Dissertation

Exploring the Influences of External Factors on the Veteran Disability Compensation Program

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Abstract

The veteran disability compensation program (VADC) has grown considerably in the last two decades, both in terms of the total number of veterans receiving compensation and the average amount of compensation per recipient. Previous research has identified changes in the composition of the veteran population and in the processes and regulations governing benefit receipt as major proximate causes of this growth. These explanations tend to underemphasize the ways in which conditions outside of the system can affect its performance and scope. In this dissertation, I explore three of these external factors.

In the first chapter, I present descriptive evidence on the relationship between conditions in local labor markets and trends in VADC expenditures and participation. These estimates show a modest positive association between labor market conditions and expenditures in regular times, which strengthens in the aftermath of the Great Recession of 2007 – 2009. Labor market conditions are also positively associated with local changes in the number of veterans with disability ratings of 50 percent or more.

In the second chapter, I examine whether the incomplete implementation of the Patient Protection and Affordable Care Act (ACA), which encouraged adoption of health insurance by uninsured people, affected participation in the VADC program. Using several quasi-experimental methods, I find that veterans residing in states that did not expand their Medicaid program as part of the ACA were 0.5 – 1.5 percentage points more likely to claim a disability rating of 50 percent or more than those residing in states that expanded Medicaid. The results indicate that Medicaid eligibility and take-up of VA health care were key mechanisms driving this effect.

Finally, in the third chapter I explore whether the 2011 expansion of the Work Opportunity Tax Credit (WOTC) increased employment rates for veterans experiencing unemployment and veterans with service-connected disabilities, two groups targeted by the credit. I find no evidence that the tax credit increased employment rates for service-disabled veterans or veterans with six or more months out of work. For veterans living in families receiving benefits from the Supplemental Nutrition Assistance Program (SNAP), the WOTC increased the employment rate by approximately 2.5 percentage points.

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Abbreviations

ACS	American Community Survey
BDD	Benefits Delivery at Discharge
BLS	Bureau of Labor Statistics
CDR	combined disability rating
CPS	Current Population Survey
DoD	U.S. Department of Defense
EITC	Earned Income Tax Credit
GAO	Government Accountability Office
GDX	General Description of Geographic Distribution of the Department of Veterans Affairs Expenditures
IDES	Integrated Disability Evaluation System
IU	total disability based on individual unemployability
MDD	Major Depressive Disorder
NAM	National Academy of Medicine
NCVAS	National Center for Veterans Analysis and Statistics
OEI	U.S. Department of Veterans Affairs Office of Enterprise Integration
PTSD	Post-Traumatic Stress Disorder
SCM	synthetic control method
SDVOSB	service-disabled veteran-owned small business
SNAP	Supplemental Nutrition Assistance Program

SSDI	Social Security Disability Insurance
TAP	Transition Assistance Program
USCAVC	U.S. Court of Appeals for Veterans Claims
VA	U.S. Department of Veterans Affairs
VADC	veteran disability compensation program
VBA	Veterans Benefits Administration
VSOs	veteran service organizations
WOTC	Work Opportunity Tax Credit

Introduction

Compensation for injuries sustained during military service is one of the oldest forms of social insurance in the United States. The Continental Congress of 1776 made half-pay pensions available to severely disabled soldiers as a recruitment incentive during the Revolutionary War, and the system of benefits provided to soldiers during and after the Civil War predated major expansions of the federal welfare state in the 20th century (Commission, 2007; Skocpol, 1995). Today, the veteran disability compensation program (VADC) is a significant function of the Veterans Benefit Administration (VBA): in FY 2019, more than 4.9 million veterans received an estimated $85 billion in compensation for service-related disabilities, and more than 300,000 new compensation recipients were added to the rolls.[1] As shown in Figure 0.1, the number of veterans receiving disability benefits has grown considerably since 2001, even as the total veteran population has fallen. Most of this growth has been concentrated in the highest disability rating categories.

Monthly cash benefits for service-disabled veterans are intended to compensate for the *average earnings losses* due to the rated impairment without regard to age, rank, or other factors that may affect civilian labor market earnings.[2] This contrasts with other disability systems, such as Social Security Disability Insurance (SSDI), where benefit amounts are tied to lifetime earnings, and workers' compensation, where benefits are most often a function of pre-injury earnings in addition to the severity of the injury. Several observers have challenged the average earnings loss standard, noting, for example, that it ignores the large variation in labor force participation and wages across disabled cohorts and does not allow for the benefit to compensate for reduced quality of life caused by service-connected disabilities (Barnes, McCutchen, Ford, & McGeary, 2007; Buddin & Han, 2012). Focusing on average effects also obscures the fact that earnings losses will dynamically interact with labor market conditions and policies in ways that may lead to medium- or long-term deviations from policy goals. One broad trend that exemplifies this dynamic, highlighted in a recent editorial by former Secretary of Veterans Affairs David Shulkin, is the potential imbalance between the nature of work and the distribution of benefits: "The current system places a high priority on physical attributes necessary for manual labor and does not acknowledge present day opportunities for many disabled veterans to hold jobs in an increasingly digital economy" (Shulkin, 2019).

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[1] *VBA Annual Benefits Report Fiscal Year 2019*, accessed at: https://www.benefits.va.gov/REPORTS/abr/docs/2019-compensation.pdf.

[2] 38 CFR § 4.1. Earnings loss is a complex concept but refers broadly to the gap between the observed earnings of an impaired person and the same person's unobserved counterfactual earnings in the absence of the impairment.

Shulkin's statement points to a broader observation: that the performance of the veteran disability system—however performance is defined—will be shaped by changes external to and independent from the actions taken by its core stakeholders: the veteran population and their representatives, the Department of Veterans Affairs (VA), and the Congressional committees focused on veterans issues. The general nature and condition of the macroeconomy, for example, which determines the value of particular skills and abilities in the labor market at any given time, will affect veterans in different ways depending on their functional limitations. Opportunities to work will also vary with developments in federal and workplace policy, as well as innovations in engineering and design that enable greater or lesser access to the workplace. A stark example of this is the recent business closures precipitated by the COVID-19 pandemic and the subsequent move of many workplaces to virtual spaces, which may enable new work opportunities for some people with functional limitations and curtail them for others. In addition to economic considerations, the value of VADC to veterans will also vary with the accessibility of health services, both within and outside of the VA. To explore these relationships, this dissertation will address the following research questions:

1. *How have labor market conditions affected recent trends in VADC program participation and expenditures since 2001, and especially after the Great Recession of 2007 – 2009?*
2. *How did the incomplete expansion of Medicaid in 2014 as part of the Patient Protection and Affordable Care Act (ACA) affect participation in VADC?*
3. *What was the effect of the 2011 expansion of the Work Opportunity Tax Credit (WOTC) on veteran, and especially service-disabled veteran, employment?*

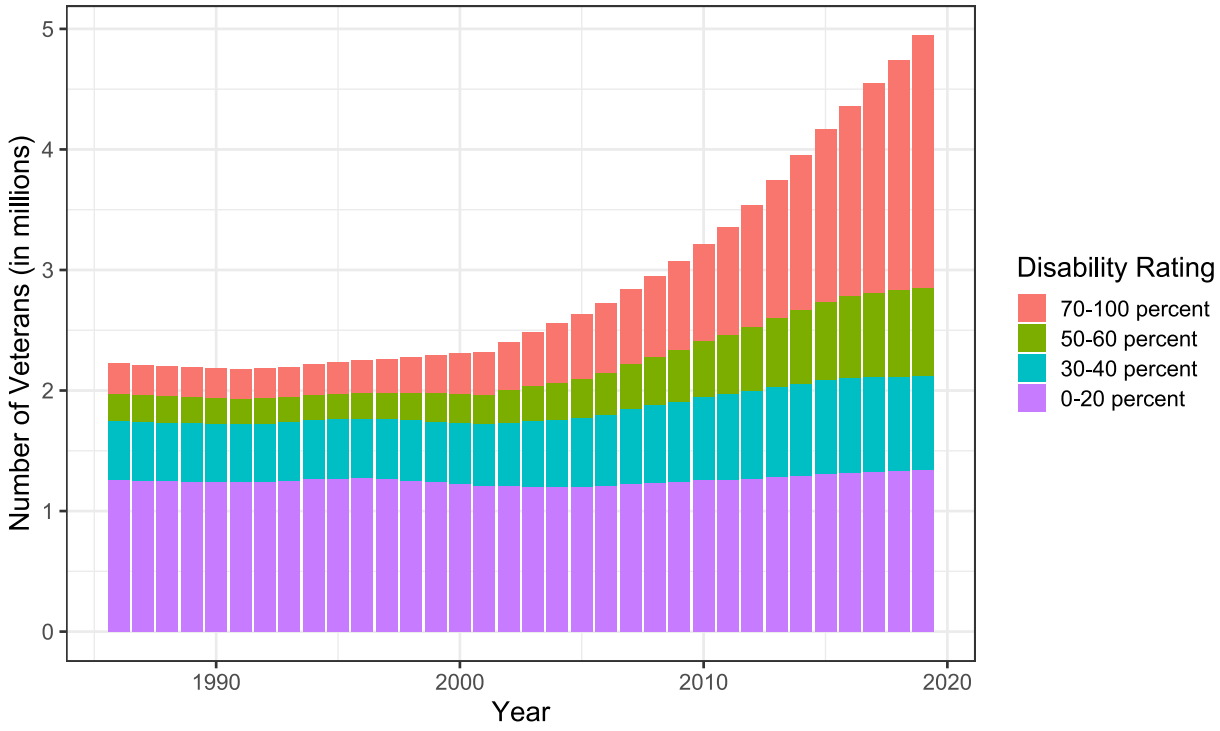
These questions are partially motivated by the following empirical observation: in the Current Population Survey (CPS), and in the American Community Survey (ACS), the share of working-age veterans with more severe disabilities (defined here as those with ratings of 50 percent or more) who are in the labor force has increased substantially since 2010. This is presented graphically in Figure 0.2, using data from the CPS. The greater variation in the series prior to 2009 is partially explained by the fact that the CPS veterans' supplement was collected biennially from 1995 to 2009 and annually since then, and even-year observations prior to 2009 include only the subset of veterans who link to the core CPS in an adjacent year. These trends are qualitatively similar to those estimated using the ACS for 2008-2018, suggesting they are not merely the result of sampling effects.

Table 0.1 shows the results of a nonlinear decomposition of changes in the labor force participation rate for the same groups between 2008 – 2010 and 2016 – 2018 using the ACS. This decomposition method is conceptually similar to the Oaxaca-Blinder method, but uses logistic rather than linear regressions to estimate labor supply equations and calculates standard errors using a bootstrap procedure (Fairlie, 2005). Similar to the CPS estimates shown in Figure

0.2, the average labor force participation rate increased for both groups over this period, but the increase for the more severe group was much larger, from 38 percent in 2008 – 2010 to 58 percent in 2016 – 2018. Roughly half of this difference can be explained by changes in observed demographics, including gender, age, race, self-reported disability and marital status. In order to understand compositional changes in the veteran population, I also include a categorical variable indicating whether the veteran served in the post-9/11 period. Somewhat surprisingly, this variable explains nearly one-third of the difference in labor force participation between 2008 – 2010 and 2016 – 2018, raising the possibility that recent growth in the VADC program has been driven by veterans with greater capacity to work than previous cohorts.

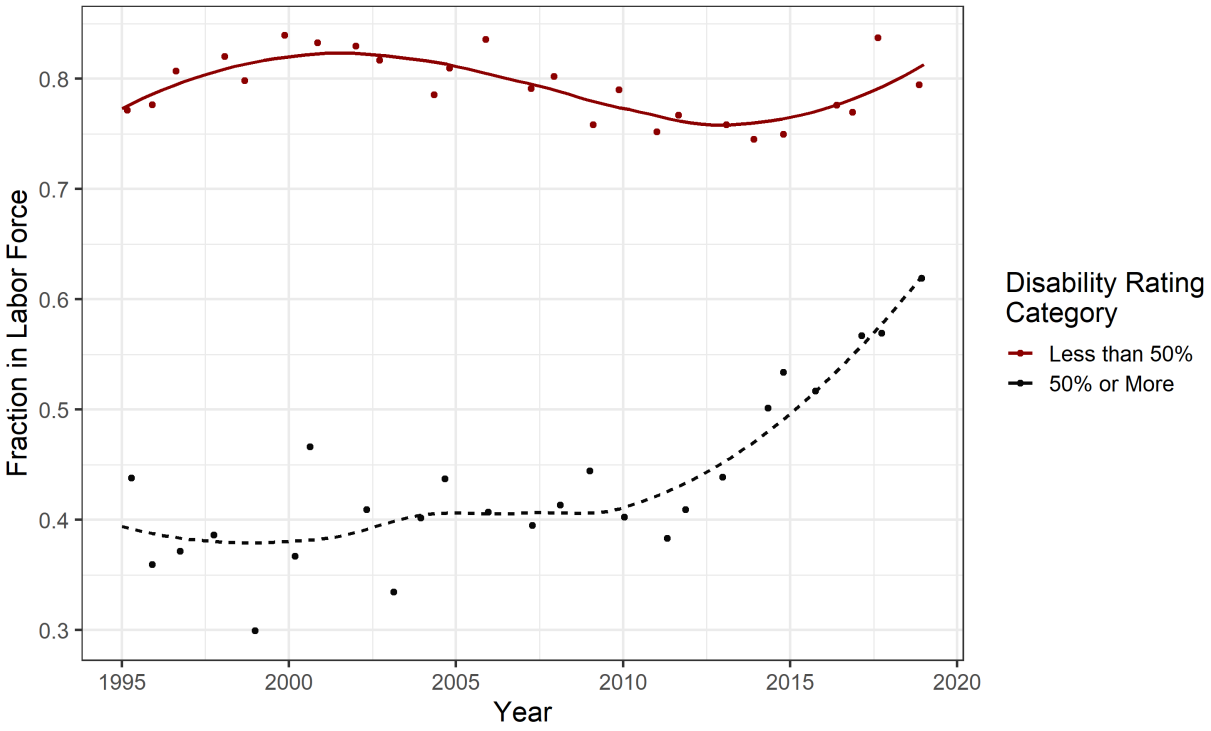
An optimistic explanation for this finding is that the labor market has become more amenable to veterans with significant service-related functional limitations, possibly as the result of informational campaigns targeted at employers, employment policies such as hiring tax credits, or advances in assistive technology. Alternatively, the result may reflect changes in the way disabilities are evaluated by the VADC system so that veterans are more likely to have higher ratings than similarly impaired veterans in previous cohorts. There are other possibilities as well—most notably that the information about functional impairments available in the CPS and ACS is too coarse to make credible comparisons over time or that the labor force participation rate is a poor indicator of the functional limitations disability ratings are meant to reflect. Nonetheless, these trends, combined with those shown in Figure 0.1, suggest that significant changes in the VADC population have occurred in recent decades. This dissertation will explore some possible explanations for these changes and will present ideas for how policymakers may respond to them.

