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The veteran wage differential

Francesco Renna and Amanda Weinstein

Department of Economics, University of Akron, Akron, OH, USA

ABSTRACT

There is debate in the literature as to whether military service is rewarded in the economy and the extent to which veterans receive either a wage premium or penalty. In this paper, we take a new approach to this question by conducting a wage decomposition of the veteran wage differential and decomposing the wage distribution of veterans and civilians instead of focusing only on the standard wage gap analysis at the averages. We find the veteran wage differential is driven by observable factors such as education, occupation, and industry, but also by location choice, a factor that has been previously overlooked in the literature. At the average, we find white men experience a veteran penalty whereas black men and women experience a veteran premium consistent with the bridging hypothesis. Additionally, we find that as we move along the wage distribution for all demographic groups, the veteran premium tends to become a veteran penalty, even after accounting for selection into military service. However, once we account for selection, we find that the premium for veteran black men disappears.

KEYWORDS
Wage differentials; decomposition; veterans

JEL CLASSIFICATION
J31; J01

I. Introduction

The well-being of military veterans from their healthcare to their economic opportunities is a constant concern for policymakers. Policymakers have created programs such as the GI Bill, the Transition Assistance Program (TAP), veteran hiring fairs, and tax credits for firms hiring unemployed veterans to address these issues and help veterans succeed in the workforce. However, once veterans enter the civilian job market, there is evidence that their jobs are a poor fit for their skills and abilities. A recent survey found that nearly half of newly separated veterans stayed in their first job 12 months or less after separation from military service (Maury, Stone, and Roseman 2014). Berger and Hirsch (1983) found that veterans' adjustment to the civilian workforce can be a slow process.

Though the process may be slow, veterans do seem to adjust eventually. In the long run, evidence suggests that the disruption associated with the transition from military service though significant is short-lived (Loughran 2014). As a group, veterans actually tend to have higher wages than non-veterans (see Figure 1 to compare the unadjusted wage distribution of veterans to non-veterans). However, this result alone is not conclusive evidence that the military experience has a positive impact on the wage of veterans. When comparing veterans to similar non-veterans, the literature is mixed as to whether their military experience and training is rewarded by the economy at all. Although military service provides its members with experience, training, and education, the set of skills veterans acquire in the military and through various government job-training programs may not translate well into civilian occupations and industries for some individuals.

To better understand the economic well-being of veterans, we conduct a decomposition of the wage differential between veterans and non-veterans to identify the potential premium/penalty associated with military service. We use American Community Survey (ACS) data from 2005 to 2015 which provides a fairly large sample size of veterans from the All-Volunteer Force (AVF). Rather than focusing only on whether military service itself helps or hinders veterans, in this paper we focus more on the specific observable factors such as education, specific skills, and industry and occupation that can explain the wage differential (positive or negative) between veterans and non-veterans. This allows us to provide detailed information to policymakers on the explained

CONTACT Amanda Weinstein aweinstein@uakron.edu Department of Economics, University of Akron, Akron, OH 44325-1908, USA

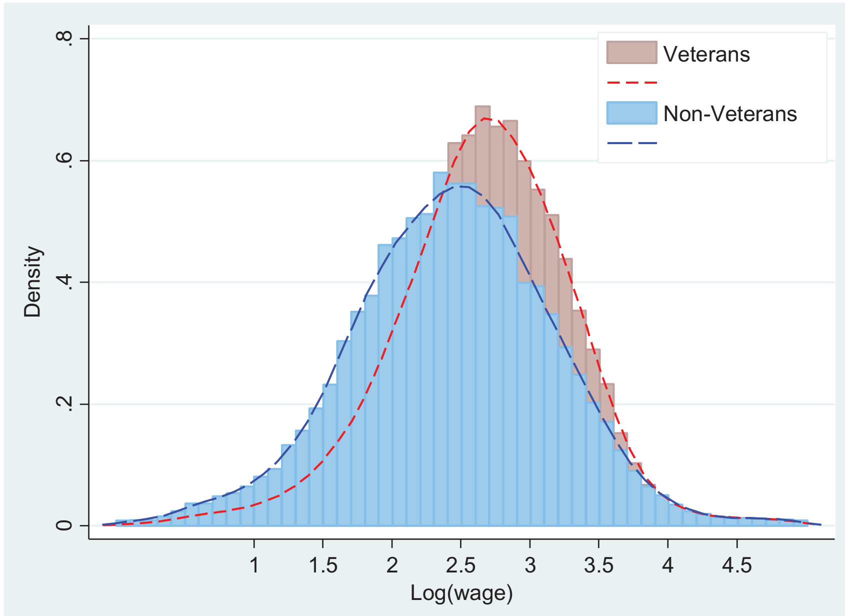

Figure 1. Different wage distributions: veterans vs non-veterans.

factors that policymakers may address to help improve veteran outcomes.

We focus on the heterogeneity of veterans economic outcomes instead of the heterogeneity in veterans' backgrounds (as in previous research). Because of the large sample size the data provide, we are better able to treat the veteran population (and their economic outcomes) as one with significant heterogeneity. Military service may very well improve the economic outcomes for some, but not all, veterans. Thus, we conduct a wage decomposition at various points in the distribution and not just the mean (as in most decompositions). We use recent development in the decomposition literature and use *recentered influence function* (RIF) regression analysis (Firpo et al. 2009) to decompose the wage distribution of civilians and veterans. The RIF can be used to estimate unconditional quintile regressions. This method is superior to the Machado-Mata quintile regression, which is a conditional quantile regression and path-dependent (Fortin, Lemieux, and Firpo 2011). Furthermore, we have a large data set and the Machado-Mata quintile regression becomes cumbersome when the data set has more than few thousand observations (Fortin, Lemieux, and Firpo 2011). Although the ACS data set provides us with a relatively large sample of veterans and detailed information on their employment outcomes, it provides relatively less information on veterans' backgrounds. The data does provide us with an individual's birthplace. We leverage this by using utilizing birthplace information and exposure to military service to account for selection into military service.

Consistent with previous research we find that, on average, white male veterans face a wage penalty while black veterans and women face a wage premium. We find that observable factors such as age, education, and industry make up the largest share of the wage differential. Veteran wage advantages are driven by observable factors such as industry and skills, whereas veteran wage disadvantages are driven by location choice, a factor that has been previously overlooked in the literature. The unobserved portion, which most of the previous literature essentially focuses on when trying to classify the impact of veteran service as either a penalty or premium, accounts for only a small share of the wage differential. Selection effects have a significant impact on the unexplained portion and suggest that on average veterans from all demographic groups may face a wage penalty. Our wage distribution decomposition reveals that the wage differential declines over the distribution with any veteran premium for individuals at the lower end of the distribution turning into a veteran penalty for the top of the distribution, especially for men. This result generally holds even after accounting for selection.

The rest of the paper is organized as follows: the next section reviews the literature on the topic and discusses the bridging hypothesis. In section III, we describe the data used for the analysis. Then, we present the results of the standard Oaxaca decomposition and the *recentered influence functions*. Finally, we examine how selection effects may affect our results and then provide some concluding remarks about the implications of our results.

II. The value of military service

When the US transitioned to an All-Volunteer Force (AVF), it became especially important (to military recruiters and others) to ascertain the value of military service. There are several proposed theories on how military service may affect subsequent civilian earnings; some suggest there is a veteran premium while others imply a veteran wage penalty. Military service may increase the human capital levels of service members through experience and military training (Little and Fredland 1979; Goldberg and Warner 1987; Mangum and Ball 1989; Kleykamp 2013). Little and Fredland (1979) suggest that military service may provide all veterans with general skills that are widely applicable to the private sector such as communication skills, quantitative skills, punctuality, and a high level of work ethic. Thus, veteran status may provide a positive signal to employers that military members are more productive because of these general skills. Military service also provides education benefits to veterans through the GI Bill and other programs. These education benefits increase their educational attainment, which increases their earnings (Martindale and Poston 1979; Angrist 1993).

When comparing the human capital levels of veterans to non-veterans, specifically experience, it seems the experience provided by military service may be a poor substitute for private sector experience (Angrist and Krueger 1994; Teachman 2004). Kleykamp (2009) uses an audit method of resumes to show that the transferability of skills is a key issue when estimating the impact of military service. For example, black veterans with transferable skills were treated more favorably while black veterans with skills that were less transferable (typically combat roles) were treated substantially less favorably. The opportunity cost of military service in terms of foregone private sector experience and education may negatively affect civilian earnings. Angrist (1990) finds that on average military experience is approximately equal to a loss of 2 years of experience in the civilian sector. Military service may also act as a negative signal to employers indicating that veterans may be less productive due to their lack of skills directly applicable to the private sector or other negative associations employers have with veterans (Berger and Hirsch 1985). Angrist and Krueger (1994) have suggested that the treatment of veterans (and whether veteran status is viewed as a positive or negative signal) is related to popular views of particular wars with World War II and Korean War veterans being viewed more favorably than Vietnam War veterans, for example. Other research finds that military service may be associated with a negative impact on civilian earnings initially, but as veterans are more fully absorbed and accepted into the workforce this negative impact will dissipate over time with veterans experiencing a steeper earnings curve (Berger and Hirsch 1983; Mangum and Ball 1989). This also suggests it may be important to decompose the veteran wage differential along the entire distribution.

