SEMPER FIDELIS: ON THE MATERIAL WELL-BEING OF VETERANS

by

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ABSTRACT

JAMES FULLER. Semper Fidelis: On the Material Well-Being of Veterans. (Under the direction of DR. KELLY VOSTERS)

The material well-being of veterans and their families is an important, policy-relevant topic. I research this topic through two crucial measures. In Chapters 1 and 2, I focus on wages, and in Chapter 3, I focus on poverty. In Chapter 1, I estimate the effect of veteran status on unconditional quantiles of wages for males across the period 1979-2017. I show there are important changes to the veteran wage differential over time across the entire wage distribution. In earlier periods, veterans enjoyed wage premiums across the entire wage distribution. Beginning in the early 1990s, wage premiums systematically declined across the wage distribution and largely became slight wage penalties across the wage distribution. Starting around 1997 and going forward, a pattern emerged showing that veterans at the low end of the wage distribution experience wage premiums of around 2% to 4%, whereas veterans at the upper end of the wage distribution experience wage penalties of around 4%. I then conduct wage decompositions of these differentials at both the beginning and end of the period of study. The results show that veterans in more recent times have had their wage premiums reduced or are now earning wage penalties compared to nonveterans. The primary reason for this is that more recent veterans have less favorable compositional differences as compared to nonveterans, especially in the upper-end of the wage distribution. Whereas veterans in the past maintained an advantage in characteristics the labor market valued throughout the wage distribution.

In Chapter 2, I examine the effect of potential non-random selection into employment on the female veteran-nonveteran median wage gap over the period 2006-2021. I find no evidence

that selection is contaminating estimates of the female veteran-nonveteran median wage gap over this period.

In Chapter 3, I estimate both the effect of veteran status on households' likelihood of poverty and deep poverty and the effect of service-connected disability on veteran households' likelihood of poverty and deep poverty. I construct two measures of service-connected disability. First, I construct an indicator for whether a veteran household has any service-connected disability. Next, I construct a categorical measure of the severity of service-connected disability. The latter allows me to test whether service-connected disability has heterogeneous effects depending on its severity. I estimate these effects over the period 2009-2019. The results are consistent with prior literature, indicating that veteran households have a much lower likelihood of poverty as compared to nonveteran households in all periods. Generally, veteran households enjoy a 1.7 to 3.3 percentage point lower likelihood of poverty depending on the year. This advantage does not transfer to the likelihood of deep poverty. Among impoverished households, veteran households generally maintain around a 2 percentage point higher likelihood of being in deep poverty. Veteran households with the presence of service-connected disability have a lower likelihood of poverty by 2 to 2.5 percentage points as compared to veteran households with no service-connected disability, depending on the year. A different pattern emerges for deep poverty. Among impoverished veteran households, those with the presence of service-connected disability have around a 4 percentage point higher likelihood of poverty. This effect is consistent across the period of study. I also find evidence for heterogeneity in the effect of service-connected disability on the likelihood of poverty and deep poverty. There is a strong pattern whereby as the severity of service-connected disability increases, the likelihood of poverty among veteran households declines. The most severe category of service-connected disability is associated with a consistent reduction in poverty by around 3 to 4 percentage points (depending on the year) as compared to veteran households with no service-connected disability or a rating of 0%. Veteran households in the second most severe category analogously experience around a 2 to 3 percentage point reduction in poverty. Veteran households in the second lowest severity category analogously experience around a 1 to 2 percentage point reduction in poverty.

ACKNOWLEDGEMENTS

I am deeply grateful to my dissertation chair, Dr. Kelly Vosters, whose guidance and instruction have been indispensable. Her constant support and expertise have not only shaped this dissertation academically but have also left a profound impact on me personally. I aspire to emulate her professionalism and precision in my future endeavors.

I extend my sincere appreciation to the other members of my committee who have generously shared their time and provided invaluable insights. Dr. Suzanne Leland's open-door policy fostered numerous enlightening discussions, enriching my understanding of the subject matter. Dr. John Szmer's guidance on research methodologies has proved invaluable, and he challenged me to approach limitations in research designs with greater scrutiny. I am indebted to Dr. Sara Amadon for the opportunities to collaborate on significant research projects, which have honed my research skills. Dr. John Stogner's insightful comments have played a pivotal role in refining the content of this dissertation.

Lastly, I express my deepest gratitude to my family for their unwavering support and understanding throughout this endeavor. Their sacrifices and encouragement have been the cornerstone of my success.

DEDICATION

This dissertation is dedicated to veterans, service members, and their resilient families. May we, inspired by their selflessness and sacrifice, strive to lead lives in the service of others. Semper Fidelis.

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LIST OF ABBREVIATIONS

CPS An acronym for Current Population Survey.

MORG An acronym for merged outgoing rotation group files.

UQR An acronym for unconditional quantile regression.

AVF An acronym for all-volunteer force.

ACS An acronym for American Community Survey.

IPUMS An acronym for integrated public-use micro dataset.

SCD An acronym for service-connected disability.

VA An acronym for Department of Veterans Affairs.

PTSD An acronym for post-traumatic stress disorder.

RIF An acronym for recentered influence function.

OPM An acronym for official poverty measure.

SPM An acronym for supplemental poverty measure.

SNAP An acronym for Supplemental Nutrition Assistance Program.

WIC An acronym for Women, Infants, and Children’s Program.

SSDI An acronym for Social Security Disability Insurance.

SIPP An acronym for Survey of Income and Program Participation.

AME An acronym for average marginal effect.

INTRODUCTION

Veterans are a large, diverse, and policy-relevant group. They face unique problems yet also have unique access to support to help overcome some of these problems. Veterans receive specialized training and skills while in-service that may also aid them once they transition to civilian life, yet they often struggle with this transition. Much research seeks to understand how veterans are faring given the uniqueness of their experience coupled with the fact that society bears the responsibility of caring for this group in exchange for their service.

I add to this research by examining common measures of material well-being, comparing veterans and their families to nonveterans. In Chapters 1 and 2, I consider wages, and in Chapter 3, I turn to poverty. In all three chapters, I compare veterans to nonveterans to assess how well veterans are faring in these critical measures of material well-being. Specifically, in Chapter 1, I estimate veteran-nonveteran wage differentials across the wage distribution and assess temporal heterogeneity for the period 1979-2017. Both for a period at the beginning and at the end of my sample timeframe, I decompose the wage gap across deciles of the unconditional wage distribution. This allows me to assess whether changes in the compositional or structure effect account for differences in wage gaps over time. In Chapter 2, I estimate the effect of potential non-random selection into employment on the female veteran-nonveteran median wage gap. In Chapter 3, I assess the effect of veteran status and service-connected disability on the likelihood a household experiences poverty and deep poverty.

Together, the three chapters provide evidence suggesting that veterans and their families experience much heterogeneity in important material well-being outcomes. I show that public policy has played a substantial role in aiding veterans. Importantly, my findings also indicate that there is still a role for public policy in improving veteran outcomes in the future.

CHAPTER 1

1.1 Statement of Problem

Wages play a vital role in helping people obtain higher levels of consumption and, in turn, well-being. The importance of wages is difficult to overstate, and it is not hard to imagine why researching the extent and causes of wage differentials is important. Hence, like other groups of interest, there exists substantial literature comparing the wages of veterans to nonveterans.

Studying veteran wage differentials differs from studying, say, gender-based wage gaps, as veteran wages are in part influenced by human capital accumulation specific to their military service. Berger and Hirsch (1985) point to this as a determinant of a (potential) veteran wage premium. Referred to as the “bridging hypothesis,” the idea is that military service acts as a way for those with lower levels of human capital to recover some of this deficit by creating a “bridge” for them to reach higher levels of human capital without pursuing formal education. The bridging hypothesis is consistent with observing a veteran premium at the lower end of the wage distribution, with no implied differentials for higher-wage workers.

On the other hand, there are several reasons to believe veterans might suffer a wage penalty. It may be that veterans are discriminated against in the workplace, that their military service displaced valuable educational attainment, or precluded important firm- or job-specific experience accumulation in the workplace. These scenarios would lead to a negative effect of veteran status on wages, potentially at any point in the wage distribution.

Taken together, the aforementioned mechanisms suggest that veteran status may have heterogeneous effects across the distribution of wages, with the possibility of wage penalties for some and wage premiums for others. There is, in fact, evidence of such heterogeneous effects for all-volunteer force veterans (Renna & Weinstein, 2019). Knowing where (and how) along the distribution of veteran status is affecting wages, even descriptively, has important implications for wage inequality, the general well-being of veterans, and associated policy design. Therefore, this chapter estimates the effect of veteran status on wages across different points in the distribution of wages.

Not only might veterans experience differing returns depending on where they are located in the wage distribution, but these returns may have changed over time as well. Such variation over time could arise from changes in the composition of the veteran population or how society views—and ultimately treats—veterans. In fact, there is some evidence of this in the existing literature. WWII veterans have been shown to earn a wage premium (Teachman & Tedrow, 2004), with larger premiums for less educated veterans. Vietnam veterans, on the other hand, have been shown to suffer wage penalties (Bryant, 1993). The evidence for more recent veterans – the all-volunteer force – suggests a wage premium (MacLean, 2013). MacLean and Kleykamp (2016) assessed trends in the effect of veteran status (pooling all generations of veterans) on wages and demonstrated that the veteran wage premium has varied over time. In the late 1970s through around 1990, veterans maintained a wage premium. However, the premium eroded and turned negative in the 1990s. The veteran wage premium returned in the early 2000s and continues to the present, although the premium is not as large as it was in the 1970s and 1980s.

Therefore, the literature contains some evidence that veterans may experience different returns to their military service across time, reflecting in part compositional changes driven by things like the draft vs. the all-volunteer force but also potential differences in the way society—and, therefore, the labor market—views veterans.

Chapter 1 examines trends over time in male veteran differentials throughout the wage distribution. I use the Current Population Survey (CPS) Merged Outgoing Rotation Group (MORG) Earnings Data from 1979 to 2017 to see how the effect of veteran status on wages has changed over time. To produce estimates that capture the heterogeneity in the effect across the entire wage distribution, I perform unconditional quantile regressions (UQR) across every decile of the wage distribution. Finally, I decompose observed differences in wages at each decile along the unconditional wage distribution for both an early period (1979-1983) and a late period (2013-2017) to examine how factors contributing to the observed wage gaps have changed over time.

1.2 Review of the Literature

Wage Differentials Over Time

As the first study to explicitly study trends in the veteran-nonveteran wage differential over time, MacLean and Kleykamp (2016) found evidence of temporal variation in the effect of veteran status on both the mean and variance of wages. They produced both estimates for every year of data between the years 1979-2013 and plotted the results to assess trends. Their takeaway was that it seems as though the veteran premium has eroded as time progressed and that, like other groups, veterans have experienced increasing within-group inequality over time.

Most of the existing evidence on how veteran wage differentials have evolved over time comes from a succession of studies, with many focusing on a given era of Veterans (e.g., WWII veterans) and using distinct econometric approaches.

WWII Veterans

There is substantial evidence suggesting that World War II veterans earned a wage premium and obtained more education (that could have led to wage premiums). Bound and

Turner (2002) exploited arguable exogenous variation in military service due to differing probabilities of being drafted across birth cohorts. They found that veterans went on to receive more education than nonveterans, likely as a result of using G.I. Bill benefits. Education has been causally linked to higher wages, among other positive benefits. Angrist and Krueger (1994) also use timing-of-birth-related variation in the probability of getting drafted to obtain an arguably causal estimate of the effect of World War II service on average wages for World War II veterans.[1] Despite the increased educational attainment finding of Bound and Turner (2002), Angrist and Krueger (1994) find an effect near zero for these veterans (i.e., veterans do not make more than nonveterans).

However, Teachman and Tedrow (2004) argued that most men did serve during World War II and that health was the most likely systematic difference between those who served and those who did not. Specifically, veterans should be healthier on average, even later in life; this relationship held true in their data. Controlling for many factors—including health—they find veterans received more education, obtained higher-status occupations, and earned higher wages than nonveterans. Gabriel (2017) also found some evidence that World War II veterans fared well in the labor market, although Gabriel's estimates are also not causal.[2]

Overall, there is substantial evidence that World War II veterans did well in terms of material well-being. They obtained more education (Teachman & Tedrow, 2004; Bound & Turner, 2002) and earned wages at least as high as those of nonveterans (MacLean & Kleykamp,

[1] Angrist and Krueger (1994) used quarter of birth as an instrumental variable and argued that quarter of birth should be largely uncorrelated with wages but was correlated with the probability of being drafted. Because the way the government issued numbers to potential service members, during certain time periods, being born earlier in the year was associated with a higher likelihood of being drafted.

[2] Gabriel uses 1960, 1970, and 1980 Decennial Census data and estimated wage equations by Ordinary Least Squares (OLS). Gabriel then used the coefficients to perform a decomposition of the observed wage gap, demonstrating that WWII veterans from 1960—1980 did tend to make higher wages than nonveterans on average, not causal but net of many confounding factors and that the wage gap between veterans and nonveterans was largely due to veterans having a more favorable distribution of characteristics that lead them to receive higher wages.

2016; Angrist & Krueger, 1994; Gabriel, 2017). The veteran wage premium estimates range from near zero (Angrist & Kruger, 1994) to 5-percentage points (Teachman & Tedrow, 2004; Gabriel, 2017).

Vietnam Veterans

The literature seems to point to a different outcome for Vietnam veterans. Angrist (1990) found Vietnam veterans suffered a large wage penalty of around 15%.[3] Similarly, Angrist et al. (2011) extended Angrist's (1990) analyses and researched the long-run effect of Vietnam-era military service on wages. Again, using draft lottery numbers as an instrument for military service, they found that early in their career, veterans suffered a substantial wage penalty but that, over time, this penalty disappeared. Similarly, Bryant et al. (1993) argued that Vietnam veterans suffered wage penalties compared to their non-veteran peers, at least upon their return and subsequent re-entry into the labor market.

AVF Veterans

The US made its last draft call in 1972 and has not needed a draft to meet its demand for national security since then, thus with subsequent veterans comprising the so-called "All Volunteer Force" (AVF). Unlike the WWII and Vietnam veteran wage literature, there exists no credible instrument for military service, so the more recent literature estimates descriptive wage differentials.

MacLean (2013) compared Post 9/11[4] veterans' wages to nonveterans' wages, demonstrating that veterans with less education may have earned a wage premium over their

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[3] Angrist (1990) identified the effect of veteran status on wages using the draft lottery as an instrument for military service.
[4] Post 9/11 veterans are veterans who served any time after September 11th, 2001.

nonveteran counterparts but that veterans with more education may not have earned a premium.[5] Additionally, the veteran effect seemed to differ by race, with Hispanic veterans earning the largest premium, followed by Black veterans, and then White veterans. Nonetheless, the study has important limitations. Top-coding wages and using data from a short time period likely limits inferences about veteran wages and their trends.

Distributional Heterogeneity in Wage Gaps

One study has examined veteran wage differentials across the unconditional wage distribution, although only for a subset of veterans (Post 9/11 veterans) and found evidence of heterogeneous effects of veteran status on wages. Renna and Weinstein (2019) found wage premiums (as high as 8%) in favor of veterans at the bottom part of the wage distribution but with wage penalties against veterans in the top part of the wage distribution. This would not be detected in studies that estimate the wage differential at the mean—and would likely lead to almost no wage gap—because the premiums and penalties observed for veterans across all points in the wage distribution would essentially be averaged together. Renna and Weinstein (2019) illustrate this point, with a mean gap around zero or slightly negative for White male veterans, although in reality, there are many veterans earning far less/more than their nonveteran counterparts than the mean wage gap would suggest. Critically, their research demonstrates that assessing veteran wage gaps at the mean alone misses important differences at other points along the wage distribution.

Makridis and Hirsch (2021) and Vick and Fontanella (2017), both with samples of veterans from more recent years, similarly found evidence of heterogeneity in the effect of veteran status on wages across the distribution of wages and by important subgroups like race

[5] MacLean (2013) also used the CPS MORG files, pooling over 2005-2011, to estimate wage equations with sets of interaction terms between veteran status and indicators of education and race/ethnicity.

and sex. Makridis and Hirsch (2021) found that the most educated veterans (both male and female) earn less than their nonveteran counterparts. However, veterans lacking a college degree earned a slight wage premium. Vick and Fontanella (2017) found that, among fully employed Post 9/11 veterans between the ages of 25-40, veterans made 3% less than nonveterans on average. Additionally, there was heterogeneity by race and across the wage distribution, with female and Black male veterans earning premiums, on average, and male veterans at the top end of the wage distribution suffering wage penalties.

Contributions

My first contribution to the literature is to provide a more comprehensive picture of how veteran wage premiums (penalties) across the entire wage distribution have evolved over time. This will further our understanding of veteran wage differentials over time, which at the mean, appear to have been positive in the 1970s and 1980s, turned to a penalty in the 1990s, and have recently returned to slight premiums (e.g., MacLean & Kleykamp, 2016). By combining the two approaches of MacLean and Kleykamp (2016) and Renna and Weinstein (2019), I will not only be able to assess trends in the veteran wage differential at the mean but also differences over time in other parts of the wage distribution.

To better understand the underlying drivers of the wage gap at different points in time, my second contribution is to examine how much of the gap in wages between veterans and nonveterans can be explained by compositional differences between the groups, and how much is due to non-compositional differences across the two groups.

1.3 Theory

I draw on three distinct components of theory for potential reasons we may observe wage differentials between veterans and nonveterans: (1) early life skills and education, (2) on-the-job training, and (3) discrimination. Human capital theory discusses early life skills, education, and on-the-job training as investments one could make that will ultimately lead to them earning higher wages. Discrimination has been put forth as a potential explanation for largely unexplainable wage gaps.

Human Capital Theory

Human capital theory highlights the potential of investments in human capital to raise one's future real income (Becker, 1962). Human capital can be defined broadly as the set of skills one "rents" out to their employer, or may be considered as one of several types, such as general human capital and firm- or job-specific human capital. The two main drivers of human capital are (1) early life skills imparted by one's parents/caregiver(s) and formal education and (2) on-the-job training (Ehrenberg & Smith, 2018).

Parents/caregivers are important sources of general human capital and are able to pass along valuable skills they have learned. Formal education increases both one's general human capital (skills that all firms would value, like reading comprehension), as well as increasing one's specific human capital through specialized training (such as taking data science classes at a university).

On-the-job training, such as learning-by-doing and formal and informal job training, play crucial roles in human capital development as well. Many jobs require firm-specific or job-specific training that one cannot obtain through formal educational channels. For instance, a data scientist might receive formal training in statistics that serves as a foundation for additional learning. However, it is not until they start working at a chemical plant that they learn the knowledge necessary to apply their statistical knowledge to questions that may only come up in the context of using proprietary technology.

Veterans may have entered the service with lower levels of general human capital compared to nonveterans because they often come from poorer backgrounds (Bareis and Mezuk, 2016). However, the military is likely to raise their general human capital through its rigid environment and focus on training. General skills such as communication, planning, punctuality, discipline, professionalism, and determinedness are all skills the military teaches to all its members. In this regard, military service is likely to lead to an increase in one's wages, all else equal, particularly at the low end of the wage distribution where these skills are most likely weak or absent prior to military service. This is the aforementioned "bridging hypothesis" phenomenon.

On-the-job training is more complicated, but still a potential channel for raising the human capital of military members in a way that increases their post-military earnings. For example, if a veteran worked on a nuclear submarine in-service and then secured employment at a nuclear power plant post-service. On the other hand, it may also be true that veterans lose valuable on-the-job training compared to similar nonveterans because of their military service. This could be due in part to serving in combat capacities with limited civilian occupational equivalency. Under this scenario, veterans may be at a disadvantage in competing for certain jobs that require multiple years of job-specific experience.

Because of these competing forces, it is unclear how the military affects one's wage upon entering the civilian workforce. On one hand, military members' general human capital is almost certainly increased while in-service. On the other hand, veterans may have missed out on opportunities to increase their specific human capital through on-the-job training.

Discrimination

Wage discrimination is also known to play a role in producing wage differentials (Blinder, 1973). Becker (1957) first developed an economic model that explained wage discrimination as arising from employers' preferences to work with a certain group. In the case of an employer who had such a preference, from this employer's perspective, they incurred an additional cost of hiring labor belonging to their unpreferred group. Therefore, the discriminating employer has an incentive to pay their unpreferred group lower wages.

Wage discrimination generally arises from personal prejudice, statistical prejudgment, or from noncompetitive forces in the labor market (Ehrenberg & Smith, 2018). One could imagine that any of these three sources could be working against veterans if actors in the labor market dislike veterans, think veterans are less productive than nonveterans, or have incentives to marginalize small groups. Anecdotal evidence for discrimination against Vietnam veterans is strong, and there is evidence that Vietnam veterans were paid far less than comparable nonveterans upon their arrival home from war (Angrist, 1990; Bryant et al., 1993).

Therefore, there is some potential for a role of discrimination in terms of veteran wage differentials over time. We might expect samples comprised in part of Vietnam veterans, for example, to have lower returns as compared to other cohorts because of their poorer treatment. Additionally, if negative returns are found for veterans, discrimination cannot be ruled out as a potential reason for the difference.

1.4 Data

This paper uses CPS MORG files covering 1979-2017. Although the ACS has also been used to study wage differentials (e.g., Renna & Weinstein, 2019; Vick & Fontella, 2017), the CPS MORG files have a few distinct advantages for my analyses. First, they contain the best point-in-time estimates of individuals' wages[6] (Lemieux, 2006) and one can create a stable wage series going back to 1979 to facilitate long-horizon comparisons. Second, top-coding affects both ACS and CPS data, but one simple fix for the wages in the CPS MORG files is to multiply top-coded[7] wages by a factor of 1.4[8] (Lemieux, 2006).

In the CPS MORG files, top-coding disproportionately affects salaried workers' wages.[9] Also, because there is a fixed nominal top-code and wage inflation over time, more and more wages become top-coded as time progresses until the top-code is increased. Fortunately, estimates in this paper only go up to the 90th percentile, which is unaffected by top-coding as top-coding generally only affects around the top 5% of observations depending on the year. Nevertheless, following other literature I utilize CPS MORG files from 1979 to 2017 and multiply all top-coded wages by 1.4.

I pool three years of data together to produce more precise estimates and construct and convert all hourly wages to 2017 dollars before taking the log of wages. Following Lemieux (2006), I drop all observations with wages below $1 or above $100 hourly wage in 1979 dollars, females, self-employed, those who never worked or are without pay, and workers with allocated wages. I keep only workers between the ages of 22 and 64 due to many veterans serving 4-year contracts at age 18 and people obtaining education in their early adult lives.

Other variables I construct are experience cells in increments of 5 years to flexibly control for variation in wages arising from variation in experience. Similarly, I create education cells to account for differential returns for different levels of education. I generate a public

[6] No construction of wages for hourly workers is needed as hourly workers are simply asked the amount of their hourly wage.
[7] There are abrupt increases in the wage top code in 1989 (to $1923) and 1998 (to $2884).
[8] This factor is used to preserve the mean and variance of top-coded wages and is based on the Pareto distribution.
[9] In addition to top-code changes and differing rates of top-coded observations over time, allocated wage flags are somewhat inconsistent over time especially between 1989-1993 (too few) and 1994-1995 (largely do not exist but should). Some researchers drop 1994-1995 data whereas I pool them together and include them.

sector work indicator as previous literature has shown veterans are more likely to work in the public sector, a Hispanic indicator, a currently married indicator[10], race/ethnicity[11], and a veteran indicator.

As previously mentioned, using MORG files that go back to 1979 allows one to do comparisons over many years. Indeed, the trends in wages by veteran status in Figure 1.1 show three stylized facts. First, veterans have enjoyed a wage premium across every year of data going back to 1979. Second, the gap between the two groups has shrunk considerably over time. Third, veteran wages in real terms differ little from 1979, whereas nonveterans' wages have increased.

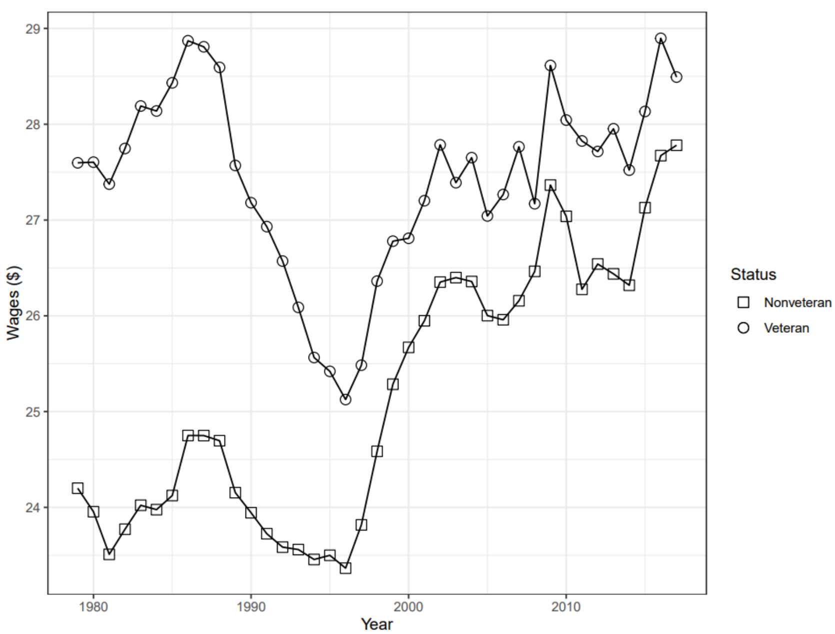

Figure 1.1: Trends in mean wages for veterans and nonveterans, 1979-2017.

[10] Although CPS includes more information on marital status than whether someone is currently married, the marital status variable has changed over time. To create a consistent variable across all years I simply create an indicator of whether someone is currently married due to widowed, divorced, and separated persons being grouped together prior to 1989.