Figure 0.1: Number of Veterans Receiving Disability Compensation by CDR Bins, 1986 – 2019



Source: National Center for Veterans Analysis and Statistics.

Figure 0.2: Labor Force Participation Rate by Severity of Service-Connected Disability Rating, 1995 – 2019



Source: CPS veterans' supplement linked to core CPS. Observations weighted by veteran supplement weight. Observed data is shown as points on the scatterplot, lines are smoothed using LOESS.

Table 0.1: Decomposition of Changes in Labor Force Participation from 2008 – 2010 to 2016 – 2018 by Severity of Service-Connected Disability Rating

	CDR < 50%		CDR >= 50%	
P(in labor force) in period 1	0.749		0.383	
P(in labor force) in period 2	0.782		0.578	
Difference	-0.033		-0.194	
Explained by changes in demographics	-0.008	24%	-0.052	27%
Explained by changes in self-reported disability	-0.008	23%	-0.048	25%
Explained by changes in geography	-0.003	9%	-0.004	2%
Explained by veteran cohort indicator	-0.011	33%	-0.060	31%
Total explained	-0.029	88%	-0.165	85%

Source: ACS. Period 1 = 2008 – 2010. Period 2 = 2016 – 2018. Veterans with combined disability ratings of less than 50 percent are considered to have less severe disabilities, and veterans with ratings of 50 percent or more are considered to have severe disabilities. Sample is restricted to working-age veterans (18 – 64) who are not enrolled in school, are not employed by state or federal governments, and are not self-employed or homeworkers.

Institutional Setting

The veteran disability system is an interconnected set of institutions and policies that govern disability evaluation and delivery of benefits to veterans with health conditions caused or aggravated by military service. Key components of this system are:

- Administrative procedures for evaluating disabilities. To receive benefits, veterans must file a disability claim with the VA, which typically involves gathering service and medical records and potentially engaging a representative from a veteran service organization (VSO). Until recently there were separate disability evaluation systems for active duty servicemembers (the DoD system) and veterans (the VA system) but these were recently streamlined into the Integrated Disability Evaluation System (IDES).
- The Veterans Affairs Schedule for Rating Disabilities (VASRD). This regulation governs how examiners determine service-connected disability ratings.[3] Ratings range in 10 percent increments from 0 to 100 and are body-part and impairment specific. Each veteran then receives a combined disability rating (CDR) based on all of their rated impairments according to guidelines in the VASRD. The VASRD primarily uses a medical/diagnostic approach to evaluate disabilities rather than a functional approach, though there have been efforts to change this focus in recent years (Barnes et al., 2007).
- The benefits schedule. Veterans who receive a CDR of greater than zero percent are eligible for monthly cash compensation. The amount of compensation, which is tax-free, depends only on the veteran's CDR and family structure, not demographic or personal characteristics, such as age, education, or military record (as long as the veteran's discharge was not dishonorable). Cash benefits increase approximately linearly for CDRs between 10 and 90 percent and nonlinearly thereafter, reflecting the fact that a person with a CDR of 100 percent is considered totally disabled and unable to work. Some VADC recipients are also eligible for additional cash benefits depending on the nature of their service-related health condition.
- Total disability based on individual unemployability (IU). Veterans with a single disability rated at 60 percent or more, or multiple impairments with a combined rating of 70 percent or more, and who are unable to engage in substantial gainful activity, can apply to receive compensation commensurate with a 100 percent rating.[4] Since IU status is the only VADC benefit that is means tested, current or prospective IU beneficiaries are the only VADC participants who face similar work disincentives to

[3] 38 CFR Part 4.

[4] In this setting, substantial gainful activity is loosely defined as the federal poverty level.

participants in the SSDI program, which has been shown to reduce labor supply (French & Song, 2014; Maestas, Mullen, & Strand, 2013).

- Other benefits. Having a disability rating may make a veteran eligible for several other benefits administered by state or federal governments. These include, but are not limited to:
    - service-disabled veteran-owned small business (SDVOSBs) set-asides for federal contracts;
    - special hiring preferences for federal employment;
    - state and federal hiring tax credits;
    - additional transition support and vocational rehabilitation services;
    - access to higher priority groupings for VA health services; and
    - death and burial benefits.

Chapter 1: Exploring the Role of Economic Conditions on Recent VADC Growth

Summary

In this chapter I explore the relationship between economic conditions and participation in VADC. For many disability programs, this relationship is highly salient in policy discussions: concerns about reduced labor force participation due to the availability of disability benefits often animate efforts to reform the Social Security Disability Insurance (SSDI) program, for example (Burkhauser & Daly, 2011; Maestas, 2019). Since VADC is not means tested for most recipients, these concerns are less relevant to this program. Nonetheless, understanding how VADC participation is affected by labor market conditions can help policymakers anticipate trends and better understand the role of VADC in veterans' lives. Using publicly available administrative data published by the VA, I explore how changes in economic conditions affect expenditures on and the number of veterans receiving VADC. These results indicate that both expenditures and participation have been somewhat responsive to labor market conditions in recent years, especially in the aftermath of the Great Recession.

Background

As shown in the previous section, growth in the VADC population rapidly accelerated around 2001 and was concentrated in the most severe disability rating categories. This compositional change in the VADC population reflects the combined effect of increases in the average severity of new VADC recipients—for example due to cognitive impairments such as post-traumatic stress disorder (PTSD) and major depressive disorder (MDD)—and increases in the combined disability ratings (CDR) of existing VADC beneficiaries, either because of new or aggravated health conditions or changes to the way health conditions are evaluated and rated. Growth in VADC participation has been attributed to several factors, which can loosely be grouped as *supply factors*— those that increase access to benefits and increase the size of the veteran population, holding constant veterans' interest in seeking benefits —and *demand factors*—those that increase interest in seeking benefits, holding constant eligibility for those benefits. Much of the research to-date has focused on supply factors, which include *changes to the claims processing system*, *changes to evidentiary standards for claiming benefits*, and *changes to the veteran population*. These are summarized below.

Supply Explanations for Recent VADC Growth

Changes to the claims processing system

The application process for VADC compensation can be highly complex and engages several stakeholders, including the veteran, the VA and DoD, veteran service organizations (VSO), legal representatives, VA and private medical providers, and the U.S. Court of Appeals for Veterans Claims (USCAVC). The initial steps of the process depend on whether the claimant has already separated from service or is awaiting separation, perhaps due to a service-connected condition: in the former case, an application for benefits, including medical and military records, must be submitted by the veteran; in the latter case, the servicemember may proactively submit a claim or may be sent through the claims processing system in the course of examining fitness for duty. Back-of-the envelope calculations using data from VA annual reports and the CPS veterans' supplement indicate that between 1999 and 2018, the majority—between 50 and 70 percent—of new successful VADC claims originated from already-separated veterans.[5]

Several changes to the VA claims processing system have occurred since 1999. The *Veterans Claims Assistance Act of 2000*, for example, established higher standards for the VA's responsibility to assist veterans with their claims. A series of case law decisions in the 1990s, culminating in the *Morton v. West* decision in 1999, established a precedent that the VA was only required to assist with claims that were "well grounded" (Griffin & Jones, 2011). The 2000 Act reversed this decision, stipulating that the VA "make reasonable efforts to assist a claimant in obtaining evidence necessary to substantiate the claimant's claim for a benefit" and that requests for information must be timely and manageable.[6] A possible consequence of this Act was to increase the number of applications for compensation that were ultimately reviewed by the VA. Since applications filed by veterans well after their date of separation are more likely to require costly searches for documentation, one might expect the law to have disproportionally affected those groups.

The *Veterans' Benefits Improvement Act of 2008* further expanded the scope of the disability compensation system and established several plans to improve the claims process.[7] These provisions included extending authority of non-VA, contract physicians to carry out medical reviews, establishing two pilot studies to explore ways to streamline the claims process, expanding authority to give temporary ratings to veterans while their case is adjudicated, and

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[5] In 2018, the VA reported 274,528 new recipients of VADC compensation. The number coming from recently separated servicemembers is not available in annual reports, but approximately 96,000 servicemembers separated in 2017 or 2018 with service-connected disability ratings according to the CPS.

[6] Public Law 106-475: Veterans Claims Assistance Act of 2000. Accessed at: https://www.congress.gov/106/plaws/publ475/PLAW-106publ475.pdf

[7] Public Law 110-389: Veterans' Benefits Improvement Act of 2008. Accessed at: https://www.govinfo.gov/content/pkg/PLAW-110publ389/pdf/PLAW-110publ389.pdf

calling for general studies on the effectiveness of the VADC program. While some VSOs have criticized the VA's implementation of the Act, its likely effects were to speed the processing and increase the supply of claims (Legion, 2010).

Other changes to the claims process during this time likely affected the share of servicemembers who received a disability rating either prior to or shortly after separation from active duty. The *Benefits Delivery at Discharge* (BDD) program, which began in 1995 and was subsequently expanded, grew out of the *Transition Assistance Program* (TAP) and allows servicemembers within 90 to 180 days of discharge to file a claim for compensation benefits, with the expectation that such benefits, if granted, would be paid shortly after discharge. A similar program, called *Quick Start*, applies to servicemembers within 60 days of separation from active duty. The expansion and greater acceptance of these programs are expected to have contributed to program growth and may also have played a role in normalizing the VADC program for separating veterans, though they have not been formally evaluated to my knowledge. In addition, the shift to an online application system and greater outreach to the veteran population plausibly lowered transaction costs and increased awareness of VADC.

Another important change was the *Integrated Disability Evaluation System* (IDES), which was first proposed in 2007 and fully implemented in 2011. The IDES applies to active duty servicemembers whose health conditions limit their ability to carry out their military duties, and was designed to streamline the VA and DoD systems for evaluating disabilities. Disability evaluations under the IDES system are conducted by the VA, and are thus applicable to the VADC system, though DoD ratings only pertain to functional limitations relevant to the servicemember's military duties, while VA ratings apply more broadly (Krull et al., 2019). Like the BDD and Quick Start programs, the IDES may have increased the share of veterans separating with a service-connected disability rating.

During this period, the VA also implemented several operational changes to manage increases in the volume and complexity of claims received, including increasing staff, redistributing workloads, upgrading technology, and developing new pilot projects for claims processing (GAO, 2010). In March 2013, the number of pending VA claims reached an historical peak at more than 600,000, creating additional pressure for change. Driven by increases in capacity and new technology, the claims backlog was dramatically reduced over the next two years and has been relatively consistent at fewer than 200,000 since then, though the GAO has identified problems with the reporting and processing of appeals claims (GAO, 2019). An expected result of the rapid increase and subsequent reduction in the backlog is variation in the lag between applications (and external events that affect the application rate) and changes in VADC population and expenditures over time.

Changes to evidentiary standards

The VA also made several changes to its evidentiary requirements for claims between 1999 and 2018. In theory, lowering evidentiary standards should increase the number of VADC claimants, either by increasing the baseline number of eligible veterans or by reducing the transaction cost of filing a claim. The most salient of these changes was the set of expansions to presumptions granted to veterans who had served in specific Vietnam theaters where the Agent Orange compound was used (VA, 2020). Presumptions significantly reduce the veteran's evidentiary burden for filing a claim by *presuming* that the health condition in question is service-related, provided it is on the list of conditions for which the veteran is presumption-eligible given his or her service period. This effectively reduces a two-step application process—proving the condition exists *and* was caused or aggravated by military service—to a single step of evaluating the existence of the condition.

