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Gender, race & the veteran wage gap

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ABSTRACT

This paper analyzes earnings outcomes of Iraq/Afghanistan-era veterans. We utilize the 2009–2013 American Community Survey and a worker-matching methodology to decompose wage differences between veteran and non-veteran workers. Among fully-employed, 25-40 year-olds, veteran workers make 3% less than non-veteran workers. While male veterans make 9% less than non-veterans, female and black veterans experience a wage premium (2% and 7% respectively).

Decomposition of the earnings gap identifies some of its sources. Relatively higher rates of disability and lower rates of educational attainment serve to increase the overall wage penalty against veterans. However, veterans work less in low-paying occupations than non-veterans, serving to reduce the wage penalty. Finally, among male and white subgroups, non-veterans earn more in the top quintile due largely to having higher educational attainment and greater representation in higher-paying occupations, such as management.

1. Introduction

Veterans face many difficult challenges and much uncertainty when they join the civilian workforce. Depending on the nature of one's military experience, various barriers exist to finding work, transferring skills from the military, and receiving compensation for those skills. Different veterans return from very different military experiences, which may impact labor force outcomes in different ways. Some veterans have skills and experiences that have a strong demand from civilian employers. Operations-support positions that hone technical, mechanical, and healthcare knowledge should serve as a springboard into high-paying jobs in the civilian workforce. Veterans who served in combat positions may have developed skills sets that are less broadly sought out by civilian employers. The additional mental and physical stress of combat service may prolong recovery and create other barriers to finding work.

This paper analyzes wage outcomes for post-2001, Iraq/Afghanistan-era veterans in the recent job market. The question of interest relates to reintegration into the civilian workforce — are post-2001 veterans paid in the same way that other workers are? Using the 2009–2013 American Community Survey (ACS), we analyze the veteran vs. non-veteran wage difference in a number of ways. First, we segment the analysis by gender and race to focus on wage outcomes for veterans with different experiences. Until recently, combat-arms roles have been reserved for men. Additionally, 53% of enlisted white Army Soldiers served in combat-arms positions, compared to 24% of black soldiers (Office of Army Demographics (2010), p. 16). Thus, a

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gender/race difference in military experiences may relate to a difference in earnings outcomes. Second, we present the wage distributions of post-2001 veterans and other workers together, to identify gaps between the two. Among males, the top of the wage distribution shows an increasing penalty against veterans. For instance, the median male veteran makes only $0.60 per hour less than the median non-veteran; however, the veteran at the 90th percentile makes $6 per hour less than the non-veteran at the same percentile. On the other hand, wage distribution comparisons favor female and black veterans (compared to their non-veteran counterparts), with large premiums along the bottom four quintiles, supporting previous findings of favorable effects for veterans from groups with lower earnings generally (Angrist, 1990; Sampson and Laub, 1996; Xie, 1992; Browning et al., 1973). Third, we compare median occupational wages for veterans and non-veterans, finding that veterans in the bottom four quintiles of earnings tend to employ in higher-paying occupations than non-veterans, an effect of occupational segregation that has been seen in studies of gender and racial pay gaps (Petersen and Morgan, 1995; Lockette and Spriggs, 2015). We explore what occupations veterans tend to work in.

Finally, we utilize the matching methodology of Ñopo (2008) to decompose the wage gap against veterans. Rather than compare all veterans to all non-veterans, this methodology uses direct matching to segment the workforce into four groups: 1) veterans who "match" a non-veteran across a combination of labor-market related characteristics (same age range, race, gender, education level, disability status, and civilian occupation code); 2) veterans who do not have a combination match with a non-veteran; as well as 3) non-veterans who "match' a veteran; and, 4) non-veterans who go unmatched. We find that veterans earn 3% less overall but opposing effects play a role in the veteran wage gap. On the one hand, both matched and unmatched veterans tend to segregate away from lower paying occupations compared to most of the civilian workforce, reducing the overall wage penalty. In addition, many veterans work in jobs that pay below- or near-median wages work in the public sector, which tend to pay more than similar jobs in the private sector, also reducing the overall wage penalty. On the other hand, comparisons of matched veterans and non-veterans — those most likely to be in similar situations — show that this group of veterans has a lower rate of educational attainment, a lower rate of work in the highest-paying occupations, and lower returns to job-related characteristics (i.e. for unobserved reasons), increasing the wage penalty against veterans.

2. Background

The potential link between veteran status and earnings is not straightforward, thus *a priori* propositions on the direction of the veteran wage difference are not clear. Various factors may pull in opposing directions. First, working in a given military occupational speciality (MOS) leads to valuable technical skills and experience that may help those veterans land in higher-paying civilian industries and occupations. Studying veterans who separated from military service in 1971, Goldberg and Warner (1987) found that differences in "general" military training and experience— namely medical, equipment repair, technical, and electronic skills — had considerable, positive effects on later earnings. However, one should not assume that all veterans will seek to continue into a civilian job related to their MOS; many likely seek education or training to switch occupations. Second, the educational and health support that veterans receive through the U.S. Department of Veterans Affairs can help veterans in the accumulation of human capital and lessen the potential health barriers to the workforce. Third, veterans may face barriers to work that stem from institutional differences between the Armed Forces and the civilian workforce and perceptions that civilian employers may have of veterans. For example, veterans must adapt to different procedures, communication norms, cultures, and command structures in the civilian workforce (Freifeld, 2010). Stigma facing veterans, either real or perceived, may affect a veteran's choices toward treatment (Ben-Zeev et al., 2012; Vogt, 2011) and potentially result in negative effects on job and earnings outcomes. Fourth, selection bias creates an additional complexity in tracking the effects of veteran status on earnings. Characteristics such as ability and drive, which are generally unobservable in data, could push people into the military and would have an effect on earnings regardless of military experience.

Studies comparing veteran and non-veteran earnings date back many years. Many early studies found a substantial income penalty against veterans, interpreting service — largely due to the draft — as a career interruption that restrained veterans from catching up to their non-veteran peers (Bailey and Cargill, 1969; Miller and Tollison, 1971). Recent studies, however, have not found earnings gaps against Iraq/Afghanistan-era veterans. In fact, Kleykamp (2013) found an earnings premium for veterans aged 18–40, using the Current Population Survey (CPS) from 2005 to 2011 (approximately 2000 veterans). Estimating a generalized linear model that controlled for demographic, family, and industry variables, the author found that veterans earned a 6% premium over non-veterans. The author estimated that this premium was larger for racial/ethnic minorities than white veterans. Additionally, much of this premium was due to the inclusion of workers without a high-school degree (1% of veterans compared to 11% of non-veterans). Tennant (2012) used propensity score matching to compare post-2001 veterans to the rest of the population with the 2009–2010 CPS (a matched sample of 1793). The author found no significant differences in mean income from salary and wages. Humensky et al. (2013b) estimated veteran vs. non-veteran outcomes for earnings, enrollment and employment by various age groups, using the 2006–2011 CPS (approximately 3000 veterans). They found that Iraq/Afghanistan-era veterans had a higher probability of being employed for pay but no difference in earnings, except for the small group of veterans aged 18–25. Additionally, an exploratory analysis by Dávila and Mora (2012) suggested that state or region may be correlated with veteran pay.

Employment in the public sector can affect veteran earnings due to the "veteran preference" given for federal government jobs. Using the CPS data from 2009, Walker (2010) found a larger veteran pay penalty for those employed in government (approximately 7% lower pay) compared to those in the private sector (1%) (p. 6). The occupation in which one works within the public sector has also been shown to affect the veteran gap. Mani (2013) found that differences in veteran/non-veteran pay vary between Department of Defense jobs and other federal jobs. From 2000 to 2009, the author found that veterans holding a Department of Defense job experienced less of a pay gap increase than other federal employees.

Many insights that have been made through research on male-female pay differences may also apply to veterans. In studies of the gender wage gap, occupational segregation has been found to play an important role. According to Petersen and Morgan (1995), earnings differences can occur in multiple fashions. One way is when women are placed into professions that generally pay lower wages. A second is when woman-dominated occupations earn less than man-dominated occupations, even though all other wage-related factors would suggest earning equivalent amounts. A third is when a woman receives less than a man within the same job. Using descriptive calculations to decompose the gap into these three parts and regression analysis to extend their analysis, Petersen and Morgan (1995) found that the largest part of the pay gap (40%) results from occupational segregation rather than pay discrepancies within the same job. Charles and Grusky (1995) show that occupational segregation is widespread across many countries, historically with women more represented in clerical and service occupations and men in more highly-paying management and production ones. Although gendered occupational segregation has been declining, the rate of decline slowed substantially in the 1980s and 1990s (Preston, 1999).

Occupational segregation by race is also stark in the United States. Approximately 90% of male occupations have a disproportionate racial composition; with over-representation of black males in lower wage earning jobs (Hamilton et al., 2011). Education reduces the effects of racial occupational segregation somewhat, as those with higher levels of education experience less occupational segregation (Lockette and Spriggs, 2015). As the veteran workforce likely differs from the non-veteran one in its gender and racial makeup, gender- and racial-occupational segregation will likely affect the veteran pay gap.

Much veteran research has focused on other outcomes that may be related to earnings. Among veterans treated for a substance abuse disorder in a U.S. Departments of Defense and Veterans Affairs (VA) clinic, Humensky et al. (2013a) find that anxiety and general medical problems predict a lower probability of any earnings. London et al. (2011) examine the relationship between veteran status, disability, and poverty status. The authors find that households with at least one person with a limiting disability have three times the odds off experiencing poverty than households with no disability. If the member experiencing poverty is also a veteran, the household has only 1.65 times the odds of experiencing poverty, likely due to health benefits available to veterans through the VA. Conversely, having a veteran in the household without a disability is associated with 27% lower odds of being in poverty. In a similar analysis, Heflin et al. (2012) find that disability roughly doubles the odds of home, medical, and bill-paying hardship, as well as food insufficiency, regardless of the presence of a veteran in the household. Other studies suggest how lower ability to find work or lower pay may deprive veterans of capabilities related to housing (Elbogen et al., 2013) and food security (Widome et al., 2015).