Browning, Lopreato, and Poston (1973) first postulated that military experience, training, and education benefits are especially important to veterans from socioeconomically disadvantaged backgrounds, called the 'bridging hypothesis'. Previous studies have found that only veterans with less than a high school education realized veteran premiums (Berger and Hirsch 1983; Kleykamp 2013). A number of studies have also found that black veterans receive a veteran premium while white veterans receive no impact at all or even a veteran penalty (Martindale and Poston 1979; Berger and Hirsch 1983; Angrist 1990; Mehay and Hirsch 1996; Angrist 1998; Hirsch and Mehay 2003; Teachman and Tedrow 2004).

The bridging hypothesis may also apply to female veterans who, through military service, gain experience they would not have otherwise in working in a bureaucratic male-dominated environment. However, female veterans may enter the private sector with different skills than male veterans because of the restrictions the military has imposed on women in terms of the military occupations they were allowed to enter. For example before 2013, women were formally banned from participating in combat roles in the military. On average, women veterans earn more than non-veterans. However, various observable characteristics can explain some of this difference. After controlling for these and other factors, some find that women veterans experience a wage penalty (Prokos and Padavic 2000) while others find that women veterans receive a premium (Kleykamp 2013; Hirsch and Mehay 2003). Mehay and Hirsch (1996) find evidence that similar to men, only nonwhite women experience a veteran premium.

There is significant heterogeneity in the economic outcomes of veterans but also in terms of the places where veterans find jobs and choose to locate after the military service. Veterans, as a whole, are a more mobile population than non-veterans. Veterans are more likely than non-veterans to live outside the state of their birth and are more likely than non-veterans to have migrated recently (Bailey 2011). This geographic mobility may provide a mechanism by which veterans can achieve higher social mobility in line with the bridging hypothesis as there is an extensive literature that connects geographic mobility to positive economic outcomes. The location choices of veterans may differ from non-veterans. For example, veterans may choose to locate in places they were stationed and found they liked or may simply want to locate near an established military community, which provides social interactions with fellow veterans as well as better services for veterans such as Veterans Administration (VA) hospitals. Places with large military communities and large military installations may also provide ample opportunity for veterans to find employment in the civilian sector through government contractors connected to the base or through civil servant positions. Conversely, veterans may find they are competing with many other veterans for a limited number of positions. The economic opportunities for veterans may actually be more limited for veterans in an area where veterans are crowded together. This may be especially true for women veterans as previous research shows that women have higher unemployment rates and lower earnings in areas with a large military presence (Booth et al. 2000). Thus, when measuring the impact of military service on veterans, it is important to include both individual characteristics as well as location information.

Evidence supporting the bridging hypothesis along with the conflicting results of many previous studies has encouraged researchers to take a more nuanced approach by viewing the veteran population as a more heterogeneous group. The impact of military service has since been separated not only by race and gender but also by branch of service, period of service, military occupation, etc. (Bryant and Wilhite 1990; Goldberg and Warner 1987). Mehay and Hirsch (1996) and Vick and Fontanella (2017) conduct wage decompositions to separately examine the endowment effect and coefficient effect that comprise the veteran wage differential. Mehay and Hirsch (1996) focus on female veterans whereas Vick and Fontanella focus on recent Iraq/Afghanistan-era post-2001 veterans. Vick and Fontanella conduct a wage decomposition using a matching approach suggested by Nopo (2008). However, they match only on observable characteristics provided in the American Community Survey (ACS). Hirsch and Mehay (2003) find such a matching technique may not provide any benefits as such measurable individual characteristics are not important determinants of veteran status. Hirsch and Mehay (2003) use the Reserve Components Surveys to compare male reservists who are veterans to male reservists without active-duty service (arguably a better counterfactual and better match based on differences in veterans backgrounds that affect veteran status through similar entrance requirements and selection by the military and the individual). Still, Hirsch and Mehay (2003) find the selection effects by the military (screening) and the individual (self-selection) largely cancel each other out.[1] They find that screening by the military eliminates lower ability individuals and

[1]Bryant and Wilhite (1990) also find no evidence of selection bias.

selection by the individual eliminates higher ability individuals. Thus, observable factors may be sufficient controls to compare veterans to non-veterans and determine the impact of military service at least in the analysis at the average.[2]

Although our sample does not provide the background information that Hirsch and Mehay have access to, our large dataset allows us to compare the wage distribution of veterans to the wage distribution of civilians and analyze how the value of having served in the military changes along the wage distribution. We build upon previous literature by decomposing the entire wage distribution to capture the heterogeneity in the skill set of veterans. In line with the bridging hypothesis, we expect a wage premium for minorities and women. Also, we predict that the wage premium should decrease as we move along the distribution, because according to the bridging hypothesis, the value of the experience in the military should decrease as the worker skill set increases. This large data set also allows us to examine the impact of previously unexplored factors such as location choice.

III. Data

In this paper, we use American Community Survey (ACS) data in order to obtain a large representative sample of veterans from across the US (over 100,000 veterans). We use ACS data from 2005 to 2015 focusing our analysis on recent veterans from the AVF. We therefore limit our sample to those veterans not affected by the draft.[3] We use the ACS to compute the log hourly wage for our employed sample.[4] On average, veterans earn an hourly wage of $18 compared to just $15 for non-veterans. A comparison of the average wages of veterans to the average wages of non-veterans ignores how the entire distribution of wages between veterans and non-veterans may vary. Figure 1 provides an initial look at the entire unadjusted wage distribution of our veteran population compared to the non-veteran population. Figure 1 shows that veterans and non-veterans seem to be no different in the right tail, but veterans seem to be doing better than non-veterans in the left tail providing some initial evidence of the bridging hypothesis. Typical wage decompositions (as in Mehay and Hirsch 1996) measure the wage differential only at the average of the distribution and ignore the other points in the distribution. It seems a quantile decomposition may provide additional insight into the impact of military service on the wage differential. A quantile decomposition may also provide additional insight into the bridging hypothesis. The ability to conduct a quantile decomposition is another benefit of the large sample size provided by ACS data.

Figure 1 provides a first look at the unadjusted wage differential between veterans and non-veterans. However, it does not account for a number of observable factors that differ between veterans and non-veterans. One possible explanation for why, on average, veterans out earn non-veterans is that veterans who received a low wage offer may withdraw altogether from the labor force. This process may inflate the average wage for veterans. To check if veterans withdrew from the labor market at a faster rate than non-veterans, we compute the labor force participation rate for the two groups of workers. As shown in Figure 2, we do not find evidence that veterans withdrew from the labor market at a faster rate than non-veterans.[5] Veterans have a number of other characteristics that could be driving these results such as the fact that they are older and more likely to be men (with 82 percent of the veteran population compared to about 50 percent of non-veterans). However, veterans also have a higher share of minorities than the general population, specifically blacks (at 14 percent of the veteran population compared to 11percent of non-veterans). For this reason,

[2]Without accounting for the self-selection process, we find that male veterans face a penalty of 1.3% similar to Hirsch and Mehay (2003) which found a penalty of 2.4% for white male veterans after estimating a treatment effect to control for selection by individuals and the military from the 1986 and 1992 Reserve Component Survey. Similarly, Bryant, Samaranayake, and Wilhite (1993) found a penalty of 2.6% for white veterans using an endogenous switching regression model.

[3]The draft ended in 1955. However, we further limit our sample to veterans born after 1969 based on the availability of the data associated with our selection strategy described in part IV of the results section. We also limit our sample to those aged 18 or older.

[4]We limit our sample to those observations where inflation adjusted hourly wage is at least $1 and no more than $150.

[5]The labor force participation rate of veterans is even more similar to non-veterans when broken out by white men, black men, and women.