The current process for identifying health conditions eligible for Agent Orange presumptions was established and is regulated by the Agent Orange Act of 1991.[8] Under that Act, the VA is directed to partner with the National Academy of Medicine (NAM) to research the *association* between Agent Orange exposure and various diseases; authority to interpret the strength of this evidence is left to the VA (Panangale, Scott, Weimer, Moulta-Ali, & Nichols, 2010). In 2000, a NAM report found suggestive evidence of a positive association between diabetes and Agent Orange, and in 2001 the VA added diabetes mellitus to the list of Agent Orange presumptions (Institute of Medicine, 2000). This policy change is estimated to have increased participation in the VADC program among Vietnam veterans by 6 percentage points, and to have increased the CDR of 1.7 percent of existing VADC recipients (Duggan, Rosenheck, & Singleton, 2010). Further, the policy significantly reduced labor supply for Vietnam veterans, increased their rate of self-employment (Coile, Duggan, & Guo, 2015), and increased the reported prevalence of diabetes among veterans by 2.7 percentage points (Singleton, 2009). In 2010, other health conditions, such as certain forms of leukemia, Parkinson's disease, and ischemic heart disease were added to the list of Agent Orange presumptions. These changes, with the possible exception of ischemic heart disease, are unlikely to have affected VADC participation or veteran labor supply in significant ways given their rarity.

In another significant change to evidentiary standards, the VA in 2010 issued a ruling lessening the burden for veterans of all service eras filing a claim for post-traumatic stress disorder (PTSD)-related VADC claims.[9] In order to determine that a PTSD claim is service-related, claimants must show that they experienced an in-service stressor. Prior to the policy

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[8] Public Law 102-4: Agent Orange Act of 1991. Accessed at: https://www.govinfo.gov/content/pkg/STATUTE-105/pdf/STATUTE-105-Pg11.pdf

[9] 75 FR 39843: Stressor Determinations for Posttraumatic Stress Disorder. Accessed at: https://www.federalregister.gov/documents/2010/07/13/2010-16885/stressor-determinations-for-posttraumatic-stress-disorder

change, in many cases this required proving proximity to a specific potentially traumatizing event. The 2010 decision amended this so that veterans are only required to show that they served in a combat zone or that their claimed stressor rises to the level of PTSD as diagnosed by a psychiatrist or psychologist and "is consistent with the places, types, and circumstances of the Veteran's service."[10] This policy is estimated to have increased the number of PTSD-related VADC compensation cases for combat veterans, and may have changed veteran attitudes towards PTSD (Contreary, Tennant, & Ben-Shalom, 2017).

Changes to the veteran population

The composition of the veteran population has also changed significantly since 1999, and in ways that are likely to affect receipt of disability compensation. Table 1.1 summarizes some of these changes using data from the CPS veterans' supplement. Veterans in 2018 were slightly older than veterans in 1999, though working-age veterans were slightly younger. Also, veterans in 2018 were more likely to have a college degree, be female, and have a service-connected disability rating, and were less likely to be in the labor force.

Many of these demographic changes reflect changes in the share of veterans representing different service eras, and especially the transition from a conscripted force to an all-volunteer force in the early 1970s (Rostker & Yeh, 2006). The share of all veterans who served for fewer than five years fell by nearly 13 percentage points in this period, possibly reflecting the greater professionalization of the force and indicating a potential source of new disability claims. Since VADC is linked to military service, at the individual level the probability of contracting a service-related health condition increases monotonically in the length of service. This may not hold, however, at the population level, since different cohorts of veterans will have different exposures to risk, driven, for example, by the share of active duty in combat situations and the nature of combat. The most significant compositional change for the working-age veteran population is the aging-out of the Vietnam cohort (falling from 38.3 percent in 1999 to just 2.1 percent in 2018) and their replacement with veterans who served in the post-9/11 conflicts (33 percent of all working-age veterans in 2018). Some observers have suggested that recent growth in VADC is driven by lower mortality and greater casualty rates among recent cohorts compared to the Vietnam era, though available data on known casualties and forced evacuations from service areas—one measure of the number of serious injuries sustained during military operations—do not necessarily support this view (McNally & Frueh, 2013; Tanielian & Jaycox, 2008).

[10] 75 FR 39843.

Demand Explanations for Recent VADC Growth

In addition to supply factors, the demand for VADC may have also changed during this period due to external factors that may have made the benefit more appealing to eligible veterans. Research on the SSDI program has consistently found, for example, relatively strong associations between negative shocks in labor market conditions and applications for and receipt of disability compensation (D. H. Autor, Dorn, & Hanson, 2016; Black, Daniel, & Sanders, 2002). Demand-side explanations for growth in the VADC program are, however, less straightforward than those for the SSDI program, which imposes a very high implicit marginal tax on earnings for beneficiaries and applicants. More than 90 percent of all VADC recipients do not have individual unemployability (IU) status and therefore do not face explicit incentives to substitute work for disability payments.[11] Nonetheless, drawing on the conceptual framework developed in the literature on the low take-up of social programs, it is reasonable to expect that 1) veterans may significantly underutilize the VADC program, and 2) demand factors may contribute to program growth (Currie, 2004).

Demand factors could affect VADC program participation in three ways: by *changing the value of seeking benefits due to income effects*; by *changing the value of expected benefits*; and through *substitution effects*. According to a simple behavioral model, individuals will apply for benefits when the marginal value from doing so is greater than the cost of applying, where costs include both direct administrative burdens and psychological costs associated with stigma and other factors. This framework predicts that claiming rates will be higher when 1) the marginal utility of additional benefits is higher, when 2) the expected amount of the benefit increases, or 3) when the costs of applying for the benefit—broadly construed—are lower. Consider the following model of VADC claiming behavior:

- i indexes impairment types. I assume this incorporates both the nature of the impairment (i.e., severity and body part) and its service-connectedness. Veterans have enough information about their impairments to make informed subjective judgements about the compensability of their condition.
- $w \in \mathrm{R}^{+}$ is the hourly wage available in the labor market, assumed to be exogenous. Veterans choose the number of hours to work, $h \in [0, H]$, so that total earnings are represented by wh.
- $\bar{e} \in \mathrm{R}^{+}$ is the maximum earnings allowable to maintain eligibility for IU. In most cases this is the federal poverty level, though examiners are allowed some discretion.

[11] IU enables a veteran with a disability rating of less than 100% to receive the maximum possible benefit if they can show they are unable to work.

- $p(i) \in [0,1]$ is the subjective probability of a successful disability benefit application for an individual with impairment i.
- $\bar{B}(i) \in [0, B^{MAX}]$ is the expected benefit for an individual with impairment i. B^{MAX} is the statutorily determined maximum benefit.
- $\lambda(i) \in [0,1]$ is the subjective probability of being granted IU benefits. While this may vary by impairment types, it is also likely to be driven by idiosyncratic individual factors.
- $s(i)$ is the cost of applying for disability benefits. I assume $s(i) \sim N(\mu_s(i), \sigma_s^2)$. Note that this cost is not necessarily positive—it is reasonable to think, for example, that some veterans may feel a "duty" to apply for disability benefits even if doing so is not cost-effective.
- V is the veteran's value function. I assume $V' > 0$ and $V'' < 0$.

Consider three possible states of the world: the veteran does not apply for VADC, the veteran applies for VADC but not IU, and the veteran applies for VADC and IU. The value function describing the first state is as follows (suppressing i throughout for clarity):

$$v_w = \max_h V(wh)$$

The utility in this state is determined entirely by the available wage and the optimal value of h, which is chosen to balance the additional utility gained from higher earnings with the disutility of work. In reality, the cost of working will be closely related to the veteran's health condition, but I do not consider that relationship in this model. With this baseline, the *marginal* value from receiving VADC is as follows:

$$v_{dc} = \max_h V(wh + \bar{B}) - \max_h V(wh)$$

In other words, the additional value from receiving VADC is equal to the difference in the value function evaluated at optimal levels of h when VADC benefits are available and when they are not. The veteran's expected utility when applying to VADC is therefore $EU_{dc} = v_w + pv_{dc}$. Finally, the *marginal* value from receiving IU in addition to VADC is as follows:

$$v_{iu} = \max_h V(\min(\bar{e}, wh) + B^{MAX}) - \max_h V(wh + \bar{B})$$

The first term corresponds to the veteran's value from receiving IU benefits, and depends on whether potential wage earnings are greater or less than the maximum amount to maintain IU eligibility. This builds into the analysis a role for macroeconomic conditions, since an acute economic shock may bring a veteran's potential earnings below the IU threshold. The expected utility from applying to both VADC and IU is $EU_{iu} = v_w + p(v_{dc} + \lambda v_{iu})$. To maintain simplicity, I assume the cost of applying to VADC alone is identical to applying to VADC and IU together. While this assumption is implausible, relaxing it is unlikely to significantly affect the analysis absent concrete evidence on the distributions of these costs. Within this framework, a veteran will apply to VADC and IU if the following condition holds:

$$v_w + p(v_{dc} + \lambda v_{iu}) - v_w \equiv \Delta > s$$

Or if:

$$p(v_{dc} + \lambda v_{iu}) > s$$

If $v_{iu} < 0$ and $pv_{dc} > s$, then the veteran will apply to VADC but not IU. Conversely, if $pv_{dc} < s < p(v_{dc} + \lambda v_{iu})$, the veteran will apply for VADC and IU, but would not apply for VADC without the possibility of receiving IU benefits. This condition may hold, for example, when the veteran's earnings capacity is below $\bar{e}$—i.e., when the IU eligibility criterion does not bind—and when B^{MAX} is sufficiently large relative to $\bar{B}$.

Since $V' > 0$, the decision to apply for disability benefits can be fully characterized by a threshold value of s, denoted by $s^* = \Delta$, such that a veteran will always apply if their observed costs are less than this value and will never apply otherwise. In other words, this model assumes that the veteran first assesses their expected value from applying for the benefit, and then compares this value to their individual costs from applying for the benefit, which are drawn from a known distribution. The outcome of interest is $F_s(s^*) = p(s \leq s^*)$, and dynamics can be captured by comparative statics of s^*. Consider a few cases of interest:

Case 1: Only apply to VADC

In the case where the veteran only applies to VADC, $pv_{dc} > s$ and $v_{iu} < 0$. This may be considered the canonical case, since it likely applies to most veterans on VADC and will tend to obtain when potential earnings are well above the maximum amount to receive IU and when the difference between $\bar{B}$ and B^{MAX} is small. The threshold cost is then given by $s^* = pv_{dc} = p[\max_h V(wh + \bar{B}) - \max_h V(wh)]$. Using the envelope theorem, we can derive the following expression for how s^* will vary with wage opportunities in the labor market:

$$\frac{\partial s^*}{\partial w} = p[\bar{h}V'(w\bar{h} + \bar{B}) - h^*V'(wh^*)]$$

where $\bar{h} = argmax_h V(wh + \bar{B})$ and $h^* = argmax_h V(wh)$. Under the assumptions that work is costly and leisure is a normal good, $\bar{h}$ will tend to be less than h^* through an income effect induced by $\bar{B}$. Since by assumption $pv_{dc} > 0$, $w\bar{h} + \bar{B} > wh^*$, implying that the expression above will always be negative due to the concavity of V. Thus, negative shocks to wages will tend to increase the probability of applying for VADC by increasing s^*. Note that this analysis abstracts away from the possibility that the optimal hours worked will also respond to wages in potentially ambiguous ways, as this relationship is not central to the dynamics I am most interested in.

Now consider how the probability of claiming changes with the value of the benefit and the probability of receiving it:

$$\frac{\partial s^*}{\partial \bar{B}} = pV'\left(w\bar{h} + B\right) > 0$$

$$\frac{\partial s^*}{\partial p} = V\left(w\bar{h} + \bar{B}\right) - V(wh^*) > 0 \text{ (by assumption)}$$

These comparative statics have intuitive interpretations: the probability of claiming the benefit will increase with the value of the benefit and with the subjective probability of claiming it, as long as its marginal value is greater than zero.

Now consider the effect of IU on these dynamics.

Case 2: Apply to VADC and IU, $\bar{e}$ binding

In this case the veteran applies to both VADC and IU and the earnings limit for IU binds, so $pv_{dc} > 0$, $v_{iu} > 0$ and $wh \gg \bar{e}$. Then, $s^* = p(v_{dc} + \lambda v_{iu}) =$
$p[\max_h V(wh + \bar{B}) - \max_h V(wh) + \lambda(\max_h V(\bar{e} + B^{MAX}) - \max_h V(wh + \bar{B}))] =$
$p[(1 - \lambda)\max_h V(wh + \bar{B}) + \lambda \max_h V(\bar{e} + B^{MAX}) - \max_h V(wh)]$. This has an intuitive interpretation: the expected marginal value of obtaining VADC and IU is given by the difference between the convex combination of the values that obtain with and without IU and the value that obtains with no VADC benefit. The threshold cost value will vary with market wages as follows:

$$\frac{\partial s^*}{\partial w} = p[(1 - \lambda)\bar{h}V'\left(w\bar{h} + \bar{B}\right) - h^*V'(wh^*)]$$

Following the logic above, this will always be negative since $\lambda \in [0, 1]$.