Analysis of the veteran pay gap must account for various mechanisms. One, veterans may be paid more or less because of their human capital investments through working in a given MOS and/or utilizing the G.I. Bill to continue their education. Potential barriers to such investments, such as disability, also need to be considered. Two, they may be paid more or less due to entering into certain sectors or occupations that are less represented by non-veterans — occupational segregation. Three, veterans may be paid more or less even if they have similar human capital to non-veterans and work in the same jobs.

The current paper contributes to the literature on veteran pay in a number of important ways. First, while studies have focused on mean veteran vs. non-veteran differences, no research has looked at veteran outcomes across the distribution of wages. A descriptive analysis of the wage distributions of veterans and non-veterans can hint at potential veteran penalties or premiums at the tails, which may be hidden by analyzing only mean differences. Second, due to gender and racial differences in military training, an analysis of the veteran wage gap should highlight different gender and racial outcomes in the civilian labor market. This paper is one of few to estimate the veteran wage gap for male, female, white, and black workers separately; Kleykamp (2013) controlled for race, gender, and interaction effects for recent veterans, and Browning et al. (1973) performed a comparative analysis by separate ethnic groups for a previous generation of veterans. Third, by using the 2009–2013 ACS, we have hourly wage data for a relatively large sample of veterans ($N = 37{,}530$). The large sample allows for sample segmentation by race and gender as well as more specific controls by occupation.

Finally, this paper is the first to our knowledge to use decomposition methods to study the veteran wage gap, thus contributing to both the study of veteran reintegration and the broader literature on earnings differences. Such methods allow us to identify the relative importance that occupational segregation, characteristic differences, and potential discrimination have on the veteran pay gap.

3. Data on veterans & earnings

3.1. Data description

This paper utilizes the five-year public use microdata sample (PUMS) for 2009–2013, a subset of the American Community Survey (ACS). The United States Census Bureau fully implemented the ACS in 2005 to provide yearly estimates of demographic, social, economic, and housing information that had previously been captured only once a decade. The Census Bureau selects independent addresses from each of the 3143 counties and county equivalents in the U.S., including the District of Columbia, to include in its sample — approximately 2.9 million total from 2005 to 2010 and 3.54 million after 2010. The sampling design has a coverage rate of approximately 99% of housing units and 94% of the total population. Response rates are near 98% for the years used in this analysis. Data collection occurs on a monthly basis through a 4-step strategy: housing units first receive a mailed request to respond via Internet. This is followed by an option to complete a paper questionnaire and return it by mail. For non-response, the Census Bureau follows up with computer-assisted telephone interviewing or computer-assisted personal interviewing. Survey weights are used to bring the characteristics of the sample more into agreement with those of the full population by compensating for differences in sampling rates across areas, age, sex, race, and Hispanic origin.

The primary comparison of interest is post-2001 veteran status, whether recently-returned veterans make more or less than similar non-veterans. The ACS asks respondents if they served in the military, whether they are now on active duty, and whether they served September 2001 or later. The title "post-2001 veteran" used in this study refers to those post-2001 veterans — many who are recently returned from Iraq or Afghanistan — while "non-veteran" refers to all workers who never served. Veterans who served prior to 2001 are dropped from the sample in order to focus on recent veteran vs. non-veteran differences; however, their inclusion had little effect on estimations in robustness checks.

The outcome of interest is the hourly wage. In the ACS, this is computed based on the individual's report of annual wage earnings, weeks worked in the previous year, and usual hours worked per week. Since the ACS weeks-worked variable is categorical (e.g. 48–49 weeks or 50–52 weeks), labor researchers commonly use the median values (e.g. 48.5 weeks and 51 weeks for the above categories) to convert annual to hourly wages (Welsh-Loveman et al., 2014). Previous wage studies suggest the need to truncate data to avoid extreme hourly wages. Similar to related literature (Kleykamp, 2013; Lemieux, 2006), wages below \$3.21 and over \$321 (3.81% of full-time workers) are removed from the sample. Hourly wages are adjusted for inflation and reported in 2013 dollars.

The empirical investigation in this paper limits the sample in two additional ways. First, the paper focuses on earnings outcomes among fully-employed workers, thus respondents that were not fully employed for most of the previous year (<27 weeks) are dropped from the sample. If veterans are more or less likely to be fully employed than non-veterans, potential selection effects need to be addressed. Preliminary logistic regressions tested whether veteran status associated with being fully employed, controlling for demographic, educational (including current enrollment), family, disability, and regional characteristics. Estimates showed veterans status to have a positive and statistically significant association with full-time employment. However, the difference is small: the predicted probability of non-veterans having full-time employment for the year is 63.3% compared to 64.5% for veterans ($p < 0.001$).

Second, age and educational limitations are placed on the sample. Workers over age 40 are dropped to isolate comparisons of early-to-mid career workers — intended to focus on the role of occupation selection and potential discrimination on returned veteran earnings, rather than on the role that experience in the civilian workforce plays. Kleykamp (2013) also suggests that comparisons of returning veterans be limited to those 40 years and younger since most who enlist at 18–22 years old qualify for pension at 40. Workers under age 25 are also dropped to reduce non-participation due to college and to reduce comparisons to those just entering the job market. Finally, workers with less than a high school degree are dropped. With few exceptions, a high school degree is required to join the Armed Forces. After limiting the sample, no additional observations had to be removed due to missing data. The sample under analysis includes 37,530 post-2001 veterans compared to 1,452,536 non-veterans. ACS survey population weights are used in all calculations for a weighted sample of 910,603 veterans and 33,172,234 non-veterans.

Table 1 describes mean characteristics for fully-employed non-veterans and veterans aged 25–40 (standard errors are included for testing means differences). The group of veterans have several notable differences from non-veteran workers. First, veterans are constituted of a lower percentage of female workers, those with a Bachelor's degree, and those having other

Table 1
Descriptive Statistics of Employed Post-2001 Veteran and Non-Veteran Full-time Workers, ages 25–40: Mean (SE).

Variable	Non-veteran	Veteran	Difference
Age	32.53 (0.01)	31.37 (0.03)	−1.16 *** (0.03)
Female	46.46 (0.05)	15.81 (0.24)	−30.66 *** (0.25)
White	73.99 (0.05)	75.74 (0.30)	1.75 *** (0.30)
Black	11.62 (0.04)	14.54 (0.25)	2.91 *** (0.25)
High School Only	23.42 (0.05)	19.91 (0.27)	−3.51 *** (0.27)
Some College	22.87 (0.05)	38.54 (0.33)	15.67 *** (0.33)
Associate	9.87 (0.03)	13.65 (0.23)	3.78 *** (0.23)
Bachelor	28.89 (0.05)	19.85 (0.26)	−9.04 *** (0.26)
More Than Bachelor	14.96 (0.04)	8.04 (0.17)	−6.91 *** (0.17)
Married	56.74 (0.05)	58.54 (0.33)	1.81 *** (0.34)
Single	11.72 (0.03)	13.71 (0.24)	1.99 *** (0.24)
Children Under 5	15.54 (0.04)	18.77 (0.25)	3.23 *** (0.26)
Children Under 17	23.54 (0.04)	19.34 (0.26)	−4.20 *** (0.26)
Other Workers in Family	57.23 (0.05)	52.06 (0.33)	−5.17 *** (0.34)
Any Disability	2.30 (0.02)	5.81 (0.16)	3.50 *** (0.16)
Earnings (\$/hr)			
Mean-Hourly-Wage	24.29 (0.02)	23.61 (0.10)	-0.68 *** (0.10)
Median Hourly Wage	19.96	20.32	0.36
Observations	1,452,536	37,530	

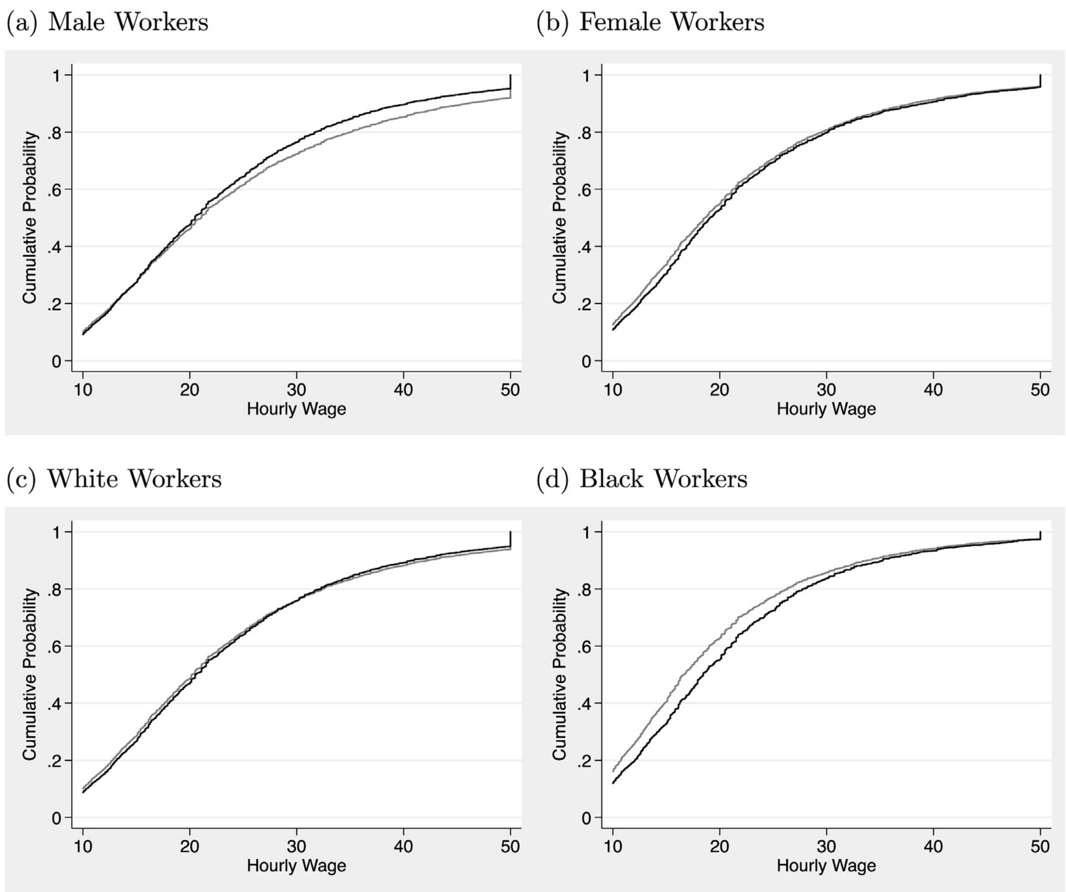
Wald tests are used to measure whether means differences are statistically different from zero. ACS sampling weights are used in all calculations.
* $p< 0.05$; ** $p< 0.01$; *** $p< 0.001$.

workers in the family. Second, the group of veterans include a higher percentage of black workers, those having children under five, and those having some disability. Third, veterans have a lower hourly wage on average but a higher wage at the median.