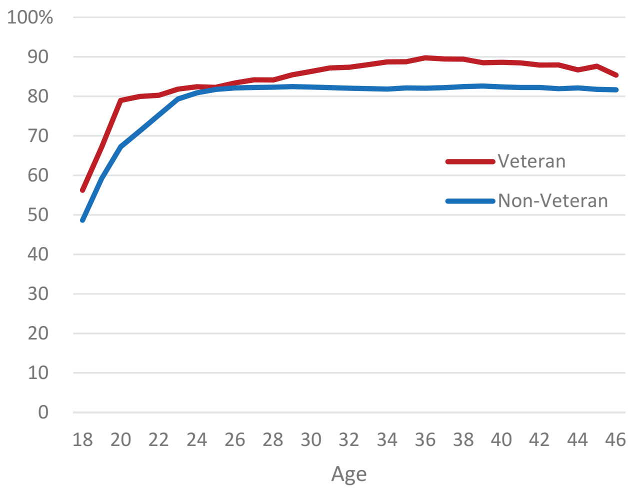

Figure 2. Similar labor force participation rate of veterans and non-veterans by age (Labor force participation rate, %).

previous research (and our research) separately examines the impact of military service on white men, black men, and women. Table 1 provides descriptive statistics broken out by white men, black men, and women. Veterans are 3 to 4 years older than non-veterans depending on the demographic group. Age alone could explain why veterans have higher average earnings.

Figures 3 and 4 show how veterans and non-veterans find jobs in different occupations and industries. Veterans are more likely to find government jobs and social service occupations such as police and fire, possibly as a way to continue their service to the country. Veterans' skills may also be transferred more easily into these types of occupations and industries. Veterans are less likely to find jobs in the service sector and service occupations compared to non-veterans. The industry and occupation breakout shows some differences between white men, black men, and women most notably in managerial and business occupations with veteran women and black men more likely to find jobs in managerial and business occupations and veteran white men less likely to find jobs in these occupations.

We compare not only the individual (and family) characteristics of veterans to non-veterans, but we also account for the location choice of veterans by incorporating information about their county of residence.[6] Specifically, we focus on the county's population, educational attainment as measured by the percentage of the population with a college degree, and the size of the active duty military population. Table 1 shows that veterans tend to live in counties that are less populated (and with worse economic outcomes in terms of earnings and the employment to population ratio). Instead, veterans are choosing to live in areas with a larger military population.

In the selection equation, we choose to convert each occupation (at the 3 digit code level) into a set of specific skills and analyze the wage differential across skills. By linking the ACS occupation codes to O*Net data, we derive the skill component associated with the occupation held by the respondent.[7] We use the broad skill and ability categories provided by O*Net and take an average of the specific skills and ability measures that each category comprises (this method is similar to those used in Autor, Levy, and Murnane 2003; Deming 2015; to find average measures for broad categories such as routine tasks, for example). The average skills and abilities for veterans and nonveterans are provided in Table 1. Higher levels of skills and abilities (like education as measured by the number of years of schooling) for veterans help explain why veterans are out-earning non-veterans. Veterans may also be positively selecting into military service.

IV. Results

The OLS approach

Before running a wage decomposition, we first run a standard OLS regression regressing log wages on veteran status (a dummy variable equal to 1 if the person is a veteran and 0 otherwise) and include various other standard factors such as education and age similar to most of the previous research examining whether veterans experience a premium or penalty (Table 2). We see the expected sign on all of our human capital variables and other controls. Our OLS regression suggests white men typically receive a veteran penalty of over 1 percent and black men typically experience a veteran premium of over 2 percent, in line with

[6]County population, employment, and per capita income data was obtained from the US BEA; county education data is from the USDA ERS.
[7]See the Appendix 1 for a more detailed explanation of the O*Net data and how it was matched to the ACS data.

Table 1. Descriptive statistics for veterans and non-veterans.

	White Men			Black Men			Women		
	Veteran	Civilian	Difference	Veteran	Civilian	Difference	Veteran	Civilian	Difference
No. of Obs	73,918	1,213,383		12,090	154,573		18,414	1,697,411	
Hourly Wage	18.265	16.615	1.650	15.571	12.719	2.852	15.582	13.891	1.691
Income	52,961	46,364	6,596	42,247	31,225	11,022	39,519	32,955	6,564
Education	14.684	14.606	0.079	14.415	14.114	0.300	15.217	15.048	0.168
AGE	33.770	30.359	3.411	34.369	30.126	4.243	32.937	30.230	2.707
Married	0.603	0.435	0.169	0.484	0.284	0.200	0.449	0.396	0.053
Children	1.044	0.745	0.299	1.028	0.644	0.384	1.072	0.845	0.227
Population	1,157,600	1,508,823	−351,223	1,308,185	1,531,179	−222,994	1,175,315	1,645,724	−470,409
% College	0.287	0.300	−0.014	0.294	0.304	−0.011	0.289	0.302	−0.013
Military Population	8,859	6,561	2,299	10,075	5,859	4,216	11,527	7,177	4,351
O*NET									
Technical	1.458	1.285	0.173	1.321	1.136	0.186	0.945	0.804	0.141
Physical	1.343	1.261	0.081	1.371	1.406	−0.034	0.986	0.970	0.016
Psychomotor	1.878	1.719	0.160	1.842	1.786	0.056	1.375	1.267	0.109
Sensory Abilities	2.126	1.978	0.147	2.058	1.935	0.122	1.825	1.741	0.084
Systems Skills	2.772	2.639	0.134	2.584	2.356	0.227	2.732	2.608	0.124
Complex Problem	3.087	2.980	0.107	2.922	2.737	0.185	3.004	2.893	0.111
Cognitive Abilities	2.944	2.834	0.110	2.826	2.668	0.158	2.914	2.820	0.095
Resource Management	2.173	2.128	0.046	2.025	1.901	0.124	2.116	2.031	0.085
Basic Reasoning	2.738	2.626	0.111	2.580	2.388	0.192	2.777	2.660	0.117
Basic Communication	3.403	3.300	0.103	3.281	3.094	0.187	3.566	3.460	0.107
Social	2.979	2.904	0.075	2.869	2.754	0.115	3.071	3.015	0.056

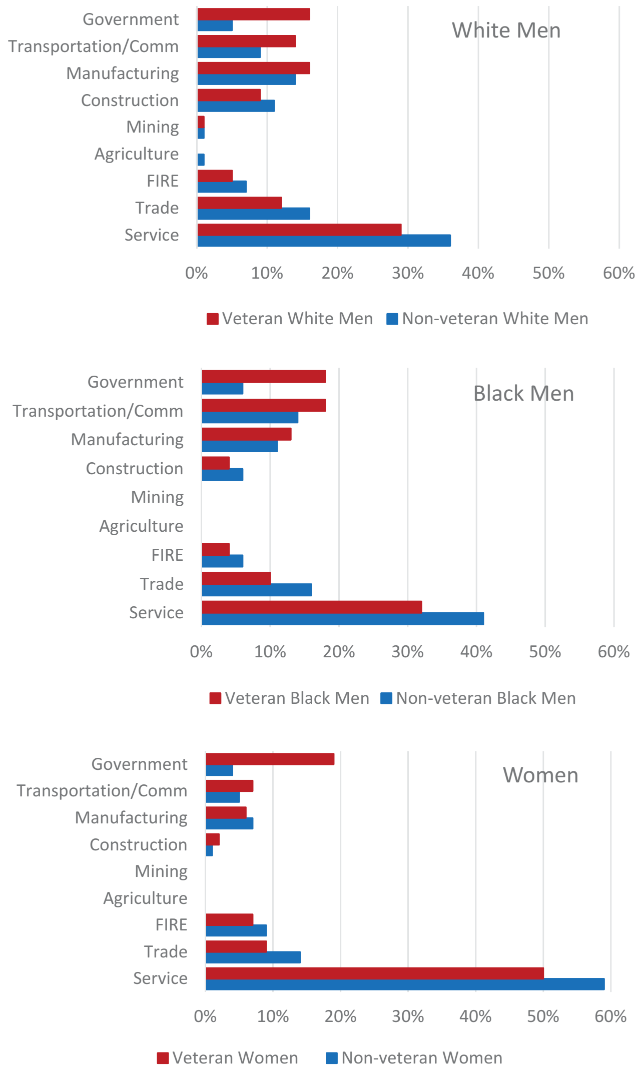

Figure 3. Industry composition.