Case 3: Apply to VADC and IU, $\bar{e}$ not binding

Finally, consider the case where potential wages are well less than $\bar{e}$. Then, $s^* = p[(1-\lambda)\max_h V(wh+\bar{B}) + \lambda \max_h V(\bar{e}+B^{MAX}) - \max_h V(wh)]$. The comparative static of interest is then:

$$\frac{\partial s^*}{\partial w} = p[(1-\lambda)\bar{h}V'(w\bar{h}+\bar{B}) + \lambda\hat{h}V'(w\hat{h}+B^{MAX}) - h^*V'(wh^*)]$$

where $\hat{h} = argmax_h V(wh+B^{MAX})$, which by assumption is less than or equal to h^*. Under the assumption that $(1-\lambda)(w\bar{h}+\bar{B}) + \lambda(w\hat{h}+B^{MAX}) > wh^*$, this will be negative. Note that while each of these cases lead to the same qualitative conclusions, the strength of the comparative static with respect to wages will vary across cases. A side-by-side comparison of the magnitudes of the three comparative static expressions, however, would be inappropriate since they describe different domains of the value function.

Data

To empirically examine whether market conditions affect VADC expenditures and participation, I use publicly available data published by the VA. My measure of expenditures comes from the General Description of Geographic Distribution of the Department of Veterans Affairs Expenditures (GDX) series, published annually by the VA's Office of Enterprise Integration (OEI). The GDX series reports annual spending on a variety of VA programs at the state, county, and Congressional District levels for the following categories: Compensation and Pension; Education and Vocational Rehabilitation and Employment; Insurance and Indemnities; Construction and Related Costs; General Operating Expenses and Related Costs; Loan Guarantee; and Medical Expenditures. For this analysis I am most interested in Compensation and Pension spending, which combines spending on four programs: monthly disability compensation, disability pensions, dependency and indemnity compensation (DIC), and burial allowances. These data are available from 1996 – 2019, and I use data from 2000 – 2019 in the results presented here. In all estimates, county-level data is aggregated to the commuter zone level to create a balanced panel.

A key limitation of the GDX data is that compensation expenditures are not separately identified from pensions, DIC, and burial expenses. To examine the magnitude of this problem, Figure 1.2 plots annual total GDX compensation and pension (GDX C&P) expenditures alongside annual compensation spending derived from VA benefit reports for 2002 – 2018. While the GDX series is more volatile than compensation spending, compensation accounts for nearly 70 percent or more of GDX C&P spending in all years, and the two series exhibit qualitatively similar trends. The share of GDX C&P spending attributable to pensions (not

shown) declined steadily from nearly 10 percent in 2002 to less than 5 percent in 2018. While the imprecision of this data is a concern, especially the deviations from trend in 2011 – 2012 and 2017 – 2018, most of the variation in the GDX series appears to be driven by compensation.

To examine changes in the VADC population I use VA data on program recipients at the county level available from the National Center for Veterans Analysis and Statistics (NCVAS). These are available for 2008 and 2010 – 2018, and my estimates focus on the 2010 – 2018 period. Reporting standards for this data have changed somewhat over time. From 2008 – 2013, county-level counts of VADC recipients were reported for each disability rating (0 – 100 percent) and for several age categories. From 2014 onwards, the data were aggregated into the following rating bins: 0 – 20 percent, 30 – 40 percent, 50 – 60 percent, and 70 – 100 percent. In order to create a balanced panel, I aggregate the data to these bins and report results for two rating categories: CDRs less than 50 percent, and CDRs of 50 percent or more. I also aggregate the county-level observations to the commuter zone level. In order to avoid complications caused by commuter-zone–CDR groups with zero observations, I restrict the sample to commuter zones with non-zero population for each year. This sample restriction removes less than 1 percent of the population-adjusted sample. Figure 1.3 plots the total VADC population for the two disability severity categories in my refined sample. The trends in this data closely mirror those shown in Figure 1.1, which is derived from aggregate data, suggesting conformity between the datasets and minimal costs from restricting to commuter zones with a positive population in all categories and years.

Research Approach

VADC participation is an inherently dynamic process: since very few veterans stop receiving compensation for reasons other than death, the number of recipients and amount spent on VADC is highly correlated across years. To capture these dynamics, I estimate models of the following form:

$$\Delta Y_{mt} = (\alpha - 1)Y_{m,t-1} + \beta_0 \Delta lnVetpop_{m,t} + \beta_l D^l_{m,t} + \mu_{m,t}$$

$$\mu_{m,t} = \gamma_m + \epsilon_{m,t}$$

where Y_{mt} is either log expenditures or the log number of VADC participants in commuter zone m in year t, $lnVetpop_{m,t}$ is the log of the veteran population, Δ is the first differences operator, and $\mu_{m,t}$ is a mean-zero error term comprised of commuter-zone (unobserved) fixed effects and a random disturbance. $D^l_{m,t}$ is a measure of labor market conditions at lag $l \in [0, 4]$, where lags are measured annually.

I estimate models using two measures of labor market conditions: the annualized unemployment rate, and a measure of year-to-year changes in labor demand (Bartik, 1991). Data on unemployment comes from the Bureau of Labor Statistics (BLS), and labor demand is measured using annual employment estimates from the Quarterly Census of Employment and Wages (QCEW). I define the change in labor demand in market m at time t as $\Delta G = 100 \times \frac{L_{m,t} - L_{m,t-1}}{L_{m,t-1}}$, where L is the amount of labor employed by firms. Since L can only be observed using data on equilibrium employment, which at any given time is jointly shifted by supply and demand factors, ΔG will reflect simultaneous supply and demand shocks and models using ΔG as a measure of demand will produce biased coefficients. A common method for removing the effects of supply shocks from ΔG, and the one I use here, is to instrument ΔG with a "shift-share" measure of the following type:

$$\Delta \hat{G}_{m,t} = 100 \times \sum_k s_{m,k,1995} \frac{\left(\hat{L}_{m,k,t} - \hat{L}_{m,k,t-1}\right)}{\hat{L}_{m,k,t-1}}$$

where k indexes industries at the 2-digit NAICS level, $s_{m,k,1995}$ is the employment share of industry k in market m in 1995, and $\hat{L}$ is the number employed at the national level after removing market m. This instrument is plausibly exogenous from local supply shocks because it depends only on national changes in employment and industry shares from the pre-analysis period. It is a relevant instrument to the extent that industry-level demand shocks are common across markets. Recent work has attempted to formally establish the validity of this instrument (Borusyak & Jaravel, 2017; Goldsmith-Pinkham, Sorkin, & Swift, 2020; Jaeger, Ruist, & Stuhler, 2018). A key insight from these papers is that shift-share instruments, which are in fact sums of many individual instruments, are primarily identified by local industry shares, and that effects can be driven by just a few industries. Also, the instrument may not fully satisfy the exclusion restriction if supply shocks exhibit long-term dynamics. The results I present here are vulnerable to these limitations and should be interpreted as suggestive, rather than definitively capturing the effects of labor demand shocks on VADC.

Table 1.2 presents estimates of the first-stage regression of ΔG on $\Delta \hat{G}_{m,t}$, verifying the relevance of the instrument. Figure 1.4 plots mean annual unemployment rates for the veteran sample and mean predicted values from the first-stage labor demand regression. As shown in the figure, the unemployment and labor demand measures capture slightly different temporal dynamics in labor market conditions. Unemployment rates peaked in 2010, for example, and lingered at high levels for multiple years afterwards, while year-on-year labor demand shocks recovered quickly after a deep trough in 2009. This is consistent with the recent observation that recoveries from labor demand shocks are very often slow and linear regardless of the cause of the shock (Hall & Kudlyak, 2020).

A well-known problem with dynamic panel models of this kind is bias created by the correlation between the unobserved panel unit fixed effect (in this case, γ_m) and the lagged dependent variable (Nickell, 1981). This is especially relevant in short panels such as those considered here: an abnormally large or small observation in one year will simultaneously affect the estimation of the unit fixed effect and the coefficient on the lagged dependent variable, violating the exogeneity assumption of OLS and potentially contaminating the estimation of other model coefficients. Standard methods for removing fixed effects (i.e., the within estimator) do not fully resolve this problem, since the transformed lagged dependent variable will still be correlated with the error term (Roodman, 2009). To address this problem, I estimate models using what is commonly known as the Arellano-Bond (AB) estimator, which addresses dynamic panel bias by instrumenting for the lagged dependent variables with additional lags of those variables. Several versions of this estimator have been proposed, and I present results using the standard AB estimator with first-differenced lags as instruments. As sensitivity analyses, I compare these results to several other estimators (not shown), including OLS with dummy variables, the within-estimator, and general method of moments (GMM) implementations of the AB approach using both differences and orthogonal deviations to remove fixed effects. Results are qualitatively similar across most specifications, suggesting the results are reasonably robust to modeling choices (White, 1982). The AB estimator presented here and the dummy variable OLS estimators were most stable across models and consistently produced reasonable coefficients on lagged variables.

Results

Table 1.3 shows results from the baseline expenditure model using log unemployment rates to measure labor market conditions, and Table 1.4 shows results for a model in which unemployment rates are interacted with two periods of interest: 2008 – 2010, the contraction from the Great Recession; and 2011 – 2013, the beginning of the economic recovery following the Great Recession. All estimates include time fixed effects and are weighted by the veteran population in 2001. Since the outcome in this model is the change in log expenditures from $t-1$ to t, the coefficient on $lnUrate$ can be interpreted as the percent change in VADC expenditures attributable to a 100 percent change in the unemployment rate. The coefficients on lagged expenditures and first differences of the log veteran population validate the modeling approach: these variables are strongly correlated over time and relatively stable across model specifications. The results from Table 1.3 indicate that VADC expenditures are mildly responsive to labor market conditions, and that this relationship takes at least two years to fully materialize. The coefficient on the contemporaneous unemployment rate (i.e., lag 0) is indistinguishable from zero but is positive and significantly different from zero for lags two, three, and four. According to these results, a 100 percent change in the unemployment rate will contribute to a 3 – 4 percent change in VADC expenditures in two to four years. The results from

Table 1.4 suggest that this effect was especially strong in the 2011 – 2013 period, likely reflecting the lingering high unemployment rates after the Great Recession shown in Figure 1.4. For example, the total effect of the three-year lag in this period is 0.0428 + 0.0241 =0.0669 and is statistically significantly different from the estimate for all years.

Tables 1.5 and 1.6 replicate Tables 1.3 and 1.4 using the demand instrument predicted from the first-stage model as a measure of labor market conditions. Since $\Delta\hat{G}_{m,t}$ is a linear measure of changes in employment scaled by 100, the exponent of its coefficient can be interpreted as the percent change in VADC expenditures associated with a 1-unit change in the employment growth rate. Here, there is no evidence of a general association between labor demand shocks and VADC expenditures: all the coefficients on $\Delta\hat{G}_{m,t}$ in Table 1.5 are indistinguishable from zero. There is some evidence of an association in the recession years, however. During the 2008 – 2010 period, unit changes in lagged demand shocks contributed to reductions in VADC expenditures of between 0.3 and 1 percent, compared to approximately 0.5 percent in the 2011 – 2013 period. Note that in substantive terms the third lag effect in the 2011 – 2013 period is significant given the magnitude of the demand shock in 2009 shown in Figure 1.4.

The differences between the unemployment rate and demand shock specifications are notable and reflect the differential dynamics of the two series shown in Figure 1.4. Whereas the unemployment rate is highly correlated over time in the sense that a spike in unemployment in one year is likely to be reflected in the unemployment rate in subsequent years, the demand measure recovers much more quickly. And while the two sets of models produce qualitatively similar results—both suggest a relatively strong effect of the third lag in the 2011 – 2013 period, and the signs of the effects imply similar dynamics (i.e., unemployment rates are positively associated with expenditures and demand shocks negatively so)—they also differ in important ways. In some ways, the demand instrument estimates during the 2008 – 2010 period, which show a very strong negative effect in the third lag, are puzzling. While it is reasonable to expect that negative demand shocks during the recession period would lead to increases in VADC expenditures, it is surprising that the third lag of this effect is so strong, given that it captures employment dynamics from before the Great Recession. This result also strongly contrasts with the unemployment rate results, which find no additional effect during the recession period. This reflects the fact that these measures capture different economic phenomena, and that the unemployment rate more comprehensively incorporates the various conditions that affect job seekers at any given time. For this reason, my preferred set of results are those in Tables 1.3 and 1.4, which reflect changes in the unemployment rate.