3.2. Post-2001 veteran vs. non-veteran wage distributions, by gender and race

The large number of veterans in the sample is a strength of the five-year ACS, allowing for a closer exploration of veteran pay gaps by race, gender, and occupation — issues not fully explored in previous studies (Humensky et al., 2013b; Kleykamp, 2013; Heflin et al., 2012; Tennant, 2012; Walker, 2010). To highlight the very different labor market experiences of veterans and the potential effects of race and gender on the wage gap, we describe the distributions of wages for males and females separately and white and black workers separately.

Fig. 1 presents the cumulative distribution function (CDF) of hourly wages for non-veterans and veterans. When the CDF for veterans lie to the right of the CDF for non-veterans, the veteran in a given percentile of wages has a higher wage than the non-veteran in that percentile. The top-left Fig. 1a illustrates a veteran wage *penalty* for male workers starting around the median — the gray line for non-veterans moves to the right of the veteran's black line around the 40th percentile and the gap between gray and black widens toward the top of the distribution. In other words, while male veterans below the 40th percentile make approximately the same as male non-veterans, veterans make $2.48 per hour less at the 75th percentile and almost $6 per hour less at the 95th percentile. The female distributions tell a different story: Fig. 1b shows a slight veteran wage premium beginning at the bottom of the female distribution, which continues until around the 80th percentile of female workers. Veteran wages remain close to those of other females for the top ten percent of female workers.



Solid gray line represents non-veterans; solid black line represents post-2001 veterans. Top wages are censored at $50/hour in this figure for clarity.

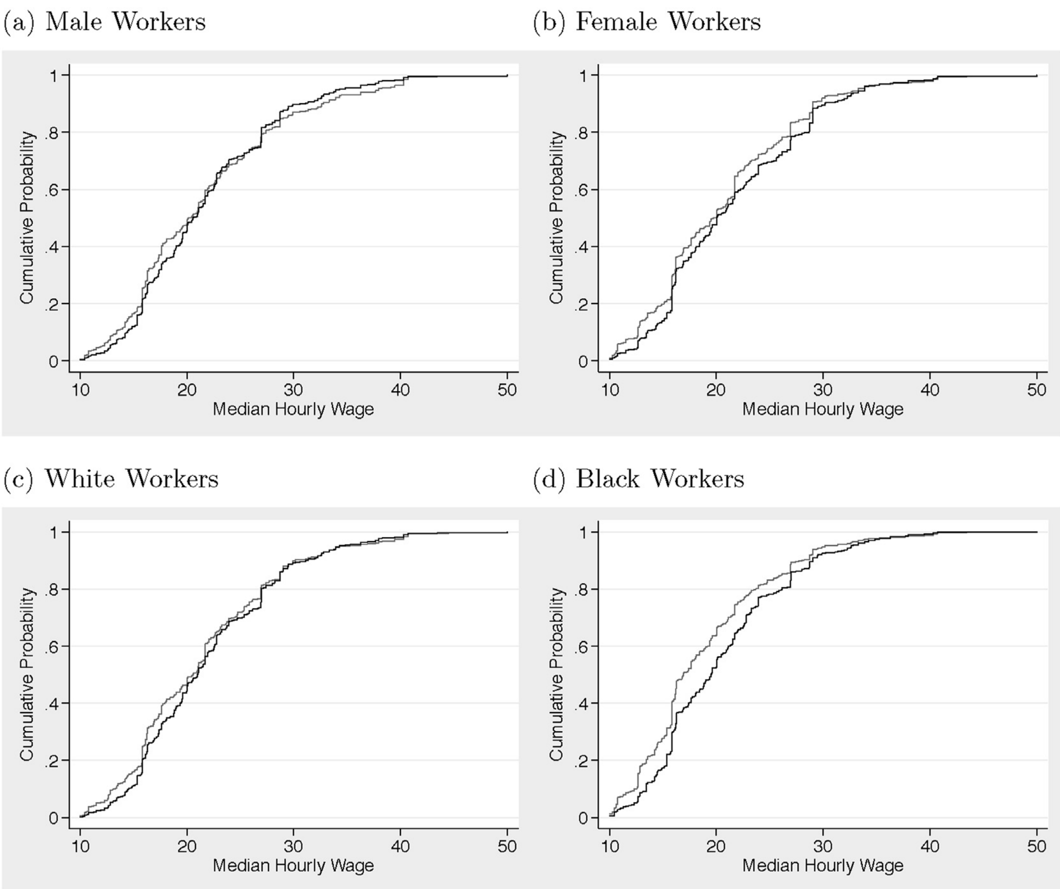
Fig. 1. Cumulative Distribution of Hourly Wages, by Veteran Status. Solid gray line represents non-veterans; solid black line represents post-2001 veterans. Top wages are censored at $50/hour in this figure for clarity.

Similar differences appear when breaking down the wage difference by race. Among white workers (close to 75% of both fully-employed veterans and non-veterans) in Fig. 1c, little difference appears between veterans and non-veterans, except for a slight veteran premium below the median and a slight penalty above the 80th percentile. However, for nearly 90% of black workers, Fig. 1d shows a relatively large veteran premium. This veteran premium begins at the bottom of the distribution, widens near the median and converges at the top.

Occupational differences likely explain part of these gaps in the wage distribution. Fig. 2 shows how veterans and non-veterans differ in their distribution across occupations. The horizontal axis measures the median occupational wage for 499 Standard Occupational Classification categories. If the veteran CDF lies to the right of the non-veteran CDF, the veteran at a given percentile works in a higher-paying occupation (according to that occupation's median) than the non-veteran at the same percentile. Each subfigure shows how veterans tend to work in higher-paying occupations in the bottom three quintiles. However, male veterans are less represented than non-veterans in high-paying occupations. Veteran wage premiums are larger among female and black workers, and female and black veterans are more strongly represented in higher-paying occupations.

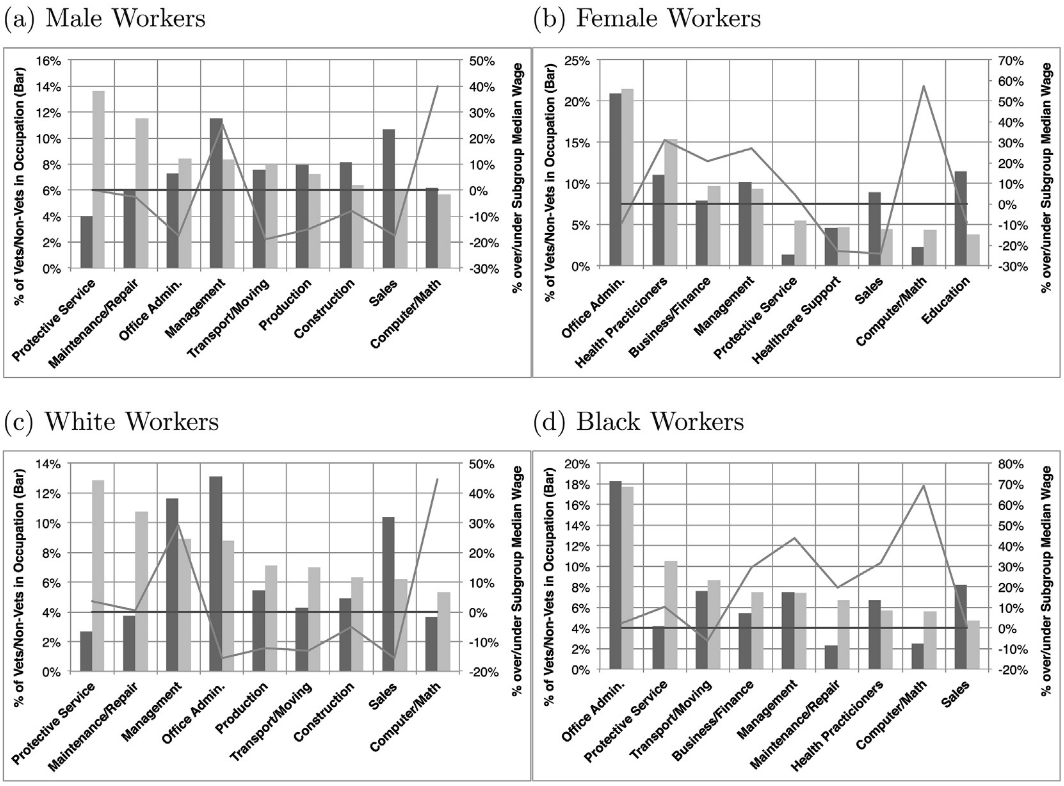
3.3. Veteran distribution across occupations & earnings premiums

Fig. 3 illustrates the occupations where veterans are most heavily distributed (from left to right), compares differences in veteran/non-veteran occupational makeup, and measures what veterans make in a given occupation to the subgroup (male, female, white, black) median. In Fig. 3a male veterans are heavily distributed in protective services, maintenance/repair, and office administration occupations (indicated by the light gray bars). The light-gray line shows how veteran wages in these occupations fall at or below the overall male median (the horizontal black line). Altogether, only 31% of male veterans work in



Solid gray line represents non-veterans; solid black line represents post-2001 veterans. Top wages are censored at $50/hour in this figure for clarity.