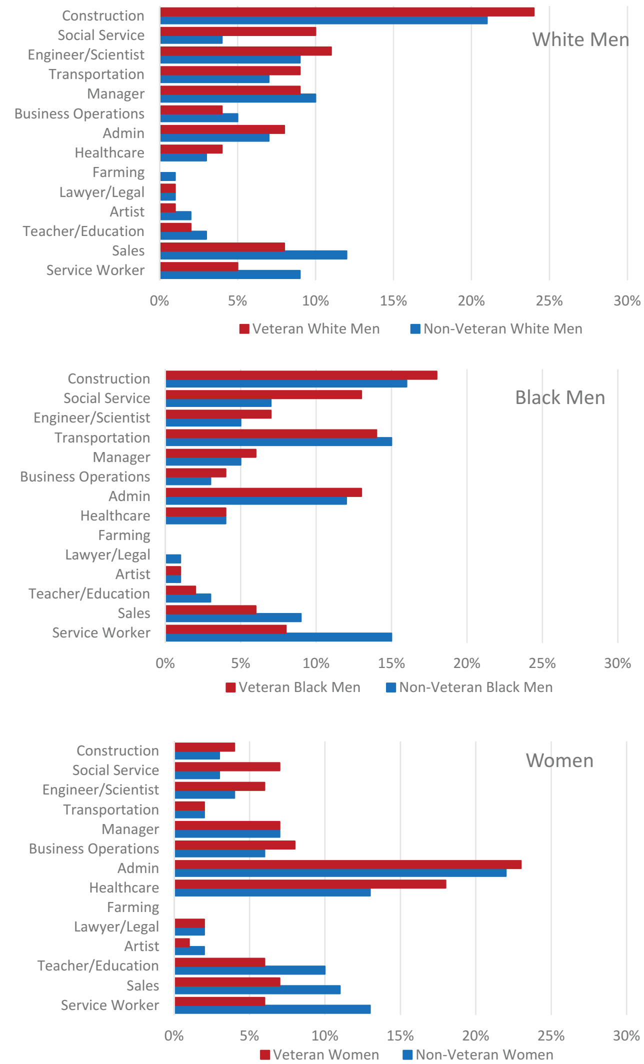

Figure 4. Occupation composition.

previous literature (Martindale and Poston 1979; Berger and Hirsch 1983; Angrist 1990; Mehay and Hirsch 1996; Angrist 1998; Hirsch and Mehay 2003; Teachman and Tedrow 2004). We find that women also receive a veteran premium of 2.5 percent (in line with Kleykamp 2013). This type of regression provides little information as to what factors are improving the economic outcomes of veterans and which are hindering them. It also doesn't provide information on how this penalty or premium may vary along the entire distribution of veterans.

The standard Oaxaca decomposition

Because previous research suggests that the impact of military service may differ by race and gender, we run separate wage differential decompositions for white men, black men, and women. We do not separate women by race though we do control for it, as the sample of women veterans is relatively small. In the Oaxaca decomposition, the unexplained component is the counterpart to the coefficient on the dummy variable for veteran status in the OLS. The results of our decompositions in Table 3 show the same level of penalty/premium found in Table 2. Note that Black male veterans and women make respectively 25 percent and 16 percent more than their non-veteran counterpart. However, between 85 and 90 percent of that gap can be explained by differences in the observable characteristics. The remaining part is the wage premium associated with the veteran status. White male veterans earn approximately 17 percent more than their

Table 2. OLS results.

	Ln(Wages)		
VARIABLES	White Men	Black Men	Women
Veteran	−0.0129***	0.0237***	0.0251***
	(0.00213)	(0.00571)	(0.00415)
Age	0.0967***	0.0912***	0.107***
	(0.000623)	(0.00180)	(0.000552)
Age^2	−0.00104***	−0.00105***	−0.00128***
	(9.93e-06)	(2.88e-05)	(8.78e-06)
Education	0.0588***	0.0469***	0.0689***
	(0.000215)	(0.000715)	(0.000194)
Married	0.156***	0.120***	0.101***
	(0.00129)	(0.00399)	(0.00102)
Children	0.0221***	0.00165	−0.0245***
	(0.000547)	(0.00158)	(0.000454)
Ln(Population)	0.0337***	0.0354***	0.0413***
	(0.000701)	(0.00186)	(0.000579)
%College	0.528***	0.343***	0.503***
	(0.00588)	(0.0165)	(0.00505)
Ln(Military)	−0.0148***	−0.0184***	−0.0154***
	(0.000609)	(0.00175)	(0.000511)
Black	-	-	−0.0722***
	-	-	(0.00131)
Industry FE	YES	YES	YES
Occupation FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	1,321,101	170,226	1,756,879
R-squared	0.425	0.293	0.373

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3. Wage decomposition.

VARIABLES	White Men	Black Men	Women
Veteran	2.705***	2.549***	2.536***
	(0.00232)	(0.00574)	(0.00476)
Civilian	2.532***	2.295***	2.378***
	(0.000665)	(0.00178)	(0.000543)
Difference	0.174***	0.254***	0.159***
	(0.00242)	(0.00600)	(0.00479)
Explained	0.187***	0.230***	0.134***
	(0.00148)	(0.00333)	(0.00267)
Unexplained	−0.0129***	0.0237***	0.0251***
	(0.00207)	(0.00552)	(0.00411)
Observations	1,321,101	170,226	1,756,879

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

non-veteran counterpart; however the wage gap is smaller than we would expect based on the observables yielding a wage penalty (our main results are similar to Vick and Fontanella (2017).[8] Table 3 suggests that whether there is a wage premium or a wage penalty (represented by unexplained component of the standard decomposition), this effect is most likely just a small fraction of the entire wage gap. However, the conclusion that at the mean the unexplained difference between veterans and non-veterans may be quite small, does not exclude the possibility that the effect may be more sizable in the tails of the distribution.

We provide a further analysis of the explained and unexplained portion of the wage differential in Table 4. We use the pooled regression in Table 2 to determine the reference coefficients needed to derive the explained and unexplained components. As a reminder, a positive sign on the coefficient in the 'Explained' columns in Table 4 indicates that either the endowment for veterans is larger than for the non-veterans and the corresponding coefficient in the pooled regression is positive or that endowment for veterans is smaller than for the non-veterans and the corresponding coefficient in the pooled regression is negative. A negative coefficient in the 'Explained' columns in Table 4 indicates that either the endowment for veterans is larger than for the non-veterans and the corresponding coefficient in the pooled regression is negative or that endowment for veterans is smaller than for the non-veterans and the corresponding coefficient in the pooled regression is positive.

Veterans earn higher wages for having higher levels of traits typically rewarded in the labor force (for example, higher educational attainment that could be a result of policies such as the G.I. Bill). The insignificant impact of education on the unexplained part of the decomposition suggests that the return to schooling is the same across veterans and civilians (see Appendix 2). Although veterans have more children than civilians independently from their gender, their fertility choices increase the explained part of the wage gap for white men, but it decreases the explained part of the wage gap for women because having children is positively correlated with wages for men but negatively correlated with wages for women. Marriage consistently increases the explained part of the decomposition and decreases the unexplained part of the decomposition, a result of the fact that veterans are more likely to be married and that the correlation between marital status and wages is lower for civilians. In Appendix 3, we provide the detailed breakout for industry and occupation. Industry explains some portion of the wage differential with many industries and occupations that veterans choose comparatively more than nonveterans increasing the

[8]Vick and Fontanella focus only on post-2001 veterans and do not examine location, specific skills, and industry.

Table 4. Detailed decomposition by individual characteristics.

	White Men		Black Men		Women	
VARIABLES	Explained	Unexplained	Explained	Unexplained	Explained	Unexplained
Education	0.00463***	0.0202	0.0141***	0.00829	0.0116***	0.0368
	(0.000462)	(0.0182)	(0.000878)	(0.0527)	(0.00110)	(0.0374)
Age	0.330***	−0.309***	0.387***	−0.434	0.291***	−1.132***
	(0.00317)	(0.119)	(0.00966)	(0.320)	(0.00524)	(0.225)
Age^2	−0.214***	0.161***	−0.273***	0.264	−0.204***	0.559***
	(0.00268)	(0.0618)	(0.00885)	(0.168)	(0.00416)	(0.116)
Married	0.0264***	−0.0169***	0.0240***	−0.0109*	0.00536***	−0.0168***
	(0.000355)	(0.00291)	(0.000936)	(0.00584)	(0.000369)	(0.00385)
Children	0.00661***	0.00325	0.000634	0.00930*	−0.00557***	0.0113***
	(0.000191)	(0.00205)	(0.000587)	(0.00485)	(0.000231)	(0.00424)
Ln(Population)	−0.00779***	0.0721**	−0.00715***	−0.146*	−0.0117***	−0.0390
	(0.000217)	(0.0356)	(0.000524)	(0.0812)	(0.000380)	(0.0636)
%College	−0.00716***	−0.0273***	−0.00366***	0.0206	−0.00658***	0.0259*
	(0.000186)	(0.00738)	(0.000337)	(0.0187)	(0.000323)	(0.0146)
Ln(Military)	−0.00113***	0.0357**	−0.00448***	0.0212	−0.00433***	0.0214
	(9.48e-05)	(0.0158)	(0.000486)	(0.0406)	(0.000227)	(0.0281)
Black					−0.00765***	1.17e-06
					(0.000263)	(0.00230)
Observations	1,321,101	1,321,101	170,226	170,226	1,756,879	1,756,879
OCC FE	YES	YES	YES	YES	YES	YES
IND FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

gap. The finance, insurance, and real estate (FIRE) industries are one exception with veterans less likely to be employed in FIRE industries which reduces the explained portion of the differential. The impact of occupation tends to vary comparatively more across demographic lines.