Tables 1.7 and 1.8 show results from models relating changes in the VADC population to log unemployment rates, stratified by CDR category. All regressions include time fixed effects and are weighted by the 2008 veteran population. In Table 1.7, which reports results for those with ratings of less than 50 percent, VADC population changes are negatively associated with lagged market conditions, and this relationship is strongest in the 2011 – 2013 period. In contrast, as shown in Table 1.8, the 50 percent or more category grew faster in high unemployment areas,

and especially in the years immediately after the Great Recession. For example, the total effect of the two-year unemployment rate lag in 2011 – 2013 is -0.0943 for the less severe group and 0.1211 for the more severe group. Tables 1.9 and 1.10 replicate these results using the demand instrument instead of unemployment rates. The results are qualitatively similar, but not identical. There is no meaningful statistical relationship between demand shocks and changes in the VADC population for the less severe population, and suggestive evidence that negative demand shocks contributed to VADC growth in the more severe category. Focusing on the 2011 – 2013 period in particular, unit changes in negative demand shocks at lags two and three are associated with VADC population growth of between 0.9 and 1.5 percent, and these estimates are statistically significant from zero. Interestingly, this effect is only observed for the second and third lags, and there is a positive relationship between demand shocks and population in the first lag. This is an encouraging echo of the results using logged unemployment rates: as discussed earlier, demand shocks are likely to be negatively correlated over time, in the sense that economic growth out of businesses cycles tends to be faster than growth before the cycle. Thus, this result seems to indicate that it is actually the labor market conditions in the third lag that are relevant to changes in population (or expenditures), and not a spurious correlation over time in the unemployment series.

Discussion

The aim of this chapter was to explore the relationships between changes in VADC participation and local labor market conditions. The analysis was motivated by a conceptual model arguing that barriers to obtaining a disability rating may prevent some qualified veterans from using the program, and that in weaker labor market conditions—i.e., those in which income from work is more difficult to obtain—these barriers will be less preventative. This model mirrors a 2014 Congressional Budget Office report on VADC trends, which suggested that lost employment opportunities due to the Great Recession "may have prompted some veterans to apply for disability to replace lost earnings" (Bass & Golding, 2014).

My research design is not causal, and I cannot eliminate the possibility that compositional changes in the veteran population within commuter zones, possibly driven by migration patterns or selective relocation decisions of recently-separated servicemembers, are confounding the results. Nonetheless, the results suggest that growth in VADC expenditures tends to be higher in labor markets with higher unemployment rates, that this relationship was stronger in the period after the Great Recession of 2007 – 2009, and that one of the mechanisms driving this is an increase in the number of veterans with more severe disability ratings in commuter zones with weaker labor market conditions. In most cases, acute demand shocks less consistently explain the variation in VADC growth than lagged unemployment rates, possibly reflecting more irregularity in that series over time due to changes in employment levels (i.e., growth rates may appear higher after a negative shock even if employment to population ratios are below target). For this

reason, I regard the estimates using unemployment rates as being more reliable than those using demand shocks.

One notable finding is that labor market conditions appear to influence VADC over intervals of as many as three to four years, as is reflected in the large third-year lags in Table 1.3, 1.4, and 1.7. While lags of one year or more between applications for VADC and rating decisions by the VA are well known, the average length of these lags is not sufficient to explain a three or four year VADC response to labor market shocks. One possible explanation for this finding is that labor market shocks precipitate a sequence of actions by veterans, which sometimes culminate in the veteran making, appealing, or updating a disability claim. According to this view, the disability program is a relatively low priority for the veteran, and he or she will only interact with it when other options fail to materialize or when health conditions change. For example, consider a veteran who loses her civilian job during an economic downturn. A distinctive feature of the recovery after the 2007 – 2009 recession was the replacement of well-paying jobs with full benefits with less stable part-time work opportunities. This veteran, then, may quickly return to the labor force after the separation, but in a reduced capacity and with greater reliance on alternative sources of income and social services. She may regard the monthly cash benefit from VADC as a way to supplement her income, but may also come to the program while seeking out other benefits. For example, she may continue to receive health insurance from her employer for a period of time after separation (say, up to 18 months), but will look towards other sources of health insurance when COBRA benefits expire. Since veterans with disability ratings have higher priority ratings for VA health care, this may induce her to apply for VADC. The potential lags built into this sequence of events—the veteran must first lose her job, then run out of COBRA benefits, and then go through the VADC application process—may explain the lags observed in my results.

In the story above, the veteran's health is assumed to be constant over time. Another possibility is that labor market shocks aggravate or reveal underlying health conditions with service-connected origins. The canonical example of such a condition is PTSD, which is highly prevalent among veterans in general and especially those who served in the post-9/11 conflicts, and may be triggered by acute stressors in civilian life, such as job loss (Tanielian & Jaycox, 2008). There is some reason to believe PTSD or related diagnoses are playing a role in the results observed here. According to VA annual reports, the number of new VADC recipients with a PTSD diagnosis nearly doubled from 26,817 in 2007 to 50,147 in 2012, capping out at 63,049 in 2015.[12] In 2019, a total of more than one million PTSD disabilities were reported by the VA, making it one of the five most rated conditions alongside tinnitus, hearing loss, limitation of flexion in the knee and cervical strain. Note that this explanation may also explain the lags observed between labor market shocks and changes in VADC, since it will likely take some time

[12] See: https://www.benefits.va.gov/REPORTS/abr/.

for a new health condition to materialize, and then more time to self- diagnose it as service-connected and decide to seek out benefits.

Another possible explanation for the results I observe is an increase in the number of veterans near retirement age participating in the IU program. IU is means tested and veterans who apply for it must keep their labor market earnings below a threshold amount, which is typically defined as the federal poverty level. A veteran with a service-connected disability who has recently lost their job in an economic downturn and who is near retirement age—or whose disability significantly limits work opportunities—may decide to stay out of the labor force in order to become eligible for IU. Also, since eligibility for IU requires having a disability rating of at least 60 percent, some veterans may be incentivized to submit additional disability claims in order to increase their CDR and have a better chance of receiving IU. While this channel does not explicitly explain the lags observed in my results, it is reasonable to think that the decision to retire early and seek out IU benefits may evolve after multiple years with irregular attachment to the labor force. Also, some veterans may only begin seeking out alternative sources of income after exhausting their unemployment benefits. Further, if a veteran's disability requires significant workplace accommodations, they may only turn to IU after searching for but failing to find significant work opportunities.

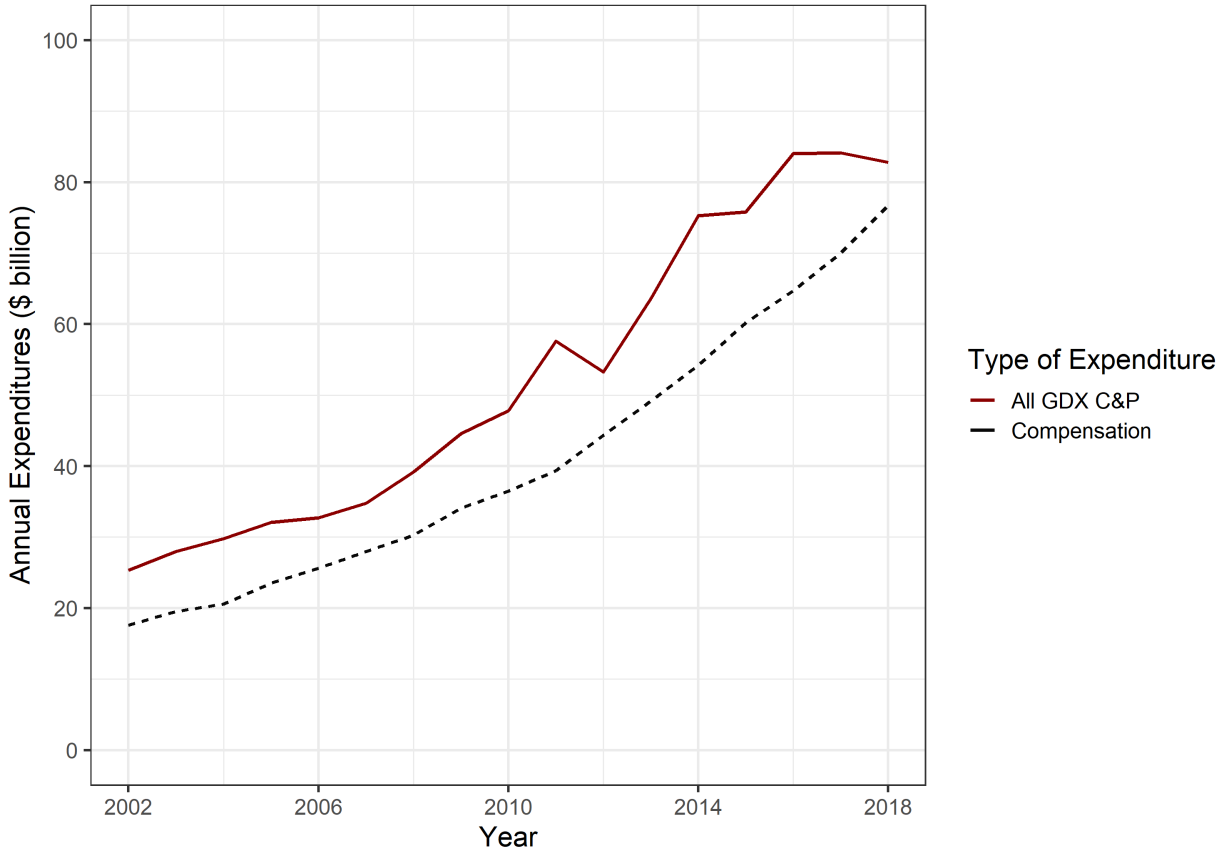
Chapter 1 Figures and Tables

Table 1.1: Changes in Demographics of Veteran Population, 1999 – 2018

	All Veterans		Working-age Veterans (18 – 64)	
	1999	2018	1999	2018
Median Age	57	63	50	49
Average Age	57	60	47	47
w/ College Degree	24%	33%	24%	33%
Female	6%	10%	8%	15%
White	87%	83%	85%	77%
In Labor Force	60%	49%	83%	77%
With Service-Connected Disability Rating	9%	20%	9%	23%
With Service-Connected Disability Rating >= 50 Percent	2%	10%	2%	11%
Pre-Vietnam	32%	8%	6%	0%
Vietnam	27%	24%	38%	2%
Post-Vietnam (including first Gulf War)	25%	25%	39%	37%
Post-9/11	0%	18%	0%	33%
Unspecified	16%	26%	17%	28%
Served < 5 Years in Active Duty	68%	55%	65%	47%

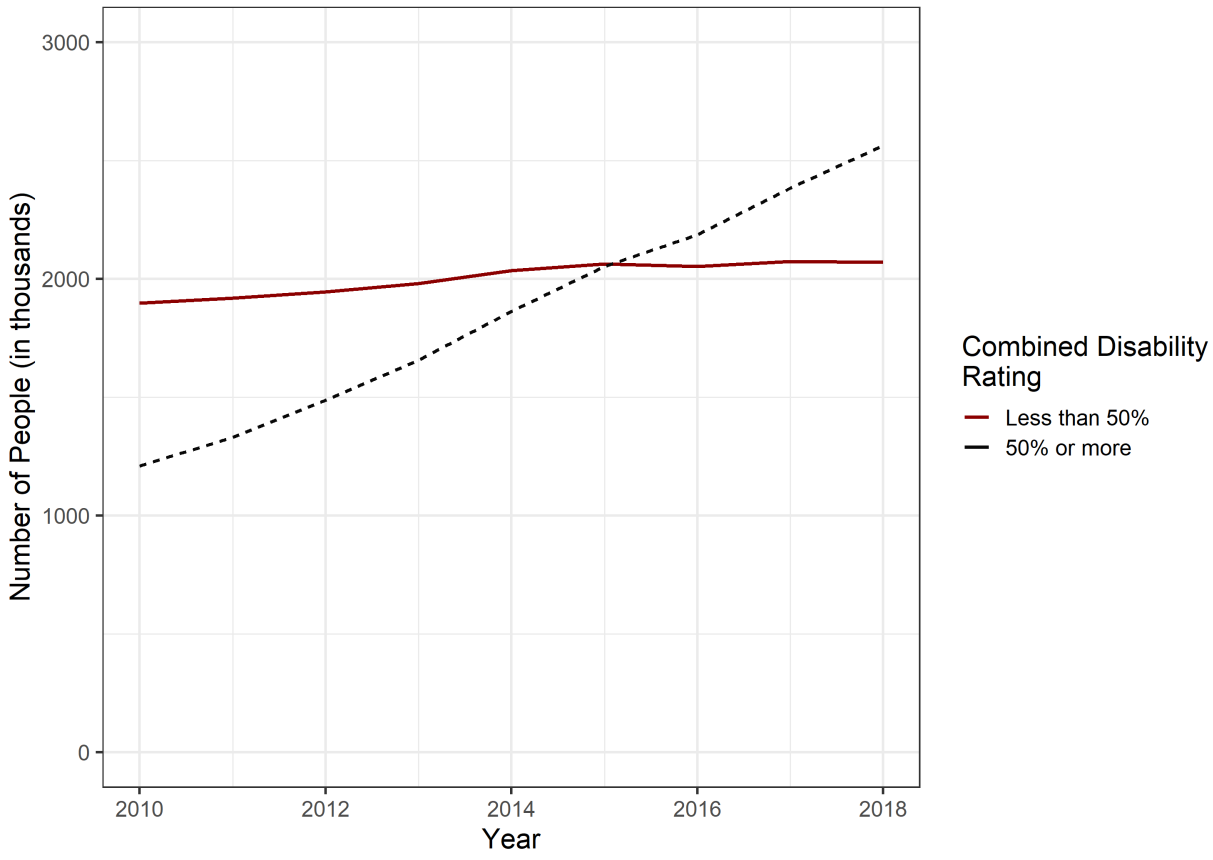
Source: CPS Veterans' Supplement, 1999 and 2018.