Fig. 2. Cumulative Distribution of Median Occupation Hourly Wage, by Veteran Status. Solid gray line represents non-veterans; solid black line represents post-2001 veterans. Top wages are censored at $50/hour in this figure for clarity.



Light-gray bars represent the percentage of veterans in the given occupation, measured along the left axis. Only the top nine occupations on the veteran worker distribution are shown, along with the percentage of non-veterans in that occupation (dark-gray bars). Lines represent the percent difference between the veteran median wage in each occupation (light-gray line) and the gender/race subgroup median (horizontal black line), measured along the right axis.

Fig. 3. Distribution of Workers Across Occupations & Veterans Median Wage Penalty/Premiums, Sorted by Top Veteran Occupations. Light-gray bars represent the percentage of veterans in the given occupation, measured along the left axis. Only the top nine occupations on the veteran worker distribution are shown, along with the percentage of non-veterans in that occupation (dark-gray bars). Lines represent the percent difference between the veteran median wage in each occupation (light-gray line) and the gender/race subgroup median (horizontal black line), measured along the right axis.

occupations that pay a premium over the median male wage. Management and computer/math are the top two high-paying occupations shown; however, a larger percentage of non-veterans work in these occupations. Compare this to Fig. 3b showing the female veteran distribution. Although office administration makes up the largest occupation for female veterans and pays lower than the female median, the next three largest occupations (health practitioners, business/finance, and management) each pay a 20%–30% premium over the female median. Close to 50% of female veterans work in premium-paying occupations, and veterans are more distributed toward these occupations than non-veterans.

Fig. 3c and d shows occupational wage premiums for white and black workers, respectively. Of the top ten occupations that white veterans work in, only three pay a wage premium, and 46% of white veterans work in one of these. However, six of the top ten occupations pay a premium to black veterans, with 76% black veterans working in a premium-paying occupation.

Descriptive analysis of the wage and occupational distributions show clear differences in the veteran and non-veteran workforces and are important in better understanding pay differences. However, further analysis needs to differentiate whether the wage penalty (or premium) arises due to veterans having different job-related characteristics than non-veterans (i.e. working in different occupations) or whether it arises even for veterans with similar characteristics to non-veterans.

4. Analytical strategy

4.1. Background on wage decompositions

Wage gap studies have typically utilized Blinder-Oaxaca (BO) decomposition techniques, which require estimating linear regression equations of earnings for two comparison groups separately (Blinder, 1973; Oaxaca, 1973). Estimates show how various observed characteristics (such as age, race, educational level, experience, and occupation) associate with mean earning differentials between compared groups.

However, this approach will be misspecified if the two groups have differences in the empirical distribution of characteristics (i.e. they do not share a *common support*). For instance, meaningful comparisons cannot be estimated if a significant proportion of one group substantially differs from the other, perhaps by being overly represented in an occupation and/or educational attainment level that is not observed in the comparison group. The previous analysis suggests that veterans and non-veterans differ greatly in a number of characteristics related to wage. In the covariate space that describes how veteran status interacts with these characteristics in a wage estimation, there may exist characteristic combinations where there are not enough veteran and non-veteran observations to make inferences about these workers. This would suggest a *lack of common support* between veterans and non-veterans.

BO decomposition assumes that any estimated covariates influence the earnings of those out of the common support in the same way they influence those in the common support. However, the different gender, racial, and occupations makeup of veterans may create earnings dynamics that affect those in and out of the common support in different ways.

We implement the matching methodology of Ñopo (2008) to differentiate the part of veteran wage gap due to non-comparable, out-of-the-support workforce differences from the part that occurs between comparable workers in the common support. Unlike BO decomposition, the Ñopo method is fully nonparametric, relying on the exact matching of veterans to non-veterans by labor force related characteristics, including gender, age, race, education, occupation, and family makeup. The nonparametric decomposition does not impose the assumption that various characteristics affect wages linearly across the wage distribution, as in the BO, least-squares method. However, this matching method requires a balance between match criteria and observations — a more precise match across a broader set of characteristics requires a larger sample size of workers. Fortunately, the 2009–2013 ACS provides a large sample of fully-employed veterans and non-veterans.

A number of recent studies have used the Ñopo framework to decompose differences in outcomes across many applied social science disciplines. Görzig et al. (2005) decomposed differences in wages paid by Western and Eastern Germany in 1994 and 1998. Their estimates suggested that structural differences in the types of establishments found in Western and Eastern Germany played a small role in overall wage differences. Rather, 90% of the difference came from pay differences between comparable establishments — those in Eastern Germany paid less than similar, western counterparts (p. 459). Anspal (2015) decomposed the gender wage gap in Estonia, the largest gap in the European Union as of 2015. Using a large, detailed employer dataset, estimates showed that most of the gender wage gap occured between comparable workers and only half of that was explained by work-related characteristic differences. Similarly, Staneva and Arabsheibani (2014) studied formal-informal pay differences in Tajikistan, finding that most of the 43% penalty against formal-sector workers could be explained by characteristic differences (p. 21). In a study of obesity discrimination, Caliendo and Lee (2013) used a kernel matching method similar to Ñopo (2008) but better suited to the smaller sample size under observation. They found no statistical evidence of obesity discrimination, with the exception that obese women had to fill out more job applications and participated in more job training programs than other women to obtain similar outcomes.

Out-of-the support comparisons have been found to play a large role in a number of gap studies utilizing Ñopo decomposition. Mussa (2014) studied rural-urban differences in child malnutrition. Out-of-the support differences were found to be dominant — urban characteristics not found in rural areas account for about 90% of stunting and underweight gaps (p. 9). This finding would of been missed using the BO method which ignores the common support problem (Gevrek and Seiberlich, 2014). Similarly, a study by Ramos et al. (2014) highlighted the relative importance of out-of-the-support comparisons. In decomposing the public-private wage gap in Spain, findings suggested that much of the 35% premium for public employees was due to lower wages for unmatched private workers. In an analysis of immigrant vs. native women in Spain, Nicodemo and Ramos (2012) used the Ñopo method to decompose wage differences for all immigrants, as well as wage gaps for immigrants from developed and developing countries separately. The authors found that immigrant women from developing countries experienced a larger penalty, partially due to being segregated to particularly low-paying jobs.

A final reviewed study suggests how the Ñopo decomposition can identify nuances in a wage gap. Out-of-support workers may influence the wage gap in different ways, as found in a Gamboa and Zuluaga (2013) study on the motherhood penalty. Estimates found that both out-of-the-support non-mothers (more educated) and out-of-the-support mothers (older) made more than those in the common support. However, out-of-the-support non-mothers making more served to increase the overall motherhood penalty while out-of-the-support mothers making more served to lower the penalty. Thus, methods that specify common support differences can add a number of insights as to the source of pay differences between two groups.

The Ñopo method is a good fit for the study of veterans in the civilian workforce because 1) veterans are not homogenous: they have different military experiences and enter the civilian workforce in different ways; and 2) veterans are highly represented in occupations that have relatively few non-veterans, and vice-versa.

4.2. Mediation analysis, decomposition, and matching

The methodology for this research rests on a framework of mediation analysis, as opposed to treatment evaluation. In program evaluation research, regression and matching methods are sometimes used to establish causality in estimating the effect a treatment has on some outcome. Use of these methods requires a number of strong assumptions. For instance, the research design must hold to the conditional independence assumption (CIA), requiring that any covariates related to the outcome occur pre-treatment and all potential confounders be included (Imbens, 2004; Huber, 2015). In our analysis, since veteran status acts as the treatment effect, CIA would arguably broken if we include covariates dependent on that status. Marriage, children, education, and occupation status all vary between veterans and non-veterans and many of these choices occur after military service and are likely affected by military service.

However, estimating treatment effects must be distinguished from decomposing outcome differences — the later relies on much weaker assumptions. Decomposition separates an outcome difference into two estimates: 1) the gap explained by differences in observed characteristics; and 2) the unexplained gap due to unmeasured or unobserved factors left out of the analysis. CIA need not hold in decomposition analysis: if potentially relevant variables are left out for fear of breaking CIA, any potential effects they would of had on the outcome will be captured by the unexplained gap (Caliendo and Lee, 2013). If they are included in the analysis, their effects will simply be shifted to the explained gap.

More importantly, Huber (2015) argues that the treatment evaluation framework is ill suited to decompose outcome gaps based on group differences that occur early in life. Gender and ethnicity occur first on any causal chain, so no confounder occurs prior to group selection at birth. However, decomposition analysis has usefully explored how different factors contribute to the pay gap against women and minorities. The same can be argued for veteran status; since enlistment typically occurs early in adulthood, many relevant confounders to earnings occur after, such as training, education, and family decisions.

Rather than treating such variables that occur after veteran status as confounders to be excluded, they more likely represent intermediate outcomes, or mediators, on the causal pathway from veteran status to earnings. Mediation analysis requires inclusion of such variables to distinguish the indirect, or mediated, effects of veteran status on earnings (i.e. via different educational, occupational, or familial choices), from the direct effects of veteran status on earnings (Baron and Kenny, 1986; Huber, 2015). In the Ñopo (2008) decomposition outlined below, indirect effects via mediators will be picked up through the explained gap while the direct effect will be estimated by the unexplained gap.

Expected mediating characteristics and other factors related to wages make up the matching criteria used in the decomposition. This group of variables, denoted X, is based on the following set of characteristics from the ACS survey: gender, race, five education categories, five three-year age categories, nine region dummies, disability status, and family characteristics (married, single, other workers in family, children under 5 and/or 17). Family characteristics may impact earnings via job mobility decisions; one is potentially less likely to move or change careers with a young family; or, one may be content to take a lower-paying job if there is a second earner in the family.