In Table 2, we see that wages are higher in more populated areas and places with higher levels of educational attainment (which corresponds with previous literature in urban economics). Since veterans choose to live in less populated and less educated areas and areas with a higher military population, their location choice lowers the explained component of the wage gap. Women and black men seem more negatively affected by the decision to locate in military towns (in line with Booth et al. 2000). However, only white male veterans experience an increase in the unexplained part of the wage gap for locating in military town, suggesting that the wage penalty associated with locating in military towns is higher for civilians than for veterans.[9] This fact would naturally lead a wage premium in favor of veterans.

Quantile decomposition

Limiting the analysis of the wage decomposition to the average masks the heterogeneity in the distributions of wages of veterans and non-veterans. A convenient way to compare two distributions is compute the decomposition at different deciles. We use a RIF regression analysis (Firpo et al 2009) because this method is considered superior to the conditional quintile regression when it comes to the decomposition (Fortin, Lemieux, and Firpo 2011). Figure 5(a-c) show the results of RIF analysis. The total wage gap line represents the unadjusted wage gap over the wage distribution. When it is positive, veterans are earning more than civilians. The explained wage gap line represents the portion of the total wage gap that is explained by the observables. When the explained wage gap line is below the total wage gap line, veterans experience a wage premium equal to the distance of the two lines. Conversely, when the explained wage gap is above the total wage gap line, veterans are facing a penalty in the labor market. An examination of Figure 5(a) reveals a more intricate relationship between veteran wages and labor market outcomes for white men than initially derived in Table 3. While Table 3 indicates that on average veterans are earning higher wages than non-veterans (17.4 percent), Figure 5(a) shows that the unadjusted wage gap is declining over the entire distribution and it becomes almost equal to zero in the last decile. Moreover, while Table 3 suggests that, on

[9]Comparing the coefficients on the military population in Appendix 2.

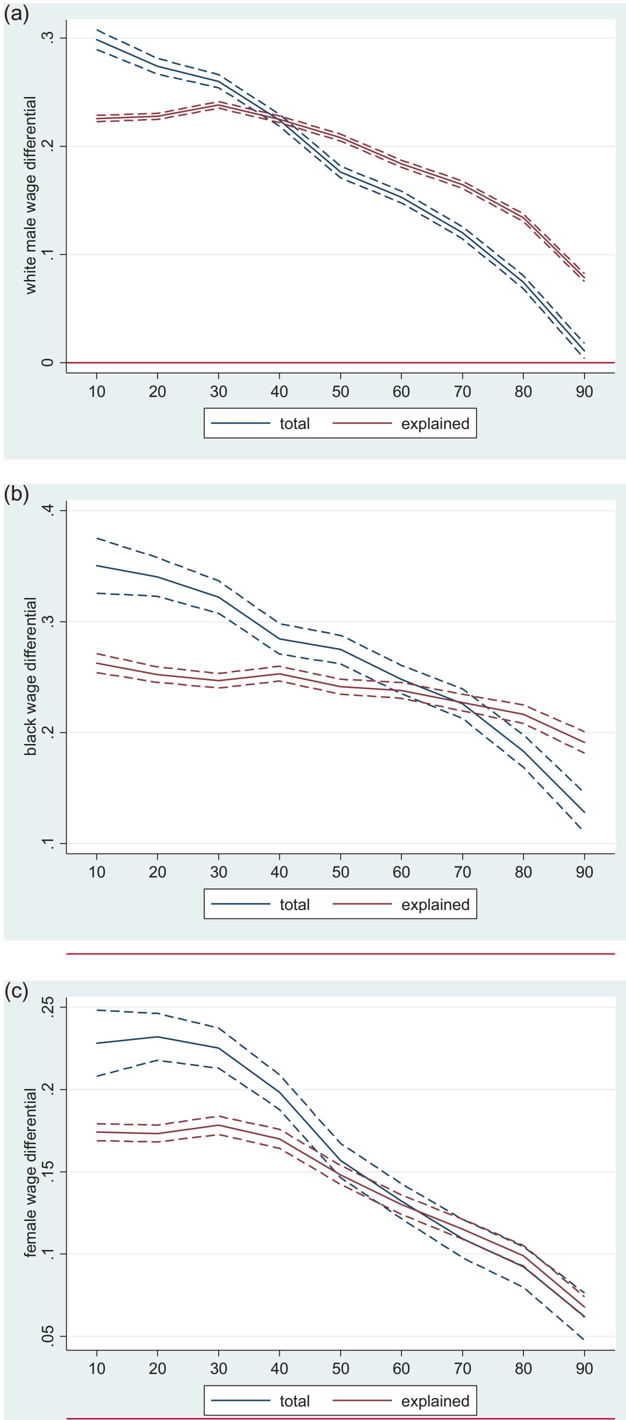

Figure 5. **(a)** Wage differential over the white male wage distribution. **(b)** Wage differential over the black male wage distribution. **(c)** Wage differential over the female wage distribution.

average, white male veterans face a penalty equal to 1.3 percent of the non-veteran wages, Figure 5(a) indicates that white male veterans in the first three deciles of the distribution actually face a premium which turns into a penalty for veterans after the 4th decile. For example, while veterans at the first decile are earning a premium of about 7 percent, veterans at the 8th decile are facing a penalty of about 6 percent. A more dramatic story can be said about black veterans: although on average they earn 25.4 percent more than their civilian counterpart (Table 3) Figure 5(b) reveals that black veterans in the top 25 percent of the distribution are actually earning less than black civilians. After accounting for observable difference in endowments, the wage premium for black veterans was equal to about 2.3 percent while in Figure 5(b) we observe a premium for only black veterans in the first half of the distribution and a penalty for black veterans in the second half of the distribution. Similarly, in our comparison between veteran and civilian women we observe an unadjusted wage gap declining over the wage distribution (Figure 5(c)). In Table 3, we reported that veteran women face a wage premium of about 2.5 percent. In Figure 5(c) we find that this premium is mostly driven by veteran women in the first half of the distribution (e.g. women at the 1st decile enjoy a premium of 5 percent). For women in second half of the distribution the unadjusted wage gap is completely explained by the difference in endowment of workers.

Next, we break down the explained component of the wage gap into its components. For white men (Table 5), we find that differences in age explain most of expected wage gap for white men (veterans are older that non-veterans).[10] In fact, age alone explains 2/3 of the endowment effect for individuals in the 1st decile and 84 percent of the endowment effect of, veterans in the 9th decile. Differences in educational attainment have a statistically significant role in explaining the wage gap, but the effect is quite negligible. Interestingly, the overall sorting of veterans across industry and occupation would predict a positive wage gap except for the occupation choices of individuals at the very top of the distribution. Marital status seems to be playing an important role in explaining why we would expect white male veterans to have higher

[10]For ease of interpretation, we combine the linear and square term effect of age in just one factor. We do the same for the set of variables representing the industries and the skill endowment.

Table 5. Detailed decomposition for white men – RIF regressions.