Figure 1.2: Annual GDX and Compensation Expenditures, 2002 – 2018



Source: GDX and VA annual benefits reports.

Figure 1.3: VADC Population in Analysis Sample by CDR Category, 2010 – 2018



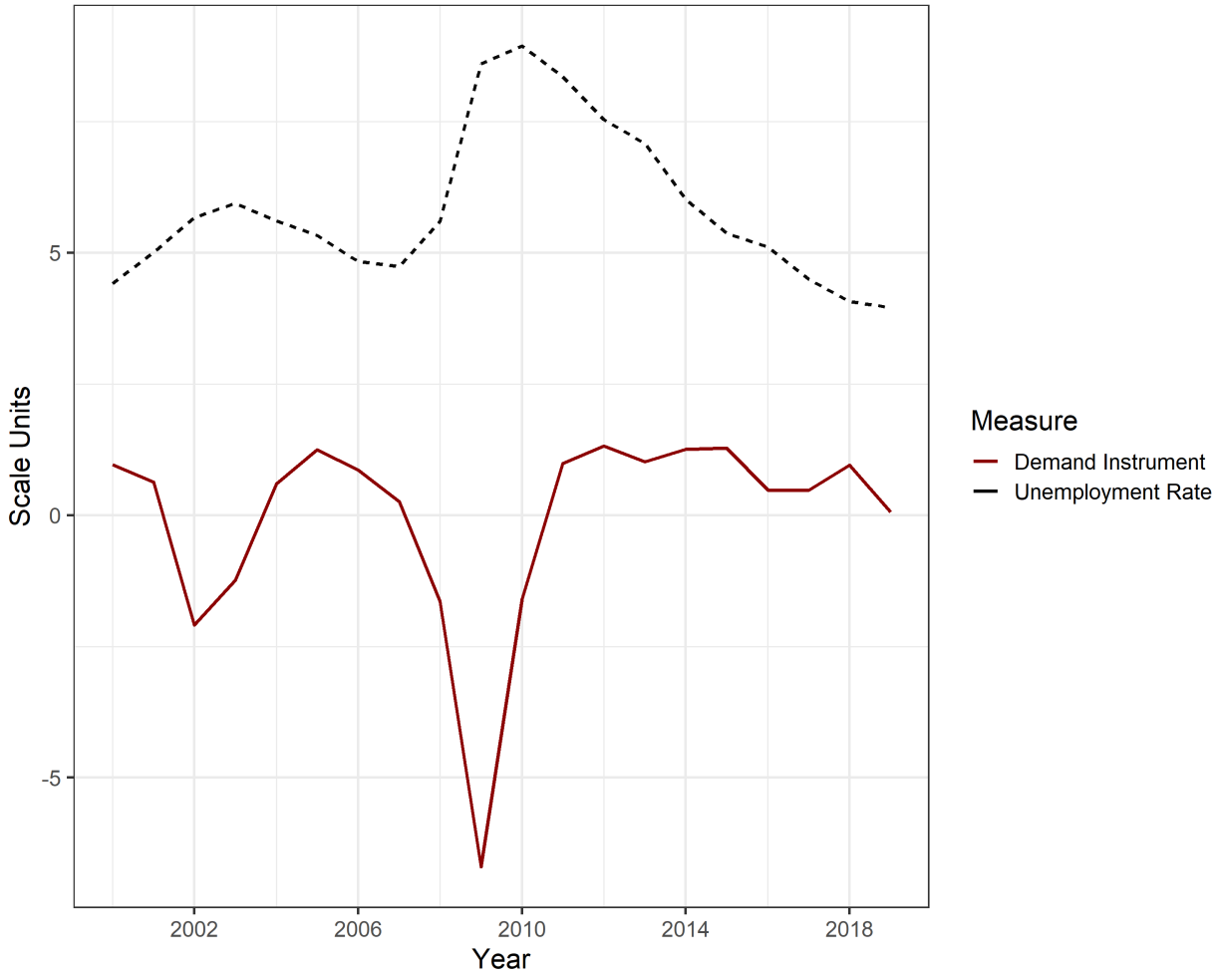
Source: NCVAS.

Table 1.2: First Stage Regressions, Demand Instrument, 2001 – 2019

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
Shift-share Instrument	0.983	1.0038	1.0087	1.0461	0.905
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
ln(Comp and Pens_t-1)	0.3276	0.3873	0.6937	0.1287	0.0266
	[0.5287]	[0.3973]	[0.1186]	[0.8226]	[0.9445]
Δ(lnVetpop)	0.6774	1.3999	0.8205	1.4499	2.375
	[0.4377]	[0.1259]	[0.2749]	[0.0080]**	[0.0013]**
Time Fixed Effects	X	X	X	X	X
N	14,800	14,800	14,800	14,800	14,800

Note: P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2001.

Figure 1.4: Predicted Labor Demand and Sample Unemployment Rates by Year, 2001 – 2019



Source: BLS and QCEW.

Table 1.3: Dynamic Panel Regressions, Unemployment Rate, GDX, 2001 – 2019

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
lnUrate	0.0064	0.0115	0.0249	0.0454	0.0396
	[0.5639]	[0.2735]	[0.0010]**	[0.0000]***	[0.0000]***
ln(Comp and Pens_t-1)	0.913	0.9089	0.9088	0.897	0.8895
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	0.2692	0.2677	0.2679	0.2656	0.2607
	[0.0000]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***
Time Fixed Effects	X	X	X	X	X
N	14,800	14,800	14,800	14,800	14,800

Note: Each column represents a different regression model, where the only difference between models is the lag of the unemployment rate (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2001.

Table 1.4: Dynamic Panel Regressions with Period−Unemployment Interactions, GDX, 2001 – 2019

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
lnUrate	0.0068	0.01	0.0225	0.0428	0.0384
	[0.5463]	[0.3513]	[0.0022]**	[0.0000]***	[0.0000]***
lnUrate x Year in [2008, 2010]	-0.0145	-0.0054	0.0004	0.0024	-0.0011
	[0.1694]	[0.5685]	[0.9558]	[0.7454]	[0.8966]
lnUrate x Year in [2011, 2013]	0.0212	0.0239	0.024	0.0241	0.0141
	[0.0037]**	[0.0018]**	[0.0018]**	[0.0015]**	[0.0990]
ln(Comp and Pens_t-1)	0.9143	0.9104	0.9104	0.8987	0.8903
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	0.2707	0.2693	0.2692	0.2666	0.2612
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0001]***	[0.0001]***
Time Fixed Effects	X	X	X	X	X
N	14,800	14,800	14,800	14,800	14,800

Note: Each column represents a different regression model, where the only difference between models is the lag of the unemployment rate (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2001.

Table 1.5: Dynamic Panel Regressions, Labor Demand, GDX, 2001 – 2019

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
ΔG	-0.0013	0.0015	0.002	-0.0008	0.0002
	[0.5415]	[0.3052]	[0.1792]	[0.6972]	[0.9348]
ln(Comp and Pens_t-1)	0.9149	0.9098	0.9081	0.9048	0.8993
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	0.2714	0.2661	0.2669	0.2668	0.2631
	[0.0000]***	[0.0001]***	[0.0000]***	[0.0001]***	[0.0001]***
Time Fixed Effects	X	X	X	X	X
N	14,800	14,800	14,800	14,800	14,800

Note: Each column represents a different regression model, where the only difference between models is the lag of G (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2001.

Table 1.6: Dynamic Panel Regressions with Period−Labor Demand Interactions, GDX, 2001 – 2019

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
ΔG	0.0015	0.004	0.0025	0.0011	-0.0006
	[0.5410]	[0.0123]*	[0.0777]	[0.6115]	[0.8542]
ΔG x Year in [2008, 2010]	-0.009	-0.0077	-0.0077	-0.0101	-0.0036
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.5622]
ΔG x Year in [2011, 2013]	0.0001	0.002	-0.0002	-0.0067	0.0033
	[0.9678]	[0.5950]	[0.9149]	[0.0023]**	[0.2492]
ln(Comp and Pens_t-1)	0.9111	0.9064	0.9032	0.9006	0.9001
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	0.2671	0.2609	0.2641	0.2624	0.265
	[0.0001]***	[0.0001]***	[0.0000]***	[0.0001]***	[0.0001]***
Time Fixed Effects	X	X	X	X	X
N	14,800	14,800	14,800	14,800	14,800

Note: Each column represents a different regression model, where the only difference between models is the lag of G (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2001.

Table 1.7: Dynamic Panel Regressions, Unemployment Rate, VADC Population with CDR < 50 Percent, 2011 – 2018

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
lnUrate	-0.06	-0.0437	-0.0757	-0.0739	-0.0563
	[0.0153]*	[0.0225]*	[0.0001]***	[0.0006]***	[0.0002]***
lnUrate x Year in [2010, 2013]	0.0125	-0.0051	-0.0186	-0.0274	-0.0054
	[0.1414]	[0.5417]	[0.0436]*	[0.0041]**	[0.6011]
ln(Comp and Pens_t-1)	0.6118	0.5956	0.5433	0.5165	0.5185
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	-0.0611	-0.06	-0.0546	-0.0573	-0.0526
	[0.0008]***	[0.0004]***	[0.0005]***	[0.0001]***	[0.0001]***
Time Fixed Effects	X	X	X	X	X
N	9,952	9,952	9,952	9,952	9,952

Note: Each column represents a different regression model, where the only difference between models is the lag of the unemployment rate (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2008.

Table 1.8: Dynamic Panel Regressions, Unemployment Rate, VADC Population with CDR >= 50 Percent, 2011 – 2018

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
lnUrate	-0.0302	0.0306	0.039	-0.0015	-0.0245
	[0.3648]	[0.2452]	[0.1428]	[0.9552]	[0.2053]
lnUrate x Year in [2011, 2013]	0.0559	0.0699	0.0821	0.0681	0.0741
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
ln(Comp and Pens_t-1)	0.8679	0.8634	0.8574	0.88	0.8613
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	-0.0561	-0.0502	-0.0537	-0.0515	-0.0492
	[0.0203]*	[0.0240]*	[0.0183]*	[0.0288]*	[0.0355]*
Time Fixed Effects	X	X	X	X	X
N	9,952	9,952	9,952	9,952	9,952

Note: Each column represents a different regression model, where the only difference between models is the lag of the unemployment rate (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2008.

Table 1.9: Dynamic Panel Regressions, Labor Demand, VADC Population with CDR < 50 Percent, 2011 – 2018

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
ΔG	0.0066	-0.0025	-0.0008	0.0017	0.0023
	[0.0001]***	[0.1763]	[0.7425]	[0.4347]	[0.2964]
ΔG x Year in [2011,					
2013]	-0.0015	-0.0013	-0.0037	0.0003	0.0002
	[0.0980]	[0.3093]	[0.1642]	[0.5083]	[0.5548]
ln(Comp and Pens_t-1)	0.5555	0.5621	0.5419	0.5566	0.5407
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	-0.0552	-0.0453	-0.0534	-0.0551	-0.0624
	[0.0003]***	[0.0037]**	[0.0005]***	[0.0004]***	[0.0004]***
Time Fixed Effects	X	X	X	X	X
N	9,952	9,952	9,952	9,952	9,952

Note: Each column represents a different regression model, where the only difference between models is the lag of G (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2008.

Table 1.10: Dynamic Panel Regressions, Labor Demand, VADC Population with CDR >= 50 Percent, 2011 – 2018

	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4
ΔG	0.0072	-0.0049	0.0002	-0.0014	0.0077
	[0.0002]***	[0.0473]*	[0.9102]	[0.5764]	[0.0098]**
ΔG x Year in [2011,					
2013]	0.0183	0.0233	-0.016	-0.0077	-0.0079
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
ln(Comp and Pens_t-1)	0.8516	0.8429	0.8583	0.8747	0.8662
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Δ(lnVetpop)	-0.0789	-0.0838	-0.0653	-0.0733	-0.086
	[0.0015]**	[0.0005]***	[0.0050]**	[0.0064]**	[0.0024]**
Time Fixed Effects	X	X	X	X	X
N	9,952	9,952	9,952	9,952	9,952

Note: Each column represents a different regression model, where the only difference between models is the lag of G (e.g., Lag 0 includes unemployment rates from year t, Lag 1 from year t – 1, etc.). P-values are given in brackets. Regressions are weighted by commuter zone veteran population in 2008.

Chapter 2: Linkages Between Federal Health and Disability Policy—Estimating the Effect of the ACA on VADC Growth

Summary

In this chapter I explore whether the Affordable Care Act (ACA) affected participation in VADC. I propose the VA's priority group schedule for receiving health services, which advantages veterans with disability ratings, combined with the individual mandate of the ACA, as a potential mechanism for linkages between the ACA and VADC. Namely, uninsured veterans may have been incentivized by the ACA to receive a disability rating from the VA in order to improve their chances of receiving health care from the VA, or may have been informed of their eligibility for the VADC program when exploring health services at the VA. I exploit the incomplete expansion of Medicaid in 2014 to estimate the magnitude of this effect. Since uninsured veterans residing in states who expanded Medicaid had greater access to public alternatives to VA health care, I expect changes in VADC participation in non-expansion states to be positive and greater than in expansion states. I employ several empirical approaches, and in each case the results are broadly consistent with this hypothesis.