Workers are also matched by occupation categories. Workers in the ACS sample are distributed across 499 different occupational categories. This highlights a potential drawback of the decomposition algorithm used. When the matching criteria are too stringent, few observations may share the common support, and the analysis may over-estimate the components of the wage gap related to unmatched workers, referred to in the literature as the "curse of dimensionality" (DiNardo et al., 1996; Ñopo, 2008). To address this potential problem, we re-specify criteria X by using 22 higher-level, occupational categories and present results for both specifications. An additional variable indicates what type of industry one performs their occupation in: namely whether one works in the public sector as opposed to private industry. Public sector industries including executive or legislative bodies, public finance, government support, administration of various programs, justice, and national security.

4.3. The Ñopo decomposition model

Ñopo (2008) details an algorithm for matching workers between comparison groups. Every veteran's wage will be compared with a synthetic wage calculated from the average of non-veterans who match that veteran's set of characteristics X. This process of matching one veteran to many non-veterans is repeated for every veteran in the sample, resampling veterans without replacement until exhausted and resampling non-veterans with replacement so that the wages of all matching non-veterans can be averaged for comparison. This procedure ensures that the empirical distribution of characteristics for veterans is preserved and a common support is created with the group of synthetic non-veterans. The algorithm for partitioning the data into matched and unmatched workers follows:

1. First, one veteran is selected, without replacement, from the sample.
2. All non-veterans matching the characteristics of *Veteran 1* are then selected and denoted as *matched.* The mean wage is calculated for these non-veterans, creating a synthetic *Non-Veteran 1.* The group of non-veterans are placed back in the sample.
3. *Veteran 1* and synthetic *Non-Veteran 1* are placed in their respective *matched* groups. By design, these groups share the empirical distribution of probabilities for characteristic set X.
4. The prior steps are repeated until exhausting the veteran sample. If a veteran is not matched, she is placed in the *unmatched veteran* group. The non-veterans who are never used in step 2 are placed in the *unmatched non-veteran* group.

For example, suppose *Veteran 1* has the following characteristics: male, black, 31 years old, has a bachelor's degree, has no family, lives in the northeastern U.S., and has a management occupation in the private sector. The algorithm searches the sample of non-veterans, perhaps finding 200 exact matches. *Veteran 1* and the 200 non-veterans are coded as "matched" and the non-veteran mean wage is calculated. The process is repeated for *Veteran 2*. If *Veteran 2* has the same characteristics as

Veteran 1, he will match the same 200 non-veterans. If not, the algorithm searches for new matches. If none are found, *Veteran 2* is labeled "unmatched." After the sample has been sorted, we may find that just because some veterans and non-veterans share a characteristic or occupation, the rates of having that characteristic may differ between the matched groups.

Now that the matching process has been defined, the veteran/non-veteran wage gap can be decomposed into pieces attributable to matched and unmatched subgroups. The overall veteran gap is defined as the difference in expected mean wages $E[Y]$ between veterans v and non-veterans nv:

$$\Delta = E[Y|v] - E[Y|nv]. \tag{1}$$

Four additive components make up the overall difference in wages, representing how relative characteristic differences affect earnings:

$$\Delta = \Delta_v + \Delta_{nv} + \Delta_x + \Delta_0. \tag{2}$$

The out-of-the-support groups must be accounted for. First, *unmatched veterans* are compared to *matched veterans*. The effect that unmatched veterans have on the wage premium is Δ_v, calculated by the probability of being unmatched μ_v times the wage difference between unmatched and matched veterans ($_{v,u}$ and $_{v,m}$ respectively):

$$\Delta_v = \mu_v \left[E_{v,u}[Y|v] - E_{v,m}[Y|v]\right]. \tag{3}$$

If unmatched veterans make more than matched ones, Δ_v is positive and adds to any veteran premium over non-veterans (or reduces a veteran wage penalty). Second, the effect that unmatched non-veterans have on the wage premium is Δ_{nv}, calculated by the probability of being unmatched μ_{nv} times the wage difference between matched and unmatched non-veterans ($_{nv,m}$ and $_{nv,u}$ respectively):

$$\Delta_{nv} = \mu_{nv} \left[E_{nv,m}[Y|nv] - E_{nv,u}[Y|nv]\right]. \tag{4}$$

If unmatched non-veterans make more than matched ones, $\Delta_{nv} < 0$ increases the wage penalty against veterans. For instance, if non-veterans work in high wage occupations that have no veterans, the overall wage penalty against veterans will be larger due to this lack of opportunity. The reverse effect may also occur when non-veterans work in low-paying occupations that veterans do not — an over-representation of non-veterans near the bottom of the wage distribution would make a veteran wage penalty smaller.

A third group must also be accounted for: veterans and non-veterans in the common support are referred as *matched veterans and non-veterans*. Δ_x yields the difference in the wage explained by veterans holding various characteristics at different relative frequencies than non-veterans. For example, a relatively high rate of both veterans and non-veterans work in a management occupation; however, this rate is larger for non-veterans. Δ_x is calculated as the difference between the expected wage of veterans with their actual distribution of characteristics ($_{v,m}$) versus what veterans would make if they had the characteristics distribution of non-veterans ($_{nv,m}$):

$$\Delta_x = E_{v,m}[Y|v] - E_{nv,m}[Y|v]. \tag{5}$$

If $\Delta_x < 0$, veterans experience a wage penalty because non-veterans hold certain characteristics that correlate with higher wages in higher rates than veterans (i.e. non-veterans having a higher proportion of managers or higher educational attainment).

Finally, veterans and non-veterans with exact characteristic matches may achieve different wage outcomes. This may be due to unobserved differences between the two, or it may be due to favoritism for the veteran or discrimination against the veteran. The difference in wages due to different outcomes for workers with similar characteristics is called the *unexplained gap*. Δ_0 shows the wage premium unexplained by characteristic differences — wage differences along similar characteristics. It is calculated by comparing expected veteran wages minus expected non-veteran wages over the non-veteran distribution of characteristics ($_{nv,m}$):

$$\Delta_0 = E_{nv,m}[Y|v] - E_{nv,m}[Y|nv]. \tag{6}$$

The four additive components in equation (2) correspond to portions of the BO decomposition. The explained portion of the BO-decomposed gap is $\Delta_v + \Delta_{nv} + \Delta_x$ and it explains how much of the gap is due to differences in observed and measured characteristics across workers. The unexplained portion of the BO-decomposed gap is interpreted here as Δ_0 and captures unobserved or unmeasured reasons for the wage gap. A Stata program coded by Atal et al. (2010) was used to implement Ñopo's algorithm. As before, ACS population weights are used in these calculations.

5. Results

Using the 2009–2013 ACS, we first decompose the wage gap for the full sample of workers and detail characteristic differences among veterans and non-veterans in and out of the common support. Then, we perform decompositions of the veteran wage gap for male, female, white, and black workers separately.

5.1. Distribution of characteristics for matched & unmatched workers

Understanding results of the Ñopo wage decomposition requires understanding how work-related characteristics are distributed differently 1) across veterans that match and do not match the non-veteran workforce and 2) across non-veterans that match and do not match the veteran workforce. In performing the Ñopo decomposition on the full sample of workers, the four groups are created and their characteristics are presented in Table 2, with the two matched groups in the common support and the unmatched groups out of the support. On average, unmatched veterans make roughly $2 per hour less than matched veterans, who in turn make $2 per hour less than matched non-veterans.

The four groups differ in a number of areas that likely influence earnings outcomes. Table 2 shows strong gender, racial, and educational differences across the four groups. In-support differences between matched veterans and non-veterans are particularly large across educational attainment with matched veterans having lower rates of having a bachelor's degree or higher education (29% vs. 44% for matched non-veterans). Differences between matched veterans and non-veterans are expected to affect the Δ_x gap. Additionally, unmatched veterans have a lower rate of Bachelor's degree completion and a higher proportion of black workers than the other groups. Unmatched veterans also have a lower marriage rate, a higher rate of being single, a higher children-under-5 rate, and a lower rate of having other workers in the family — each rate being associated with lower household incomes in general. One of the largest differences across the four groups is also likely associated with earnings outcomes — the disability prevalence of unmatched veterans is 14 percentage points higher than that of matched veterans, which is two points higher than matched non-veterans. Such differences are expected to affect the Δ_v portion of gap. Again, if these variables are left out of the matching criteria, their potential effects on wage differences will still be captured in the unexplained gap. By including them, the analysis will quantify to what extent they mediate the veteran wage gap.

Differences in how the groups are distributed across occupations likely also affect wage outcomes. Table 3 presents occupational distributions across the groups. Particularly large in-support differences include higher rates of matched non-veterans in management (+5pp), education (+3pp), and sales (+3pp) with matched veterans more highly concentrated in protective services (+9pp) and maintenance/repair occupations (+3pp). Unmatched veterans also have higher concentrations in these two occupations, a finding that likely highlights the particular focus veterans have on occupations related to skill sets developed during their military tenures. On the other hand, unmatched non-veterans are more concentrated in education, food preparation, cleaning/maintenance, personal care, and office administration and support — generally lower-paying occupations. A final difference relates to public-sector employment (as compared to private sector), where veterans are much more likely to be employed.

Table 2
Distribution of characteristics, matched and unmatched veterans and non-veterans, ages 25–40: Mean (SE).