	Decile								
Variable	10	20	30	40	50	60	70	80	90
Age	0.151***	0.139***	0.138***	0.126***	0.113***	0.0980***	0.0878***	0.0784***	0.0663***
	(0.0011)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0008)	(0.0009)
Education	0.00199***	0.00295***	0.00374***	0.00410***	0.00435***	0.00446***	0.00476***	0.00499***	0.00499***
	(0.0002)	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Married	0.0181***	0.0231***	0.0289***	0.0308***	0.0317***	0.0296***	0.0280***	0.0247***	0.0193***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Children	−0.00240***	−0.00210***	−0.00116***	0.000724***	0.00361***	0.00677***	0.0107***	0.0149***	0.0192***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0005)
Ln(Population)	−0.00304***	−0.000858**	−0.00174***	−0.00372***	−0.00625***	−0.00858***	−0.0115***	−0.0140***	−0.0160***
	(0.0004)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
% College	−0.00294***	−0.00371***	−0.00429***	−0.00501***	−0.00596***	−0.00695***	−0.00860***	−0.0108***	−0.0135***
	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Ln(Military)	−0.000248*	−0.000212**	−0.000520***	−0.000841***	−0.00106***	−0.00124***	−0.00150***	−0.00164***	−0.00201***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Ind	0.0309***	0.0376***	0.0457***	0.0489***	0.0499***	0.0477***	0.0435***	0.0307***	0.00183*
	(0.0008)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Occ	0.0311***	0.0302***	0.0277***	0.0222***	0.0168***	0.0124***	0.00962***	0.00517***	−0.00307***
	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
year	0.00148***	0.00134***	0.00167***	0.00176***	0.00170***	0.00164***	0.00166***	0.00167***	0.00170***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Total	0.226***	0.228***	0.238***	0.225***	0.208***	0.184***	0.165***	0.134***	0.0787***

Standard Errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

earnings than civilians; the number of children instead has a very small and negative impact on the explained component of the wage gap for individuals at the bottom of the distribution and a large and positive impact on the explained component of the wage gap for individuals at the top of the distribution. Location choices always reduces the explained component of the wage gap, but the negative effect becomes larger as we move along the distribution. Overall, we conclude that veteran status mostly benefits people in the lower part of the distribution. This advantage decreases as we move along the distribution and eventually it becomes a penalty for people in the upper portion of the distribution. The penalty is mostly driven by location choice. These results seem consistent with the bridging hypothesis, but they also raise the question of the potential discrimination that veterans at the top of the distribution may be facing.

Turning to black men (Table 6), we find that differences in age are the largest contributor to the explained wage gap between veterans and civilians similarly to white males. However, different from white males, Table 6 indicates that the difference in educational endowments are a significant contributor to the explained wage gap of black male veteran, suggesting that joining the military may open the door for black men with higher abilities to get more education through programs such as the GI Bill. On average black veterans earn 1–2 percent more that their non-veteran counterpart because of their higher education level. This effect is increasing over the wage distribution. The effect of marital status, while positive and fairly constant at 2 percent across the distribution while fertility decision do not affect the explained wage gap. All location choice variables have a negative effect on the explained portion of the wage gap with a small but increasing negative impact as we move along the distribution. The effect of the industry and occupation of employment is positive and substantial indicating that we would expect on average veterans to earn about 8 percent more than civilians because they sort themselves in the right industry/occupation..

For women (Table 7), we find again that differences in age account for more than half of the explained components of the wage gap. The impact of schooling is not as large as the one for black males but definitively larger than the impact of education for white males. The contribution of the family choices to the explained wage gap is small but biased in favor of veteran women in the top of the distribution. Conversely, the location variables indicate that the decision of where to live reduced the explained wage gap of women at the top of the

Table 6. Detailed decomposition for black men – RIF regressions.

	Decile								
Variable	10	20	30	40	50	60	70	80	90
Age	0.1589***	0.1414***	0.1295***	0.1274***	0.1144***	0.1064***	0.0975***	0.0880***	0.0754***
	(0.0031)	(0.0023)	(0.0020)	(0.0019)	(0.0018)	(0.0017)	(0.0018)	(0.0019)	(0.0022)
Education	0.0080***	0.0091***	0.0105***	0.0124***	0.0131***	0.0147***	0.0161***	0.0185***	0.0219***
	(0.0007)	(0.0006)	(0.0007)	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0012)	(0.0014)
Married	0.0191***	0.0226***	0.0240***	0.0262***	0.0263***	0.0279***	0.0265***	0.0253***	0.0221***
	(0.0015)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0012)	(0.0013)	(0.0017)
Children	0.0003	0.0000	0.0005	0.0001	−0.0006	0.0001	−0.0002	0	0.0017
	(0.0012)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0009)	(0.0012)
Ln(Population)	−0.0051***	−0.0058***	−0.0058***	−0.0067***	−0.0067***	−0.0075***	−0.0080***	−0.0088***	−0.0082***
	(0.0009)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0008)
% College	−0.0027***	−0.0032***	−0.0034***	−0.0034***	−0.0032***	−0.0037***	−0.0040***	−0.0046***	−0.0052***
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Ln(Military)	−0.0014	−0.0030***	−0.0037***	−0.0046***	−0.0043***	−0.0048***	−0.0054***	−0.0062***	−0.0051***
	(0.0010)	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0008)
Ind	0.0320***	0.0385***	0.0455***	0.0515***	0.0552***	0.0574***	0.0570***	0.0555***	0.0442***
	(0.0021)	(0.0016)	(0.0015)	(0.0016)	(0.0017)	(0.0018)	(0.0019)	(0.0021)	(0.0026)
Occ	0.0477***	0.0471***	0.0438***	0.0451***	0.0425***	0.0428***	0.0424***	0.0445***	0.0406***
	(0.0019)	(0.0016)	(0.0015)	(0.0016)	(0.0017)	(0.0019)	(0.0021)	(0.0024)	(0.0028)
year	0.0057***	0.0054***	0.0059***	0.0050***	0.0047***	0.0047***	0.0050***	0.0044***	0.0036***
	(0.0008)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Total	0.2626***	0.2522***	0.2468***	0.2531***	0.2414***	0.2380***	0.2270***	0.2165***	0.1912***

Standard Errors in parenthesis
*** p < 0.01, ** p < 0.05, * p < 0.1

Table 7. Detailed decomposition for women – RIF regressions.

	Decile								
Variable	10	20	30	40	50	60	70	80	90
Black	−0.0102***	−0.0068***	−0.0061***	−0.0062***	−0.0066***	−0.0069***	−0.0075***	−0.0081***	−0.0081***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Age	0.1264***	0.1113***	0.1065***	0.0993***	0.0866***	0.0767***	0.0667***	0.0577***	0.0455***
	(0.0018)	(0.0015)	(0.0014)	(0.0014)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Education	0.0055***	0.0079***	0.0101***	0.0117***	0.0124***	0.0133***	0.0141***	0.0147***	0.0145***
	(0.0005)	(0.0008)	(0.0010)	(0.0011)	(0.0012)	(0.0013)	(0.0014)	(0.0014)	(0.0014)
Married	0.0026***	0.0036***	0.0045***	0.0054***	0.0058***	0.0061***	0.0063***	0.0066***	0.0066***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Children	−0.0089***	−0.0095***	−0.0102***	−0.0101***	−0.0084***	−0.0066***	−0.0040***	−0.0008***	0.0036***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Ln(Population)	−0.0066***	−0.0057***	−0.0066***	−0.0090***	−0.0113***	−0.0136***	−0.0158***	−0.0175***	−0.0185***
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0006)
% College	−0.0028***	−0.0042***	−0.0051***	−0.0058***	−0.0064***	−0.0071***	−0.0079***	−0.0092***	−0.0109***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Ln(Military)	−0.0005	−0.0011***	−0.0020***	−0.0030***	−0.0042***	−0.0055***	−0.0068***	−0.0074***	−0.0072***
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Ind	0.0202***	0.0259***	0.0346***	0.0404***	0.0414***	0.0402***	0.0385***	0.0322***	0.0174***
	(0.0008)	(0.0007)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0010)
Occ	0.0467***	0.0503***	0.0508***	0.0453***	0.0368***	0.0315***	0.0294***	0.0289***	0.0233***
	(0.0011)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0016)	(0.0017)	(0.0017)
Year	0.0017***	0.0016***	0.0018***	0.0020***	0.0020***	0.0018***	0.0021***	0.0020***	0.0019***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Total	0.1741***	0.1733***	0.1782***	0.1700***	0.1481***	0.1300***	0.1151***	0.0990***	0.0679***

Standard Errors in parenthesis
*** p < 0.01, ** p < 0.05, * p < 0.1

distribution more than for women at the bottom of the distribution. Interestingly, we find that the impact on sorting across industry, while positive, has an inverse U shape. Finally, the positive impact of sorting across occupation on the explained wage gap is declining along the distribution of wages for women.

Selection process

Finally, within the context of our standard Oaxaca wage decomposition, we examine the role selection may play on the effect that military service in the AVF has on the wages of veterans. First, we estimate the probability that an individual will serve in the military. From this probit analysis we compute the Inverse Mill's Ratio (IMR), for both veterans and civilians and we correct the estimation of the wage equations for both groups after including this new variable.[11] We prefer to include only variables that predate the decision of joining the military. We posit that an individual's exposure to military service will, all else equal, increase the likelihood of volunteering for military service. We use the number of active duty military members as a share of total employment in the birth year and birth state of an individual to measure exposure to military service. Moreover, we use the O*Net skills as a proxy for the unobserved individual skill set.[12] Table 8 shows the results of the selection equation. As expected, we find evidence of a strong impact between the concentration of veterans in an individual's birth state and the choice of serving in the military later in life. Among the skill sets, we find that technical, physical, cognitive abilities, and basic communication increase the odds of joining the military. Social skills, basic reasoning, resource management, and abilities to solve complex problem decrease the odds of joining the military.