[11] Similar to marital status, prior to 1989 the only categories reported are White, Black, and Other. To create a consistent race/ethnicity variable, I use these categories in all years even if more information is available in later years.

Notes: This figure shows mean wages in 2017 dollars for veterans and nonveterans for 1979-2017 based on the authors' calculations using CPS MORG files. Person-level weights are used.

Although veteran wages in real terms have changed little, it is important to look across the wage distribution to see which workers' veteran premium has been eroded as time has progressed. This is because, as MacLean and Kleykamp (2016) showed, veterans are experiencing increasing within-group wage inequality.

Figure 1.2 provides another descriptive perspective, now pooling all years together to compare the full (log) wage distributions of veterans and nonveterans. Because my focus is on changes over time, I do this for the early (1979-1983) and late (2013-2017) periods of our sample timespan. Consistent with other literature, the veteran wage distribution lies to the right of nonveterans, in both time periods.[12] This implies veterans are making more on average than nonveterans. The narrower distributions imply their wage distribution displays less variance as well. It would appear from this that one might prefer the wage distribution of veterans. However, this could also be due to other things that are correlated with higher wages and veteran status, and not veteran status itself.

[12] There is substantial heaping of wages around 4.5 log points. This is due to top-coded wages, which occur at the 99th percentile of wages in both periods. My estimates only go up to the 90th percentile.

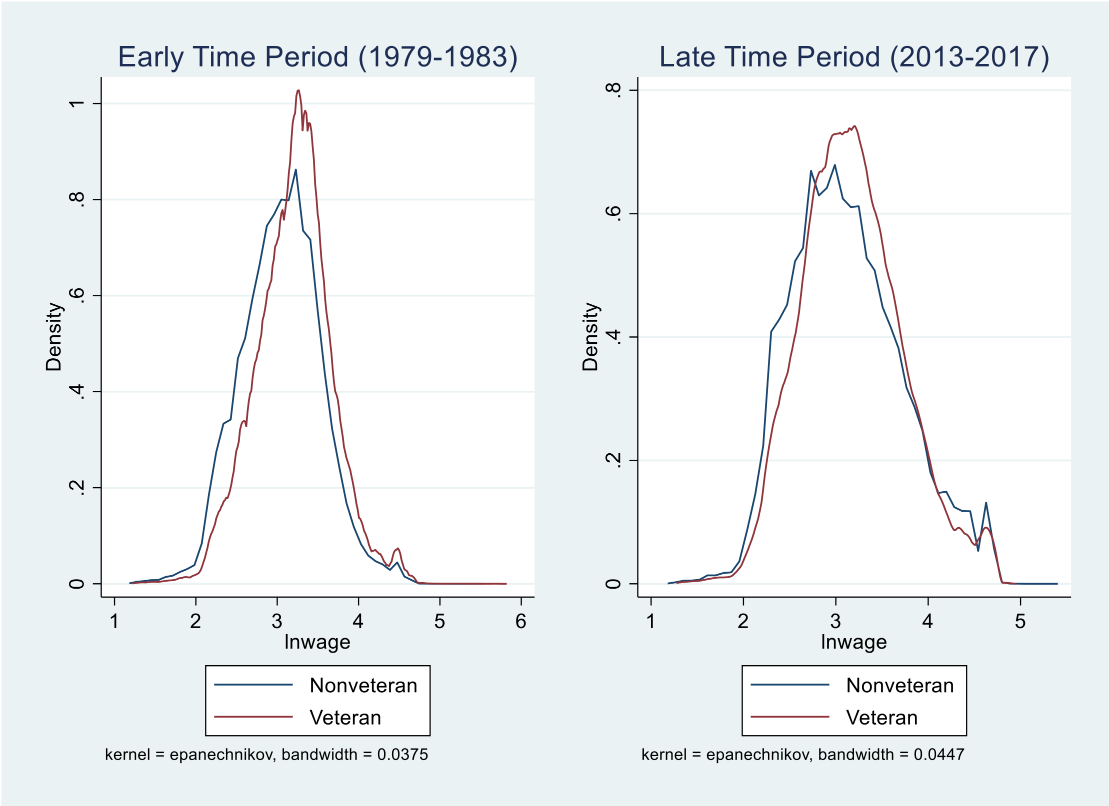

Figure 1.2: Veteran and nonveteran wage distributions.

Notes: This figure shows the wage distributions of male veterans and male nonveterans for both the early time period and late time period used in the decompositions. Wages are weighted by person weights and usual hours worked.

Table 1.1 below shows descriptive statistics on several such characteristics that affect wages, illustrating some differences for veterans. In both time periods, veterans are more likely to work in the public sector, more likely to be older (more mature wage profile), more likely to be married, have less bachelor’s and advanced degrees, and less likely to be Hispanic. Over time, veterans have become less White, and nonveterans have become older and have closed the observed wage gap. In the later time period, it appears veterans are “looking” more similar to nonveterans except for the proportion in public sector work. With this in mind, we might expect the wage gap to have shrunk over time.

Table 1.1: Descriptive statistics.

	Early Time Period (1979-1983)			
	Veterans		Nonveterans	
Variable	**Mean**	**SD**	**Mean**	**SD**
Wage	27.53	14.17	23.76	12.7
Education				
< High School	0.17	0.37	0.21	0.41
High School	0.38	0.48	0.32	0.47
Some College	0.24	0.42	0.2	0.4
Bachelors	0.12	0.32	0.14	0.35
Advanced	0.1	0.31	0.13	0.34
Experience	25.28	11.41	15.39	11.29
Public Sector Worker	0.21	0.41	0.15	0.35
Age	44.39	10.79	34.39	10.14
Married	0.83	0.37	0.71	0.46
Race/Ethnicity				
Black	0.07	0.26	0.1	0.3
Other	0.01	0.1	0.03	0.17
Hispanic	0.03	0.17	0.08	0.27
	Late Time Period (2013-2017)			
	Veterans		**Nonveterans**	
Variable	**Mean**	**SD**	**Mean**	**SD**
Wage	28.5	18.23	27.62	19.46
Education				
< High School	0.02	0.13	0.09	0.28
High School	0.29	0.46	0.28	0.45
Some College	0.39	0.49	0.25	0.43
Bachelors	0.19	0.39	0.25	0.43
Advanced	0.11	0.31	0.13	0.34
Experience	27.12	10.66	21.29	11.75
Public Sector Worker	0.24	0.43	0.12	0.32
Age	47.08	10.54	41.2	11.5
Married	0.69	0.46	0.61	0.49
Race/Ethnicity				
Black	0.14	0.35	0.1	0.3
Other	0.05	0.22	0.1	0.29
Hispanic	0.09	0.28	0.18	0.38

Notes: Weighted means and standard deviations are reported. Weights are composite weights based on person weights and usual hours worked.

1.5 Methodology

To examine veteran wage differentials throughout the wage distribution, I use the unconditional quantile regression (UQR) approach proposed by Firpo, Fortin, and Lemieux (FFL) (2009). When studying many interesting questions, estimating parameters other than effects on means becomes important. Wages are one such area where we would want to study the effects of different variables across potentially the entire distribution and not just effects on mean wages. As an example, it may be important to target policy toward veterans below a certain wage if it is deemed their wages are significantly lower than comparable nonveterans. If, however, we only looked at average effects, we may miss this important result as perhaps veterans earn a large premium in the 99th percentile of wages that increases their average wage to a level comparable to nonveterans. In this scenario, estimates of mean effects miss an opportunity to potentially improve policy.

I fit a wage model to the data following FFL's (2009) specification. I provide estimates of the effect of veteran status on wages at the mean, as well as every unconditional decile of the wage distribution starting at the 10th and going up to the 90th. The methodological approach is similar to Renna and Weinstein (2019), but I produced these estimates over time to assess *trends* in the effect of veteran status on wages. My sample period starts much earlier (in 1979 compared to 2005), and their choice to pool over 2005-2015 could obscure important heterogeneity even during that time period.

The wage model I estimate takes the form:

$$lnwage_{it} = \beta_0 + \beta_1 veteran_{it} + \boldsymbol{X}_{it}\boldsymbol{\delta} + u_{it} \tag{1}$$

where, following FFL (2009), the vector $\boldsymbol{X}$ contains indicators for public worker status, education, race, experience cells, Hispanic status, marital status, and year. This is done separately for consecutive 3-year periods during 1979-2017. Because this regression is missing important information that is likely correlated with veteran status, it is not expected that the coefficient on *veteran* is able to be interpreted as a causal estimate.

Next, following FFL (2018), I decompose the raw, observed (log) wage difference between veterans and nonveterans at the 10th, 50th, and 90th unconditional quantiles of wages. These decompositions are analogous to Blinder-Oaxaca decompositions (Blinder, 1973; Oaxaca, 1973) of wage differences at the mean. Blinder-Oaxaca decompositions use regression estimates (along with group means) to reconfigure differences in average wages between two groups (or other measures of interest) into two components. One component is made up of the part of the difference in average wages that can be explained by differences in observed characteristics between the two groups (e.g., one group may have higher levels of advanced education). The other component is made up of differences that cannot be explained by observable differences in characteristics (e.g., one group may get paid higher returns for the same amount of education). Analogously, unconditional quantile regression estimates can also be used to reconfigure observed differences in any unconditional quantile of interest into the same two components as the Oaxaca-Blinder decompositions.

The FFL approach differs slightly from the traditional Oaxaca-Blinder decomposition approach. FFL (2018) demonstrated a two-stage approach to UQR decompositions. Their methodology reweights data in a first-stage regression to ensure the composition effect reflects true differences in observable information between the two groups. At the end of the first-stage regression, both the composition and structure effect estimates are obtained. Their methodology produces a “reweighting error” to assess the first stage. In a second-stage regression, FFL (2018) decompose the composition effect and structural effects into a detailed composition.

"Specification error" is provided to gauge the success of the second-stage regression. FFL (2018) note that "specification error" is unavoidable but should be statistically insignificant or small relative to the overall decomposition effects.

I perform this decomposition separately for the first and last periods (both composed of 5 years) to infer how much of the observed veteran wage differential is due to observable differences (e.g., higher educational attainment) versus unobservable differences (e.g., receiving higher returns to education or potential discrimination). I use the same specification as the UQR regressions in the decompositions. Like the UQR regressions, this is a descriptive exercise, so the unexplained portion of the observed wage gap is not necessarily attributable to discrimination or other unethical factors.

1.6 Results

UQR Estimates

In Figure 1.3 are plots of the effect of veteran status on unconditional deciles of wages along with an OLS estimate of the average effect of veteran status on wages. One striking pattern is that in the early years of the data (1979-1990) there existed a large veteran premium across the entire unconditional distribution of wages. This implies that veterans make more, on average, than nonveterans at every point (decile) along the wage distribution. As time progresses it is evident that the veteran premium is eroding and there are pronounced shifts in the effect of veteran status on wages. By the mid-1990s, veterans at the top end of the wage distribution develop a substantial wage *penalty* that persists throughout the rest of the time periods.

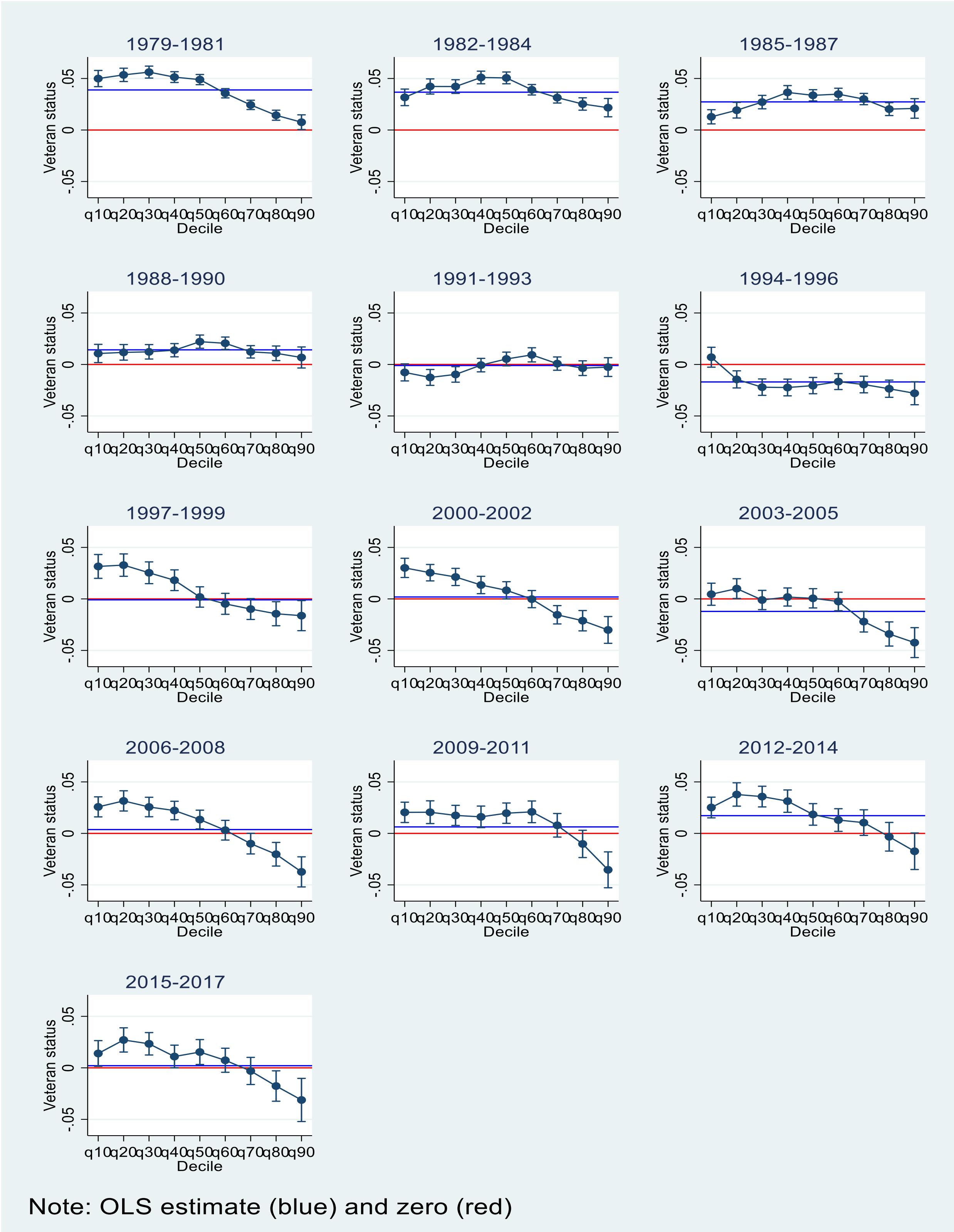

Figure 1.3: OLS and UQR estimates of the effect of veteran status on log wages.

Notes: Observations are weighted by person weights and usual hours worked. 95% confidence intervals are provided for the UQR estimates.

Additionally, during the 1990s veteran status's effect begins to exhibit a strong and nearly monotonically *decreasing* return to military service as one moves up the wage distribution.

From around 1997 onward, we see a pattern consistent with the bridging hypothesis; that is, it appears persons with the most to gain from military service are the lowest wage earners. Persons who would earn at the upper-end of the wage distribution are penalized should they become veterans, and this effect is consistently significant and large in magnitude, around a 2-4.2% penalty depending on the time period.

UQR Decompositions

Next, I provide UQR decomposition results for an early (1979-1983) and late (2013-2017) time period. Following the two-stage FFL (2018) approach, I reweight observations to obtain both the composition and structure effects. Then, I decompose these effects into detailed components. Table 1.2 provides reweighting and specification errors relative to the composition effects for context.

We see that reweighting errors from the first stage are either statistically insignificant or not meaningfully large. This is an indication that the reweighting procedure successfully identified the composition and structure effect, given our model. Figure 1.4, which follows, graphically shows these effects. Specification errors are obtained from "reconstructing" the composition and structural effects, using the individual variables' estimates from the second-stage RIF regressions, and comparing them to the composition and structural effects from the first stage's reweighting approach.

Table 1.2: Decomposition errors relative to composition effect.

	Quantile	Composition Effect	Specification Error	Reweighting Error
1979-1983	10th	0.124*	0.017*	0.001
	20th	0.145*	0.024*	0.002*
	30th	0.130*	0.005*	0.003*
	40th	0.138*	0.012*	0.003*
	50th	0.124*	0.009*	0.003*
	60th	0.116*	0.006*	0.003*
	70th	0.109*	0.003	0.004*
	80th	0.097*	0.004*	0.005*
	90th	0.114*	0.012*	0.007*
	Quantile	Composition Effect	Specification Error	Reweighting Error
2013-2017	10th	0.116*	0.044*	0.001
	20th	0.099*	0.012*	0.001
	30th	0.098*	0.012*	0.001
	40th	0.079*	-0.006*	0.001
	50th	0.078*	0.003	0.001
	60th	0.049*	-0.008*	0.001
	70th	0.034*	-0.002	0.001
	80th	0.023*	0.004	-0.001
	90th	-0.001	0.001	-0.001

Notes: * pvalue<.05

If there is meaningful specification error, this is evidence that the detailed decomposition estimates likely are contaminated with error.[13] This is the case for the 10th quantile late time period estimates. These detailed decomposition estimates likely contain error and should be interpreted with caution, although this proves to be largely unimportant in what follows. Figure 1.4 shows that the wage gap at this quantile has not substantially changed. Thus, interpreting the detailed estimates from the 10th quantile is not a necessity. I focus my interpretation on the upper-end quantiles because they have experienced the most change over time, particularly to the detriment of veterans.

[13] It is possible for there to be a problem in the reweighting model that produces biased estimates of the composition and structure effects that the second-stage compares against. While plausible, this seems unlikely because the other models do not exhibit the same specification error.

Figure 1.4 provides graphs of the overall decomposition results from the first-stage.[14] I produce these decompositions after pooling five years of data together at the beginning and end of my period of study. The graphs show the total difference in real log wages at each decile and decomposes this difference into two parts—a compositional effect (differences in observable characteristics) and a structure effect (due to differences in unobservables)—to visually assess the relative role of each in both time periods. The square line is the simple difference in real log wages between veterans and nonveterans at every decile. The circle line is the part of the difference due to compositional effects, such as veterans having more education or public sector employment in higher proportions, again at each decile. The triangle line shows the structural effects, which include the part of the difference due to differences in returns, discrimination (if it exists), etc.

In both time periods, it is evident that veterans have higher observed wages in lower quantiles of the wage distribution. However, the difference diminishes as one moves up the wage distribution, although in the early period, the wage gap remains large in magnitude. Additionally, the veteran premium declines more rapidly across the wage distribution in the later time period, eventually turning into a slight wage penalty (i.e., nonveterans having higher wages).

[14] The estimates in Figure 1.4 are from the first-stage and are unaffected by the specification error from the second-stage RIF regressions.

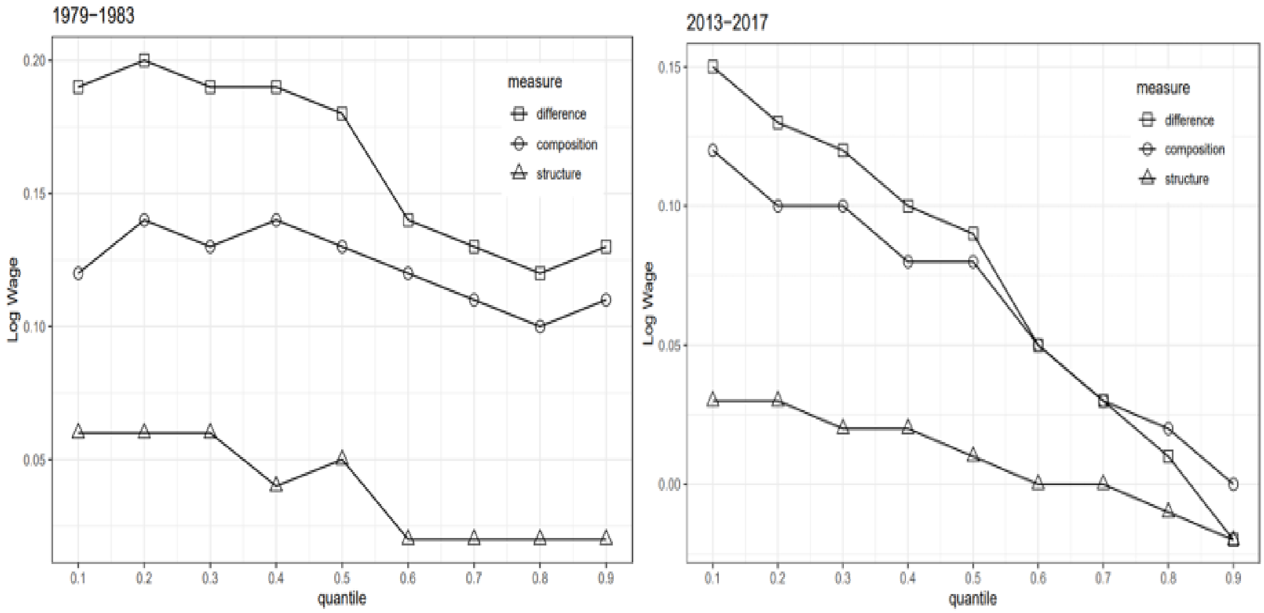

Figure 1.4: Reweighted Decomposition of the veteran-nonveteran wage gap by decile into compositional and structural components.

Notes: Observations are weighted by person weights and usual hours worked.

Figure 1.4 also makes clear that in more recent times, veterans earning at the upper-end of the wage distribution have less favorable (to the labor market) compositional characteristics. We see this from the circle line's precipitous fall at the 70th, 80th, and 90th quantile of wages in the 2013-2017 time period. Indeed, when one looks at the detailed decompositions[15] (Tables 1.3 and 1.4), at the top end of the wage distribution, veterans have lower wages by 4.8%[16] on average (the summation of the bachelor's degree and advanced degree compositional effects) in the earlier period because they do not have as much bachelor's degrees and advanced degrees.

[15] The detailed decompositions are expressed in log points. As such, the differences are not exactly equal to percent differences. Essentially, log point values tell us how many times to compound a 1% difference. This means, a 2 log point difference is roughly equal to a 2% difference; however, a 18.8 log point difference (as seen in Table 1.3) is closer to a 20% difference. The detailed decomposition estimates are generally quite small. Therefore, I read off log point differences as percent differences to increase interpretability.

[16] The combined effect of any two or more decomposition effects is the simple summation of the individual effects.

In more recent times, this deficit is larger at 7.8%, indicating that veterans suffer almost twice the wage penalty from lower educational attainment in more recent times.

Table 1.3: Detailed reweighted RIF decompositions for veteran-nonveteran wage gap, 1979-1983.

Log Wages	10th quantile	50th quantile	90th quantile
Overall			
Veteran	2.602	3.234	3.766
Nonveteran	2.413	3.058	3.640
Difference	.188*	.175*	.126*
Total Explained	.124*	.133*	.115*
Total Unexplained	.064*	.042*	.011*
Composition (Structure) Effects			
Education			
High School	.019* (-.057*)	.017* (-.031*)	.010* (-.009*)
Some College	.017* (-.032*)	.018* (-.027*)	.015* (-.013*)
Bachelor's Degree	-.016* (-.013*)	-.018* (-.013*)	-.021* (-.005*)
Advanced Degree	-.014* (-.008*)	-.020* (-.010*)	-.027* (.004*)
Experience			
0-4 Years	-.026* (.008*)	-.039* (-.001)	-.041* (-.008*)
5-9 Years	-.008* (.038*)	-.013* (-.001)	-.014* (-.021*)
10-14 Years	.003* (.043*)	.006* (-.001)	.008* (-.020*)
15-19 Years	.005* (.035*)	.009* (-.001)	.010* (-.015*)
20-24 Years	.013* (.041*)	.024* (-.002)	.028* (-.013*)
25-29 Years	.022* (.042*)	.038* (.001)	.043* (-.015*)
30-34 Years	.022* (.045*)	.042* (.004)	.047* (-.015*)
35+ Years	.015* (.045*)	.033* (.003)	.041* (-.016*)
Public Sector Work	.001* (.002)	-.004* (.002*)	-.010* (-.001)
Race/Ethnicity			
Black	.005* (.003)	.004* (.003*)	.002* (.001)
Other	.002* (.002*)	.002* (.002*)	.001* (.001*)
Hispanic	.012* (.005*)	.009* (.004*)	.005* (.001*)
Married	.027* (-.043*)	.016* (-.026*)	.006* (-.003)
1980	-.001* (-.003)	-.001* (-.002)	-.001* (.008*)
1981	.001 (.004*)	.001 (-.005*)	.001 (.009*)
1982	.002* (-.011*)	.001* (-.001)	.001* (.008*)
1983	.004* (.003)	.002* (-.011*)	.001* (.009*)

Notes : All regressions are weighted by person weights and usual hours worked.

* p-value < .05

Table 1.4: Detailed reweighted RIF decompositions for veteran-nonveteran wage gap, 2013-2017.