Variable	Veteran		Non-veteran	
	Unmatched	Matched	Matched	Unmatched
Mean Hourly Wage ($)	22.23 (0.16)	24.06 (0.12)	26.32 (0.04)	23.48 (0.02)
Age (years)	31.22 (0.06)	31.43 (0.03)	32.19 (0.01)	32.67 (0.01)
Female (%)	19.14 (0.55)	14.69 (0.27)	24.48 (0.08)	55.20 (0.06)
White (%)	53.75 (0.70)	83.09 (0.30)	92.48 (0.05)	66.64 (0.06)
Black (%)	23.08 (0.61)	11.68 (0.26)	5.40 (0.05)	14.10 (0.05)
High School Only (%)	15.96 (0.52)	21.23 (0.31)	22.27 (0.08)	23.88 (0.06)
Some College (%)	40.17 (0.69)	38.00 (0.37)	26.64 (0.09)	21.37 (0.05)
Associate (%)	19.46 (0.56)	11.71 (0.24)	7.56 (0.05)	10.79 (0.04)
Bachelor (%)	16.11 (0.50)	21.10 (0.30)	31.63 (0.09)	27.80 (0.06)
More Than Bachelor (%)	8.30 (0.37)	7.96 (0.18)	11.91 (0.06)	16.17 (0.04)
Married (%)	53.85 (0.70)	60.11 (0.38)	67.38 (0.09)	52.51 (0.06)
Single (%)	15.40 (0.53)	13.14 (0.26)	11.06 (0.06)	11.98 (0.04)
Children Under 5 (%)	22.50 (0.58)	17.52 (0.28)	14.37 (0.06)	16.00 (0.05)
Children Under 17 (%)	22.76 (0.56)	18.20 (0.29)	19.45 (0.07)	25.16 (0.05)
Other Workers in Family (%)	43.34 (0.69)	54.98 (0.38)	64.11 (0.09)	54.49 (0.06)
Any Disability (%)	16.62 (0.50)	2.19 (0.11)	0.28 (0.01)	3.11 (0.02)
Observations	8338	29,192	440,849	1,011,687
Common Support	Out	In	In	Out

Groups sorted using the Ñopo algorithm. Matching criteria include gender, age (three-year categories), race, education, family variables, disability, region, 22 occupation categories, and employment in the public sector.

Table 3
Distribution of occupation & public-sector, matched and unmatched veterans and non-veterans.

Occupation group	Veteran		Non-veteran	
	Unmatched	Matched	Matched	Unmatched
Management	7.03 (0.35)	8.99 (0.21)	14.15 (0.07)	9.56 (0.04)
Business/Finance Operations	7.32 (0.38)	5.00 (0.16)	5.92 (0.04)	6.76 (0.03)
Computer/Math	6.19 (0.33)	5.22 (0.17)	4.31 (0.04)	4.34 (0.03)
Architect/Engineer	5.16 (0.31)	3.39 (0.13)	2.71 (0.03)	2.34 (0.02)
Sciences	2.03 (0.20)	0.61 (0.05)	0.37 (0.01)	1.71 (0.02)
Social Services	2.38 (0.21)	0.92 (0.07)	0.49 (0.01)	2.77 (0.02)
Legal	1.14 (0.14)	0.66 (0.05)	0.65 (0.01)	1.88 (0.02)
Education	4.36 (0.29)	2.13 (0.10)	5.93 (0.04)	7.81 (0.03)
Arts/Entertainment/Media	1.77 (0.18)	0.75 (0.06)	0.60 (0.01)	2.61 (0.02)
Healthcare Practitioners	6.05 (0.34)	5.36 (0.16)	7.11 (0.05)	6.75 (0.03)
Healthcare Support	2.55 (0.21)	1.17 (0.08)	0.81 (0.02)	3.12 (0.02)
Protective Service	10.24 (0.40)	13.04 (0.25)	4.15 (0.04)	2.17 (0.02)
Food Preparation	2.16 (0.21)	2.12 (0.12)	1.49 (0.03)	4.23 (0.03)
Cleaning/Maintenance	1.57 (0.18)	1.61 (0.10)	0.90 (0.02)	2.40 (0.02)
Personal Care	1.40 (0.16)	0.74 (0.07)	0.37 (0.01)	2.88 (0.02)
Sales	2.23 (0.20)	7.07 (0.19)	10.66 (0.06)	9.54 (0.04)
Office Admin/Support	9.70 (0.43)	10.77 (0.24)	12.19 (0.06)	14.19 (0.04)
Farming/Fishing/Forestry	0.54 (0.10)	0.21 (0.04)	0.08 (0.005)	0.52 (0.009)
Construction	3.41 (0.25)	6.15 (0.19)	7.00 (0.05)	3.46 (0.02)
Maintenance/Repair	12.73 (0.47)	9.15 (0.22)	5.98 (0.05)	2.35 (0.02)
Production	3.76 (0.26)	7.49 (0.20)	7.66 (0.05)	4.68 (0.03)
Transport/Moving	6.29 (0.32)	7.44 (0.21)	6.47 (0.05)	3.93 (0.03)
Work in Public Sector	60.70 (0.67)	20.51 (0.31)	5.25 (0.04)	5.50 (0.03)
Observations	8338	29,192	440,849	1,011,687
Common Support	Out	In	In	Out

Groups sorted using the Ñopo algorithm. Matching criteria include gender, age (three-year categories), race, education, family variables, disability, region, 22 occupation categories, and employment in the public sector.

5.2. Decomposing the veteran wage gap

Table 4 presents the total and decomposed veteran hourly-wage gap. Among all workers in the sample, veterans are paid 3% less than non-veterans on average, but this difference varies significantly across gender and race.

Column (1) presents the wage decomposition for the full sample. When matching workers by 22 occupation categories, in addition to other related characteristics, approximately 75% of veterans and 28% of non-veterans matched into the common support, corresponding to the breakdown presented above in Tables 2 and 3 The components Δ_v, Δ_{nv}, Δ_x, and Δ_0 sum to equal the overall gap Δ and represent percentage terms of the non-veteran wage. The first component $\Delta_v = -1.9\%$ suggests that unmatched veterans are paid less than matched veterans. This result is likely related to differences between veterans across educational attainment, disability prevalence, and public sector employment and occupational distribution.

The second component $\Delta_{nv} = 8.37\%$ indicates a large premium for matched non-veterans over unmatched non-veterans. Part of this relatively large premium occurs due to unmatched non-veterans being more represented by females (54% vs. 24% among matched nonveterans) working in lower-paying occupations described above (food preparation, office administration, etc.).

The final two components compare veterans and non-veterans within the common support. The third component $\Delta_x = -6.33\%$ shows that matched veterans hold relatively fewer wage-favorable characteristics than matched non-veterans, such as lower educational attainment and lower rates of work in higher-paying occupations. Were veterans to hold these characteristics at the same rates as non-veterans, the veteran penalty would decrease by 6.33%. However, $\Delta_0 = -2.95\%$ suggests that a penalty would remain even if veterans shared the same distribution of characteristics as non-veterans. This Δ_0 gap represents the unexplained gap, suggesting that potential discrimination against veterans or other unobserved phenomena serves to widen the pay penalty against them.

The lower half of Column (1) shows results from a second decomposition modifying the matching criteria X to use specific occupation codes (499 in total), rather than 22 categories. As the second decomposition uses more specific occupation codes, the size of the common support is reduced; although over 15,000 veterans found a characteristic match with some 100,000 non-veterans. Two effects should be noted by this change in specification. First, Δ_{nv} increases to 12.51%, further suggesting that unmatched non-veterans work in many specific occupations that pay low wages. Second, the unexplained Δ_0 gap also increases to -5.23% — returns in specific, shared occupations favor non-veterans for unobserved reasons. However, this portion of the gap remains relatively small compared to what is explained by observables in the data.

Table 4
Decomposed veterans hourly wage gap: Fully employed persons, age 25–40.[a]

	(1) All	(2) Male	(3) Female	(4) White	(5) Black
Mean Hourly Wages					
Veteran (V) ($/hr)	23.61	23.81	22.53	24.11	21.16
Non-Veteran (NV) ($/hr)	24.29	26.21	22.08	24.65	19.76
Δ = Raw Veteran Gap (% of NV)	−2.80 (0.411)***	−9.15 (0.422)***	2.07 (1.085)	−2.19 (0.466)***	7.10 (1.293)***
Decomposed Gap[b] (%)					
Matched by 22 Occupation Groups					
Δ_v = Unmatched - Matched V	−1.90	−1.61	−2.68	−1.35	0.46
Δ_{nv} = Matched - Unmatched NV	8.37	4.00	6.16	8.06	−3.64
Δ_x = Matched: V-NV	−6.33	−7.93	−1.43	−5.68	5.07
Δ_0 = Unexplained: V-NV	−2.95 (0.131)***	−3.62 (0.149)***	0.02 (0.222)	−3.22 (0.134)***	5.21 (0.508)***
% V who match a NV[c]	74.94	75.94	69.65	82.22	60.22
% NV who match a V	28.43	40.11	14.98	35.54	13.20
Matched by Specific Occupation					
Δ_v = Unmatched - Matched V	−3.61	−3.39	−2.76	−3.06	6.60
Δ_{nv} = Matched - Unmatched NV	12.51	6.62	13.63	11.60	−4.36
Δ_x = Matched: V-NV	−6.47	−7.36	−3.86	−5.58	5.42
Δ_0 = Unexplained: V-NV	−5.23 (0.285)***	−5.03 (0.314)***	−4.94 (0.528)***	−5.15 (0.286)***	−0.55 (1.145)
% V who match a NV	47.23	48.42	40.86	54.74	29.76
% NV who match a V	7.60	11.13	3.54	9.65	2.89
V Sample	37,530	31,761	5769	29,668	4308
NV Sample	1,452,536	768,239	684,297	1,124,729	132,933

*$p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
[a] Results of Ñopo matching wage gap decomposition of Veteran (V) - Non-veteran (NV) hourly wages. Standard errors of total and unexplained gaps are reported in parentheses.
[b] The sum of Δ_v, Δ_{nv}, Δ_x, and Δ_0 equal the raw Veteran gap.
[c] Common support indicates the percentage of Veterans (Non-Veterans) who have an exact match with a corresponding Non-Veteran (Veteran), according to the following characteristics: gender, age (three-year categories), race, education, family variables, disability, region, occupation, and work in the public sector.