The results in Tables 9–11 suggest that selection in the military increases the average wage for black male veterans and female veterans while it decreases the wage for white male veterans. This finding leads to larger premiums/penalties than the ones found in Table 3. In fact, white male veterans face on average a penalty of about 26 percent while black male veterans enjoy a premium of 33 percent and women a premium of 26 percent. Hence, one can think of the results in Table 3 as the lower bound of the true impact of veteran status on later in life earnings.

There is concern that selection may vary across the distribution as well, particularly at the low and high end of the distribution. Hence, we run the decomposition corrected for selectivity for individuals in the bottom and top 20 percent of the sample (column 2 and 3 of Tables 9–11). These results should be interpreted as the decompositions conditional on being in a specific quintile of the distribution. Our results confirm the brid-

Table 8. Selection equations.

VARIABLES	White Men	Black Men	Women
Military Employment	5.061***	9.578***	1.551***
(at birth)	(0.313)	(0.853)	(0.478)
Technical	0.0926***	0.143***	0.145***
	(0.00496)	(0.0142)	(0.00991)
Psychomotor	−0.00797	−0.0765***	0.0175
	(0.00722)	(0.0197)	(0.0109)
Sensory Abilities	0.169***	0.100***	0.141***
	(0.0102)	(0.0267)	(0.0181)
Physical	0.0740***	0.105***	0.0490***
	(0.00598)	(0.0156)	(0.00969)
Systems Skills	0.0136	−0.0383	0.0135
	(0.00978)	(0.0262)	(0.0170)
Complex Problem	−0.149***	−0.128***	−0.0175
	(0.0109)	(0.0283)	(0.0183)
Cognitive Abilities	0.189***	0.292***	0.107***
	(0.0231)	(0.0621)	(0.0353)
Resource Management	−0.120***	−0.0703***	0.000536
	(0.00539)	(0.0146)	(0.00819)
Basic Reasoning	−0.111***	−0.109***	−0.115***
	(0.0130)	(0.0372)	(0.0193)
Basic Communication	0.191***	0.458***	0.194***
	(0.0130)	(0.0365)	(0.0183)
Social	0.0321***	−0.199***	−0.209***
	(0.0110)	(0.0297)	(0.0164)
Constant	−3.678***	−3.862***	−3.473***
	(0.0487)	(0.117)	(0.0631)
Observations	1,095,458	138,948	1,395,128
COHORT FE	YES	YES	YES
BPL FE	YES	YES	YES

Standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

Table 9. Selection decompositions for white men.

VARIABLES	Full Sample	1st Quintile	5th Quintile
Veteran	2.551***	1.696***	3.335***
	(0.0296)	(0.0600)	(0.0310)
Civilian	2.620***	1.483***	3.619***
	(0.00221)	(0.00275)	(0.00286)
difference	−0.0689**	0.213***	−0.284***
	(0.0296)	(0.0601)	(0.0312)
explained	0.189***	0.0516***	−0.0415***
	(0.00166)	(0.00146)	(0.00125)
unexplained	−0.258***	0.161***	−0.243***
	(0.0299)	(0.0599)	(0.0311)
Observations	1,095,458	209,159	226,409

Table 10. Selection decompositions for black men.

VARIABLES	Full Sample	1st Quintile	5th Quintile
Veteran	2.813***	1.320***	3.185***
	(0.0608)	(0.142)	(0.0534)
Civilian	2.229***	1.293***	3.286***
	(0.00567)	(0.00627)	(0.00779)
difference	0.584***	0.0265	−0.101*
	(0.0611)	(0.142)	(0.0540)
explained	0.252***	0.0320***	−0.0137***
	(0.00368)	(0.00363)	(0.00241)
unexplained	0.332***	−0.00554	−0.0874
	(0.0608)	(0.142)	(0.0537)
Observations	138,948	28,946	26,926

[11]This is equivalent to conducting a decomposition on a switching regression model.
[12]While we recognize that the O*Net skills reflect the skills used on the workplace, we assume that in equilibrium people will sort themselves among occupations which require the skills sets for which they may have a competitive advantage. We cannot include these variables in the log wage equations because they would be collinear with the occupation dummies.

Table 11. Selection decompositions for women.

VARIABLES	Women	1st Quintile	5th Quintile
group_1	2.778***	1.674***	3.201***
	(0.0853)	(0.166)	(0.0768)
group_2	2.377***	1.350***	3.356***
	(0.00148)	(0.00193)	(0.00165)
difference	0.402***	0.324*	−0.155**
	(0.0853)	(0.166)	(0.0768)
explained	0.140***	0.0357***	−0.0226***
	(0.00292)	(0.00157)	(0.00160)
unexplained	0.262***	0.288*	−0.133*
	(0.0851)	(0.166)	(0.0767)
Observations	1,395,128	275,723	273,742

Robust standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

ging hypothesis for white men and women. Selection seems to explain the entire difference in the wage gap for black individuals while black veterans in the highest quintile seem to receive a substantial penalty (9 percent) for their time served in the military, which is very close to reaching statistical significance. This imprecision in the estimation of the component may be driven by the small number of black veterans in the top quintile.

V. Conclusion

Evidence suggests that veterans, on average, do relatively well in the private sector after they adjust to the disruption of separating from military service. In this study, we show that these benefits are not experienced by everybody. Hence, if policymakers are looking to further improve the economic outcomes of veterans, our results provide insight into which group of veterans needs to be targeted.

Former Federal Reserve Chairman, Ben Bernanke, believes that helping veterans do better in the private sector is important for a number of reasons including helping to offset the tremendous cost of maintaining a 1.4 million-person military (Beauchamp 2015). In 2014, the US Department of Defense budget had grown 31percent since the year 2000 to $502 billion (adjusted for inflation), about 3.5 percent of GDP. The two biggest contributors to the increasing costs were operations and maintenance costs and higher costs for military personnel (The World Bank, 2016; Congressional Budget Office, 2014). The military remains the largest single employer of young people in the US. Whether military service is rewarded in the private sector is important to potential enlistees and military recruiters, active duty military members, and private sector employers.

We find that there is significant heterogeneity in veterans' success in the private sector, which is typically missed when analyzing the labor outcomes at the mean. Our results suggest that military experience may be helpful for individuals in the lower end of the distribution to succeed in the labor market. Men in the top end of the distribution tend to face considerable penalties for their time spent in the military. For example, when looking at individuals at the 90th percentile of their distribution, white male veterans face a penalty of almost 7 percent, black male veterans face a penalty of more than 6 percent while women veterans face a penalty of 0.6 percent. When translating these percentages into dollar values using the earnings of the respective civilians in the 90th percentile, our estimates suggest that white male veterans earn $6,392 less per year, black male veterans earn $4,101 less per year, and female veterans earn $401 less per year. Policymakers should also note that some veterans may be willing to give up earnings in order to choose occupations where they can continue to serve their country. This result highlights two important conclusions: first, while the decomposition at the mean points to a very marginal premium/penalty (in the order of 1–2 percent), the decomposition of the distribution reveals a larger premium/penalty in the tails of the distribution. Second, those veterans that face the largest penalties in the civilian job market are not the individuals in the bottom of the distribution (i.e. those who are typically thought of needing help from transition program tailored to build the skills that increase earning), but those at the top of the distribution. Even if these individuals are doing relatively well, veterans foregoing wages by choosing to continue to serve their country in other occupations should be viewed less as a 'penalty' associated with military service and more as a 'reward' to society.

Previous research mainly focuses on the component of the wage gap that is not due to differences in the observable characteristics (veteran premium or penalty). In this research, instead, we try to disentangle the link between of the wage gap and the observables. We consistently find that location choices are one reason for a reduction in the explained component of the wage gap. Veterans may be willing to give up earnings by choosing locations where there is an established military community to welcome them. This can allow policymakers to place a monetary value of VA services and other military services provided to veterans in these areas. However, there may also be issues associated with spatial mismatch as we find that veterans (which tend to be a mobile population) are locating in places with higher unemployment rates and generally more struggling economies. Many of the job training programs (for veterans and non-veterans) focus on marketable skills (rightly so) with little to no emphasis on choosing the right place to market those skills. Encouraging veterans to locate in productive places may be just as important as occupation and industry choice.