Log Wages	10th quantile		50th quantile		90th quantile	
Overall						
Veteran	2.511		3.157		3.925	
Nonveteran	2.361		3.066		3.949	
Difference	.150*		.091*		-.024*	
Total Explained	.116*		.078*		-.001	
Total Unexplained	.034*		.013*		-.024*	
Composition (Structure) Effects						
Education						
High School	.005*	(-.049)	.004*	(-.013)	.001*	(-.008)
Some College	.066*	(-.082)	.066*	(-.038*)	.026*	(-.015)
Bachelor's Degree	-.036*	(-.039)	-.053*	(-.029*)	-.047*	(-.035*)
Advanced Degree	-.015*	(-.023)	-.025*	(-.017*)	-.031*	(-.025*)
Experience						
0-4 Years	-.005*	(.016*)	-.012*	(-.002)	-.019*	(-.008)
5-9 Years	-.007*	(.023*)	-.013*	(-.002)	-.017*	(-.014)
10-14 Years	-.006*	(.019*)	-.013*	(-.002)	-.016*	(-.009)
15-19 Years	-.001	(.030*)	-.001	(.001)	-.001*	(-.011)
20-24 Years	.008*	(.037*)	.017*	(-.002)	.023*	(-.023)
25-29 Years	.012*	(.041*)	.025*	(-.005)	.034*	(-.027*)
30-34 Years	.014*	(.026*)	.029*	(-.013)	.036*	(-.023)
35+ Years	.018*	(.019*)	.032*	(-.008)	.036*	(-.016)
Public Sector Work	.003*	(.005*)	.002*	(.007*)	-.032*	(.018*)
Race/Ethnicity						
Black	-.006*	(.011)	-.009*	(.006*)	-.006*	(-.001)
Other	-.001*	(.005)	.001*	(.002*)	-.001*	(.002)
Hispanic	.012*	(.011*)	.015*	(.011*)	.009*	(.006*)
Married	.008*	(.014)	.010*	(-.002)	.007*	(.004)
2014	.001	(.001)	.001	(-.001)	-.001	(-.008*)
2015	-.001	(-.004)	-.001	(-.002)	-.001	(-.008*)
2016	-.001	(-.001)	-.001	(.002)	-.001	-0.001
2017	-.001	(-.016*)	-.001	(.004*)	-.001	(-.012*)

Notes : All regressions are weighted by person weights and usual hours worked.

* p-value < .05

A similar story is at work with public sector work. What once was a slight disadvantage (1.0%) for veterans at the top end of the wage distribution has now increased to lowering veterans' wages by 3.2% relative to nonveterans. This is because at the 90th quantile of wages public sector employment tends to reduce one's wages, and veterans are overrepresented in public sector work at this wage level. Although when one considers the nonpecuniary benefits associated with public sector work, this difference becomes less important.

Sensitivity Analysis

In addition to FFL's reweighting approach, I produce the simpler Oaxaca-Blinder decomposition and contrast the two.[17] The results are very similar apart from the 10th quantile late time period estimates, where the estimates from the two approaches diverge. The most likely source of this complication is what FFL term a violation of the "linearity assumption". FFL (2018) note that specification error in their reweighting approach is evidence of a violation of the linearity assumption that is crucial for the second-stage regression to produce accurate estimates. The RIF regressions that their methodology relies on for its second-stage only provide a linear approximation of a potentially highly nonlinear functional. If, for instance, the relationship between the distribution of wages at the 10th quantile and the distribution of my explanatory variables was nonlinear, FFL's approach is unlikely to produce accurate estimates. Unfortunately, switching to the simpler Oaxaca-Blinder decomposition is not a solution because it suffers from the same issue (analogous to the Gauss-Markov linearity assumption).

In the case of a violation of the linearity assumption, the reweighting approach has one advantage over the simpler approach. That is, the simpler approach relies on traditional Ordinary Least Squares estimation that, when the conditional expectation of the dependent variable given the explanatory variables is nonlinear, the estimates OLS produces will depend on the distribution of the explanatory variables (White, 1980). The reweighting approach does not suffer from this issue because it reweights the groups to hold fixed the distributions of their explanatory variables. The implication being that the composition and structure effects estimates

[17] The results of the simpler approach are in Appendix B.

under the reweighting approach are likely more accurate than their counterparts from the simpler approach in this scenario. Because of this, I prefer the reweighted results to the simpler approach. However, the detailed estimates in the 10th quantile in both approaches still suffer from the same issue and should be interpreted with caution.

Reconciling Results with Prior Literature

This paper has shown that the effect of veteran status on wages is heterogeneous across the unconditional distribution of wages and that it has changed over time. In some years veterans earned a substantial wage premium on average, whereas in other years they are penalized substantially, on average. Trends have changed over time, in the late 1970s and 1980s, veterans experienced large returns to their military service in the labor market. The premium was eroded over time and turned into a wage penalty by the late 1990s for many veterans, particularly those at the top end of the wage distribution. This pattern persists into the more current time period with veterans earning premiums on the low end of the wage distribution and penalties on the upper-end of the wage distribution. These effects are averaging out to produce near-zero OLS estimates on mean wages.

This overall trend is very consistent with MacLean and Kleykamp's (2016) findings where they estimate a veteran wage premium from 1979 to 1991, a veteran wage penalty from 1991 to 2001, and then a veteran wage premium again beginning in 2001 and continuing until their last year of data in 2010. Vick and Fontanella's findings from their research of veteran wages using 2009-2013 ACS data revealed a veteran wage penalty of around 2.8%, which stands in contrast to this chapter's findings of a slight wage premium during that same time period. However, Vick and Fontanella's sample is very different from the one employed in this chapter as they wanted to "isolate comparisons of early to mid-career workers", so their sample only included those aged 25-40, did include females, and did not include those with less than a high school education.

Renna and Weinstein's (2019) findings in their research of veteran wages pooling 2005-2015 ACS data revealed a wage premium for males at the lower end of the wage distribution and a wage penalty for those at the top of the wage distribution, consistent with my results. Noteworthy, Renna and Weinstein try to deal with unobserved ability's correlation with veteran status with a selection model. The results from this model imply the White male veteran penalty becoming larger and the Black male veteran premium becoming larger. This is consistent with unobserved ability being negatively correlated with military service for White males and positively correlated with military service for Black males (assuming it is positively correlated with wages for both groups).

1.7 Conclusion

Overall, it would appear those making the least have the most to gain from service in most time periods. Workers at the 10th percentile to 50th percentile have enjoyed a premium in more time periods, and generally larger premiums, than those at the 90th percentile. Conversely, those making the most have been penalized or have had smaller returns to their military service over most time periods.

However, this paper highlights the complexity of the relationship between military service and wages. Military service, veterans, and the way the public views veterans have all changed over time. In some time periods, all veterans gain, though some more than others. In other time periods, all veterans lose but some more than others. Finally, in some time periods, we see that some veterans gain and some veterans lose. It is not always the same veterans who are gaining and losing. Thus, while there is certainly a pattern to the overall trend in the return to military service, there is much heterogeneity across who ultimately gains/loses within time periods, and this heterogeneity changes over time.

In more recent times veterans' lower levels of bachelor's and advanced degrees and higher rates of public sector employment are contributing the most to the observed wage gap at the 90^{th} percentile of wages. Fortunately, nonpecuniary benefits in the public sector such as job security (Bellante & Link, 1981) surely tempers the effect of lower wages on the welfare of veterans employed in the public sector. As such, a policy with the goal of increasing this group of veterans' wages by changing the rates of public sector employment would likely be ineffective at increasing welfare among these veterans.

On the other hand, advancing education (quantity and quality) among veterans is policy relevant. Helping veterans increase their education (bachelor's degrees and advanced degrees) should boost their wages in the upper end of the wage distribution; this will help alleviate the persistent wage penalty observed by all recent veteran wage differential scholarship. However, in order to be eligible to receive advanced education like bachelor's degrees and above, veterans must navigate the transition from the military to the classroom. According to Ackerman et al. (2009), veterans overwhelmingly chose this transition as the toughest one they had faced. Cook and Kim (2009) noted in their research, less than one-quarter of schools provide transition services that are tailored to veterans. This is an oversight and seemingly a costly one from at least the perspective of veterans, but potentially costly from the perspective of universities. If veterans leave school, they take with them tuition payments from the VA as well as their unique experiences and qualities.

Additionally, Barr et. al (2021) showed that veterans with the lowest skill (as measured by military experience and military aptitude examination score) had the lowest returns to their earnings from usage of their G.I. Bill benefits among veterans. They argue this is in part because these veterans overwhelmingly choose to attend for-profit institutions. If veterans were constrained to choose more high-quality sources of education, more veterans may go on to receive bachelor and advanced degrees that the labor market values.

1.8 Limitations

As noted above, the wage effects of veteran status estimated in this chapter cannot be given a causal interpretation. While earlier studies were able to exploit exogenous variation in military service induced by drafts for WWII and the Vietnam War, a readily available instrument for military service does not exist for AVF veterans.

The 10th quantile late time period detailed decomposition estimates likely are biased because of a violation of the linearity assumption. As stated previously, I did not need to interpret these estimates. However, this is still an important limitation worth noting.

Parental socioeconomic status is an important predictor of one's wages (Chetty et al., 2014; Black & Devereux, 2011; Currie & Goodman, 2020) and it is also negatively correlated with veteran status (Spence et al., 2013); however, I am unable to include this cofounder.

Combat veterans are likely to differ systematically (higher rates of disability, higher rates of substance abuse, undiagnosed and untreated mental illness, etc.) from noncombat veterans in ways that could impact their ability to find and keep well-paying employment. The number of combat veterans, as well as the intensity of the combat these veterans were exposed to, has changed over time. It is possible that these temporal changes could impact veteran wage differentials over time.

We also might expect the experience of officers and enlisted in the labor market to differ even if enlisted veterans go on to receive advanced education. For instance, it could be the case that officers have better "connections" in the labor market or that their credentials stand out more to potential employers. Unfortunately, my data do not include information on the veteran's military service, so I cannot speak to the ways enlisted members and officers differ.

Future research opportunities in this area could involve more detailed analyses of various subgroups within the veteran population, such as officers versus enlisted military members, different racial and ethnic groups, veterans from different branches of service, combat veterans, or female veterans. However, these analyses would require richer data than is currently publicly available.

It is not well-known whether the patterns of selection into employment for male veterans resembles that of male nonveterans. If they do not, observed wage trends may reflect differences in selection into the labor force rather than actual disparities in wages.

Furthermore, it is worth noting that the Federal Reserve of St. Louis's database reveals a long-term decline in the male labor force participation rate over several decades. It is not obvious whether this pattern would be similar if one looked at male veterans alone. On one hand, it could be that veterans are healthier or that they "show up" at higher rates than do nonveterans. On the other hand, generous social assistance from the VA along with combat traumas might make veterans more likely to select out of the labor market. Future research could assess these patterns to ensure comparisons of veterans and nonveterans are reasonable.

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1.10 Appendix A: Sensitivity Analysis

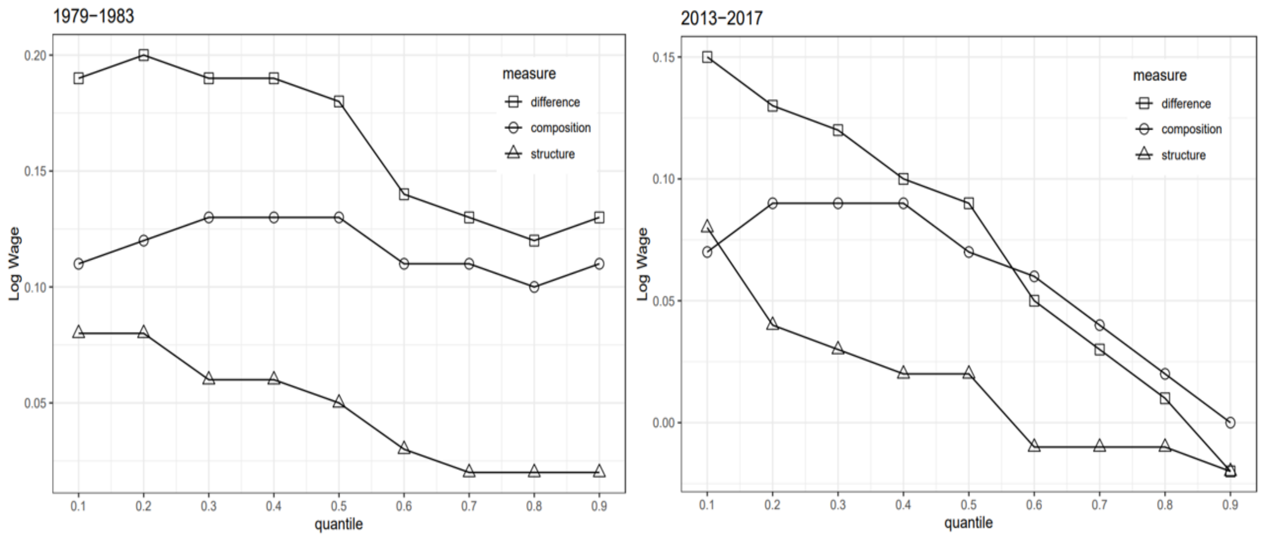

Figure 1.5: Decomposition of the veteran-nonveteran wage gap by decile into compositional and structural components.

Notes: Observations are weighted by person weights and usual hours worked.

Table 1.5: Detailed RIF decompositions for veteran-nonveteran wage gap, 1979-1983.

Log Wages	10th quantile	50th quantile	90th quantile
Overall			
Veteran	2.602	3.233	3.766
Nonveteran	2.413	3.058	3.640
Difference	.188*	.175*	.126*
Total Explained	.108*	.127*	.108*
Total Unexplained	.080*	.048*	.018*
Composition (Structure) Effects			
Education			
High School	.016* (-.043*)	.014* (-.047*)	.009* (-.020*)
Some College	.015* (-.025*)	.015* (-.036*)	.013* (-.015*)
Bachelor's Degree	-.011* (-.016*)	-.013* (-.020*)	-.015* (.006*)
Advanced Degree	-.012* (-.007*)	-.018* (-.020*)	-.024* (-.001)
Experience			
0-4 Years	-.026* (.013*)	-.040* (-.004*)	-.041* (-.011*)
5-9 Years	-.008* (.049*)	-.013* (-.005*)	-.014* (-.032*)
10-14 Years	.003* (.055*)	.005* (-.002)	.006* (-.032*)
15-19 Years	.005* (.042*)	.009* (-.004*)	.010* (-.022*)
20-24 Years	.015* (.050*)	.026* (-.002)	.030* (-.018*)
25-29 Years	.023* (.052*)	.040* (-.001)	.046* (-.018*)
30-34 Years	.023* (.053*)	.044* (-.001)	.049* (-.017*)
35+ Years	.013* (.051*)	.029* (.002)	.037* (-.017*)
Public Sector Work	.001* (.008*)	-.004* (.005*)	-.011* (.005*)
Race/Ethnicity			
Black	.006* (-.001)	.004* (.003*)	.002* (.001)
Other	.002* (.001*)	.002* (.001*)	.001* (.001)
Hispanic	.012* (.004*)	.009* (.004*)	.005* (.001*)
Married	.027* (-.034*)	.016* (-.049*)	.006* (.001)
1980	-.001* (-.010*)	-.001* (-.006*)	-.001* (.010*)
1981	.001 (.007*)	-.001 (-.005*)	-.001 (.009*)
1982	.002* (-.004*)	.001* (.003*)	.001* (.007*)
1983	.004* (.004*)	.002* (-.004*)	.001* (.016*)

Notes : All regressions are weighted by person weights and usual hours worked.

* p-value < .05

Table 1.6: Detailed RIF decompositions for veteran-nonveteran wage gap, 2013-2017.

Log Wages	10th quantile	50th quantile	90th quantile
Overall			
Veteran	2.511	3.157	3.925
Nonveteran	2.361	3.066	3.949
Difference	.150*	.090*	-.024*
Total Explained	.072*	.075*	-.002
Total Unexplained	.078*	.015*	-.022*
Composition (Structure) Effects			
Education			
High School	.005* (-.012)	.004* (-.023*)	.001* (-.015)
Some College	.066* (-.020)	.066* (-.052*)	.026* (-.023)
Bachelor's Degree	-.035* (-.005)	-.052* (-.047*)	-.047* (-.034*)
Advanced Degree	-.015* (-.002)	-.025* (-.029*)	-.031* (-.030*)
Experience			
0-4 Years	-.005* (.021*)	-.012* (-.003)	-.019* (-.011*)
5-9 Years	-.007* (.035*)	-.013* (-.004)	-.017* (-.022)
10-14 Years	-.006* (.035*)	-.012* (-.004)	-.016* (-.019)
15-19 Years	-.001 (.053*)	-.001 (-.002)	-.001 (-.024*)
20-24 Years	.008* (.065*)	.018* (-.005)	.024* (-.038*)
25-29 Years	.012* (.070*)	.025* (-.007)	.034* (-.043*)
30-34 Years	.014* (.054*)	.028* (.015)	.035* (-.035*)
35+ Years	.018* (.039*)	.031* (-.013*)	.036* (-.025*)
Public Sector Work	.003* (.007*)	.002* (.008*)	-.031* (.035*)
Race/Ethnicity			
Black	-.007* (.004)	-.009* (.007*)	-.007* (.001)
Other	.003* (.003)	.002* (.001)	-.002 (.001)
Hispanic	.012* (.009*)	.015* (.013*)	.009* (.005*)
Married	.008* (.023*)	.010* (-.007)	.007* (.004)
2014	.001* (-.003)	.001 (-.003)	-.001 (-.009*)
2015	-.001 (-.006*)	-.001 (-.005*)	-.001 (-.009*)
2016	-.001* (-.005)	-.001* (-.001)	-.001* (-.001)
2017	-.001* (-.021*)	-.001* (-.002)	-.001* (-.012*)

Notes : All regressions are weighted by person weights and usual hours worked.

* p-value < .05

CHAPTER 2

2.1 Statement of Problem

There has been a significant shift in the demographic makeup of the armed forces, with females playing a far more prominent role in the modern military. During the Vietnam War, females comprised less than 2% of all active-duty military personnel. According to a recent report (Department of Defense, 2020), that same number is 17.2% as of 2020. Females are also serving in roles once reserved for males, and many have seen combat service during the Global War on Terror or have served in combat zones. For instance, according to MacKenzie (2012), as of 2012, almost 150 female service members had been killed in action, and at least two female service members had earned combat medals for valor. Given their expanded role and the well-established gender differentials (for civilians) in the labor market, there is now more than ever an incentive to study female veterans. Furthermore, there is little reason to believe that the results on male veteran wage differentials would apply to female veterans. In this paper, I will explore veteran wage differentials specifically for females.

To compare female veteran wages to nonveteran wages, one must first consider whether female veterans select into employment differently than female nonveterans. It is well-known that females, in general, select into the labor force, and thus employment, at much lower rates than males. However, little is known about whether this pattern carries over to female veterans. For instance, it is possible that female veterans with the lowest potential earnings select out of the labor force, which would be consistent with patterns established for male Vietnam veterans following increases in their disability payments from the United States Department of Veterans Affairs (VA) (Autor et al., 2011; Autor et al., 2016). On the other hand, female veterans selected into the military, a very male-dominated organization. It is thus possible that they make labor supply decisions more similar to males than female nonveterans and may participate in the labor market at much higher rates than (female) nonveterans.

Therefore, in Chapter 2, I examine the effect of selection into employment on the female veteran-nonveteran median wage differential, considering how this changed over the period 2006-2021.

2.2 Review of the Literature

Wages

There is evidence that female veterans earn wage premiums over their nonveteran counterparts. Both Padavic and Prokos (2017) and Kleykamp (2013) used similar data and found a wage premium in favor of female veterans of around 6% at the mean, controlling for a typical set of covariates. Renna and Weinstein (2019) researched the effect of veteran status on wages across the unconditional wage distribution. They found that, consistent with the "bridging hypothesis," female veterans make a 2.5% premium (unexplained portion of wage decomposition) at the mean. In the lower end of the wage distribution, females make wage premiums, but these turn negative in higher deciles of the wage distribution. The bridging hypothesis, developed by Berger and Hirsch (1985), suggests that military service acts as a way for those with lower levels of human capital to increase their human capital – this helps them "bridge" the gap between themselves and those with higher human capital.

The bridging hypothesis is consistent with observing those with lower wages earning a veteran premium and those at higher wages, with presumably more human capital, earning less of a premium, if at all, because the value of military service is not worth as much to those with already high levels of human capital. This is the pattern Renna and Weinstein (2019) found for female veterans. Female veterans earned more than their nonveteran counterparts in the first

40% of the wage distribution. However, as one progresses higher up the wage distribution, the premium is eroded to the point of being a penalty.

Standing in contrast to the above results however, Vick and Fontanella (2017) found a slight and statistically insignificant premium of 2% in favor of female veterans. However, Vick and Fontanella (2017) relied on an exact matching methodology, and noted there are far more low-paid female nonveterans that went unmatched compared to the number of low-paid male nonveterans that went unmatched. This contributed to the stark difference between the male veteran-nonveteran wage gap and the female veteran-nonveteran wage gap. Male veterans earned a substantial wage penalty (9%), whereas female veterans essentially earned the same as nonveterans. Vick and Fontanella (2017) demonstrated that there are lower rates of low-paid workers among veterans (both female and male) but that there are particularly low rates of low-paid workers among female veterans.

Employment

Vick and Fontanella's (2017) findings, along with Kleykamp's (2013) finding of substantially lower rates of employment for female veterans, raise concerns that female veterans and nonveterans may not be as comparable as male veterans and nonveterans. As such, an important innovation would be to assess selection into employment and whether it affects wage differentials.

Although no literature has examined female veteran selection into employment, there is some evidence that female veterans may be employed at lower rates than female nonveterans. An important distinction should be made, that is, people are only unemployed if they are actively seeking employment (participating in the labor market) and not matching to employment. Therefore, the unemployed are only a subset of people who we would potentially not be able to observe a wage. Thus, we are interested in the unemployed, but we are also interested in people who potentially do not have a wage to observe because they are not participating in the labor market. The literature that does exist on this issue focuses on unemployment and has not accessed selection into employment that includes both the unemployed and those not participating in the labor market.

Kleykamp (2013) and Hamilton et al. (2015) found that female veterans had the highest rates of unemployment as compared to female nonveterans or males (whether veteran or nonveteran). In fact, Kleykamp's findings suggest that female veterans had nearly double the rate of unemployment as compared to female nonveterans (13.72% vs. 7.35%). This may matter for research of wages because unemployed workers may not have a reported wage[18], thus inducing possibly nonrandom sample selection. If this missingness is related to other confounding influences like unobserved ability, this could induce bias in estimated wage equations.

Contributions

Although there is existing evidence on female veteran wages, no one has assessed the role selection may be playing in the estimated wage differentials. Evidence suggests female veteran-nonveteran wage differentials range from slightly negative to more than 6%, on average, depending on the methodology employed. Given that female veterans have experienced alarmingly high unemployment rates, there may be something systematically different happening to them that could have implications for their earnings (since employment must precede wage

[18] This would depend on data collection procedures and the design of survey items asking respondents about their income. Surveys may ask about current or previous year's income and time spent working, or usual income and time spent working. Thus, in some surveys, the same person could be unemployed and have no wage information or could still be unemployed and have wage information because it is usual income or previous year's income.

offers). Before one can credibly argue they have identified a wage gap, selection into employment should be assessed to ensure comparisons are reasonable.

Therefore, I examine whether female veterans select into employment differently than female nonveterans and whether this selection changes over time. Then, I examine how selection affects the female wage gap at the median for veterans compared to nonveterans. I assess the role of selection by "imputing" missing wages using a methodology similar to Olivetti and Petrongolo (2008) and then conduct a decomposition, developed by Firpo et al. (2018), of the observed median wage gap (similar to Blau et al., 2021).

2.3 Theory

Human capital theory, attitudes about work, and discrimination all offer valuable insights into why we might suspect a wage differential to arise between female veterans and female nonveterans. Because of female veteran's military service, we might suspect them to have received skills and training the labor market values, and also be found in occupations typically staffed by males (human capital theory). The military is heavily composed of males and has a distinct culture found in few other work environments. Because of this, it is possible female veterans will have adopted attitudes about work more like males. Finally, it is also possible that female veterans will be treated inequitably because of their military service.

Human Capital Theory

Becker (1962) identified the role of certain investments aimed at the development of skills that one eventually "rents" out to firms as important determinants of one's wage. For instance, when one attends university, they temporarily give up the opportunity to work for a wage (among other things). They do so because they are hopeful that foregone wages will be (more than) offset by future returns to the additional education they are receiving. The military may act as an investment in two sets of skills that could eventually lead to returns in the civilian labor market.

For veterans who work in an occupation in the military that has a civilian equivalent or matches civilian occupations closely, the military leads to the development of job-specific human capital. When service members enter the military, they select (or are assigned) a military occupational specialty. Like any organization, the military consists of many folks working in many different occupations toward a shared goal. Many of these occupational specialties have civilian equivalents, such as nuclear technicians, medical personnel, welders, divers, etc. This job-specific human capital accumulation may lead to a wage premium in favor of these veterans. Once these veterans enter the civilian labor market, they already have high-quality training, often in austere environments and under stress. The civilian labor market may choose to pay a premium for these workers both because of the quality of their training and because the firm may incur a lower cost of training these workers.

In addition to job-specific human capital, the military may increase all veterans' general human capital by imparting skills like punctuality, discipline, professionalism, etc. Again, firms may be willing to pay a premium for workers with these skills as they may enable firms to be more productive and develop a positive culture.

Attitudes

Beliefs about work are likely influenced by social norms around gender roles in the workplace and home (Eagly & Wood, 2016). Female military members, to some degree, do not conform to traditional gender roles. Once in the military, female service members enter both occupations traditionally stocked by males and enter into a workplace dominated by males. Social influence theory posits that individuals' behavior can be influenced by others, whether by another individual or a group (Kelman, 1958). For instance, identification with a particular group may lead a person to adopt the beliefs of the group. The military is likely to be an environment where one may strongly identify as belonging to a group, and the group is likely to influence individuals and their beliefs. These beliefs may change one's attitudes about work, the types of roles one can (should) aspire to, and how to conduct oneself in the workplace.