Background

The Patient Protection and Affordable Care Act (ACA) was passed and signed into law in March 2010, with most of its provisions phasing in by January 2014. The primary purpose of the law was to expand access to health insurance for Americans not covered through employer-sponsored or other public plans, such as Medicare or Medicaid. It did this through two channels: first, the enactment of guaranteed issue and the creation of an infrastructure for purchasing subsidized private plans through Marketplace exchanges; and second, the expansion of Medicaid to cover individuals whose household income was within 138 percent of the federal poverty level. The Supreme Court in *National Federation of Independent Business v. Sebelius* ruled the Medicaid expansion to be overly coercive to states, and thus unconstitutional, creating a "natural experiment" for researchers to exploit: 28 states and the District of Columbia electively expanded Medicaid coverage by the beginning of 2015, and 22 did not. These states are shown in Table 2.1.

Veterans receive health coverage from several sources, including through employers, from Medicaid and Medicare, and the VA. Immediately prior to the full enactment of the ACA in 2014, nearly 10 percent of non-elderly veterans were uninsured (Dworsky, Farmer, & Shen, 2017). By 2015, this number had fallen by 3.3 percentage points, with the largest decreases

occurring in states that accepted federal funds to expand their Medicaid programs. Previous work has found that the rate of dual-insured low-income veterans—that is, veterans simultaneously enrolled in VA health care and Medicaid—increased by 4.87 percentage points in states that expanded Medicaid (O'Mahen & Petersen, 2020). Other work has found that low-income and disabled veterans were especially responsive to the ACA's individual mandate, and that these veterans are more likely than others to receive care through the VA (Oh & Berry, 2019).

The question I explore in this chapter is whether the implementation of the ACA in 2014 affected enrollment in VADC. By penalizing individuals for not carrying health insurance, and by establishing a norm of universal coverage, the ACA introduced new incentives for uninsured veterans to obtain health insurance. Since health coverage through the VA satisfied the individual mandate, the ACA plausibly increased demand for VA health coverage among veterans. Moreover, VA priority groups for health services, shown in Table 2.2, strongly advantage individuals with service-connected disability ratings, and especially ratings of 50 percent or more; thus the individual mandate also possibly increased the rate of VADC claiming, or at least the propensity of already-rated veterans to submit additional disability claims to receive a CDR of at least 50 percent. This incentive operates through two channels. Veterans in higher priority groups have preferential access to VA health services and are more likely to be served in a timely manner in areas with wait times. Also, service-disabled veterans pay lower copays for VA health services. It is beyond the scope of this analysis to quantify the value of these benefits for veterans, and I cannot separately identify changes in VADC participation driven by program incentives from changes driven by information revelation or norm-following behavior. Nonetheless, in this analysis I will attribute differences between expansion and non-expansion states before and after 2014 to the environmental changes created by the ACA.

Data

My data source for this analysis is the 2008 – 2018 American Community Survey (ACS), accessed through IPUMS USA (Ruggles et al., 2020). The ACS is the largest nationally representative survey in the United States and has included questions about service-connected disability status since 2008. A key strength of the ACS is its geographic detail: the Public Use Microdata Area (PUMA) variable approximately divides the country into populations of 100,000 – 200,000 people, enabling analysis of sub-state geographies. Using crosswalks and weights developed by David Dorn and David Autor, I map each PUMA into one or more time-consistent commuter zone (D. Autor & Dorn, 2013).

Figure 2.1 plots the estimated VADC population using ACS sampling weights against the VADC population derived from annual VA benefit reports. These comparisons are not exact: the population estimates from the VA reports include, for example, American veterans in Puerto

Rico and other territories who are not counted in the ACS.[13] For most years in the period the ACS-estimated VADC population is within 5 percentage points of the VA estimates, with the ACS slightly overcounting VADC recipients prior to 2013 and slightly undercounting them after 2014. ACS estimates by VADC rating category (not shown) suggest that most of the overcounting prior to 2014 occurred among veterans with low disability ratings, and that the ACS estimates capture the large increase in VADC recipients with ratings of 50 percent or more during this period.

While ACS data (and other detailed, cross-sectional microdata) can be used to control for observed characteristics such as age, gender, and education, some characteristics are not observed in the data. To the extent that these characteristics are related to behavior, such as the decision to participate in VADC, changes in them over time could affect VADC participation but be statistically ascribed to changes in observed characteristics. That is, the unobserved characteristics could confound comparisons over time. Further, minor changes to sampling methods and question texts may bias estimates. A notable change occurred between the 2012 and 2013 surveys, when the question, "Has this person ever served on active duty in the U.S. Armed Forces, military Reserves, or National Guard?" was revised in a way that plausibly led to fewer respondents self-identifying as veterans (Holder & Raglin, 2014). To mitigate confounding caused by this change, I use respondents' reported period of active duty service to identify veteran status.

My analytic sample is restricted to veterans aged 18 – 64 who are not enrolled in Medicare. I remove elderly veterans because they are covered by Medicare and would not necessarily have clear incentives to seek out VA health coverage. Non-elderly Medicare beneficiaries, most of whom participate in the SSDI program, also have qualitatively different health insurance options from my target population. I also remove people residing in four states—Alaska, Indiana, Louisiana, and Montana—who partially expanded Medicaid after 2014 and whose inclusion would potentially confound the comparison between expansion and non-expansion states.

Table 2.3 presents basic descriptive statistics for the four groups included in this analysis, where "Pre-ACA" and "Post-ACA" refer to the full implementation of the ACA in 2014, not the passage of the law in 2010. Veterans in non-expansion states are more likely to be college educated, female, Black, and have a self-reported disability. Veterans in expansion states are older on average and have higher hourly wages and labor market earnings (adjusted to 2018$). The share of veterans with a service-connected disability rating of 50 percent or more grew more in absolute terms over the pre- and post-ACA period in non-expansion states than in expansion states—6 versus 4.1 percentage points, respectively. Growth in the share of veterans with any disability rating was also higher in non-expansion states but lower than for the 50 percent category.

[13] They are counted in the Puerto Rico Community Survey (PRCS), but the IPUMS data I use does not include the PRCS.

Figure 2.2 shows raw trends in the share of veterans with any disability rating, a rating of less than 50 percent, and a rating of 50 percent or more for expansion and non-expansion states from 2008 to 2018. All series increased over this period, and there is a persistent gap in claiming rates between expansion and non-expansion states. The difference in the share of veterans with ratings of 50 percent or more clearly grew over this period, with an apparent change in the growth rate occurring around 2014. Given the differential trends in the series, however, it is difficult from these figures alone to reject the hypothesis that the change occurred before the ACA.

Research Approach

The descriptive evidence above indicates that VADC participation increased more in non-expansion states than in expansion states after the implementation of the ACA, and that this increase was predominantly driven by people with disability ratings of 50 percent or more. In order to assess the statistical significance and robustness of this evidence—and to make plausible statements about the causal relationship between the ACA and VADC—I will present results using several quasi-experimental methods, each of which relies on different assumptions about the underlying data generating process. First, I present baseline event-study models, which attempt to isolate changes over time in the gap in VADC claiming between non-expansion and expansion states, controlling for various factors. Second, I augment the event-study with a clustering method that identifies sub-state geographies that have similar pre-ACA trends in VADC claiming. Third, I use a synthetic control method to balance pre-ACA trends. For these analyses my main outcome of interest is having a disability rating of 50 percent or more. I focus on this outcome because most of the changes in VADC during this period are in this category, and it is the rating level required to receive priority group 1 status for VA health care. Finally, I present difference-in-difference estimates to quantify causal effects.

Baseline Event-Study

My baseline model is an event-study of the following form:

$$Y_{i,t} = \sum_{t=2009}^{2018} \gamma_{0,t}\, \mathbf{1}\{Year = t\} + \sum_{t=2008}^{2018} \gamma_{NE,t} \mathbf{1}\{Year = t\} * \mathbf{1}\{Expansion = 0\} + \epsilon_{i,t}$$

where $Y_{i,t}$ is a binary indicator of VADC status, t indexes time, NE indexes states that did not expand their Medicaid programs following the ACA, and $\epsilon_{i,t}$ is a mean-zero error term (covariates are suppressed but are included in the models and shown in the tables below). The coefficients $\gamma_{NE,t}$ capture the difference in VADC claiming rates between non-expansion and expansion states for each year between 2008 and 2018. If the ACA affected VADC participation differentially across non-expansion and expansion states, a statistical test of these coefficients

before and after 2014—for example, H_0: $\gamma_{NE,2013} = \gamma_{NE,2015}$, H_1: $\gamma_{NE,2013} < \gamma_{NE,2015}$—should reject the null hypothesis.

The event-study model above is analogous to a two-way fixed effects model in which the key comparisons are before and after 2014 and between expansion and non-expansion states. Two main assumptions are required to interpret the $Treatment * Post$ coefficient from this model as a causal effect. First is the "stable unit treatment value" (SUTVA) assumption, which holds that the composition of comparison groups must remain consistent over the analysis window. This is largely untestable, but the size and consistency of the ACA suggests that sampling-related effects are likely to be small. It is important to note, however, that the composition of the veteran population changed considerably over this period (see Table 2.3) and that my approach assumes unobserved cohort changes did not differentially occur between non-expansion and expansion states. The other main assumption is that of "parallel trends"—that in the absence of the treatment, the relative trajectories of the comparison groups would be constant. I use the six years of pre-ACA data and several model specifications to explore the validity of this assumption.

Table 2.4 shows regression output for four specifications of the event study model. Each model is run as a logistic regression to avoid misspecification that could occur from estimating linear probability models on a relatively rare binary outcome. The first column includes no covariates, the second indicators for each of the six self-reported disabilities in the ACS, the third disability and demographic factors (including five-year age bins, gender and age interactions, race, college status, marital status, veteran cohort status, and marital status), and the fourth disability, demographic, and veteran cohort factors. Coefficients on covariates are suppressed and standard errors are clustered at the local labor market level. Key takeaways from Table 2.4 are: the gap between expansion and non-expansion states has a noticeable jump at 2015; much of the pre-ACA difference in levels between non-expansion and expansion states is eliminated by controlling for demographic and veteran cohort factors; and even after controlling for these factors, the pre-ACA difference between non-expansion and expansion states remains statistically different from zero in most years.

Clustering

The analysis above suggests the differential pre-trends observed between non-expansion and expansion states are not only due to imbalance on covariates, but also to unobservable differences across geographies. Here I present a simple clustering method intended to improve the granularity of comparisons across labor markets. The idea amounts to adding a fixed effect, λ_k, to the event study model shown above:

$$Y_{i,t} = \sum_{t=2009}^{2018} \gamma_{0,t}\, \mathbf{1}\{Year = t\} + \sum_{t=2008}^{2018} \gamma_{NE,t} \mathbf{1}\{Year = t\} * \mathbf{1}\{Expansion = 0\} + \lambda_k + \epsilon_{i,t}$$

where λ_k is an unobserved categorization of sub-state geographies with similar pre-ACA VADC claiming patterns. The goal of this method is to identify markets that are similar to each other in outcomes in the pre-ACA period independent of their status as an expansion or non-expansion state, and to use this similarity to balance observations over the full period. I implement this approach in three steps: First, for each of the 682 commuter zones in my sample (this is less than the 742 commuter zones defined by David Dorn because I drop observations from four states), I calculate the share of veterans who report having a disability rating of 50 percent or more in 2010, 2011, 2012, and 2013. These years are chosen to balance competing goals: I want enough observations from each labor market to produce reliable similarity estimates while also having enough pre-intervention data not included in the clustering algorithm (i.e., in 2008 and 2009) for validation. Second, I apply the k-means clustering algorithm to the data. This algorithm searches for clusters by attempting to minimize the sum of squared errors between points in each cluster and its centroid, where errors in this case are based on the Mahalanobis distance, which accounts for the covariance between observations within a geographic unit. This is potentially important in this case since I use annual VADC claiming rates for four adjacent years at the commuter zone level to identify clusters. Results are very similar when using the Euclidean distance to identify clusters.

The k-means method requires selecting the number of clusters to estimate. If clusters are too large, they will be uninformative. If they are too small, each cluster will be unlikely to include observations from both expansion and non-expansion states. Figure 2.3 shows the estimated within-cluster sum of squares for a range of ks. For the results presented here, I use $k = 68$, which ensures that, on average, each cluster will contain approximately ten commuter zones. Table 2.5 replicates Table 2.4, adding a cluster fixed effect to each model. Interestingly, including cluster fixed effects alone does not remove the estimated difference between expansion and non-expansion states, but once all controls are added to the model the differential pre-trend disappears. Note also that there is no statistical difference between the coefficients for 2009 and 2010, suggesting the clustering algorithm is not introducing an artifact from the 2010 – 2013 period into the model. Figure 2.4 plots 95 percent confidence intervals of the $Year * Nonexpansion$ coefficients for the regressions in column four of Tables 2.4 and 2.5. While the qualitative pattern is nearly identical between the two specifications, the clustered model removes statistically significant pre-2014 differences between non-expansion and expansion states.