This research focused on analyzing the heterogeneity in veterans' economic outcomes rather than in their backgrounds. Initial evidence suggests that selection effects may significantly affect the veteran premium/penalty. Future research should consider the heterogeneity in both the background of veterans and their economics outcomes, though we recognize data limitations may be a significant hindrance.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendices

Appendix 1. Skills and Occupations

The O*NET version 16 was used to obtain measures for the abilities and skills required for each occupation. The O*NET 16 occupation codes are based on the 2010 SOC codes. These codes were then matched to the IPUMS ACS OCC codes based on year. There is no one-to-one mapping between these codes. Whenever multiple O*NET SOC occupation codes map to one ACS occupation code, the average importance rank is calculated and used for the given occupation code.

Basic Skills (10 elements) – Developed capacities that facilitate learning or the more rapid acquisition of knowledge

Complex Problem Solving Skills (1 element) – Developed capacities used to solve novel, ill-defined problems in complex, real-world settings

Resource Management Skills (4 elements) – Developed capacities used to allocate resources efficiently

Social Skills (6 elements) – Developed capacities used to work with people to achieve goals

Systems Skills (3 elements) – Developed capacities used to understand, monitor, and improve socio-technical systems

Technical Skills (11 elements) – Developed capacities used to design, set-up, operate, and correct malfunctions involving application of machines or technological systems

Cognitive Abilities (21 elements) – Abilities that influence the acquisition and application of knowledge in problem solving

Physical Abilities (9 elements) – Abilities that influence strength, endurance, flexibility, balance and coordination

Psychomotor Abilities (10 elements) – Abilities that influence the capacity to manipulate and control objects

Sensory Abilities (12 elements) – Abilities that influence visual, auditory and speech perception

Appendix 2. OLS estimates used for the decomposition in Table 4.

	white men		black men		women	
	Veterans	Civilians	Veterans	Civilians	Veterans	Civilians
Education	0.06***	0.059***	0.047***	0.047***	0.071***	0.069***
	(0.001)	(0.000)	(0.004)	(0.001)	(0.002)	(0.000)
Age	0.088***	0.097***	0.08***	0.092***	0.073***	0.108***
	(0.003)	(0.001)	(0.009)	(0.002)	(0.007)	(0.001)
Age^2	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.13***	0.158***	0.099***	0.122***	0.063***	0.101***
	(0.005)	(0.001)	(0.012)	(0.004)	(0.009)	(0.001)
Children	0.025***	0.022***	0.01**	0.001	−0.014***	−0.025***
	(0.002)	(0.001)	(0.005)	(0.002)	(0.004)	(0.000)
Ln(Population)	0.039***	0.034***	0.025***	0.036***	0.038***	0.041***
	(0.003)	(0.001)	(0.006)	(0.002)	(0.005)	(0.001)
%College	0.437***	0.532***	0.407***	0.337***	0.592***	0.502***
	(0.025)	(0.006)	(0.061)	(0.017)	(0.050)	(0.005)
Ln(Military)	−0.011***	−0.015***	−0.016***	−0.018***	−0.013***	−0.016***
	(0.002)	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)
Black					−0.072***	−0.072***
					(0.010)	(0.001)
_cons	−0.647***	−0.652***	−0.049	−0.367***	−0.54***	−1.085***
	(0.062)	(0.013)	(0.169)	(0.037)	(0.123)	(0.011)
Occupation FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N. Obs	76,041	1,245,060	12,416	157,810	18,925	1,737,954

Appendix 3. Detailed breakout of the quantile wage decomposition.

	White Men		Black Men		Women	
VARIABLES	Explained	Unexplained	Explained	Unexplained	Explained	Unexplained
Agriculture	0.00130***	4.73e-05	0.000163**	0.000357	0.000258***	0.000137
	(6.99e-05)	(0.000165)	(7.53e-05)	(0.000224)	(4.55e-05)	(0.000139)
Mining	0.000657***	−0.000316*	4.40e-05	−6.77e-05	−6.84e-05	−3.48e-06
	(7.36e-05)	(0.000185)	(7.57e-05)	(0.000275)	(4.99e-05)	(0.000124)
Construction	4.39e-05	−0.000888	−4.91e-05	−0.00210	3.50e-05**	−0.000346
	(4.72e-05)	(0.000733)	(7.32e-05)	(0.00129)	(1.55e-05)	(0.000478)
Manufacturing	1.01e-05	0.00280***	−0.000156*	−0.00145	−0.000114**	0.000420
	(1.50e-05)	(0.000904)	(8.17e-05)	(0.00232)	(4.88e-05)	(0.00121)
Trade	0.00603***	0.000509	0.00780***	−0.00283	0.00708***	−0.00626**
	(0.000186)	(0.00111)	(0.000584)	(0.00290)	(0.000327)	(0.00249)
FIRE	−0.00157***	−0.00285***	−0.000292***	−0.00152	−0.000679***	−0.00157
	(7.86e-05)	(0.000527)	(9.43e-05)	(0.00136)	(7.57e-05)	(0.00151)
Tran/Comm	0.00149***	0.00485***	0.00152***	0.00671**	0.000516***	0.000258
	(8.29e-05)	(0.000882)	(0.000260)	(0.00331)	(7.10e-05)	(0.00148)
Service	0.0108***	0.0110***	0.0108***	−0.00533	0.0130***	0.00764
	(0.000247)	(0.00216)	(0.000795)	(0.00693)	(0.000477)	(0.0107)
Government	0.0132***	−0.00193	0.0245***	−0.0129***	0.00783***	0.00241
	(0.000390)	(0.00139)	(0.00138)	(0.00424)	(0.000465)	(0.00440)
Manager	−0.000446**	−0.000503	0.00144***	−0.00266**	0.000547	−0.00267**
	(0.000198)	(0.000646)	(0.000365)	(0.00121)	(0.000350)	(0.00107)
Business Op	−0.000926***	−0.00199***	0.00232***	−0.00396***	0.00244***	−0.00492***
	(0.000142)	(0.000457)	(0.000355)	(0.00120)	(0.000361)	(0.00121)
Engineer/Sci	0.00456***	−0.00141*	0.0114***	−0.00188	0.00484***	0.00224**
	(0.000270)	(0.000838)	(0.000801)	(0.00169)	(0.000397)	(0.00103)
Artists	0.000114***	−0.000288	−0.000469***	0.000180	−0.000343***	0.000218
	(4.38e-05)	(0.000226)	(0.000109)	(0.000608)	(4.13e-05)	(0.000454)
Legal	−0.00191***	−0.000545***	−0.000476**	−6.35e-06	−0.000343	−0.00195***
	(0.000119)	(0.000189)	(0.000211)	(0.000261)	(0.000263)	(0.000464)
Education	0.00199***	−0.000263	1.61e-05	−0.00184**	0.00288***	−0.00549***
	(8.41e-05)	(0.000338)	(5.90e-05)	(0.000881)	(0.000132)	(0.00117)
Health	0.00178***	−0.000842*	0.000714***	−0.000746	0.0112***	−0.000518
	(0.000105)	(0.000501)	(0.000165)	(0.00132)	(0.000552)	(0.00256)
Comm Service	−0.00557***	0.00979***	−0.00467***	0.00676***	−0.000984***	0.00172
	(0.000225)	(0.00101)	(0.000453)	(0.00254)	(9.80e-05)	(0.00119)
Services	0.0172***	−0.00116*	0.0260***	−0.00388**	0.0178***	−0.00763***
	(0.000266)	(0.000603)	(0.000905)	(0.00198)	(0.000489)	(0.00146)
Sales	−0.000463***	0.000941	0.00478***	0.00146	0.00467***	−5.58e-05
	(6.44e-05)	(0.000888)	(0.000377)	(0.00179)	(0.000198)	(0.00163)
Admin	0.000771***	0.00138**	−3.99e-05	0.00321	−0.00236***	0.000430
	(0.000176)	(0.000699)	(0.000497)	(0.00258)	(0.000277)	(0.00276)
Farmer	0.00128***	−4.45e-05	0.000263***	0.000175	0.000412***	7.41e-05
	(6.81e-05)	(0.000143)	(9.77e-05)	(0.000203)	(5.79e-05)	(0.000117)
Construction	−0.00195***	0.0140***	−0.00330***	0.00931***	−0.00294***	0.00740***
	(0.000119)	(0.00163)	(0.000385)	(0.00332)	(0.000297)	(0.000940)
Transportation	−0.000282	0.00474***	0.00477***	0.00298	−0.00161***	0.00310***
	(0.000206)	(0.000749)	(0.000648)	(0.00261)	(0.000241)	(0.000687)
Constant		0.0110		0.301*		0.564***
		(0.0628)		(0.171)		(0.123)
Observations	1,321,101	1,321,101	170,226	170,226	1,756,879	1,756,879