Fortin (2005) researched the effects of differing attitudes regarding values and work on wages. Fortin highlighted channels by which wage differentials could materialize from previous work. Previous scholarship showed how different attitudes toward work and gender roles were related to investments in human capital and salary negotiations (Vella, 1994; Babcock & Laschever, 2003). Fortin found that men prefer work that allows them to make more money and be leaders, whereas women prefer more altruistic work. Additionally, Fortin found differences in attitudes toward gender roles. For example, women are more likely to experience guilt for not spending as much time at home – impacting their likelihood of taking part-time work. Using a hedonic wage model, Fortin demonstrated these differing attitudes have significant effects on one's wage.

The military is and has always been comprised mostly of males, and as Fortin (2005) shows, men tend to differ in their beliefs and attitudes around work. It is possible, if not likely, that female veterans differ systematically from female nonveterans in their values, attitudes toward work, and perspectives on gender roles both before and after their military service. These attitudes are likely to, all else equal, lead female veterans into more traditionally male-dominated work environments and leadership positions. This should, all else equal, lead to wage premiums in favor of female veterans.

Discrimination

Becker (1957) originally formulated an economic theory that showed employers' preferences to work with certain groups would impact the wages they offered. In scenarios where employers hold preferences against certain groups, they perceive an added expense when hiring labor from the group they don't prefer. Scholarship has found evidence of wage discrimination, although not for female veterans specifically (Blinder, 1973). There are several ways an employer might discriminate against a certain group and pay them lower wages than others for the same work or refuse to hire members from the group. Refusing to hire members from a group may effectively lower wages within the group due to search costs. If female veterans have a difficult time finding employment, they may take the first wage offer that comes along, even if the wage offer is low. Wage disparities may result from individual bias, preconceived statistical notions, or noncompetitive market forces (Ehrenberg et al., 2021).

Individual bias occurs when an employer does not like associating with a particular group. Some employers may simply not agree with what the military does or may harbor negative notions of what kinds of things veterans value. This type of employer may not hire female veterans at all or choose to pay female veterans lower wages to compensate for the disutility of being around them.

Preconceived statistical notions occur when an employer has perceptions about a group that it applies to individuals in the group. Some employers may think that female veterans are generally more likely to have characteristics that would inhibit them from being productive workers. In this scenario, the employer may not want to hire female veterans or choose to pay them lower wages to compensate for the perception of female veterans being lower productivity workers.

Noncompetitive market forces occur when employers have power over the wages they pay and choose to pay a group a wage below the wage that would persist in a competitive labor market. For instance, firms could collude together and pay female veterans wages below their market value. This could occur because female veterans are a very small group and are easily identified, generally. Firms could use this information against female veterans, and because they are such a small group, they may not have enough power to effectively fight against the discrimination.

2.4 Methodology

To assess the potential effect of any difference in selection into employment by female veterans, I employ a methodology similar to Olivetti and Petrongolo (2008). They argue that one may not be able to impute a wage for someone with enough certainty to be useful; however, one could more easily predict whether a missing wage was likely to fall above or below the median wage. With this information, one could model the median wage gap between veterans and nonveterans, both with and without the position of the imputed wages, to see how selection could be affecting the wage gap between the two groups. Olivetti and Petrongolo (2008) point readers to Bloomfield and Steiger (1983) for a formal proof of why, if one correctly predicts whether the missing wage would be above or below the specified median wage, that the parameter of interest is recovered in a median regression using the "imputed" wages. Intuitively, the median is not sensitive to the distance from a particular value, only whether the value falls below or above the median.

Additionally, I follow the decomposition methodology of Firpo et al. (2018) to explore explained and unexplained portions of the female veteran wage differential. Firpo et al. (2018) demonstrate a method to decompose, analogously to an Oaxaca-style decomposition, distributional statistics other than the mean.[19] Firpo et al.'s (2018) methodology has two features worth noting. First, it uses a reweighting technique to ensure the explained and unexplained portions of the wage gap are properly identified. Second, it can model nonlinear functionals like quantiles. Third, it produces an estimate of both the reweighting error and specification error, allowing researchers to assess how well the methodology models the nonlinear functional.

The first step in this approach is to estimate a first stage regression predicting whether an individual's wage will be above the median wage. Like Olivetti and Petrongolo (2008) and Blau et al. (2021), this and the second stage wage models I estimate only include human capital information. This "human capital" specification[20] does not include arguably endogenous characteristics, such as family structure and other sources of income (e.g., spouse's income). The relationship (simultaneity) between these variables and my dependent variables will induce bias in my veteran estimates. The first-stage regression equations take the following form:

$$Above\ Median\ Wage_{i,j} = \beta_0 + \boldsymbol{\delta X_{i,j}} + \gamma_{i,j} region_{i,j} + \varepsilon_{i,j} \tag{2}$$

where the dependent variable is a binary indicator of whether the respondent (in group *j)* has an above median wage (above their group's median). $\boldsymbol{X_{i,j}}$ includes potential experience, education, employment status, race and ethnicity. I also include an indicator for each observation's region (i.e. northeast, southeast, northwest, or southwest). Following Olivetti and Petrongolo (2008), I fit a probit model separately to both the veterans and nonveterans and then produce fitted probabilities (probability of being above their group's median wage) for the observations missing

[19] Blau et al. (2021), another study that addresses differential selection into employment with various wage imputation approaches, use this methodology to decompose the median wage gap between males and females into an explained component and an unexplained component.

[20] Blau et al. (2021) refer to their analogous specification as their "human capital" specification.

a wage using their group-specific coefficient estimates. American Community Survey (ACS) provided person weights are used throughout the analysis.

With the first stage results, I produce imputed-wage samples where the observations with an observed wage keep their observed wage, but the individuals (observations) that are missing a wage each have two observations created. In both observations they retain all their observed information but are assigned different wage scenarios. In the individual's first (second) observation, they are assigned a wage above (below) the median wage with sampling weights *p* (*1-p)* where *p* is the observation-specific probability of having a wage below the median wage (i.e., the predicted value from the first-stage regression).

Next, separately for the observed data and data expanded by the observations with imputed wages, I decompose the observed median wage gap into an explained portion and an unexplained portion (similar to Firpo et al. (2018) and Blau et al. (2021)). The second-stage regression equation takes the following form:

$$RIF(wage_i |\, q_{.5}, F_{wage}) = \beta_0 + \beta_1 veteran_i + \boldsymbol{\delta X_i} + \gamma_i region_i + \varepsilon_i \tag{3}$$

Where now I am estimating the recentered influence function about the median of the distribution of wages. Similar to the first-stage equation, $\boldsymbol{X_i}$ includes potential experience, race, ethnicity, and region (but excludes employment status). The sample includes both veterans and nonveterans, thus veteran status is also included in the specification. This equation is estimated using the weights obtained in the first-stage, in addition to ACS-provided person weights.

Following Blau et al. (2021) and analogous to Renna and Weinstein (2019), I define the wage premium to be the portion of the median wage gap that is unexplained following a decomposition. Intuitively, we could imagine a scenario where veterans and nonveterans only differed in education, with veterans having more education. If, at the median, veterans also earned more, a decomposition would credit this difference entirely to the explained portion (being explained by veterans having more education). The unexplained portion then only exists if there are no observable differences in which to attribute differences in wages. Therefore, the unexplained portion of a wage decomposition is the most readily available measure of a wage premium. I then compare the unexplained portions estimated using the observed-wage samples to the unexplained portion estimated using the imputed-wage samples to assess the potential role of selection in the veteran-nonveteran median wage gap for females, and how it is evolving over time.

2.5 Data

The American Community Survey (ACS) data has the largest sample of veterans among publicly available data, an important factor when wanting to research female veterans as they comprise a relatively small, though increasing, portion of all military members. I use ACS data from 2006 to 2021. Using data prior to 2006 is complicated by two concerns. First, the share of veterans who are female declines substantially as the period extends earlier. Second, one cannot identify (and exclude) institutionalized individuals in prior years, making comparability an issue; this issue affects 3.5% of observations from 2006 to 2021. I construct three pooled samples using the time periods 2006-2009 (beginning), 2012-2015 (middle), and 2018-2021 (end).[21]

I focus my samples on prime working age (aged 25-54) females who were not self-employed or currently in the military. I also do not limit my samples to full-time workers only, as research has shown there to be little difference between their wages and the wages of part-time workers (Blank, 1990; Hirsch, 2005). Furthermore, it would be impossible to limit the

[21] This is analogous to Blau et al. (2021) who study the period between 1981-2015 but do so using five waves of the PSID (1981, 1990, 1999, 2011, and 2015).

imputed samples to just full-time workers because many observations needing a wage imputed are not full-time workers.

I construct wages by taking a respondent's total pre-tax wage and salary income and dividing it by the product of their reported hours worked per week and the midpoint of their weeks worked category.[22] For potential experience, I create dummy variables for 5-year increments from 0 years to 35+ years. For education, I create dummy variables for high school or high school equivalency, some college, bachelor’s degree, and advanced degree. These specifications allow me to flexibly control for variation in wages arising from variation in experience and education. For race and ethnicity, I create dummy variables for American Indian and Alaskan Native, Asian or Pacific Islander, Black, Other, and White along with an indicator of Hispanic status. Finally, I also create an indicator of whether the individual is currently married.

Table 2.1 shows descriptive statistics for both the observed sample observations and the imputed sample observations. Veteran workers earn higher wages compared to nonveteran workers. This wage advantage is consistent across both observed and imputed samples. Because wages are lower for both groups in the imputed sample, this implies that observations missing wages are systematically predicted to have lower earnings potential. This means that in both groups, workers are “positively selected” into employment; those with the highest potential wages are working in higher proportions than those with less favorable labor characteristics. Because both groups are positively selected, it is uncertain whether, and by how much, estimates of the wage gap might differ across the two samples.

[22] The ACS asks respondents how many weeks they worked and then places each observation into a fixed-width cell of weeks worked (e.g., 50-52 weeks).

Table 2.1: Descriptive statistics.

	Observed Sample		Imputed Sample	
	Veteran	**Nonveteran**	**Veteran**	**Nonveteran**
Mean (SD)				
Log wage	3.20 (.7)	3.14 (.7)	2.91 (1.3)	2.84 (1.3)
Education				
High School	21.5 (41.1)	29.4 (45.5)	23.0 (42.1)	32.7 (46.9)
Some College	38.5 (48.7)	28.0 (45.0)	39.8 (48.9)	27.8 (44.8)
Bachelor's	24.3 (42.9)	26.8 (44.3)	23.1 (42.1)	25.3 (43.5)
Advanced	15.7 (36.4)	15.9 (36.5)	14.2 (34.9)	14.2 (34.9)
Experience	20.6 (8.4)	18.9 (9.1)	20.8 (8.5)	19.2 (9.1)
Hispanic	9.3 (29.1)	13.2 (33.8)	9.4 (29.3)	13.8 (34.5)
Race				
AI/AN	1.0 (10.0)	0.7 (8.5)	1.1 (10.6)	0.8 (8.9)
Asian	2.5 (15.8)	6.3 (24.2)	2.5 (15.6)	6.7 (24.9)
Black	23.6 (42.5)	13.8 (34.5)	23.1 (42.2)	13.5 (34.2)
Other	6.8 (25.2)	7.6 (26.5)	7.0 (25.5)	7.9 (27.0)
White	66.0 (47.4)	71.6 (45.1)	66.2 (47.3)	71.1 (45.3)
Observations	76,087	4,633,413	114,599	6,928,209

Notes: The observed sample includes all observations with an observed wage. The imputed sample includes the observed sample with the addition of rows that had a wage imputed. The observed sample observations are weighted by ACS-provided person weights. The imputed sample observations are weighted by a composite weight composed of ACS-provided person weights and the imputed observations' fitted probability of being below their group's median wage.

2.6 Results

To start, I provide a descriptive picture of how employment differs during the sample period for female veterans and nonveterans. Figure 2.1 shows the evolution of the “employed” gap between female veterans and nonveterans over 2006-2021.

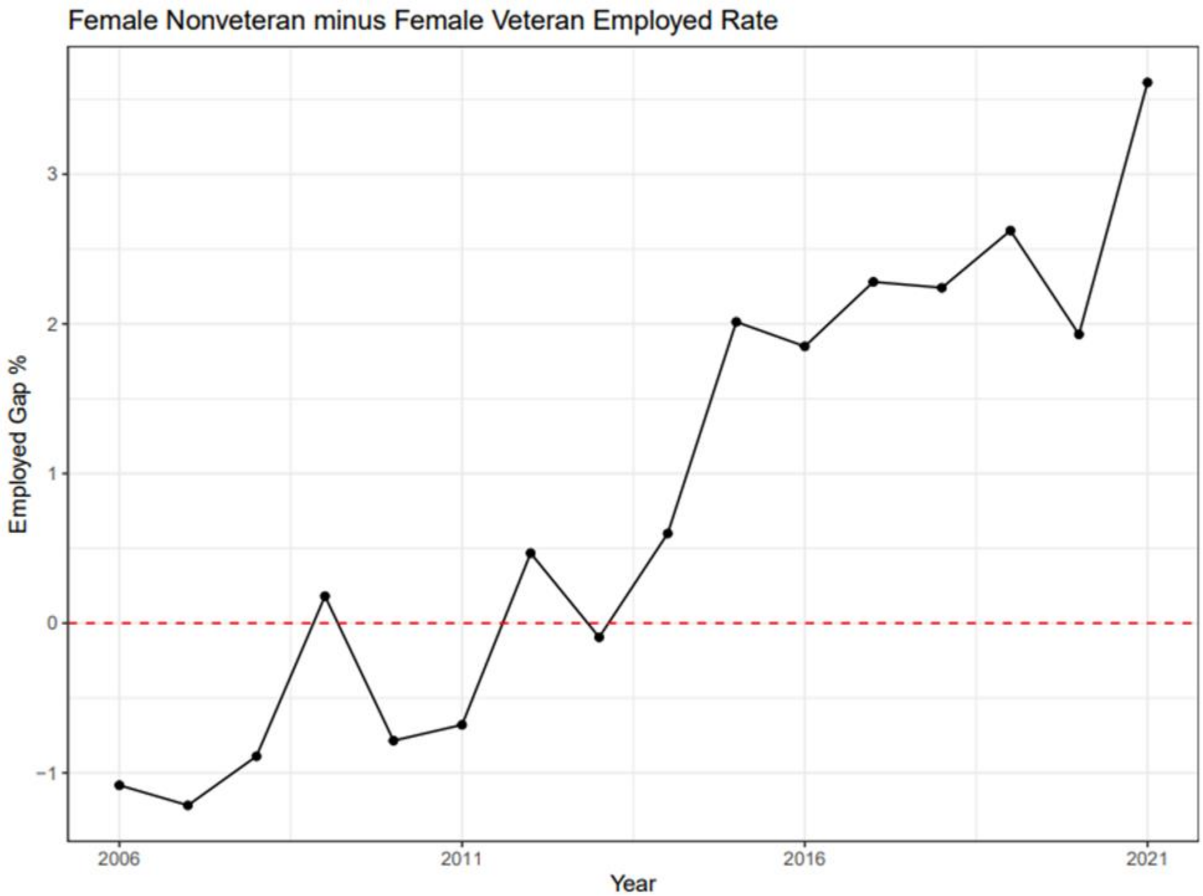

Figure 2.1: Female nonveteran-veteran employed rate difference, 2006—2021.

Notes: This figure shows the difference between the "employed" rate of female veterans and nonveterans based on the author's calculation using the ACS. Person weights are used to weight observations. Figure 2.1 sample includes females who were of working age (aged 25-54), noninstitutionalized, and non-self-employed and observations are weighted using the IPUMS provided person weights.

The y-axis reflects the employed rate gap. The "employed rate" is calculated as the number of persons who are employed divided by the sum of the number of persons who are unemployed *and* those not working who are not looking for work. This is distinct from the unemployment rate, which excludes the latter group. Many females are not in the labor force and, therefore, are not counted as unemployed. A natural issue is that without working, there is no wage to observe, so we need to "recover" this (potential) wage to build a counterfactual wage distribution. If female veterans with the lowest potential earning capacity are missing from work, so are their wages from our distribution. Furthermore, if female nonveterans with the lowest potential earning capacity are employed, we will be left comparing a group of veterans missing the lowest wage earners to a group of nonveterans that includes the lowest wage earners.

In Figure 2.1 we see that there are differences between female veterans and nonveterans in terms of rates of being employed. Initially, the employed rate for female veterans is about one percentage point higher than that for nonveterans. The disparity declines and then reverses by 2015, with the female veteran employed rate standing about 3.5 percentage points lower than that for nonveterans. One explanation for this pattern is that these veterans may be selecting out of the labor market. Another possible explanation is that, if they do select into employment, they are not being employed at the same rate as nonveterans due to increased rates of service-connected disability (SCD). Veterans may possess either one service-connected disability or multiple such disabilities. I opt to refer to both scenarios simply as an "SCD" rather than using "SCD and/or SCDs".

Increases in rates of possessing an SCD could be contributing to the pattern we see in Figure 2.1 through at least two channels. The first is that the veteran's SCD may be work-limiting, though this need not be the case. An SCD is not always work-limiting, and SCD payments are in no way affected by any income the veteran may receive from working. Therefore, it is possible, but not always the case, that a veteran's SCD inhibits them from working (either by necessity or because employers do not hire them). The second channel is that having an SCD entitles the veteran to generous compensation and disability payments from the VA, which may enable the veteran to reduce their labor supply. In this scenario, the veteran could work if they wanted to, but because they are receiving generous benefits from the VA, choose not to work.

Figure 2.2 shows trends in the percentage of veterans who have an SCD as well as trends in the percentage of veterans with an SCD whose SCD (severity) rating is 70% or higher. These figures cover 2008-2021, the years for which the ACS collected SCD information. Figure 2.2 illustrates two important pieces of information. First, among prime-age working female veterans, the rate of female veterans who have an SCD has increased sharply. In 2008, around 17% of female veterans had no reported SCD, whereas in 2021, only 33% of female veterans had no SCD. Second, this difference is almost entirely due to a precipitous increase in the percentage of female veterans whose SCD rating is at least 70% (the most severe category).

The SCD ratings are the result of disability rating exams performed by the VA to assess the severity of all service-connected injuries/traumas. Payments and the amount of healthcare the veteran receives for free (or at very little cost) are largely based on this rating. For instance, a veteran who receives a 10% rating is entitled to a monthly payment (until the end of their life) of $165 as of 2023, and VA payments are not taxable. A veteran with a 70% rating receives almost $1700 per month, and if they are married with one child, they receive over $1900 per month. Based on Figure 2.2, the percentage of female veterans who are now receiving at least $1700 in tax-free funds has increased by a factor of 8 since 2008. Additionally, although veterans may work with any disability rating, one might assume that female veterans with an SCD would work less, all else equal. A quick tabulation reveals that in my sample, around 77% of female veterans with no SCD are employed, whereas only around 58% of female veterans with an SCD are employed.

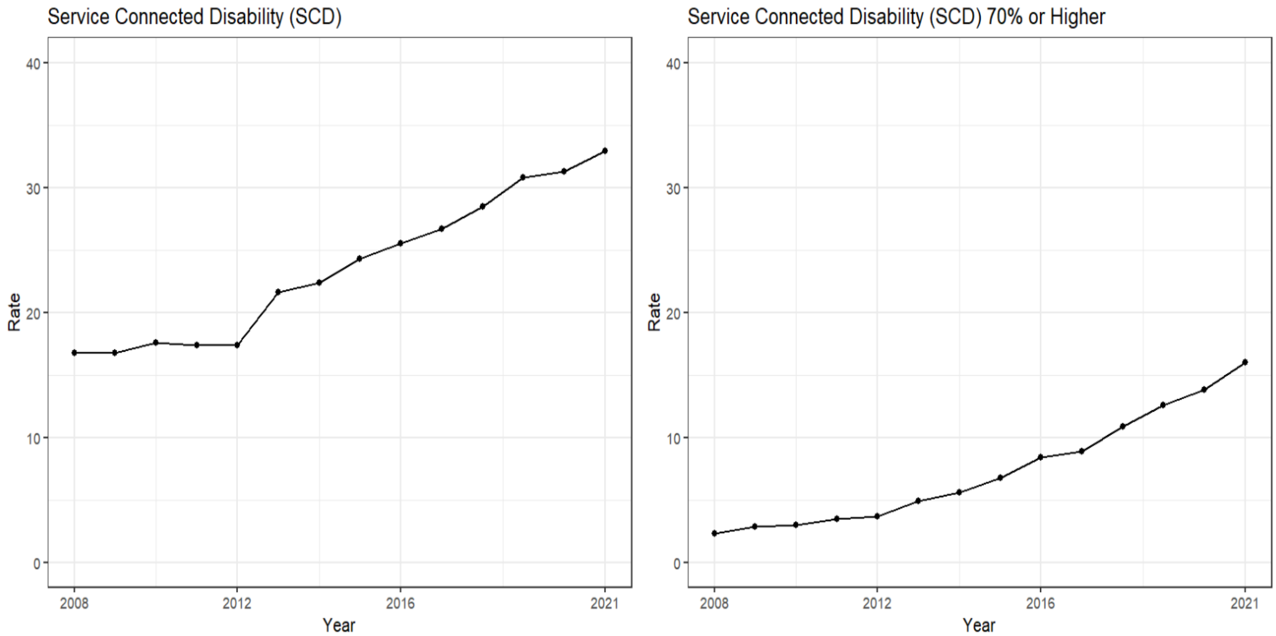

Figure 2.2: Prevalence of service-connected disabilities among female veterans: overall and severe cases, 2008—2021.

Notes: The left panel shows the percentage of female veterans that have an SCD. The right panel shows the percentage of female veterans that have an SCD with a rating of 70% or higher. Both panels are based on the author's calculation using the ACS. Observations are weighted by person weights.

There is some evidence that *male* veterans reduce their labor supply in response to an increase in their SCD rating. Autor et al. (2011), Autor et al. (2016), and Angrist et al. (2010) demonstrate that following increases in SCD ratings that led to increased VA payments, Vietnam veterans reduced their labor supply. Something similar could be at work for female veterans. Females are less likely to have combat experience, but Contreary et al. (2017) demonstrate that even non-combat veterans started receiving higher SCD ratings and more VA payments following the 2010 change in which veterans who served in non-combat roles began to be allowed to claim PTSD as an SCD. Contreary et al. (2017) also note that there was additional training provided to VA centers that handle Military Sexual Trauma claims starting in December 2011, which may have been particularly influential for female service members.

Figure 2.1 shows that as time progresses, the difference between the percentage of female veterans who are working for a wage as compared to the percentage of nonveteran females who are working for a wage is increasing. Although, admittedly, the differences in selection into employment are not as pronounced as they are when assessing selection bias in wage differentials between males and females.

Exploring these different patterns of selection over time and their effect on the median veteran-nonveteran wage gap, I produce a series of wage decompositions using Recentered Influence Functions (RIF) regressions. I do so for both a dataset containing only observations with an observed wage, and another set of decompositions for data expanded by observations with missing wages imputed. Table 2.2 contains the results from these RIF decompositions. The estimates for “Veterans” and “Nonveterans” are the median wage for veterans and nonveterans, respectively, in the particular period and sample. “Counterfactual (x1*b2)” indicates that the decomposition is performed from the perspective of veterans and provides us with a counterfactual median wage if veterans were to keep their observable information but be paid like nonveterans. The “Total Difference” is the gap between the median wage of veterans and nonveterans. “Explained” is the amount of the gap that can be explained by differences in the distributions of observable information between veterans and nonveterans. “Unexplained” is the component I am most interested in; it tells us what remains of the wage gap after we parse out the portion explained by differences in observable characteristics. When it is positive, this means veterans are earning a wage premium.

Table 2.2: RIF decompositions of median wage gap, female veterans vs. female nonveterans.

		Regular Sample		Imputed Sample	
		Estimate	**Bootstrap Std Error**	**Estimate**	**Bootstrap Std Error**
2006--2009	Veterans	3.179	0.007	3.140	0.008
	Counterfactual (x1*b2)	3.128	0.003	3.086	0.004
	Nonveterans	3.127	0.001	3.074	0.001
	Total Difference	0.052	0.007	0.066	0.008
	Explained	0.001	0.003	0.012	0.004
	Unexplained	0.051	0.007	0.054	0.008
	Specification Error	-0.004	0.002	-0.001	0.002
	Reweighting Error	0.000	0.000	0.000	0.000
		Regular Sample		**Imputed Sample**	
		Estimate	**Bootstrap Std Error**	**Estimate**	**Bootstrap Std Error**
2012--2015	Veterans	3.179	0.007	3.112	0.007
	Counterfactual (x1*b2)	3.094	0.004	3.041	0.004
	Nonveterans	3.080	0.001	3.014	0.002
	Total Difference	0.099	0.007	0.098	0.008
	Explained	0.014	0.004	0.028	0.004
	Unexplained	0.085	0.007	0.070	0.007
	Specification Error	-0.005	0.001	-0.001	0.002
	Reweighting Error	0.000	0.000	0.000	0.000
		Regular Sample		**Imputed Sample**	
		Estimate	**Bootstrap Std Error**	**Estimate**	**Bootstrap Std Error**
2018--2021	Veterans	3.261	0.011	3.214	0.008
	Counterfactual (x1*b2)	3.206	0.003	3.155	0.004
	Nonveterans	3.172	0.002	3.114	0.003
	Total Difference	0.088	0.011	0.100	0.008
	Explained	0.034	0.003	0.041	0.005
	Unexplained	0.055	0.010	0.058	0.007
	Specification Error	0.001	0.002	-0.003	0.002
	Reweighting Error	0.000	0.000	0.000	0.000

Notes: Decompositions are weighted by person weights. Two-hundred boostrap replications used in each decomposition.

