Deaths/100		0.180***	0.164***		0.191**	0.113*
		[0.063]	[0.058]		[0.075]	[0.064]
State Unemployment	-0.006	-0.004	-0.030***	-0.012*	-0.011*	-0.030***
	[0.006]	[0.006]	[0.006]	[0.007]	[0.006]	[0.006]
County Unemployment	0.016***	0.016***	0.018***	0.016***	0.016***	0.018***
	[0.005]	[0.005]	[0.004]	[0.005]	[0.005]	[0.004]
Observations	174,986	174,986	174,986	174,986	174,986	174,986
Number of fips	3,126	3,126	3,126	3,126	3,126	3,126
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	YES	NO	NO	YES
Likelihood	-325865	-325835	-325360	-272927	-272907	-272543

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
Notes: Table shows Poisson regression of national active duty recruits on deaths
As well as future 'lead' periods. Fixed effects are included separately by county and month
and for each state-year, as indiciated, as well as a state-specific linear trend.
The first four columns show applicants and the last four show contracts.
Filename:forwardPbasic.txt

Table A9:
1990-2006 Log County Applicants vs Deaths and Unemployment

VARIABLES	(1) Applicants	(2) Applicants	(3) Applicants	(4) Contracts	(5) Contracts	(6) Contracts
In-County Deaths/100	0.100	0.109	0.005	0.334	0.348	0.173
	[0.427]	[0.411]	[0.257]	[0.458]	[0.446]	[0.293]
Lag In-County Deaths/100	0.362	0.385	0.188	0.307	0.331	0.066
	[0.645]	[0.633]	[0.435]	[0.662]	[0.650]	[0.449]
Out-of-County Deaths/100		0.171***	0.019		0.206***	0.042
		[0.057]	[0.031]		[0.066]	[0.035]
Lag Out-of-County Deaths/100		0.182***	0.034		0.158***	-0.002
		[0.059]	[0.038]		[0.054]	[0.037]
County Unemployment		0.011***	0.012***		0.011***	0.012***
		[0.002]	[0.002]		[0.002]	[0.002]
State Unemployment		0.014**	-0.011**		0.015***	-0.009
		[0.005]	[0.005]		[0.005]	[0.006]
Observations	621,126	621,009	621,009	621,126	621,009	621,009
R-squared	0.955	0.955	0.958	0.945	0.946	0.950
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	YES	NO	NO	YES

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1
Notes: Table shows linear regression estimates of log (national active duty recruits +1) on deaths.
Fixed effects are included separately by county and month, and for each state-year, as indiciated,
The first three columns show applicants and the last three show contracts.
Filename:LNLinear90.tex

Table A10:
Log County ALL Applicants vs Deaths and Unemployment

VARIABLES	(1) Basic	(2) State	(3) w/Stateyear	(4) Basic	(5) State	(6) w/Stateyear
Current In-County Deaths/100	-0.360	-0.452	-0.593***	-0.376	-0.453	-0.598**
	[0.328]	[0.327]	[0.192]	[0.361]	[0.350]	[0.235]
Lag In-County Deaths/100	-1.141***	-1.179***	-1.275***	-1.140***	-1.178***	-1.265***
	[0.185]	[0.198]	[0.207]	[0.233]	[0.238]	[0.285]
Current Out-of-County Deaths/100		0.215***	0.156***		0.165**	0.130*
		[0.057]	[0.048]		[0.067]	[0.069]
Lag Out-of-County Deaths/100		0.065	0.009		0.016	-0.036
		[0.062]	[0.049]		[0.084]	[0.068]
County Unemployment		0.018***	0.016***		0.015**	0.013**
		[0.005]	[0.004]		[0.006]	[0.005]
State Unemployment		0.007	-0.043***		-0.000	-0.031***
		[0.007]	[0.007]		[0.007]	[0.011]
Observations	178,809	178,739	178,739	178,809	178,739	178,739
R-squared	0.969	0.970	0.971	0.957	0.957	0.958
County FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Stateyear FE	NO	NO	YES	NO	NO	YES

Robust standard errors in brackets
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: Table shows linear regression estimates of log (national recruits +1) on military deaths.
Fixed effects are included separately by county and month, and for each state-year, as indiciated,
The first three columns show applicants and the last three show contracts.
Filename:allrecLNLinearW.tex

Table A11: Deaths by War, Poisson

VARIABLES	(1) Applicants	(2) Applicants	(3) Contracts	(4) Contracts
In-County Deaths/100	-0.044	-0.047	-0.068	-0.071
	[0.315]	[0.316]	[0.310]	[0.310]
Iraq Lag In-County Deaths/100	-0.839***	-0.848***	-0.778***	-0.790***
	[0.306]	[0.312]	[0.281]	[0.281]
Afghanistan Lag In-County Deaths/100	1.270	1.199	0.734	0.735
	[0.898]	[0.909]	[1.155]	[1.148]
Out-of-County Deaths/100	0.183***	0.179***	0.139**	0.133*
	[0.062]	[0.061]	[0.071]	[0.070]
Iraq Lag Out-of-County Deaths/100		0.170***		0.126**
		[0.059]		[0.063]
Afghanistan Lag Out-of-County Deaths/100		-0.334		-0.145
		[0.240]		[0.232]
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]
Lag Out-of-County Deaths/100	0.162***		0.107*	
	[0.059]		[0.064]	
Observations	178,169	178,169	178,112	178,112
Number of fips	3,127	3,127	3,126	3,126
County FE	YES		YES	
Month FE	YES		YES	
State Trend FE	YES		YES	
Likelihood	-331198	-331195	-277676	-277675
Test	0.0380		0.205	
State		0.0377		0.240
County		0.0487		0.198

Robust standard errors in brackets

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

Notes: Table shows Poisson regression estimates of national active duty recruits on deaths from different wars. Fixed effects are included separately by county and month as indiciated, The first two columns show applicants and the last two show contracts.

Filename:redefPwar.tex