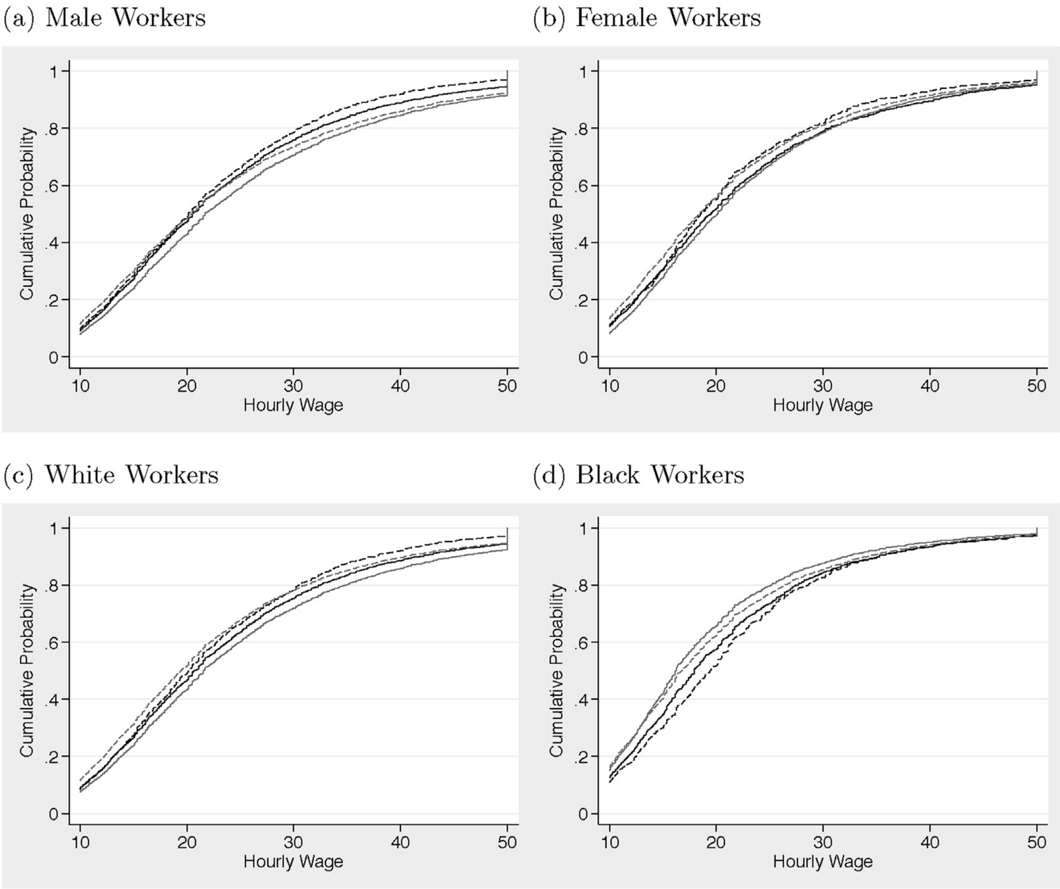
5.3. Decompositions by gender and race

Columns 2–5 of Table 4 show how the veteran wage gap decomposes for male, female, white, and black subgroups respectively. A large veteran wage penalty exists among male workers — the mean hourly wage for veterans is 9% less than the hourly wage of non-veterans. The part of the penalty not attributable to characteristic differences (Δ_0) is lower, at −3% to −5%, depending on the specification. Female veterans however, experience a 2% premium over non-veterans, although this is not statistically different from zero due to a large standard error. The unexplained gap for female veterans (Δ_0) is 0 in the first specification but rises to −5% in the second; again, smaller than the explained portion of the gap.

The source of the wage penalty/premium differs across gender. In-support differences ($\Delta_0 + \Delta_x = -11.55\%$) drive most of the male penalty, and disfavors veterans. This suggests that male veterans compete with more of the non-veteran workforce (40% of non-veterans are matched) and experience relatively worse outcomes. However, out-of-the-support differences ($\Delta_v + \Delta_{nv}$) combine to explain most of the female premium, favoring veterans. Female veterans simply do not compete with a large section of the rest of the female workforce (85% unmatched), serving to increase the female premium ($\Delta_{nv} > 0$) and again suggesting a lack of veterans in lower-paying occupations — true among both males and females, but a stronger effect for the latter.

Racial segmentation of the analysis reveals further differences in the gap — white veterans experience a penalty of 2% while black veterans see a premium of 7% over black non-veterans. While the decomposition of the wage gap experienced by white veterans tracks similarly to the overall sample (as it is three-quarters white), the analysis of black workers shows a number of differences. First, in-support differences ($\Delta_0 + \Delta_x > 0$) result in a 5%–10% premium for black veterans, compared a 9%–11% penalty for white veterans. Among black workers, veterans hold relatively more of the characteristics associated with higher wages than non-veterans. Second, $\Delta_v > 0$ adds to the premium for black workers, suggesting unmatched black veterans do relatively well; unlike the experience of white veterans.

A graphical analysis of the matched and unmatched groups in Fig. 4 provide additional insights as to the sources of the overall veteran wage gaps. Panel 4a shows that among males, both matched and unmatched veterans have slightly higher wages than unmatched non-veterans along the bottom two quintiles. However, much of the in-support penalty occurs in the top half of the earnings distribution, where the CDFs between matched veterans and matched non-veterans widen (the solid black and gray lines, respectively). Unmatched veterans also see large pay penalties compared to other groups in the top quintile. The CDFs for female workers in Panel 4b gives further evidence of veterans having less representation in lower-paying jobs, as unmatched non-veterans again show lower earnings throughout the bottom half of the distribution. Finally, Panel 4d reflects the strong wage outcomes that black veterans experience compared to black non-veterans. Veterans see relatively large wage premiums across the bottom 90% of the distribution, especially favoring unmatched veterans.



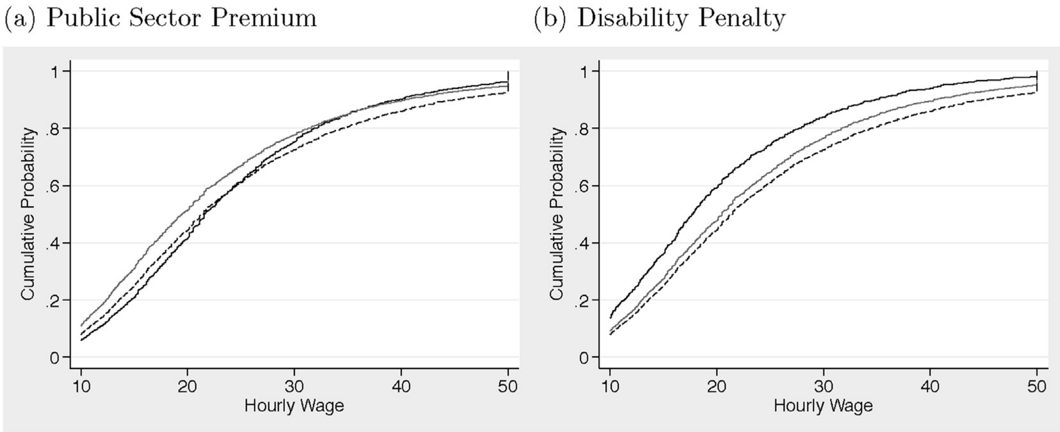
Dashed black line represents unmatched veterans; solid black line represents matched veterans; solid gray line represents matched non-veterans; and dashed gray line represents unmatched non-veterans. Top wages are censored at $50/hour in this figure for clarity.

Fig. 4. Cumulative Distribution of Hourly Wages, Matched and Unmatched Veterans and Non-Veterans. Dashed black line represents unmatched veterans; solid black line represents matched veterans; solid gray line represents matched non-veterans; and dashed gray line represents unmatched non-veterans. Top wages are censored at $50/hour in this figure for clarity.

5.4. Disability & public sector work

Unmatched veterans have much higher rates of public-sector employment and disability, with different effects on the veteran gap. Fig. 5a illustrates how veterans who work in the public sector experience a wage premium for the bottom four quintiles of the earnings distribution, which disproportionately helps unmatched veterans (61% of unmatched and 21% of matched veterans work in the public sector). Below the median earner, veterans in the public sector have higher wages than matched non-veterans at a given percentile. On the other hand, having a disability associates with a large wage penalty across the distribution, in Fig. 5b. This also penalizes unmatched veterans disproportionately, as 17% of unmatched veterans report a disability compared to only 2% of matched veterans.

The results presented above are robust to changes in the matching criteria and sample. A number of checks were performed, with minimal effects on these results. First, the age range was extended to include workers between 40 and 50 years to see if veterans caught up after a longer-time in the workforce; however, white and male veterans penalties remained while female and black premiums grew slightly. Second, five-year age categories were tried in place of three-year ones to allow for a wider age range in matching (i.e. veterans who finish service and attend college likely enter the workforce at a later age). Again, this only had minor effects on estimations. Third, a different comparison group was used, including pre-2001 veterans with the non-veteran sample; however, the decomposition results were essentially unchanged.



Black lines represents veterans working in the public sector (left panel) or having a disability (right panel). Gray lines represent working in the private sector (left panel) or having no disability (right panel). The dashed-gray line represents matched veterans for comparison.

Fig. 5. Veteran-Only Cumulative Distribution of Hourly Wages, by Public/Private Sector and Disability Status. Black lines represents veterans working in the public sector (left panel) or having a disability (right panel). Gray lines represent working in the private sector (left panel) or having no disability (right panel). The dashed-gray line represents matched veterans for comparison.

6. Conclusions & discussion

6.1. Conclusions

Although veterans and non-veterans earn a similar wage at the mean, this analysis uncovers substantial gaps that differ 1) by race and gender; 2) at the bottom of the wage distribution compared to the top of the distribution; and, 3) by workers in and out of the common support, the part of the sample where veterans and non-veterans overlap in their characteristics and occupations. Female and black veterans experience a premium in wages over their non-veteran counterparts. This veteran premium begins at the bottom of the wage distribution and continues until the top quintile. Male veterans, on the other hand, experience a wage penalty, largely at the top of the distribution. Much of these differences are due to occupational selection effects — female and black veterans work in higher-paying occupations at higher rates than female and black non-veterans respectively, whereas male veterans have less representation in high-paying occupations compared to other males.