The Firpo et al. (2018) decomposition methodology relies on influence functions, which have an associated approximation error when used to estimate effects on any statistic(s) of interest that is not the mean. Thus, the specification and reweighting errors are metrics that reflect how well the model is performing. The specification error tells us whether we should be concerned about the fact that RIF regressions provide linear approximations to nonlinear functionals (i.e., quantiles). Specification errors are thus unavoidable, but fortunately, the specification errors in Table 2.2 are not meaningfully different from zero. The reweighting error reflects the quality of the reweighting in the decomposition.[23] Like the specification errors, the reweighting errors are also not meaningfully different from zero. The implication is that, given our model, we have identified the explained portion (and therefore the unexplained portion) reasonably well using a linear approximation of a nonlinear functional.

Like wage gap studies of males and females[24], both veterans and nonveterans are positively selected into employment, as indicated by a lower median wage in the imputed sample compared to the observed sample. In other words, the observations that had to have a wage imputed were disproportionately predicted to have a wage below the median wage. Positive selection implies that, in both groups, those earning wages have higher earning potential than those not working. Put differently, those with the most to gain from working are those who work. Because both groups are positively selected, for the unexplained portion to be different from the imputed samples, one group would need to be less positively selected.

Crucially, there is no evidence of differential selection systematically affecting estimates of the veteran-nonveteran median wage gap. This is evidenced by the unexplained portion in the imputed samples not changing in a systematic way.[25] In the beginning and ending periods, the unexplained portions in the two samples are not meaningfully different. In the first period, the observed sample wage premium in favor of veterans is 5.1% and in the imputed sample is 5.4%. Analogously, in the last period these same premiums are 5.5% and 5.8% in favor of veterans. In

[23] The reweighting error is easier to reduce than the specification error because flexible modeling strategies (e.g., adding complexity to the specification) are feasible.
[24] See Blau et al. (2021) as an example of this.
[25] The results are not sensitive to using the simpler Blinder-Oaxaca style decomposition instead of the reweighting approach, whether with the arguably endogenous explanatory variables or without them. Results of these analyses are available upon request.

the middle period, the wage premium in favor of veterans is 8.5% in the observed sample and 7.0% in the imputed sample. This is a likely meaningful difference, but the difference is in the opposite direction of the other two periods, which is not strong enough evidence to suggest that selection substantially affects the female veteran-nonveteran median wage gap. Figure 2.1 above shows a clear pattern of female veterans disproportionately selecting out of the labor market as time progresses. However, it appears that this so far is not leading to selection systematically affecting the female veteran-nonveteran median wage gap, at least not in an obvious pattern or in a way easily discerned.

2.7 Conclusion

Previous studies have found a wage premium in favor of female veterans, but these studies all pool over several years and do not investigate the potential role of differential selection patterns into employment. Using a procedure proposed by Olivetti and Petrongolo (2008) to account for potentially changing effects of veteran status on wages due to selection, I decomposed the median wage gap between female veterans and nonveterans. I did this for three different periods, for both the observed sample not accounting for selection, and again for a sample that did account for selection.

Although there has been a notable shift in the “employed” rate between prime-age female veterans and nonveterans, consistent with prior literature that analyzed static samples pooled over many years, I find that female veterans earn wage premiums throughout my study period 2006-2021. Importantly, I find that the employed rate for female veterans is declining. This coincides with a precipitous increase in the rates of possessing a severe SCD. Nonetheless, it has not led to any detectable difference in the wage premium earned by female veterans. However, it is worrisome that female veterans are experiencing significant increases in their rates of SCD, especially because this appears to be driven primarily by an increase in the rates of SCD in the most severe category. Therefore, future research should seek to understand the role of SCD in the well-being of female veterans and their families.

Additionally, it is possible that as female veterans age, their ability to work for wages may diminish. Given the substantial increase in possessing an SCD among them, this may be the most likely future. The implication is that the results of an analysis such as this may change with time. It is essential for future research to revisit this topic, reassess patterns of selection, and determine if they have diverged enough to affect studies on wage gaps between female veterans and nonveterans.

2.8 Limitations

Although this study demonstrates that female veteran selection into employment is changing over time, it does not tell us *why* it is changing over time. This is concerning given that SCD is rising precipitously and driven mostly by an increase in the most severe SCD category. It is important to understand how the rise in possessing an SCD among female veterans and the decrease in employment over time are affecting the overall well-being of female veterans.

Policymakers and researchers use and discuss the average wage gap between two groups much more than the median wage gap between two groups. However, a primary issue when studying any wage gap is assessing whether selection is in part behind the gap, something that is much easier performed on the median than at the mean. Additionally, the average (or median) wage gap is certain to mask heterogeneity across the wage distribution, which has been shown to be substantial in the case of male veteran-nonveteran comparisons (Renna & Weinstein, 2019). One would ideally study gaps across the entire unconditional wage distribution for females as well.

The estimates of veteran status on wages are descriptive in nature and do not necessarily identify the causal effect of veteran status on wages. It is also not straightforward to determine what control variables to include, or to obtain data on all control variables one would potentially want to include. For instance, potential experience is a proxy for actual experience. One can imagine scenarios where, particularly for veterans, their work experience may be interrupted or stunted, or their military experience does not quite apply as labor market experience. Other control variables that are not present, such as parental SES, may further add to potential endogeneity influencing the veteran estimate.

My specification also did not include information on the veteran's service such as rank, branch, combat veteran status, and whether they were an officer or enlisted. These could be important subgroups to understand. With this additional information, we might better identify specific veterans who are especially likely to earn wage penalties/premiums relative to similar nonveterans. Policy could then be more targeted to provide help to these veterans.

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CHAPTER 3

3.1 Statement of Problem

Poverty measures can shed light on veterans and their families in ways that will be missed by studying typical labor market outcomes (like wages and unemployment) alone. For instance, we can observe the poverty status of someone whether they work or not, and we observe this for every member of the household because poverty is measured at the household level. Poverty is also a strong proxy for material well-being, to such a degree that the government uses poverty status to administer some social programs.

Concerning veterans and their families, previous scholarship has shown that the highest rates of functional limitations and work-limiting disabilities are found among veterans (Wilmoth et al., 2011; MacLean, 2010) and that disability is strongly linked to poverty (She & Livemore, 2009). Although veterans do have high rates of disability, veteran households have access to additional support that nonveteran households do not have, such as healthcare, and disability and compensation payments from the Department of Veterans Affairs (VA). Even if veterans are not working, these programs could provide resources sufficient to protect themselves and their family from poverty.

Thus, on one hand veteran households may have higher rates of disability that may inhibit working for wages. On the other hand, veteran households have access to additional support that could insulate them from poverty. Indeed, scholarship indicates the lowest rates of poverty are found among veteran households (London et al., 2011). This relationship holds whether one compares veteran households to nonveteran households, or if one compares veteran households with a disabled veteran to nonveteran households with a disabled nonveteran (where disabled refers to having a work-limiting disability).

An important mediating factor is likely veterans' access to support from the VA. London et al. (2022) showed that there is a potentially strong relationship between service-connected disability (SCD) and poverty. They calculated poverty rates among subgroups of veterans (and nonveterans as a whole) and found that veterans with the *worst* SCD had the *lowest* rates of poverty among any group. This relationship was found outside of a regression framework, but it speaks to the likely effect that support from the VA is having on the poverty rates of veterans and their families. Thus, special attention is warranted to research the potentially mediating effect of possessing an SCD on poverty among veteran households.

Within impoverished households, there exists variation in their poverty experience. For instance, two households that are both impoverished can still have substantively different experiences because one household may be just below the poverty line while the other is far below the poverty line. If a household has less than 50% of the resources needed to be at or above the poverty line, then this household is classified as being in deep poverty (or sometimes referred to as extreme poverty). Deep poverty is associated with particularly negative outcomes for both adults and children (Roy & Raver, 2014; Nguyen et al., 2020).

Although veteran households have lower rates of poverty than nonveteran households, there are reasons to suspect this advantage does not carry over to deep poverty. For instance, some veterans may not transition well back into society following their time in the military (Ackerman et al., 2020; Humensky et al., 2013). There is some evidence that this occurs among a subset of veterans. Using data from the "Wounded Warrior Project," a non-profit that helps veterans who were wounded in combat, Barr et al. (2022) find that among those who were impoverished, 75% were in deep poverty.

Therefore, in Chapter 3, I examine the effect of veteran status on households' likelihood of poverty and the effect of possessing an SCD on veteran households' likelihood of poverty. I do so over the period from 2009-2019. Assessing trends in these effects on the likelihood of poverty is important to ensure veteran households are not trending in the wrong direction. Also, in 2010 a policy change allowed many more veterans (noncombat troops) to receive SCD support through the VA for post-traumatic stress disorder (PTSD). This policy change created two periods with different conditions that likely led to compositional differences in who, among veterans, received SCD support (Contreary et al., 2017). The implication is that these effects could have changed over time, in part, because of this important policy change. I also examine my effects of interest on the likelihood households were also in deep poverty. Similarly, I examine these effects over the period from 2009-2019[26] to examine whether this severe experience is changing over time.

3.2 Review of the Literature

Related Dimensions of Well-being

Studies have examined poverty related measures of well-being among veterans and found evidence that veterans may not be faring well following their military service. For instance, Miller et al. (2015) compared food insecurity rates among veterans and nonveterans using 2005-2013 Current Population Survey Food Supplement data. They found that overall, veterans had very similar rates of food insecurity to nonveterans. However, crucially, they also showed that effects differed by veteran cohort; more recent veterans (serving since 1975) were at higher risk of food insecurity than nonveterans (0.7 percentage point difference, or 5% higher likelihood than nonveterans). Fargo et al. (2016) focused on homelessness, finding that veterans were

[26] 2009 is the earliest year with both Service-Connected Disability and Supplemental Poverty Measure data. 2019 is the latest year that the American Community Survey contains Supplemental Poverty Measure data.

generally more likely to be homeless, and this is true of each of the subgroups considered. Male veterans were more likely to be homeless than male nonveterans, female veterans were more likely to be homeless than female nonveterans, and Black veterans were more likely to be homeless than Black nonveterans. Additionally, they showed that homeless veterans were at increased risk for chronic diseases, suggesting that their homeless experience is arguably worse than the homeless experience of nonveterans.

In terms of working and earning wages, there is mixed evidence for whether veterans fare better than nonveterans. Veterans likely earn a near-zero or slight wage premiums on average compared to nonveterans (MacLean & Kleykamp, 2016; Vick & Fontanella, 2017; Padavic & Prokos, 2017). However, importantly, veterans at the low end of the wage distribution tend to earn the largest wage premiums (Renna & Weinstein, 2019). Although, evidence suggests that veterans have a higher likelihood of being unemployed than nonveterans (Kleykamp, 2013).

Poverty Measurement

There are several ways to conceptualize and measure poverty (Chen et al., 2023); the general goal is to define and measure material deprivation. The three most common poverty measures used by policymakers and researchers in the United States are the Officially Poverty Measure (OPM), the Supplemental Poverty Measure (SPM), and consumption-based measures (Meyer & Sullivan, 2012). The OPM was the first poverty measure among the three, having been developed in the 1960s. It is an income-based measure that compares a household's income[27] to a fixed threshold (which is scaled by inflation) based on a multiple (to account for other basic needs) of the cost of the minimal diet needs of a family as measured in 1967. The weaknesses of the OPM are that it is missing key information on many sources of income, does

[27] This includes typical income sources plus Social Security, unemployment insurance (UI) Temporary Assistance to Need Families (TANF), and Supplemental Security Income (SSI).

no adjustments for cost-of-living differences, does no adjustments for potentially complex family structures, and has a fixed threshold, making it an absolute measure of poverty as opposed to a relative measure. That said, the last point can also be a strength of the measure, depending on its use. As an example, because the OPM has a fixed threshold, one can use it to compare whether people today struggle as much as people in the past did with obtaining a similar set of necessities.

To overcome some of the weaknesses of the OPM, the Census Bureau developed the SPM (released for the first time in 2011), a relative measure that includes much more information on resources and expenses. Because the SPM is a relative measure, it accounts for the fact that resources have generally increased over time in the U.S. when it measures poverty. For instance, a person may not be in poverty according to the OPM because their income meets the requirement to afford basic needs as set at the development of the OPM. However, as measured by the SPM, the person could be in poverty because they have resources far below their peers. This may be a more appropriate interpretation if the person cannot meet the requirements of modern living, such as having access to the internet, heat and utilities in their residence, healthcare, etc. In addition to the same sources of income the OPM includes, the SPM includes many more sources of income such as tax credits (e.g., the Earned Income Tax Credit), and transfers from program participation such as Supplemental Nutrition Assistance Program (SNAP) and Women, Infants, and Children's Program (WIC) benefits, energy subsidies, and others. The SPM also considers more sources of expenses such as medical expenses and child support and makes a geographic adjustment to account for cost-of-living differences.

Although the SPM was developed to overcome some of the weaknesses of the OPM, the SPM also has weaknesses. One of the main weaknesses is that it subtracts out medical expenses from households' resources which leads to more elderly households falling under the poverty line (Meyer & Sullivan, 2012). The issue is that these households are likely to use their wealth to pay for these expenses, which creates a false group of materially impoverished households. The other primary weakness is that the relative nature of the measure can lead to perverse results because of fluctuations in the macroeconomy. For instance, an economic downturn may lower all households' resources, but because households' resources are compared to a threshold that is relative to other households' consumption expenditure, the SPM can show improvements in poverty where actually all households are worse off.

Yet another measurement is also in use. Material deprivation depends most crucially not on someone's income but on what they actually consume. The implication is that consumption is more intimately related to poverty than income is and might make for more accurate depictions of who is living in material deprivation. For instance, one well-known result from macroeconomics is that economic agents participate in consumption smoothing (resulting from convex preferences leading to concave objective functions). Meaning that one dollar of consumption "buys" more satisfaction when someone is poor than when they are relatively rich. The result is that an economic agent would prefer to transfer resources from relatively high points in their lifetime (usually later in life) to relatively low points in their life (usually earlier in life). There are many mechanisms by which a household might smooth their consumption. For instance, households can take out loans, or receive resources from their parents.

Consumption-based measures have nice properties; however, as with the other measures, there are important caveats (Chen et al., 2023). The data can be difficult to get and link to other data sources. Also, there is no agreed upon definition of poverty using consumption-based measures, and it is generally impossible to determine whether the additional consumption comes from wealth or loans. Furthermore, Shaefer and Rivera (2018) show that the SPM and OPM have stronger correlations with other measures of material deprivation (food insecurity, trouble paying bills, etc.) than a commonly used consumption measure based upon Consumer Expenditure Data.

Disability

Disability is strongly correlated with poverty status (She & Livemore, 2009). We know that veterans experience disabilities at higher rates than do nonveterans, including both functional disabilities (Wilmoth et al., 2011) and work-limiting disabilities (MacLean, 2010). Both veterans and nonveterans who develop a work-limiting disability may be able to receive transfers from the government in the form of Social Security Disability Insurance (SSDI). Crucially, one may not work if receiving SSDI transfers. If a veteran sustains an injury in-service that becomes a disability (service-connected disability), the veteran may become eligible for disability and compensation payments from the VA[28]. Unlike the more traditional disability payments, these payments are unaffected by the veteran's work status. Additionally, these VA transfers are generally scaled up as the veteran's household becomes larger and are non-taxable whereas SSDI transfers may become taxable under certain circumstances (for instance, if household income becomes too high).

The veteran may also become eligible to receive healthcare through the VA. Depending on the severity of the veteran's SCD, most or all the medical expenses are waived. A veteran with a disability rating of 50% or more will generally receive all healthcare through the VA at no cost. Under some circumstances, veterans below the 50% rating threshold also receive all their healthcare (whether it is related to their SCD or not) free, or, in most cases pay low copays. One

[28] The veteran must enroll for care at the VA. Following medical exams to determine the extent of disability, the VA assigns a rating between 0% to 100% disabled.

final point, healthcare at the VA is tailored to serve veterans, and the VA provides comprehensive rehabilitation. Because poverty and health are so inextricably linked (Deeny, 1937), the VA is well-suited to fight poverty on two fronts (cash transfers and comprehensive rehabilitation).

Veteran Poverty

There is evidence that veteran households have a decreased likelihood of experiencing poverty as compared to nonveteran households, but that the households that are impoverished might have an increased likelihood of deep poverty.

London et al. (2011) used Survey of Income and Program Participation (SIPP) data from 1992-2004 to research the effect of veteran status and work-related disability—which is distinct from service-connected disability—on poverty. They found that veteran households with no work-related disability had the lowest odds of poverty overall (27% lower than similar non-veteran households with no disabled persons). But the likelihood of poverty increased for both veteran and nonveteran households if there was a work-related disability present. Still, disabled veteran households enjoyed lower odds of poverty than nonveteran disabled households (odds ratio of 1.65 vs 3.2). Heflin et al. (2012) similarly looked at the effect of veteran status and the way it interacts with disability, again using 1992-2004 SIPP data, only now considering other measures of material hardships such as food insecurity, struggle to pay bills, etc. A similar story emerges to the 2011 paper above; veterans who are disabled tend to fair better than their disabled nonveteran counterparts.

We might expect disabled veterans to fare better than nonveterans *a priori* because some of these disabled veterans will be disabled because of their service, entitling them to receive additional support that nonveterans do not receive from the VA. These benefits (discussed above) likely contribute to the poverty gaps documented by prior studies.

Two recent studies have highlighted the potential impact of these extra supports in diminishing poverty among veterans. London et al. (2022), utilizing 2019 ACS data, revealed that veterans with an SCD tend to experience lower poverty rates. Moreover, the extent of poverty among veterans varies significantly based on their SCD ratings. Veteran poverty rates were nearly monotonically decreasing in SCD rating, with all remaining below that for nonveterans. Those with no SCD rating or ratings of 0% had poverty rates around 9%, which falls to 5.8% for veterans with SCD ratings between 10%-40%, declining further to 5.1% for SCR ratings between 50%-60%. The poverty rate increased slightly to 6.2% for veterans with the highest SCD ratings (70%+), though still well below the rate for veterans without an SCD (9%). Therefore, when simply looking at raw, observed poverty rates, veterans with an SCD had the lowest rates of poverty.

Barr et al. (2022) examined poverty among a group of Post 9/11 veterans using the 2018 Survey of Wounded Warriors, a survey administered to wounded veterans by the non-profit "Wounded Warrior Project". Barr et al. (2022) found that, in their sample of Post-9/11 wounded veterans, disabled veterans had a lower rate of poverty as compared to disabled nonveterans (17% vs 25%). However, among the 17% that were impoverished, 75% met the criteria for deep poverty. Additionally, the authors found that employment status was not a significant predictor of poverty but that cash transfers were very important for protecting veterans from poverty.

Relatedly, if cash transfers are important to insulate veterans from poverty, then the percentage of veterans receiving service-connected disability compensation payments doubling from 1992-2008 (Wilmoth et al., 2015) is likely an important and growing source of the difference between veterans and nonveterans in terms of poverty rates. As Burns et al. (2016) demonstrated, VA spending on service-connected disability compensation was steady at around $20 billion from about 1980-2000; following the 2001 Global War on Terror, VA spending rose every year through 2014, to $55 billion. Burns et al. (2016) argued that VA spending on compensation increased precipitously because the total number of veterans increased with the war. They further show that per capita spending on veterans went up because of higher disability ratings.[29] Thus, VA spending on compensation increased because there are more veterans, and each veteran is receiving higher payments on average. Contreary et al. (2017) also found evidence of an expansion of veterans receiving disability and compensation benefits from the VA following the 2010 expansion of benefits to non-combat troops.

Contributions

Possessing an SCD appears to be reducing the likelihood of poverty among veterans (London et al., 2022). However, this evidence is observational, as it is based only on simple means. We cannot be sure whether the observed relationship is an artifact of other potentially correlated information, such as education. Earlier studies (London et al., 2011; Heflin et al., 2012) examined the relationship between work-limiting disability and poverty but were unable to examine the relationship between possessing an SCD and poverty as the data to do so did not exist.

We know the likelihood of poverty among veteran households is lower than that of nonveteran households (London et al., 2011). However, we know little about whether this advantage materializes in terms of deep poverty. There are reasons to suspect that, among veteran households that do experience poverty, it is possible that their likelihood of deep poverty

[29] VA assigns a rating between 0% to 100% disabled and pays scale accordingly.

is elevated compared to nonveteran households. Indeed, there is some limited evidence that this may occur among wounded veterans (Barr et al., 2022). However, it remains unclear whether this applies broadly to all veterans. The Wounded Warrior Survey is not a large, nationally representative dataset and is intended to only represent wounded veterans who had registered with the Wounded Warrior Project on or before January 18th, 2018. Thus, external validity is a concern. Barr et al. (2022) also employed a rudimentary income measure, formed using categorical income information by assigning the midpoint value of each category. It is uncertain how that may have affected their results.

Therefore, in Chapter 3, I first examine the effect of possessing an SCD on the likelihood that veteran households experienced poverty, and I assess trends in this effect over time. Next, I provide an estimate of the effect of veteran status on the likelihood a household experiences deep poverty, also assessing trends in this effect over time.

My primary poverty measure is the SPM, although I also use the OPM and report where the results are meaningfully different. The SPM crucially considers information where veterans and nonveterans tend to systematically differ, encompassing factors like cost-of-living variations, out-of-pocket medical expenses, and transfers from various social programs. Both the OPM and the SPM incorporate transfer income from the VA, thus this is not a factor in measure selection. Although a consumption-based poverty measure would be beneficial, numerous barriers (data availability, complexity involved in weighting consumption based on its source, identifying sources of consumption, etc.) inhibit using one.

3.3 Theory

Brady (2019) argued that most theories explaining the causes of poverty can be grouped into three broad categories (structural, political, and behavioral). Structural theories highlight the role of demographics and labor market context, political theories highlight the role of power and institutions, and behavioral theories emphasize individual behaviors as driven primarily by culture and incentives.

This chapter makes three comparisons, first comparing veteran households to nonveteran households, then comparing veteran households with an SCD to veteran households without an SCD, and then comparing impoverished veteran households to impoverished nonveteran households. Given these three comparisons, it is important to consider how the above categories may explain differences in the likelihood of poverty among these groups across the three different comparisons.

Veteran Households vs. Nonveteran Households

Previous research suggests that veteran households face lower poverty rates than nonveteran households (London et al., 2011). The reasons for this difference are complex and can be attributed to structural, behavioral, and political factors. Structurally, veterans may benefit from selecting higher-paying occupations related to their service, such as technical roles. They also enjoy direct structural advantages like military discounts and preferential hiring by some businesses. Politically, the government's responsibility to care for veterans and its recognition of veterans as a “deserving group” results in substantial support, including cash transfers, healthcare through the VA, and job assistance like "Veterans Preference."

Behavioral explanations may further contribute to the disparity, as veterans, having volunteered for service and persevered through rigorous training, likely exhibit systematic behavioral differences from nonveterans. It is not hard to imagine that this could also lead veterans to generally have lower rates of poverty as compared to nonveterans.

Veteran Households with an SCD vs. Veteran Households without an SCD

Poverty rates are lowest in veteran households with an SCD, and nearly monotonically declining as SCD ratings increase (London et al., 2021). Structural explanations (economics and demographics) are unlikely behind this difference. First, if these factors were important, it seems they would likely move against veterans with an SCD. For instance, employment rates are lower among veterans with an SCD than veterans with no SCD. It is also not hard to imagine how among veterans with an SCD, those who did work would be negatively impacted by their disability in the labor market (e.g., they cannot work certain jobs, long hours, etc.). If structural explanations were important, we would expect veterans with an SCD to have higher poverty, not lower.

Although it cannot be ruled out that behavioral explanations are behind the observed difference in the poverty rates of these two groups, it is also difficult to imagine how veterans with an SCD differ behaviorally from those without an SCD (at least in ways that also produce less poverty). There are veterans with an SCD who never enter the VA system to receive care; in this case the SCD goes unidentified and undocumented. As compared to these veterans, and indeed even more generally, veterans who persist through the process of documenting and receiving care for their SCD may also be more likely to “fight” against poverty. On the other hand, veterans who do not seek help from the VA may have more “fight,” thinking they can independently survive. A behavior explanation is, therefore, ambiguous in its direction, the strength of which being questionable (since this comparison is veteran vs. veteran).

A political explanation essentially means that the state has the ability to choose the level of poverty among these two groups. This explanation has merit given that the most readily available systematic structural difference would predict *higher* poverty among the SCD group, and the most readily available behavioral explanation leads to an ambiguous expectation. There is a clear channel at work, namely that veterans with an SCD are under a policy (treatment) that provides generous support protective against poverty. In fiscal year 2023, VA spending was around $300 billion (around 4% of the federal budget, similar outlays to the Department of Education or Department of Agriculture).

Impoverished Veteran Households vs. Impoverished Nonveteran Households

This comparison is more complicated than the one just discussed because these two groups are more dissimilar. There is also little prior evidence to use as a starting point. Veteran households are less likely than nonveteran households to be impoverished, but among households that are impoverished we know little. Barr et al. (2022) showed that among a subset of wounded veterans who signed up to receive support from the Wounded Warrior Project, 75% met the criteria for deep poverty. However, we do not have a similar estimate for nonveterans. We also cannot form a similar group of nonveterans to obtain a similar estimate. The closest we could get would be a group of most similarly disabled nonveterans, but these disabilities would not exactly be equivalent and are indeed not likely to have cooccurring combat traumas. Further, this would only provide insight on disabled individuals and not the population of impoverished households as a whole.

An argument could be made for structural, behavioral, and political explanations explaining any differences in the likelihood of deep poverty among these two households. It could be the case that veterans living in deep poverty are systemically discriminated against. Structural forces could be against them if society did not know how best (or refused) to care for these veterans. It is also possible that veteran households are less likely to experience deep poverty. This could be explained by structural differences in how each group is paid, household structure differences, where each group tends to live, or the occupations each select into.

Behavioral explanations could be made in either direction. For instance, if it were the case that impoverished veterans had a higher likelihood of deep poverty, it could be due to their inability to consistently work with others. If it were the case that impoverished nonveteran households were more likely to be in deep poverty, it could be due to their lack of discipline (or that they are less resilient) as compared to veterans.

A political explanation could also explain any difference. It appears that the government is playing a role in reducing poverty among veterans. If this is not transferring to the most impoverished veterans, perhaps there is not enough political will. If it is transferring to the most impoverished veterans, then a similar story as the one above is likely unfolding. That is, the state is choosing whether and how much veteran households experience deep poverty (Brady, 2019).

3.4 Methodology

I employ linear probability models, estimated by ordinary least squares, to estimate my effects of interest. First, I estimate the effect of veteran status on households' likelihood of poverty. Second, within the subset of impoverished households, I estimate the effect of veteran status on the likelihood of deep poverty. Third, within the subset of veteran households, I estimate the effect of possessing an SCD on the likelihood of poverty. Lastly, within the subset of impoverished veteran households, I estimate the effect of possessing an SCD on the likelihood of deep poverty. I also specify models analogous to the models estimating the effect of possessing an SCD on the likelihood of poverty among veteran households. In these models I switch out the indicator of an SCD for SCD severity. In all models, I interact the variable of interest with the year, to estimate unique effects for each year of data.

The regression equation takes the following base form and is estimated by ordinary least squares using ACS-provided household weights:

$$Y_{it} = \beta_0 + \delta X_{it} + \gamma veteran_{it} + \varphi_t veteran_{it} * year_{it} + \varepsilon_{it} \quad (4)$$

The dependent variable is the poverty status (whether in poverty or in deep poverty, for my first and second research questions, respectively) of household i as measured by the SPM[30]. "*veteran*" is an indicator for the presence of a veteran in the household. The vector $veteran_{it} * year_{it}$ is comprised of a set of interaction terms between each year dummy and veteran status, allowing the effect of veteran status to vary across years. The sum $\gamma + \varphi_t$ then gives the average marginal effect of veteran status on the likelihood of being in poverty in year t. The controls included in the vector *X* are the race, ethnicity, and age of the head of the household, the maximum education obtained within the household, an indicator for the presence of a disability in the household, an indicator of household structure (married/cohabitating, single male-headed, or single female-headed), an indicator of the presence of any children under age five, the number of children under age 18 within the household, the household's metro status (urban or rural), and state and year fixed effects.

The race, ethnicity, and age of the head of the household are included to control for any systematic demographic differences between veteran and nonveteran households. For instance, we know veterans tend to be more diverse than nonveterans, this could lead to higher poverty among these households due to historical, systematic differences among the different races. The indicator of disability controls for non-SCD disability differences that might exist between veteran households and nonveteran households. For instance, it could be the case that veteran households are generally less prone to disability because veterans undergo intense health screenings prior to service. Education very likely leads to lower rates of poverty over and above

[30] I will also use OPM poverty rates and note any differences that arise.

its correlation with income. Veteran households likely have higher amounts of education; thus, controlling for education is important. Services and social support may differ between urban and rural areas; therefore, it may be important to control for differences in housing location preferences. State fixed effects are included to absorb time-constant variation across states in the likelihood that a household experiences poverty, such as some states having persistently low economic activity. Year fixed effects are included to account for aggregate shocks to poverty that impact all households similarly.

Lastly, I include household structure controls. Veterans are far more likely to be males and may be married/cohabitating at different rates than nonveterans. It is well-known that males tend to make more money than females and tend to work in higher proportions. Having two persons split household production surely results in less poverty, even absent the relationship between two-earner households and household income. I also include information on the number of children in the household who are not adults and whether any very young children live in the household. Although this information is somewhat considered by the SPM (and less so by the OPM), it is still important to be included as a control. First, although the SPM and OPM thresholds are in part determined by the number of persons in the household, my controls do not exactly coincide with the number of persons in the household. Second, having very small children or being in a female-led household may increase the risk of poverty regardless of income or how much money one needs to buy food and necessities. For instance, these households may not have the capacity to seek help or attend medical appointments, etc.

To investigate the (descriptive) effect of service-connected disability (SCD) on veteran households' poverty rates, I estimate a modified version of equation (4); I replace the indicator of veteran status, $veteran_i$, with an indicator for whether the household has an SCD, in both the level term and interaction terms. In this case, I use only the sample of veterans. To explore potential heterogeneity by the severity of the SCD, I again estimate a modified version of equation (4). I replace the indicator of veteran status, $veteran_i$, with an indicator for the severity of the SCD, in both the level term and interaction terms. I again use only the sample of veterans in this analysis. The categories are constructed as “No rating or 0%”, “10%-20% (Low)”, “30%-60% (Medium)”, and “70%+ (High)”. Veterans who receive a rating of 0% or who have no SCD are very similar in their support from the VA. Starting at a 40% disability rating, the VA begins paying veterans extra depending on their household structure; this would make for the most reasonable cutoff between the “Low” and “Medium” categories. However, in ACS data, the categories are constructed in 10% increments; therefore, it is not possible to begin the “Medium” category at 40% because this category is 30%-40%. ACS data lists every veteran with an SCD rating of 70% or higher as “70%+”, this makes for a natural categorization as these veterans all have the most severe SCD and receive the most support from the VA.

Following each set of regressions, I produce and plot, over each year, the average marginal effect of each variable of interest (veteran status, SCD status, or SCD severity) on the likelihood a household experiences poverty (or deep poverty). This is necessary as the variables of interest appear in levels and interaction terms in equation (4), and their effects are now composed of two terms, one of which varies by year.

3.5 Data

The American Community Survey (ACS) is a nationally representative dataset that is comprised, in part, of the largest sample of veterans in any publicly available data. Furthermore, the ACS collects data on poverty, disability (both work-limiting and service-connected starting in 2008), and household structure. These measures are critical to studying trends in veteran poverty, as well as documenting how the association between service-connected disability and poverty has evolved over time.

Starting in 2008, the ACS began collecting data on veterans' service-connected disability status and rating, and many veterans receive VA disability and compensation benefits that will impact the poverty statuses of their households. Starting in 2009, the ACS began collecting data on the SPM, a poverty measure that considers far more information than the OPM – importantly, information that is very relevant to veterans. SPM data is only available through 2019. Therefore, the analysis sample includes ACS[31] data from 2009-2019 to get both VA disability rating information and SPM information.

Table 1 shows many systematic differences between veteran and nonveteran households. First, veteran households have far lower rates of poverty and deep poverty. This is likely due, in part, to compositional differences among veteran versus nonveteran households. Veteran households tend to be older, slightly more educated, have higher rates of cohabitation, and have lower rates of being single female-headed households. Although veteran households do have higher rates of disability[32], which is strongly associated with poverty, we know some of these veteran households have access to VA support that should help them avoid material deprivation.

In the second panel, the sample consists of only impoverished households. For both veteran and nonveteran households, disability rates are higher as compared to the overall sample. Importantly, impoverished households have lower educational attainment and lower rates of

[31] Columbia University's Center on Poverty and Social Policy releases a historical version of the SPM that can be linked to Current Population Survey (CPS) data; however, one also needs to use the veteran supplement of the CPS to get information on veteran disability and ratings. This can be done but it leads to a small sample size in every year.

[32] Betancourt et al. (2021) report that, over a sample from the years 2003-2019, veterans have higher rates of several important morbidities as compared to nonveterans.

cohabitation, although veteran households fare better than nonveteran households on these measures.

Table 3.1 Descriptive statistics.

	Overall		Impoverished	
	Veteran	**Nonveteran**	**Veteran**	**Nonveteran**
Mean				
SPM Poverty	8.7	17.0	--	--
OPM Poverty	6.3	14.7	--	--
SPM Deep Poverty	3.2	6.2	36.7	36.4
OPM Deep Poverty	2.9	6.2	41.1	42.3
# Children	0.5	0.66	0.31	0.68
Age	60.7	50.0	61.7	48.4
Any Child Under 5	5.1	11.1	4.6	12.4
Any Disability	41.2	23.7	48.7	31.4
Race				
AI/AN	0.7	0.7	1.1	1.0
Asian	2.3	5.7	2.3	6.3
Black	11.4	12.9	16.7	20.1
Other	5.2	8.3	4.3	9.8
White	80.5	72.4	75.6	62.9
Hispanic	7.5	14.8	8.6	22.7
Education				
Less than HS	1.9	5.5	5.9	14.8
HS	24.0	25.5	39.9	38.4
Some College	28.6	24.6	33.0	27.7
Bachelor's	23.8	24.4	14.1	13.3
Advanced	21.7	20.0	7.0	5.7
Structure				
Married/Cohab	74.9	55.4	55.0	36.4
Single Male	19.8	14.8	36.4	17.3
Single Female	5.2	29.8	8.6	46.3
Metro	86.4	89.1	85.3	89.1
Any SCD	21.1	--	16.9	--
SCD Severity				
No rating or 0%	80.1	--	84.5	--
10%-20% (Low)	6.6	--	5.6	--
30%-60% (Med)	6.3	--	4.9	--
70%+ (High)	7.0	--	5.1	--
Observations	1,657,699	12,804,384	121,725	1,547,950

Notes: The first panel consists of all households. The second panel consists of impoverished households. Only veteran households are capable of having a service-connected disability (SCD). The SPM is used to create the subset of impoverished households, with the exception of the OPM deep poverty rates. The deep poverty rates in the second panel are constructed from identifying impoverished households using the deep poverty measure's underlying poverty measure (e.g., OPM deep poverty is found by first indentifying which households are impoverished according to the OPM).

Interestingly, impoverished veteran households have lower rates of possessing an SCD as compared to veteran households overall. Among veteran households with an SCD, SCD severity is distributed relatively uniformly. Surprisingly, among veteran households in poverty with an SCD, they appear no more likely, and arguably slightly less likely, to be in the most severe SCD category.

Figure 3.1 shows that, whether one measures by the SPM or OPM, veteran households have lower rates of poverty as compared to nonveteran households in every year. Although there is a difference in the magnitudes of the two measures, they both trend very similarly. Using the SPM leads to higher measured rates of poverty for both groups than the OPM. Over time, there appears to be a slight convergence between the two groups. Veteran households have had stable poverty rates since 2009. Nonveteran households have experienced a slight decline in their rates of poverty, driving the convergence between the two groups.

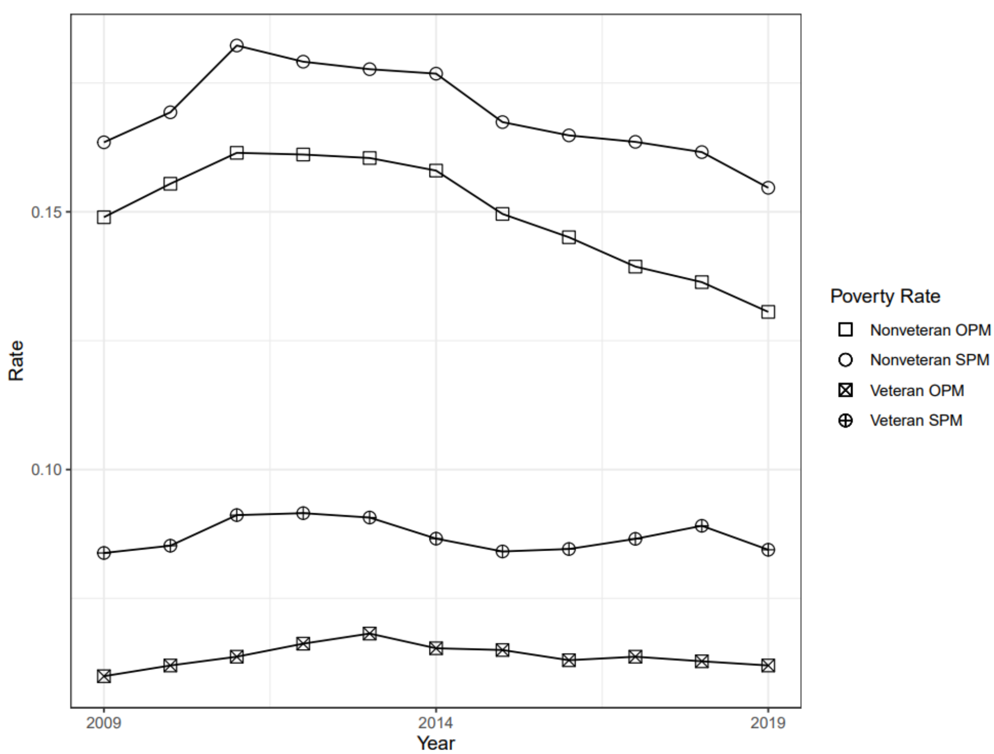

Figure 3.1: Veteran and nonveteran household poverty rates, 2009-2019.

Notes: This figure shows household rates of poverty calculated by the author using the ACS. Households are weighted by household weights.

Based on Figure 3.1, we should expect veteran households to have a lower likelihood of poverty in each year. However, once we account for the other important systematic differences between the two groups, the veteran advantage could change.

3.6 Results

In Poverty

Figure 3.2 displays average marginal effects (AME) of veteran status on households' likelihood of poverty, corresponding to $\gamma + \varphi_t$.[33] In 2009, veteran households are about 1.7 percentage points less likely to be in poverty than nonveteran households. This gap peaks at about 3.3 percentage points in 2014, but then diminishes thereafter. In 2019, veteran households are again about 1.7 percentage points less likely to be in poverty than nonveteran households. Overall, as evidenced by Figure 3.1 and Figure 3.2 and consistent with prior research, veteran households enjoy a lower likelihood of poverty in every year as measured by the SPM and OPM.

In my sample, across all years on average, the overall rate of household poverty as measured by the SPM is around 16 percentage points. To put the veteran poverty rate differential into perspective, we can compare the estimates to this baseline poverty rate. An estimate of negative 1.7 percentage points represents about a 10% lower likelihood of poverty among veteran households. An estimate of negative 3.3 percentage points represents just over a 20% lower likelihood of poverty among veteran households.

[33] Regression estimates are contained in Appendix A. All regressions use robust standard errors and are weighted using household weights.

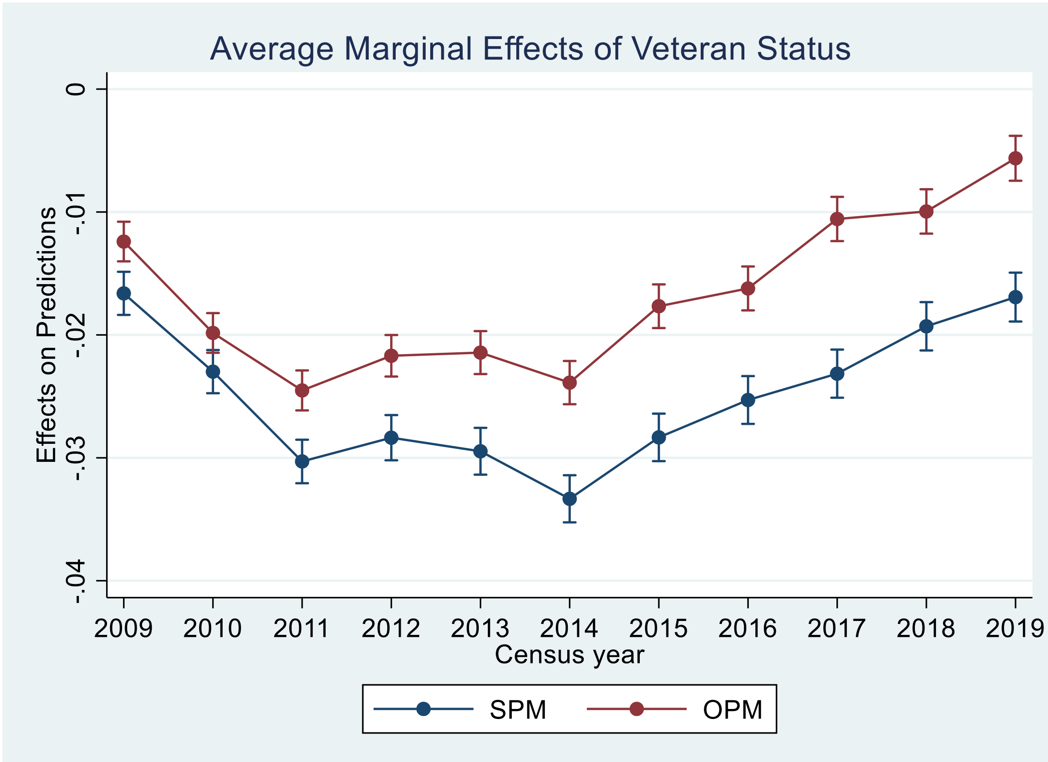

Figure 3.2: Average marginal effects of veteran status on households' likelihood of poverty, 2009-2019.

Notes: This figure shows AMEs based on estimates from a linear probability model. 95% confidence intervals provided.

Although the veteran poverty rate differential is the same in the first and the last period, as measured by the SPM, the story is incomplete without considering that in 2014 the disparity had grown to its largest but has since started to converge. Veteran households enjoy low rates of poverty, and their unconditional rates have experienced little change over time. It is plausible that the more recent convergence is due to nonveteran households "catching up" to veteran households and not veteran households faring worse.

Deep Poverty

Figure 3.3 displays AMEs of veteran status on impoverished households' likelihood of deep poverty. In 2009, veteran households are about 1.7 percentage points more likely to be in deep poverty than nonveteran households. This gap peaks at about 2.1 percentage points in 2017. Among impoverished households, both veteran households and nonveteran households have similar rates of also being in deep poverty; around 36% of impoverished households, both for veteran and nonveteran households, also meet the criteria for deep poverty. Thus, the estimates in Figure 3.3 imply a slight disadvantage for veterans (around 5% higher likelihood at a mean deep poverty rate of 36 percentage points).

The disadvantage is larger, at around a 10% higher likelihood of deep poverty for veteran households, if one uses the OPM instead. It is difficult to know why using the OPM leads to a larger veteran disadvantage than when poverty is measured using the SPM. The OPM does not account for things like regional cost-of-living differences, participating in many income supplementing programs, and medical expenses. My preferred measure is the SPM, precisely because it accounts for these things. However, it is worth noting that this difference could be because neither measure is accurately counting households in deep poverty; the truth may very well be somewhere in the middle of the two sets of estimates.

A likely contributing source of this disadvantage is that impoverished veteran households have low rates of possessing an SCD. In fact, impoverished veteran households have around 20% lower rates of an SCD than veterans overall. This is consistent with SCD-related payments and healthcare protecting veteran households from poverty. What is likely occurring is that many veteran households may have an unaddressed SCD which is leading to increases in their likelihood of poverty and deep poverty.

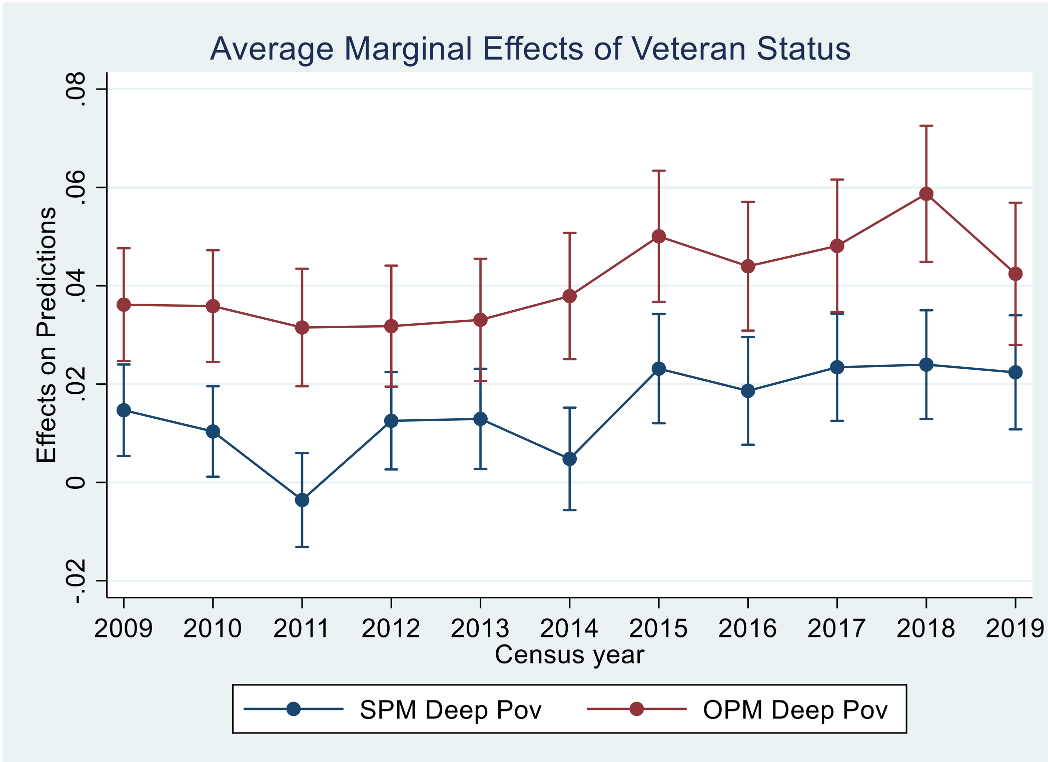

Figure 3.3: Average marginal effects of veteran status on impoverished households' likelihood of deep poverty, 2009-2019.

Notes: This figure shows AMEs based on estimates from a linear probability model. 95% confidence intervals provided.

Service-Connected Disability – In Poverty

Figure 3.4 displays AMEs of possessing an SCD on veteran households' likelihood of poverty.[34] In 2009, veteran households with an SCD are about 2.3 percentage points less likely to be in poverty than veteran households without an SCD. This gap peaks at about 2.6 percentage points in 2017 and declines to around 2.4 percentage points in 2019. The effect of an SCD on the likelihood of poverty is consistent across the period of study and is similar whether

[34] SCD and ACS-defined disability are correlated but do not coincide. Because the two are correlated, I provide sensitivity analysis in Appendix B. The sensitivity analysis removes ACS-defined disability from the estimated equation.

one uses the SPM or the OPM as the poverty measure. Among veteran households, the average poverty rate across all years is around 8.7 percentage points (as measured by the SPM). To put the estimates into perspective, an effect size of 2.3 percentage points translates into around a 26% lower likelihood of poverty among veteran households with an SCD at an average poverty rate of 8.7 percentage points.

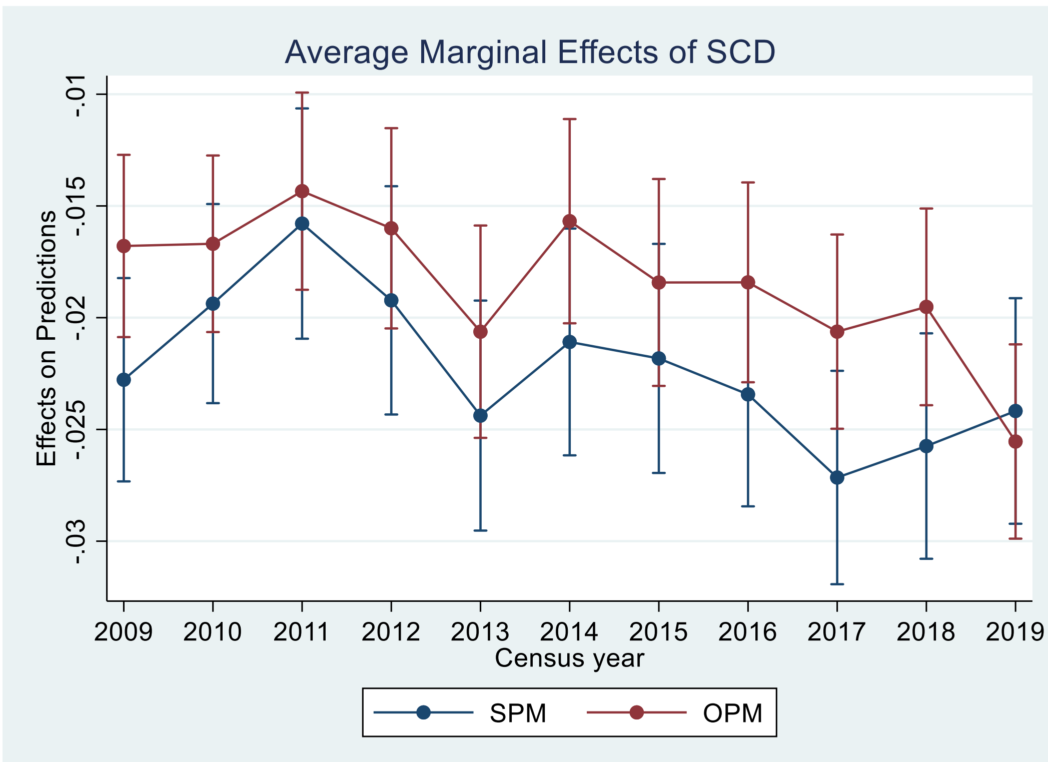

Figure 3.4: Average marginal effects of an SCD on veteran households' likelihood of poverty, 2009-2019.

Notes: This figure shows AMEs based on estimates from a linear probability model. 95% confidence interval provided.

London et al. (2022) showed, using 2019 ACS data, that veterans with a service-connected disability (SCD), entitling them to receive lucrative tax-free payments and healthcare, had the lowest rates of observed poverty among veterans with no SCD and nonveterans (13.8%

and 9% vs. 5.7%). Above, we see that estimates comparing veterans with an SCD to veterans without an SCD also bear this observed relationship to be true even after econometrically controlling for many other observable differences. Veteran households where the veteran has an SCD are expected to have around a 2 percentage point lower likelihood of poverty on average as compared to veteran households where the veteran does not have an SCD.