To highlight how differences occur at the tails of the distribution — where veteran workers see very different earnings than non-veteran workers — we use Ñopo's (2008) method of decomposition by worker matching. Veterans are compared to non-veterans and grouped by exact combination matches of the following characteristics: gender, race, education category, three-year age categories, region, disability status, family characteristics, occupation, and public-sector employment. While other decomposition models assume that the workers being compared lie along a similar distribution of work-related characteristics, the method utilized here shows the effect that unmatched veterans and non-veterans (i.e. those out of the common support) have on the overall wage gap/premium, in addition to the effect of those who match one another. While recent studies have found either no difference or a veteran premium (Kleykamp, 2013; Humensky et al., 2013b; Tennant, 2012), the use of matching methods and a large data source allows for additional controls and highlights how various aspects of the wage gap can move in opposing directions, having large effects on individuals but canceling out on average.

For the entire sample, we find a veteran hourly wage penalty of 2.8%. The decomposition of the gap illustrates the different situations faced by veteran workers. First, unmatched veterans do somewhat worse than matched ones, adding 1.90% to the overall penalty. This group of veterans has rates of characteristics that have been associated with lower wages, namely higher disability (16% vs. 2% for matched veterans or non-veterans overall) and lower rates of undergraduate and graduate degree attainment (24% vs. 29% for matched veterans vs. 43% for non-veterans overall). This finding of lower wages to unmatched veterans is in line with previous research. Recent work by Meyer and Mok (2013) found that disability was associated with large earnings declines, while Tamborini et al. (2015) found consistently positive effects of higher education on earnings. However, many unmatched veterans work in the public sector. While previous studies suggest that these workers experience a penalty at the mean (Walker, 2010), Fig. 5a shows that public sector work serves to reduce the pay penalty for veterans along the lower half of the earnings distribution; although it pays less than the private sector among the top quintile of earners.

Second, the veteran gap/premium is largely influenced by unmatched non-veterans — they are paid less than matched non-veterans and veterans on average, primarily due to relatively low-wage, female-dominated occupations that have few veteran workers. While the effects of occupational sex segregation on male-female pay gaps are well established (Mani, 2013;

O'Neill, 2003; Macpherson and Hirsch, 1995; Petersen and Morgan, 1995), similar effects of occupation selection by veterans have received less recent focus. As shown in Fig. 3b, female veterans are more highly distributed than female non-veterans in several occupations that pay at or above the female median: health practitioners, protective services, and computer/math. Alternatively, they are less distributed in relatively low-paying sales, education, food preparation, cleaning, and personal care occupations. Fig. 4b highlights how female veterans fare better than unmatched non-veterans in the bottom half of the earning distribution.

Third, matched veterans and non-veterans do not have the same distribution of characteristics, serving to increase the veteran penalty among males by 7%–8% (Δ_x). Matched veterans have lower educational attainment (29%–43%) and lower rates of being in management positions (9%–14%), compared to matched non-veterans.

Finally, we find that the unexplained gap Δ_0 serves to increase the veteran pay penalty by 3%–5% overall. This unexplained piece represents the effect that unobserved factors have on the overall pay gap. While this specifically hurts white veterans (compared to non-veterans), there is a 5% unexplained premium for the black veterans. Overall, however, more of the wage gap is explained by differences in observed characteristics than remains unexplained.

6.2. Discussion

The results of this study need to be discussed in the context of previous research on veterans. First, estimates of the adjusted wage gap differ from other recent studies on post-2001 veterans. Here, the unexplained gap estimate Δ_0 is comparable to β estimates of veteran coefficients in wage regression models. The penalty of 3%–5% against veterans stands in contrast to previous findings by Kleykamp (2013), who estimated an adjusted veteran premium of 6% (p. 845). This difference may be due to a number of factors. First, linear models that do not compensate for unmatched workers tend to overestimate coefficients of veteran effects on earnings (Gevrek and Seiberlich, 2014; Mussa, 2014; Ñopo, 2008). In our findings, negative estimates of Δ_0 are offset by a positive out-of-the support effect $\Delta_v + \Delta_{nv}$ that ranges from 6% to 8% for all veterans. In other words, linear regression would potentially interpret out-of-support differences simply as veteran/non-veteran ones, transferring these positive effects to the veteran coefficient. Second, with the larger sample size, we can control for more specific occupational categories. The broader occupational and industry categories used in Kleykamp possibly miss the effects of occupational segregation — effects that would be captured by the veteran coefficient, leading to overestimation. Third, Kleykamp (2013) does not correct for potential selection bias into employment. As Kleykamp finds higher unemployment among veterans, those who do have jobs likely have higher skill sets, potentially biasing their estimates of the veteran premium upward. Direct matching techniques do not require this additional adjustment since potential effects are captured by the unexplained gap (Staneva and Arabsheibani, 2014; Nicodemo and Ramos, 2012). Interestingly in our sample, the predicted probability of full-time employment is nearly the same for veterans and non-veterans, so selection-into-employment effects are likely small. Fourth, the current study does not include those with less than high school education since the military rarely accepts this group. As found in Kleykamp, much of the veteran premium is generated by this group. Finally, the inclusion of disability here, which is more prevalent among veterans, is not controlled for in Kleykamp's study. In those estimates, the inclusion of disability might serve to increase the estimated veteran premium, all else held constant. However, the differences in sample, methodology, and occupational coding used by the two studies will likely affect how the role of disability is estimated in different ways.

Second, differences in the veteran gap by race are consistent with previous findings. Black veterans earn more than black non-veterans, due to characteristic differences between them (i.e. better educational attainment; higher proportion working in higher-paying occupations than non-veterans). However, white veterans do worse for some of the same reasons. In studying Vietnam-era veterans, Angrist (1990) found that white veterans who were drafted into the military earned approximately 15% less than comparable non-veterans over their lifetimes; whereas, black draftees earned similar pay to black non-veterans. Browning et al. (1973) similarly found a veteran wage penalty for white workers but a premium for both black and Mexican American workers. The authors presented the idea of a "bridging environment" to explain these effects. For minorities that generally experience worse earnings outcomes than white workers, military experience may provide skills and education that are not be easily attainable otherwise. Angrist (1991) found that non-whites were more likely to voluntarily enlist into military service as it offered an attractive alternative to a civilian career. Sampson and Laub (1996) presented evidence that World War II military experience provided a large opportunity for men coming from economically disadvantaged backgrounds to enhance their economic outcomes due to the military on the job training. Likewise, Xie (1992) provided further empirical evidence of a veteran premium among socially disadvantaged groups and argued that the premium was related to both military service acting as a bridging environment and veteran status acting as a positive effect on employer screening. Our findings that veterans earn more than unmatched non-veterans along the lower two quintiles of earnings, for both males and females, suggests positive effects of military service for lower-wage workers.

Third, previous veteran research may provide clues behind the mechanism driving the unexplained gap, which adds to the penalty against white veterans and the premium for black veterans. Gender wage gap studies commonly suggest the unexplained gap is due to discrimination, which is difficult to observe in the data. Some veterans may either experience or perceive stigma associated with mental health problems, creating barriers to seeking or participating in treatments (Ben-Zeev et al., 2012; Vogt, 2011). In general, persons with severe psychiatric disorder have been found to earn lower wages than others (Vick et al., 2012). Conversely, "positive" discrimination could be indicated in the unexplained gap via veteran preference policies or more general employer screening, suggested by Xie (1992). Another possibility is that "selection at entry effects" creep into the unexplained gap (Nicodemo and Ramos, 2012; Bojilov, 2014) — veteran preference may entice veterans to enter the workforce with less experience than non-veteran counterparts and capture fewer returns over time. Veterans who are relatively less qualified than a similar non-veteran may enter into a given civilian occupation but not advance as much in the career as the similar non-veteran. Previous studies on veterans highlight that veterans may be behind non-veterans of the same age, especially in occupations where earnings are tied to seniority or on-the-job training (Cutright, 1974). Lewis (2013) found that veterans hired in the civil service tended to be older, less educated and less likely to advance as far as non-veteran hires. These findings together suggest a possible job ladder for public-sector veterans that consists of a higher floor but a lower ceiling, emphasized in Fig. 5a. Outcomes related to government preference for veterans need further study — over 30% of veterans work in public administration compared to less than 6% of non-veterans.

Furthermore, the unexplained gap may be capturing unobserved qualities that: 1) are found in an individual before he or she chooses to enter the military; 2) affect the decision to enter the military; and, 3) would also affect earnings even if the individual did not enter the military. These qualities may be correlated with positive wage outcomes in the civilian workforce — a skill for solving problems in high-stress situations or the grit to overcome difficult obstacles — and lead to greater success in both civilian and military environments. Or they could be negatively correlated with wage outcomes — growing up in a socially disadvantaged areas has been correlated both with entering the military (Angrist, 1991; Sampson and Laub, 1996; Kleykamp, 2006) and persistent poverty (Curtis et al., 2013). The inability to account for this selection-into-military effect on later earnings is a limitation of the current study. However, findings suggest that most of the veteran pay gap arises due to observed, indirect effects (i.e. the intermediate role of education and occupation, captured by $\Delta_v + \Delta_{nv} + \Delta_x$) as opposed to unexplained, direct effects of military service Δ_0. Potential selection-into-military bias would reduce the unexplained gap were it accounted for and would be small relative to observed effects.

Other potential problems related to selection effects were addressed in the paper. First, veterans were not more or less likely to be in full-time employment, thus wage differences are not likely biased by unobserved selection into employment. Second, veterans do select into certain occupations and into the public sector. One strength of the Ñopo (2008) method is that it actually pinpoints and segments areas where selection may occur. Occupational and public-sector selection is detected by the Δ_v and Δ_{nv} gaps.

Further research should seek to analyze how different MOS translates to civilian employment and earnings outcomes for recent veterans. While combat-arms skill sets may lead to an occupation in protective services, specific pay varies widely. For instance, work in the police force (the single occupation with the most veterans) generally earns at or above the median wage, close to $27 per hour; work as a security guard (with the second most veterans) earns much less at $19 per hour. Additionally, research can investigate the effects of factors possibly driving the unexplained gap — discrimination, stigma, skill/grit, and screening. These phenomena could be better understood through qualitative research on how employers view military experience across ethnicity and gender.

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