Service-Connected Disability – Deep Poverty

Figure 3.5 displays AMEs of an SCD on impoverished veteran households' likelihood of deep poverty. In 2009, impoverished veteran households with an SCD are about 4 percentage points more likely to be in deep poverty than impoverished veteran households without an SCD. The effect is consistent across the period of study. Among all veteran households, possessing an SCD helps reduce the likelihood of poverty; however, among impoverished veteran households, the presence of an SCD increases the likelihood of deep poverty. The relationship is stable over time and is similar across both poverty measures. The rate of deep poverty among impoverished veteran households is around 36 percentage points. To put the estimates into perspective, an effect size of 4 percentage points implies that the presence of an SCD increases the likelihood of deep poverty by around 11% among impoverished veteran households at an average deep poverty rate of 36 percentage points.

At first glance, this is curious given the relationship between possessing an SCD and poverty among all veteran households. However, within context, this may make sense. The presence of an SCD implies the veteran is receiving help from the VA. Part of this help is tax-free payments that, unlike traditional disability, are unaffected by the working status and income of the veteran. In most cases, it is likely that veterans with an SCD are both working and receiving disability payments from the VA. It is also possible that some disabled veterans with an SCD are receiving traditional disability and SCD compensation and disability payments from the VA. Among an already small subset of veteran households (8% are impoverished), some of these households fall into deep poverty (around one-third). These deeply impoverished households are an even smaller subset of households and likely systematically differ from other households. A component of this systematic difference is likely that these veterans have a very severe SCD that prohibits the veteran from functioning normally, increasing their household's likelihood of deep poverty. As an example, although most veterans with an SCD likely work and participate normally in society, some veterans with an SCD may have such a severe SCD that they cannot work and cannot function normally in society.

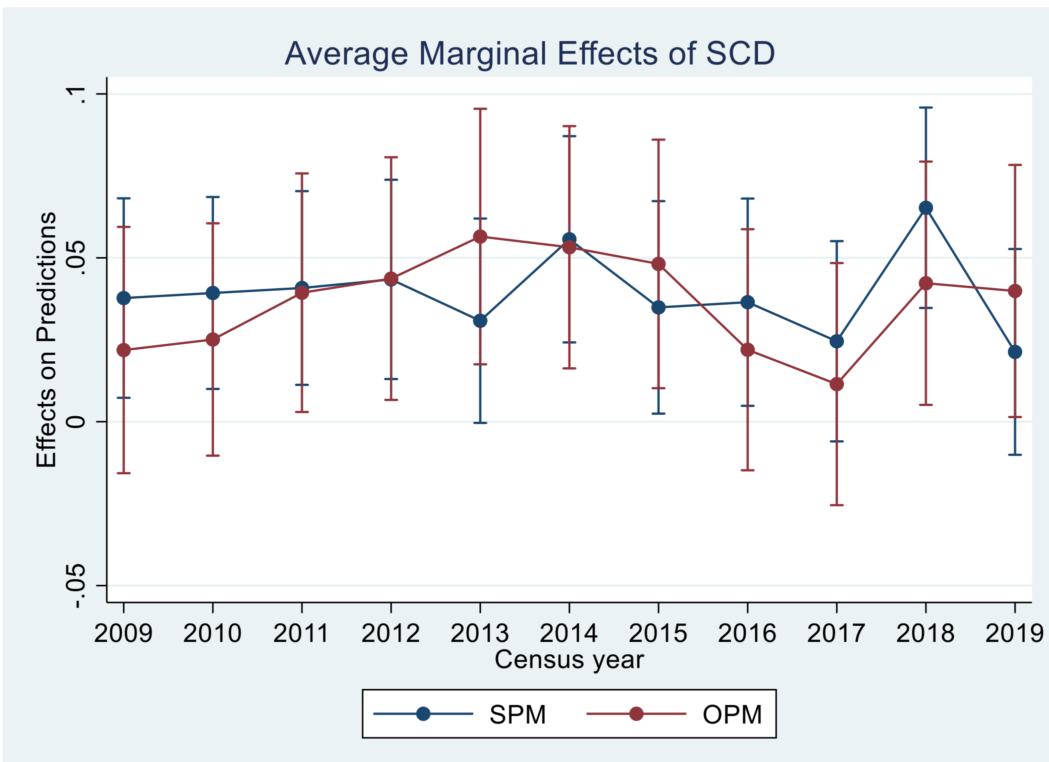

Figure 3.5: Average marginal effects of an SCD on impoverished veteran households' likelihood of deep poverty, 2009-2019.

Notes: This figure shows AMEs based on estimates from a linear probability model. 95% confidence interval provided.

Service-Connected Disability Severity

SCD ratings are assigned (by the VA) to veterans following their rating examinations. Veterans are assigned a rating between 0% to 100%, reflecting the severity of their disability. A rating of 0% is the lowest rating a veteran is assigned, and 100% implies the veteran is fully disabled (severely affected in everyday life). As SCD ratings increase, so does the help the veteran receives from the VA. Compensation and disability payments increase as rating increases, and at 30% disability rating the veteran begins receiving additional payments reflecting their household structure. Generally, at 50% SCD rating, the veteran will receive all healthcare from the VA for free or for very little money. It is also possible for veterans below 50% SCD rating to receive all healthcare from the VA heavily subsidized depending on the veteran's condition.

London et al. (2022) provided poverty rates for veterans by SCD rating category. Interestingly, there exists a near monotonic relationship between SCD rating and poverty rates among veterans. These rates were simple group averages; therefore, it is hard to know whether this relationship would also be true within a regression framework.

Figure 3.6 shows that this relationship holds true even after controlling for important covarying information among veteran households. Veteran households with an SCD in the most severe SCD category ("High") are consistently predicted to have a lower likelihood of poverty than the other SCD categories. Veteran households in the "Medium" SCD category are consistently predicted to have the second lowest likelihood of poverty. Veterans in the "Low" SCD category are predicted to have lower likelihoods of poverty as compared to veteran households with no SCD rating or a rating of 0%.

Like the results above that compared veteran households with an SCD to non-SCD veteran households, this is strong evidence that possessing an SCD is helping to reduce poverty among veteran households. Furthermore, possessing an SCD reduces poverty more as a veteran's rating increases, all else equal. The relationship between the SCD severity and the likelihood of poverty among veteran households does not appear to be changing over time. As noted earlier, there was a significant policy change in 2010 that increased the rates of an SCD among non-combat troops. This almost surely resulted in a compositional shift in which veterans receive SCD support. We might expect there to be a change in the effect of an SCD and SCD severity on the likelihood of poverty among veteran households over time; however, there is no evidence to support this expectation. Other notable but more minor changes have also occurred during my period of study, but also do not seem to be leading to any changes in the effect of an SCD on the likelihood of poverty among veteran households. In 2011 started providing specialized training to SCD claims processors to better identify Military Sexual Trauma. In 2014, Congress passed the Veterans Access, Choice, and Accountability Act, allowing veterans to seek civilian healthcare to reduce wait times and travel expenses. In 2015 the VA expanded benefits for veterans living with a traumatic brain injury, allowing them to receive extra payments for other comorbidities like dementia.

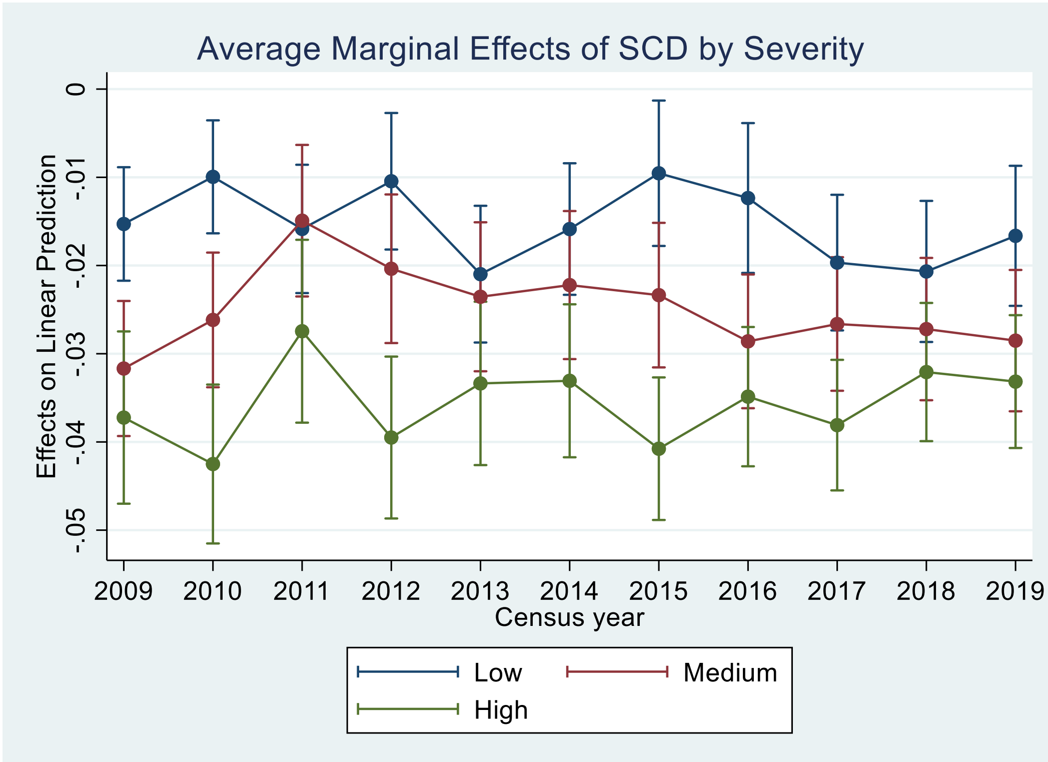

Figure 3.6: Average marginal effects of SCD severity on veteran households' likelihood of poverty (SPM), 2009-2019.

Notes: This figure shows the effect of SCD severity on the likelihood of poverty among veteran households as measured by the SPM. SCD severity is a categorical variable, and the omitted category is the "No rating or 0% rating" category. AMEs are based on estimates from a linear probability model.

Figure 3.7 shows the relationship between SCD severity and the likelihood an impoverished veteran household experiences deep poverty. Interestingly, for both the "Low" and "Medium" SCD rating groups, the effect of an SCD on the likelihood of deep poverty is not different from zero. The effect of being in the "High" SCD rating is meaningfully different from zero. These veteran households face an increase in their likelihood of deep poverty between 6 and 15 percentage points depending on the year. For instance, in 2011, impoverished veteran households with a "High" SCD rating would be expected to have an almost 15 percentage point higher likelihood of deep poverty as compared to impoverished veteran households with no SCD or an SCD rating of 0%. This effect size is very large as the average deep poverty rate among all households is around 36 percentage points.

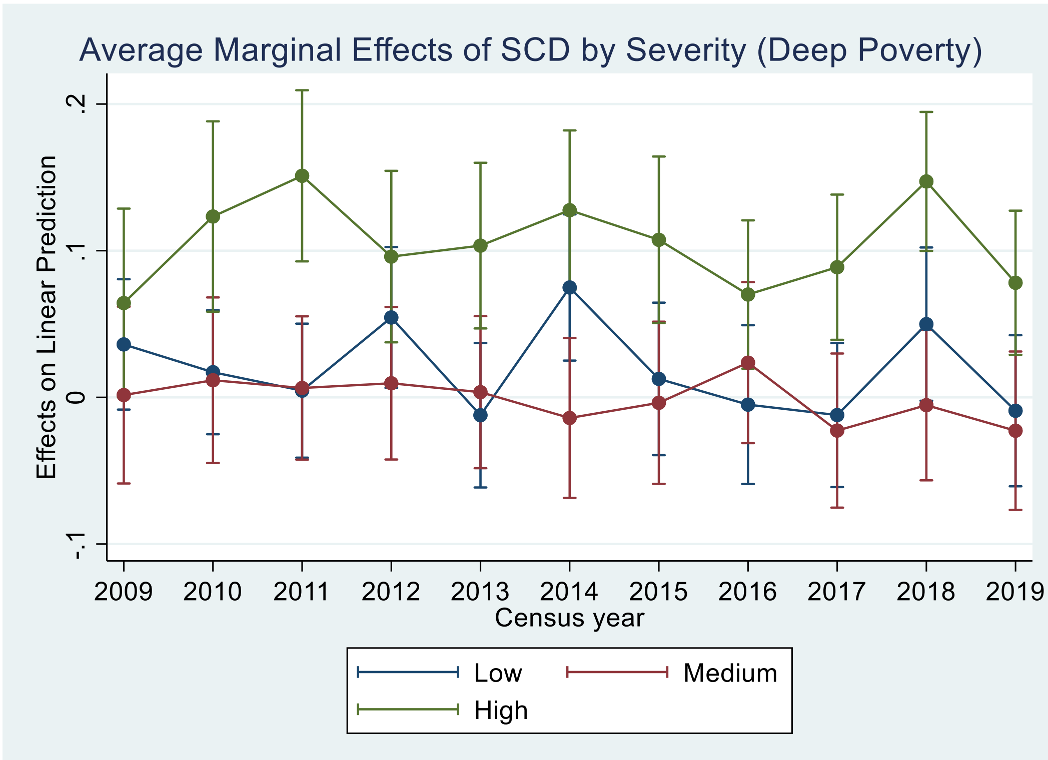

Figure 3.7: Average marginal effects of SCD severity on impoverished veteran households' likelihood of deep poverty (SPM), 2009-2019.

Notes: This figure shows the effect of SCD severity on the likelihood of deep poverty among impoverished veteran households as measured by the SPM. SCD severity is a categorical variable, and the omitted category is the "No rating or 0% rating" category. AMEs are based on estimates from a linear probability model.

This provides more evidence consistent with the discussion above concerning the effect of an SCD (comparing veteran households with an SCD to veteran households without an SCD) on the likelihood of deep poverty. Namely, that some veterans likely have such a severe SCD that they are struggling to avoid poverty and deep poverty.

Sensitivity Analysis

Some veterans list their SCD as both an SCD and as an ACS-defined disability. Because of this, SCD and ACS-defined disability are correlated. Removing ACS-defined disability from the estimated equation in the analysis of the effect of possessing an SCD on veteran households' likelihood of poverty results in smaller in magnitude estimates but the estimates remain meaningfully large and statistically significant. Analogously, the deep poverty models are not sensitive to the exclusion of ACS-defined disability from the estimated equation.

Both the SPM and the OPM internalize information on household structure. For instance, both measures' thresholds are affected by the number of persons within the household. Because of this, it is debatable whether one should include household structure information as explanatory variables. As a sensitivity check, I remove these variables from the analysis of the effect of veteran status on households' likelihood of poverty and deep poverty. The estimates of veteran status on households' likelihood of poverty become *larger* in magnitude and remain statistically significant when the household structure variables are excluded. The estimates of veteran status on households' likelihood of deep poverty become *smaller* in magnitude when the household structure variables are excluded but remain statistically significant and meaningfully large in magnitude. Importantly, the information contained in my household structure variables is either unaccounted for in both poverty measures or is not fully accounted for in both poverty measures. Household structure is also correlated with veteran status and as such an argument could be made for its inclusion in a model of household poverty. For instance, veterans are most likely to be males and we know female-headed households have high rates of poverty.

Finally, SCD severity could be constructed differently. To test two such different constructions, I reconstructed SCD severity with three categories instead of four. In the first reconstruction, I combine No rating or 0% as the base category, 10%-60% becomes "Low", and 70%+ remains the "High" category. In the second reconstruction, I combine No rating or 0% as the base category, 10%-50% becomes "Low", and 60%+ becomes the "High" category. The results are not sensitive to these changes as the same pattern emerges in both reconstructions as the original construction. Those in the highest category are still predicted to have the lowest likelihood of poverty. Those in the "Low" category are predicted to have the second lowest likelihood of poverty, and the base category is predicted, again, to have the highest likelihood of poverty.

3.7 Conclusion

In terms of poverty, consistent with prior literature, the evidence in this chapter suggests that veteran households are less likely to experience poverty than nonveteran households. More recently, there has been convergence, after a period of divergence, between the two groups' likelihood of poverty. Importantly, this is driven by nonveteran households experiencing declining poverty, and not veteran households experiencing higher rates of poverty.

Possessing an SCD appears to be an important mechanism by which some veteran households avoid poverty. Veteran poverty is around 8.7% any given year, and the effect of possessing an SCD is a reduction in this likelihood by 2 to 2.5 percentage points, depending on the year. This is a substantial reduction in the likelihood of poverty among these households and is evidence in favor of a political explanation playing a substantial role in determining why veterans have low rates of poverty. As noted earlier, the VA is well-positioned to fight poverty on two fronts. First, through substantial cash transfers to veterans. Second, through comprehensive rehabilitative health support. The presence of an SCD implies the veteran should be receiving both important interventions from the VA.

A different story emerges for deep poverty. I provide some evidence that among impoverished households, veteran households are more likely to experience deep poverty. This suggests that veteran households who do not avoid poverty are especially at risk of falling into deep poverty. The relationship between possessing an SCD and deep poverty is complex. On one hand, possessing an SCD is helping keep veteran households from falling into poverty, surely also providing some protection against deep poverty. On the other hand, among veteran households who are already in poverty, those within the highest SCD severity category are especially at risk for falling into deep poverty. Recent policy changes to SCD do not appear to be potentially contributing to any obvious systematic differences in its effect on veteran households' likelihood of poverty and deep poverty.

More research is needed to understand why some veteran households are especially at risk of deep poverty and the role of possessing an SCD in increasing the risk. For instance, these veteran households in deep poverty with 70%+ SCD ratings clearly have an SCD that is affecting their households quite severely. Are these households primarily female-led with a history of Military Sexual Trauma? Do these households contain a veteran who struggles with PTSD and has experienced loss of limbs or a traumatic brain injury? Understanding this could lead to policy that is tailored to this subset of veteran households, and there is already an established relationship that policymakers might leverage because these veterans are served by the VA.

Turning to veteran households overall, SCD rates are low among the subset of impoverished veteran households, as compared to veterans overall. More research is necessary to understand whether these rates are low because the veteran is not eligible (i.e., because of a dishonorable discharge, or the veteran applied and was denied), the process is too costly for the veteran, or if the veteran simply refuses to receive help from the VA.

3.8 Limitations

Neither my veteran nor service-connected disability AMEs can be interpreted as causal estimates of the effect of veteran status on households' likelihood of poverty. Veterans not obviously injured in combat must largely self-identify as having an SCD, potentially leading to systematic differences from disabled veterans who do not seek help. Unaccounted heterogeneity within veteran households, such as enlistment status, combat experience, and occupational specialty, could aid researchers in identifying families at risk for poverty. Including this information may also better reveal the impact of service-connected disability on poverty likelihood.

In addition, poverty is very complex and as such there exists many ways to measure poverty and compare poverty over time, and pros/cons to using different approaches. No single poverty measure is capable of accurately identifying all impoverished households. The two most common poverty measures are the SPM and the OPM. The magnitudes of my estimates change slightly across the two measures. However, ultimately, the results are consistent across both measures.

One further limitation is worth mentioning, that is, there is a subtle difference veteran households' rate of poverty (and analogously nonveteran households' rate of poverty) and the veteran rate of poverty. For instance, if all impoverished veteran households were composed of two veterans, the veteran rate of poverty would be much higher than the rate of poverty among veteran households. This chapter cannot then answer questions such, do veterans experience poverty more than nonveterans, and, if so, how much more?

3.9 References

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3.10 Appendix A: Regression Estimates

Table 3.2: Poverty and deep poverty on household veteran status.

	(1) SPM		(2) OPM		(3) SPM Deep		(4) OPM Deep	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Veteran HH	-0.017***	0.001	-0.012***	0.001	0.015**	0.005	0.036***	0.005
2010 X Veteran HH	-0.006***	0.001	-0.007***	0.001	-0.004	0.007	-0.000	0.007
2011 X Veteran HH	-0.014***	0.001	-0.012***	0.001	-0.018**	0.007	-0.005	0.007
2012 X Veteran HH	-0.012***	0.001	-0.009***	0.001	-0.002	0.007	-0.004	0.007
2013 X Veteran HH	-0.013***	0.001	-0.009***	0.001	-0.002	0.007	-0.003	0.007
2014 X Veteran HH	-0.017***	0.001	-0.011***	0.001	-0.010	0.007	0.002	0.007
2015 X Veteran HH	-0.012***	0.001	-0.005***	0.001	0.008	0.007	0.014	0.007
2016 X Veteran HH	-0.009***	0.001	-0.004**	0.001	0.004	0.007	0.008	0.008
2017 X Veteran HH	-0.007***	0.001	0.002	0.001	0.009	0.007	0.012	0.008
2018 X Veteran HH	-0.003	0.001	0.002*	0.001	0.009	0.007	0.023**	0.008
2019 X Veteran HH	-0.000	0.001	0.007***	0.001	0.008	0.008	0.006	0.008
Disabled Household	0.068***	0.000	0.080***	0.000	-0.045***	0.001	-0.061***	0.001
Single Male	0.060***	0.000	0.067***	0.000	0.068***	0.001	0.063***	0.001
Single Female	0.121***	0.000	0.125***	0.000	0.051***	0.001	0.053***	0.001
Black	0.061***	0.001	0.071***	0.000	-0.070***	0.001	-0.014***	0.001
AIAN	0.061***	0.002	0.072***	0.001	-0.005	0.005	0.024***	0.004
Asian/PI	0.078***	0.001	0.046***	0.000	0.009***	0.002	0.015***	0.002
Other	0.034***	0.001	0.022***	0.000	-0.018***	0.002	-0.013***	0.002
Hispanic	0.052***	0.001	0.028***	0.000	-0.084***	0.001	-0.074***	0.001
# Children Under 18	-0.001***	0.000	0.022***	0.000	-0.043***	0.000	-0.008***	0.000
Any Child Under 5	0.013***	0.001	0.030***	0.000	-0.047***	0.002	0.004**	0.001
HS	-0.138***	0.001	-0.186***	0.000	0.011***	0.001	0.016***	0.001
Some College	-0.193***	0.001	-0.245***	0.000	0.031***	0.002	0.022***	0.001
Bachelor's	-0.253***	0.001	-0.297***	0.000	0.064***	0.002	0.057***	0.002
Advanced	-0.280***	0.001	-0.311***	0.000	0.099***	0.002	0.103***	0.002
Reside in Metro	0.007***	0.000	-0.022***	0.000	-0.009***	0.002	0.026***	0.001
Age	-0.002***	0.000	-0.003***	0.000	-0.003***	0.000	-0.005***	0.000
Constant	0.359***	0.002	0.434***	0.001	0.547***	0.005	0.575***	0.004
R-squared	0.104		0.137		0.044		0.044	
N. of cases	11489399		11489399		1670077		1395804	

Notes: All models include state and year fixed effects and robust standard errors.

* p<0.05, ** p<.01, *** p<.001

Table 3.3: Poverty and deep poverty on veteran household SCD status.

	(1) SPM		(2) OPM		(3) SPM Deep		(4) OPM Deep	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Veteran HH w/ SCD	-0.023***	0.002	-0.017***	0.002	0.038*	0.016	0.022	0.019
2010 X Veteran HH w/ SCD	0.003	0.003	0.000	0.003	0.002	0.022	0.003	0.026
2011 X Veteran HH w/ SCD	0.007*	0.003	0.002	0.003	0.003	0.022	0.017	0.027
2012 X Veteran HH w/ SCD	0.004	0.003	0.001	0.003	0.006	0.022	0.022	0.027
2013 X Veteran HH w/ SCD	-0.002	0.003	-0.004	0.003	-0.007	0.022	0.035	0.028
2014 X Veteran HH w/ SCD	0.002	0.003	0.001	0.003	0.018	0.022	0.031	0.027
2015 X Veteran HH w/ SCD	0.001	0.003	-0.002	0.003	-0.003	0.023	0.026	0.027
2016 X Veteran HH w/ SCD	-0.001	0.003	-0.002	0.003	-0.001	0.022	0.000	0.027
2017 X Veteran HH w/ SCD	-0.004	0.003	-0.004	0.003	-0.013	0.022	-0.010	0.027
2018 X Veteran HH w/ SCD	-0.003	0.003	-0.003	0.003	0.028	0.022	0.020	0.027
2019 X Veteran HH w/ SCD	-0.001	0.003	-0.009**	0.003	-0.016	0.022	0.018	0.027
Disabled Household	0.041***	0.001	0.035***	0.001	-0.030***	0.004	-0.037***	0.004
Single Male	0.067***	0.001	0.072***	0.001	0.071***	0.004	0.066***	0.005
Single Female	0.101***	0.002	0.095***	0.002	0.065***	0.007	0.053***	0.008
Black	0.043***	0.001	0.046***	0.001	-0.038***	0.005	-0.014*	0.006
AIAN	0.056***	0.005	0.061***	0.005	-0.000	0.018	0.003	0.020
Asian/PI	0.038***	0.003	0.020***	0.002	0.019	0.012	0.011	0.017
Other	0.027***	0.002	0.025***	0.002	-0.022*	0.010	-0.037**	0.012
Hispanic	0.019***	0.002	0.010***	0.001	-0.021**	0.007	-0.024**	0.009
# Children Under 18	-0.001	0.001	0.008***	0.001	-0.043***	0.003	-0.031***	0.003
Any Child Under 5	0.020***	0.002	0.017***	0.002	-0.032**	0.011	-0.006	0.013
HS	-0.070***	0.003	-0.078***	0.003	0.052***	0.007	0.081***	0.008
Some College	-0.102***	0.003	-0.104***	0.003	0.041***	0.007	0.073***	0.008
Bachelor's	-0.131***	0.003	-0.124***	0.003	0.081***	0.008	0.118***	0.010
Advanced	-0.145***	0.003	-0.130***	0.003	0.125***	0.009	0.156***	0.011
Reside in Metro	0.000	0.001	-0.014***	0.001	-0.009	0.005	0.050***	0.006
Age	-0.000***	0.000	-0.001***	0.000	-0.001***	0.000	-0.002***	0.000
Constant	0.162***	0.004	0.191***	0.004	0.413***	0.019	0.407***	0.022
R-squared	0.044		0.054		0.020		0.025	
N. of cases	390224.00		390224.00		121725.00		85092.000	

Notes: All models include state and year fixed effects and robust standard errors.
* p<.05, ** p<.01, ***p<.001

Table 3.4: Poverty and deep poverty on veteran household SCD severity.

	(1)		(2)		(3)		(4)	
	SPM		OPM		SPM Deep		OPM Deep	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Low	-0.015***	0.003	-0.010***	0.003	0.036	0.023	-0.002	0.028
Medium	-0.032***	0.004	-0.024***	0.004	0.002	0.031	-0.034	0.036
High	-0.037***	0.005	-0.028***	0.005	0.064	0.033	0.113**	0.040
2010 X Low	0.005	0.005	-0.001	0.004	-0.019	0.031	0.022	0.039
2010 X Medium	0.006	0.006	0.002	0.005	0.010	0.042	0.016	0.050
2010 X High	-0.005	0.007	-0.005	0.006	0.059	0.047	-0.003	0.056
2011 X Low	-0.001	0.005	-0.005	0.004	-0.032	0.033	0.014	0.041
2011 X Medium	0.017**	0.006	0.014**	0.005	0.005	0.040	0.042	0.047
2011 X High	0.010	0.007	0.004	0.006	0.087	0.044	-0.007	0.054
2012 X Low	0.005	0.005	0.002	0.004	0.018	0.033	0.046	0.041
2012 X Medium	0.011	0.006	0.006	0.005	0.008	0.041	-0.015	0.048
2012 X High	-0.002	0.007	-0.003	0.006	0.032	0.044	0.066	0.054
2013 X Low	-0.006	0.005	-0.006	0.005	-0.048	0.034	0.025	0.044
2013 X Medium	0.008	0.006	0.003	0.005	0.002	0.041	0.085	0.049
2013 X High	0.004	0.007	-0.003	0.006	0.039	0.044	-0.003	0.053
2014 X Low	-0.001	0.005	0.001	0.004	0.039	0.034	0.055	0.041
2014 X Medium	0.009	0.006	0.008	0.005	-0.016	0.041	0.012	0.048
2014 X High	0.004	0.007	0.003	0.006	0.063	0.043	0.005	0.051
2015 X Low	0.006	0.005	0.001	0.005	-0.024	0.035	0.081	0.042
2015 X Medium	0.008	0.006	0.006	0.005	-0.005	0.042	0.013	0.048
2015 X High	-0.004	0.006	-0.005	0.006	0.043	0.044	-0.033	0.052
2016 X Low	0.003	0.005	0.001	0.005	-0.041	0.036	-0.018	0.043
2016 X Medium	0.003	0.005	-0.001	0.005	0.022	0.042	0.066	0.049
2016 X High	0.002	0.006	0.002	0.006	0.006	0.042	-0.076	0.049
2017 X Low	-0.004	0.005	-0.003	0.005	-0.048	0.034	0.003	0.043
2017 X Medium	0.005	0.005	0.005	0.005	-0.024	0.041	-0.032	0.048
2017 X High	-0.001	0.006	-0.004	0.006	0.024	0.041	-0.024	0.050
2018 X Low	-0.005	0.005	-0.004	0.005	0.014	0.035	0.079	0.043
2018 X Medium	0.004	0.006	0.004	0.005	-0.007	0.040	-0.012	0.049
2018 X High	0.005	0.006	0.004	0.006	0.083*	0.041	-0.021	0.049
2019 X Low	-0.001	0.005	-0.006	0.004	-0.045	0.035	0.012	0.043
2019 X Medium	0.003	0.006	-0.006	0.005	-0.024	0.041	0.023	0.050
2019 X High	0.004	0.006	-0.006	0.006	0.014	0.041	-0.009	0.050
Disabled Household	0.041***	0.001	0.035***	0.001	-0.031***	0.004	-0.038***	0.004
Single Male	0.067***	0.001	0.072***	0.001	0.072***	0.004	0.067***	0.005
Single Female	0.101***	0.002	0.096***	0.002	0.065***	0.007	0.054***	0.008
Black	0.043***	0.001	0.046***	0.001	-0.039***	0.005	-0.015*	0.006
AIAN	0.056***	0.005	0.061***	0.005	0.001	0.018	0.003	0.020
Asian/PI	0.038***	0.003	0.020***	0.002	0.020	0.012	0.010	0.017
Other	0.026***	0.002	0.025***	0.002	-0.020*	0.010	-0.036**	0.012
Hispanic	0.019***	0.002	0.010***	0.001	-0.022**	0.007	-0.024**	0.009
# Children Under 18	-0.000	0.001	0.008***	0.001	-0.044***	0.003	-0.030***	0.003
Any Child Under 5	0.020***	0.002	0.018***	0.002	-0.029*	0.011	-0.003	0.013

Table 3.4: Poverty and deep poverty on veteran household SCD severity. (continued)

HS	-0.070***	0.003	-0.078***	0.003	0.051***	0.007	0.081***	0.008
Some College	-0.102***	0.003	-0.104***	0.003	0.041***	0.007	0.076***	0.008
Bachelor's	-0.130***	0.003	-0.124***	0.003	0.079***	0.008	0.118***	0.010
Advanced	-0.145***	0.003	-0.130***	0.003	0.125***	0.009	0.159***	0.011
Reside in Metro	0.000	0.001	-0.014***	0.001	-0.009	0.005	0.050***	0.006
Age	-0.000***	0.000	-0.001***	0.000	-0.001***	0.000	-0.002***	0.000
Constant	0.161***	0.004	0.191***	0.004	0.414***	0.019	0.401***	0.022
R-squared	0.044		0.054		0.022		0.027	
N. of cases	1379454		1379454		120212		83944	

Notes: All models include state and year fixed effects and robust standard errors.

* p<0.05, ** P<.01, ***p<.001

3.11 Appendix B: Sensitivity Analysis

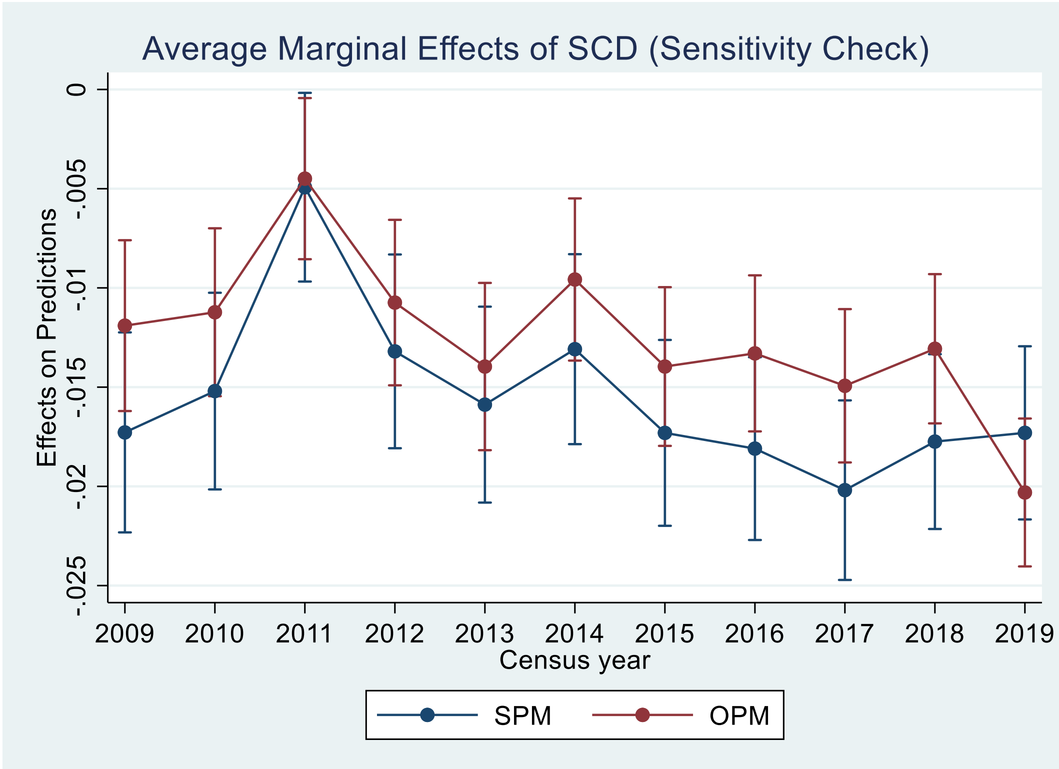

Figure 3.8**:** Average marginal effects of an SCD on households' likelihood of poverty, 2009-2019.

Notes: This figure shows the effect of an SCD on households' likelihood of poverty after excluding ACS-defined disability from the estimated equation.

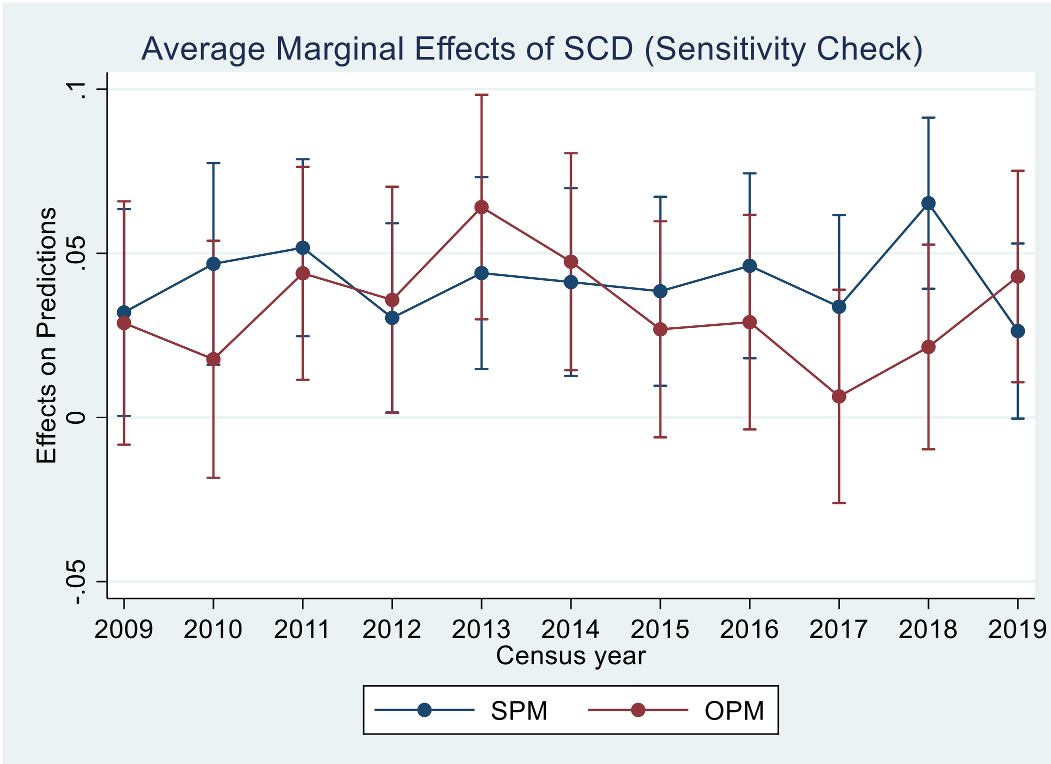

Figure 3.9: Average marginal effects of an SCD on households' likelihood of deep poverty, 2009-2019.

Notes: This figure shows the effect of an SCD on households' likelihood of deep poverty after excluding ACS-defined disability from the estimated equation.

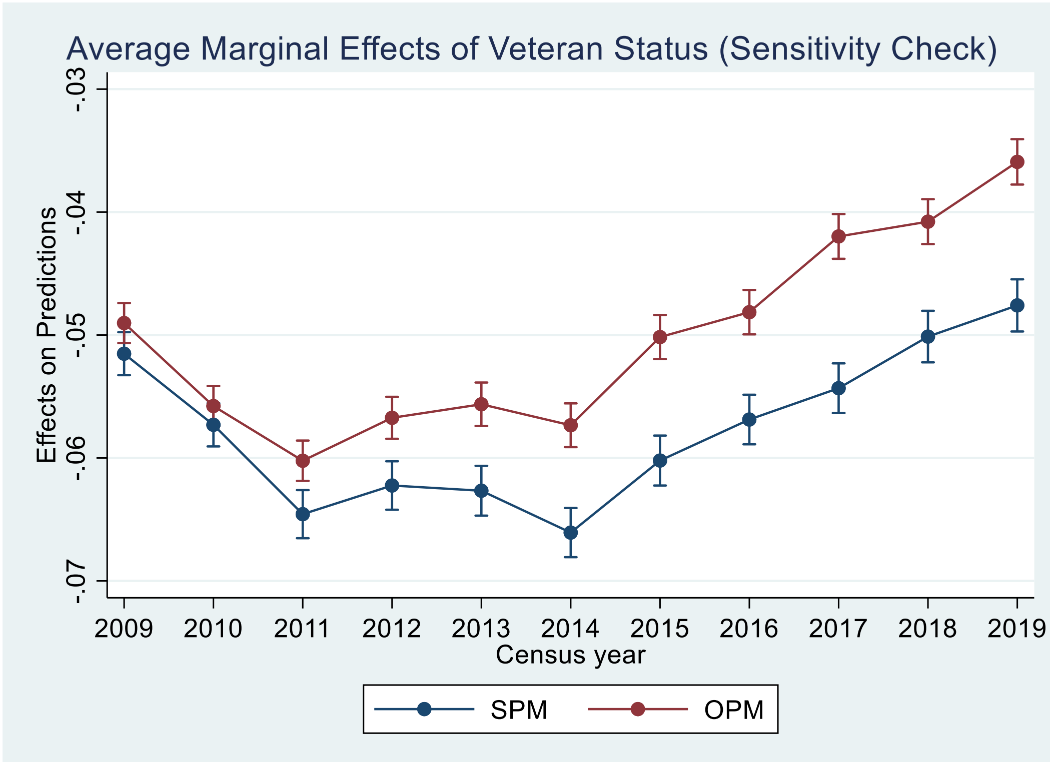

Figure 3.10: Average marginal effects of veteran status on households' likelihood of poverty, 2009-2019.

Notes: This figure shows the effect of veteran status on households' likelihood of poverty after excluding household structure variables from the estimated equation.

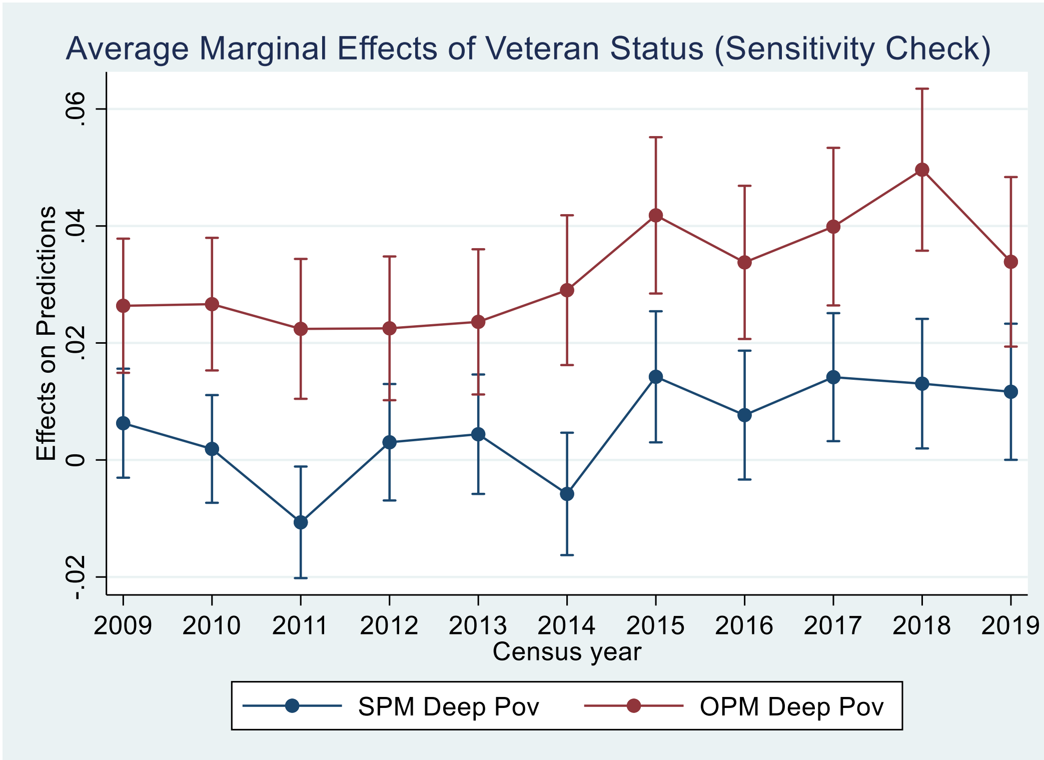

Figure 3.11: Average marginal effects of veteran status on households' likelihood of deep poverty, 2009-2019.

Notes: This figure shows the effect of veteran status on households' likelihood of deep poverty after excluding household structure variables from the estimated equation.

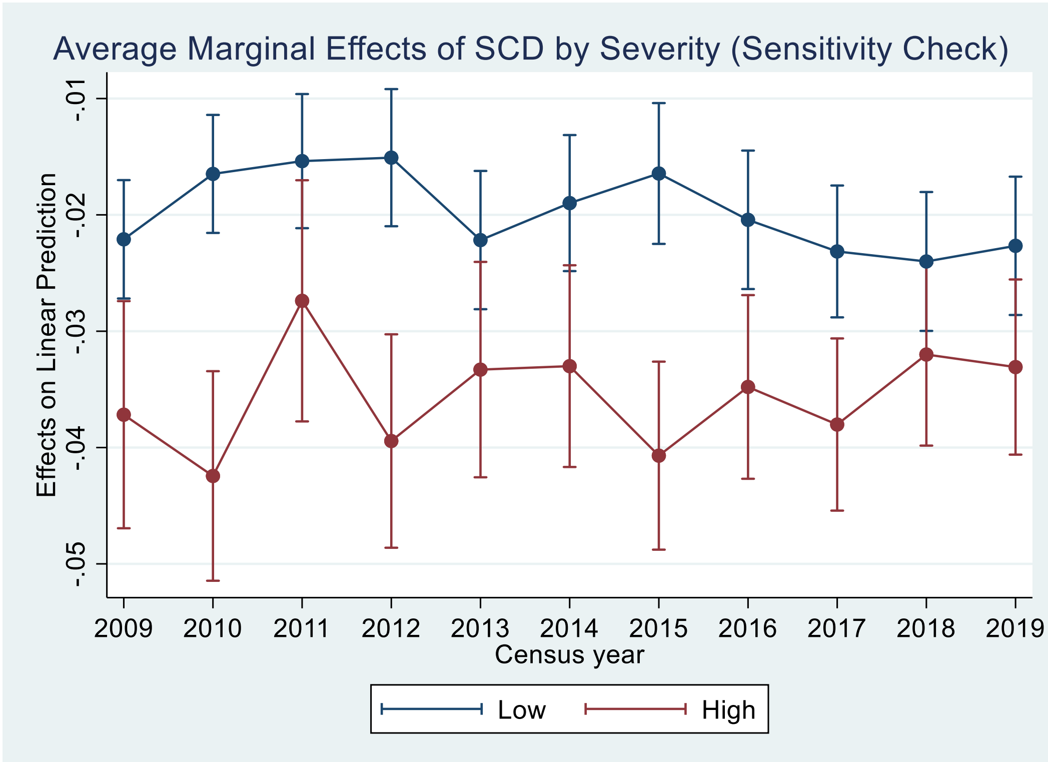

Figure 3.12: Average marginal effects of SCD severity on veteran households' likelihood of poverty, 2009-2019.

Notes: This figure shows the effect of SCD severity on the likelihood of poverty after reconstructing SCD severity with the categories No rating or 0% rating as the base category, 10%-60% rating as "Low", and 70%+ rating as "High".

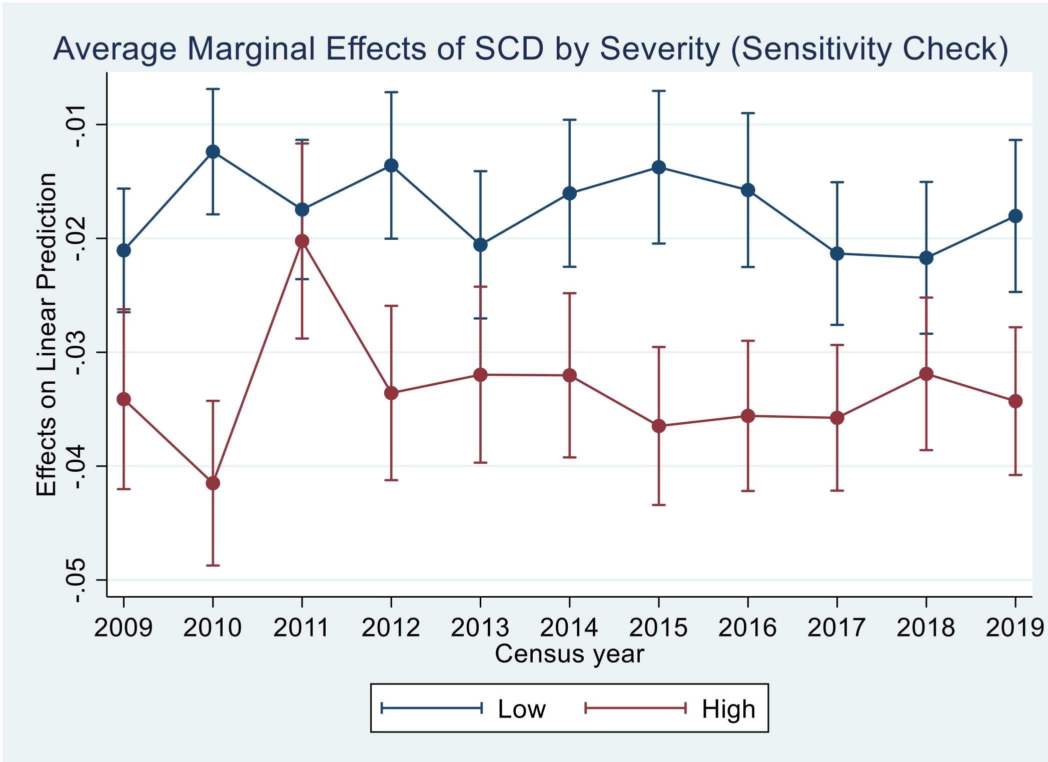

Figure 3.13: Average marginal effects of SCD severity on veteran households' likelihood of poverty, 2009-2019.

Notes: This figure shows the effect of SCD severity on the likelihood of poverty after reconstructing SCD severity with the categories No rating or 0% rating as the base category, 10%-50% rating as "Low", and 60%-70%+ rating as "High".

CONCLUSION

Two policy recommendations arise from Chapter 1. First, all recent male veterans suffer wage penalties at the top end of the wage distribution. This is due in part to male veterans obtaining advanced education at lower rates than nonveterans. Schools could provide transition services to veterans to help them navigate the transition to college. Less than one-quarter of schools provide this valuable assistance tailored to veterans (Cook & Kim, 2009). Second, as noted by Barr et al. (2021), policymakers could limit G.I. Bill funding to not include for-profit institutions or could severely limit the schools that veterans may attend. Simply, too many veterans are attending low-quality schools. These veterans have little hope of obtaining advanced education that the labor market values.

Chapter 2 shows that there has been a precipitous increase in severe SCD among female veterans and a corresponding slight decrease in their selection into employment. The development of effective public policy to combat these two worrying trends necessitates more research being conducted. This research should focus on determining how female veterans are being affected by their SCD, what is causing the swift increase in severe SCD in this group, and whether these female veterans are selecting out of the labor market because of their SCD.

In Chapter 3, I show evidence in support of public policy playing a substantial role in the reduction of poverty among veteran households. Lessons can be imported to other settings where poverty reduction is a goal. Veterans receive many supports that enable them to avoid poverty such as comprehensive rehabilitative healthcare and disability and compensation benefits from the VA. Public policy determines the level of support veterans receive. Thus, the state is in effect having a large role in determining the level of poverty observed among veteran households. This is evidence that when there is sufficient political will and funding, poverty can be reduced across a large heterogenous group.

Even though veteran poverty is largely a public policy success, I show that there is still more work that can be done among the subset of impoverished veterans. Impoverished veteran households experience deep poverty at higher rates than similar nonveteran households. Highlighting the fact that there exists a subset of veterans and their families whose well-being is likely compromised, perhaps because of the veteran household member's military service. Furthermore, these veterans have low rates of possessing an SCD as compared to veteran households that are not impoverished. It is curious that this should be the case, we might expect deeply impoverished veterans to have higher rates of possessing an SCD, not lower. As Chapter 3 shows, receiving SCD benefits is a very important component of helping veteran households avoid poverty. Because of this, more research is necessary to understand why some veterans are particularly at risk of deep poverty, and why they have such low rates of possessing an SCD. If, for instance, it can be determined that there is low SCD take-up among these veterans, a policy could be crafted to provide better support for identifying these veterans and getting them the support that they are entitled to from the VA.

A small subset of impoverished veterans are living with severe SCD (70%+ rating) and in deep poverty. The poverty models show a monotonically decreasing likelihood of poverty as SCD rating increases. However, the deep poverty models show the opposite is true. That is, among the already impoverished veteran households, those living with a severe SCD have the highest likelihood of deep poverty. More research is necessary to identify why these veterans are faring so poorly, and why support from the VA is ineffective in helping them avoid deep poverty.