Synthetic Control

Another non-parametric approach to bolstering the parallel trends assumption is the so-called "synthetic control" method (SCM) (Abadie, Diamond, & Hainmueller, 2011). Typically employed in comparative case study settings where only aggregated data is available, this

method aims to construct a single counterfactual by identifying a vector of weights for which the weighted sum of candidate comparison groups closely matches the treated group in the pre-intervention period. In my baseline analysis, I define the treatment as the set of non-expansion states in aggregate and the candidate control groups as the 28 expansion states and the District of Columbia.[14] Let t represent a period before the full implementation of the ACA and define $Y_{NE,t}$ as the average share of veterans with qualifying disability ratings at time t in non-expansion states. Then the synthetic counterfactual to $Y_{NE,t}$ is $\sum_s w_s Y_{s,t}$ where s indexes the set of expansion states. In any period T after the policy intervention, the SCM estimator for the average treatment effect of the policy is $\alpha_T^* = Y_{NE,T} - \sum_s w_s Y_{s,T}$. The vector of weights, $W = (w_1, \ldots, w_s)'$ is found by solving the following constrained optimization problem:

$$W^* = \text{argmin} \sum_{t=t_0}^{t=T-1} \left(Y_{NE,t} - \sum_s w_s Y_{s,t} \right)^2$$

$$\text{s.t.} \quad \sum_s w_s = 1 \text{ and } w_s \geq 0 \text{ for all } s$$

The conditions on this optimization ensure that the estimated counterfactual is within the convex hull of the observed comparison units, or in other words that the counterfactual does not extrapolate from observed data. The SCM estimator traditionally solves this problem in two stages, first using unit-level covariates as predictors of the outcome, Y, and then solving the problem above on predicted values of Y. In the results I present here, this two-step process is irrelevant since I include pre-intervention outcomes as one of the weighting variables. I achieve similar, but less precise, results when outcomes are excluded from the optimization.

In situations where the pre-intervention period is short, as is the case here, the optimization problem above is vulnerable to overfitting. To avoid this problem while also preserving pre-intervention observations to validate the weighting procedure, I replace the annual time variables for 2010 – 2013 with an artificial time index by splitting the ACS sample for each year by age (above and below 45) and college attainment. This redefines t in the problem above as $t = Year \times Age\ Category \times College$ and transforms the original four pre-treatment years into 16 pre-treatment "periods." In the results presented here, weights are estimated using this expanded time dimension, though all figures are shown in the annual time dimension for clarity.

Figures 2.5 and 2.6 show the main results of the SCM procedure. The synthetic control is within 0.005 percentage points of the treatment series for all of the pre-intervention years, including the two years that were excluded from the SCM estimation, lending credibility to the

[14] In sensitivity, analyses, I ran the model for each non-expansion state individually, using the expansion states as candidate controls. State-level results are noisy but are similar to the results presented here in aggregate.

counterfactual. Comparing the pre- and post-ACA difference between the expansion state average and the counterfactual implies an average treatment effect of roughly 1.5 percentage points. This effect is fully realized by 2015 and remains approximately constant through 2018.

To assess the statistical significance of these results, I conduct a simulation analysis to compare my results to many placebos in which states are randomly assigned to treatment and control categories. Specifically, I perform the following procedure 1,000 times:

1. Assign a random number to each of the 47 states and D.C. in the sample and sort states by this number.
2. Classify the first 18 states listed as NE^* states. This essentially randomly permutes the state identities and creates an artificial treatment group.
3. Run the SCM model.
4. Calculate and store the ratio of the mean squared prediction error (MSPE) in the pre- and post-intervention periods, defined as follows:

$$MSPE\ Ratio = \frac{\sum_{t=2014}^{t=2018}(Y_{NE^*,t} - \sum_s w_s Y_{s,t})^2}{\sum_{t=2008}^{t=2013}(Y_{NE^*,t} - \sum_s w_s Y_{s,t})^2}$$

The results of this procedure are shown graphically in Figure 2.7. The MSPE Ratio for the true treatment collection of states was 41.24, which ranked 994 out of the 1,000 simulations, implying that non-expansion status is a meaningful indicator of pre- and post-ACA differences in the rate of claiming a VADC disability rating of 50 percent or more.

Difference-and-Difference Models

Tables 2.6 – 2.13 show the results of difference-in-difference models in which 2013 is the base year and the post-ACA year is either 2015, 2016, 2017, or 2018. All models are run as logistic regressions, include cluster fixed effects and control for self-reported disability and demographics. In Tables 2.6 and 2.7, the outcome is an indicator for having a CDR of 50 percent or more. The coefficients on the $PostACA * Nonexpansion$ variable in Table 2.6 are positive and significant in all years but 2017, where it is nearly significant. These estimates correspond to an average marginal effect of residing in a non-expansion state in 2015 on receiving a CDR of 50 percent or more of 0.09, with a 95 percent confidence interval of [0.005, 0.015]. Comparing 2013 to 2018, the average marginal effect is 0.01 with a confidence interval of [0.001, 0.018]. Marginal effects are significantly higher for people with physical and cognitive self-reported disabilities, which captures the fact that having a disability rating, and in particular one of 50 percent or more, is more prevalent among those groups. Table 2.7 replicates Table 2.6, stratifying by Medicaid eligibility status to explore whether Medicaid eligibility is a plausible mechanism for the results in Table 2.6. I classify people as Medicaid eligible under the ACA if

their family income is within 138% of the federal poverty level. The results in Table 2.7 strongly suggest Medicaid eligibility plays a role in the aggregate results: coefficients on the $PostACA * Nonexpansion$ variable are much larger for the Medicaid eligible group. The average marginal effect of residing in a non-expansion state in 2015 on having a qualifying disability rating for the non-Medicaid eligible group is 0.007 with a 95 percent confidence interval of [0.001, 0.013]. The same effect is 0.021 with a 95 percent confidence interval of [-0.002, 0.043] for the Medicaid-eligible group. This effect strengthens to 0.038 with a 95 percent confidence interval of [0.013, 0.063] when comparing 2013 to 2018.

Tables 2.8 and 2.9 replicate these results, replacing the outcome with an indicator for having any disability rating, not just one of 50 percent or more. The coefficients on the $PostACA * Nonexpansion$ variable are in general slightly smaller than those in Tables 2.6 and 2.7, although marginal effects are similar. The average marginal effect of residing in a non-expansion state in 2015 on having any disability rating is 0.010 with a 95 percent confidence interval of [0.001, 0.019]. These results suggest that growth in ratings of 50 percent or more is primarily responsible for the trends shown above, and that some of this growth is likely driven by veterans increasing existing disability ratings, either due to new or worsened health conditions.

Tables 2.10 and 2.11 show results of similar models with an indicator for labor force participation as the outcome. As shown by Figure 2.8, the labor force participation rate among veterans in the sample fell after the Great Recession of 2007 – 2009 in both expansion and non-expansion states, but recovered much more robustly in expansion states. The tables mirror these trends, and the coefficients on the $PostACA * Nonexpansion$ variable become progressively stronger in each year after 2014. While the logistic regression coefficients do not reveal large differences in labor force participation rates between the Medicaid-eligible and non-Medicaid-eligible populations, estimated marginal effects are very different for the two samples. The average marginal effect on labor force participation of residing in a non-expansion state in 2015 for the Medicaid-eligible population is -0.01 with a 95 percent confidence interval of [-0.037, 0.016]. When comparing 2013 and 2018, the average marginal effect is -0.038 with a 95 percent confidence interval of [-0.069, -0.006]—a much stronger relationship.

Tables 2.12 and 2.13 present results of similar models with an indicator for having VA health insurance as the outcome. As with the labor force participation models, these results vary substantially by Medicaid eligibility status and seem to strengthen over time. While there is no statistically significant effect of residing in a non-expansion state on having VA health insurance in the full sample, I estimate an average marginal effect of 0.060 with a 95 percent confidence interval of [0.028, 0.093] for 2018. This is much larger than the estimated effect when looking at changes from 2013 to 2015, which may reflect a lag in the transition to VA health insurance. Alternatively, the stronger effect for 2018 may be driven by compositional changes in the population I identify as Medicaid eligible. For example, since Medicaid eligibility is in part a function of household income, this population will tend to change as the economy grows and family earnings increase. Thus, some of the people classified as Medicaid-eligible in 2013 would

plausibly not be identified as Medicaid eligible in 2018. Overall, these results suggest that some veterans who would have been eligible for Medicaid under the ACA if their states expanded the program turned instead to VA health insurance, at that some of these veterans ended up participating in the VADC program.

Discussion

Taken together, these results strongly suggest that the share of veterans with service-connected disability ratings of 50 percent or more increased by 0.5 to 1.5 percentage points in Medicaid non-expansion states relative to expansion states after 2014, and that the share of veterans with any disability rating also increased, though these results are less clear. While this is a small effect in percentage terms, it is meaningful as a share of the population, corresponding to between 18,000 and 55,000 additional VADC beneficiaries with relatively high disability ratings. At least three explanations for this finding should be considered and investigated in future research.

The first is that the incentives of the ACA drove more people to the VADC program, and especially to ratings of 50 percent or more, in order to take advantage of the benefits linked to such a rating, such as priority group 1 status for VA health services in order to satisfy the individual mandate. An implication of this explanation is that the decision of some governors to reject Federal funds to expand their Medicaid programs effectively transferred costs of health services onto the VA. A weakness of this story is that it assumes veterans are able to forecast with some accuracy their feasible disability rating, and that priority group status is a stronger incentive to claim a benefit than additional VADC cash benefits. These conditions seem unlikely to hold in most cases, though they could be empirically investigated, for example by examining the association between service delays at nearby health facilities and changes in the number of VADC applications after 2014.

A second possible explanation is that the ACA caused more people to investigate health insurance options by establishing a norm of universal coverage, and therefore led more veterans to interact with VA health services. In the course of these interactions, these veterans may have become aware of other benefits available to them, including VADC. In other words, according to this explanation it was not a specific incentive that increased participation in VADC but rather information revelation resulting from multiple new interactions with the VA health system. This explanation assumes a significant underutilization of the VADC program prior to the ACA, and strong spillovers between VA and other health insurance programs. Specifically, it implies that some of the costs of service-related health conditions have historically been borne by non-VA health systems and by veterans themselves. My results in Tables 2.12 and 2.13 lend some credibility to this view, showing that demand for VA health care grew among low-income veterans residing in non-expansion states. Still, these results do not identify the link between demand for VA health care and participation in VADC, which could be empirically examined

using qualitative interview methods to elicit veterans' information about VA benefit programs and their motivations for obtaining benefits.

A third possibility is that the results here are driven by unobserved changes in the severity of service-related health conditions in expansion and non-expansion states, and that these changes are largely independent of the incentives of the ACA. While this seems somewhat unlikely, the differential trends in labor force participation after 2014 in expansion and non-expansion states may reflect changes in disability severity among these groups that are unobserved in the data. Of course, another plausible explanation for these trends, which is consistent with prior work on the VADC program, is that the take-up of VADC benefits in non-expansion states reduced labor supply through an income effect. This interpretation of the evidence is made more plausible by the absence of any significant observed differences in the changes before and after 2014 in self-reported disability between non-expansion and expansion states, as shown in Table 2.3.

Chapter 2 Figures and Tables

Table 2.1: States and D.C. by Medicaid Expansion Status

Expansion States	Non-Expansion States	Late Expansion States
Arizona	Alabama	Alaska
Arkansas	Florida	Indiana
California	Georgia	Louisiana
Colorado	Idaho	Montana
Connecticut	Kansas	
Delaware	Maine	
Washington, D.C.	Mississippi	
Hawaii	Missouri	
Illinois	Nebraska	
Iowa	North Carolina	
Kentucky	Oklahoma	
Maryland	South Carolina	
Massachusetts	South Dakota	
Michigan	Tennessee	
Minnesota	Texas	
Nevada	Utah	
New Hampshire	Virginia	
New Jersey	Wyoming	
New Mexico		
New York		
North Dakota		
Ohio		
Oregon		
Pennsylvania		
Rhode Island		
Vermont		
Washington		
West Virginia		
Wisconsin		

Source: Kaiser Family Foundation. Michigan, New Hampshire, and Pennsylvania expanded Medicaid coverage during 2014 or by the beginning of 2015, and Alaska, Indiana, Louisiana, and Montana in 2015 and 2016.

Table 2.2: VA Health Care Priority Groups

VA Priority Group	Description
1	Combined disability rating (CDR) of 50 percent or more; or deemed unemployable; or Medal of Honor recipient
2	CDR of 30 – 40 percent
3	CDR of 10 – 20 percent; or former prisoner of war; or recipient of Purple Heart medal; or discharged for a disability caused or aggravated by active-duty service
4	Receiving VA aid and attendance or housebound benefits; or received a VA determination of being catastrophically disabled
5	CDR of 0 percent and qualifying gross family income; or receiving VA pension benefits; or eligible for Medicaid programs
6	CDR of 0 percent; or exposed to ionizing radiation during atmospheric testing or during the occupation of Hiroshima and Nagasaki; or other served in qualifying conflict
7	Qualifying gross family income and agree to pay copays
8	Non-qualifying gross family income and agree to pay copays

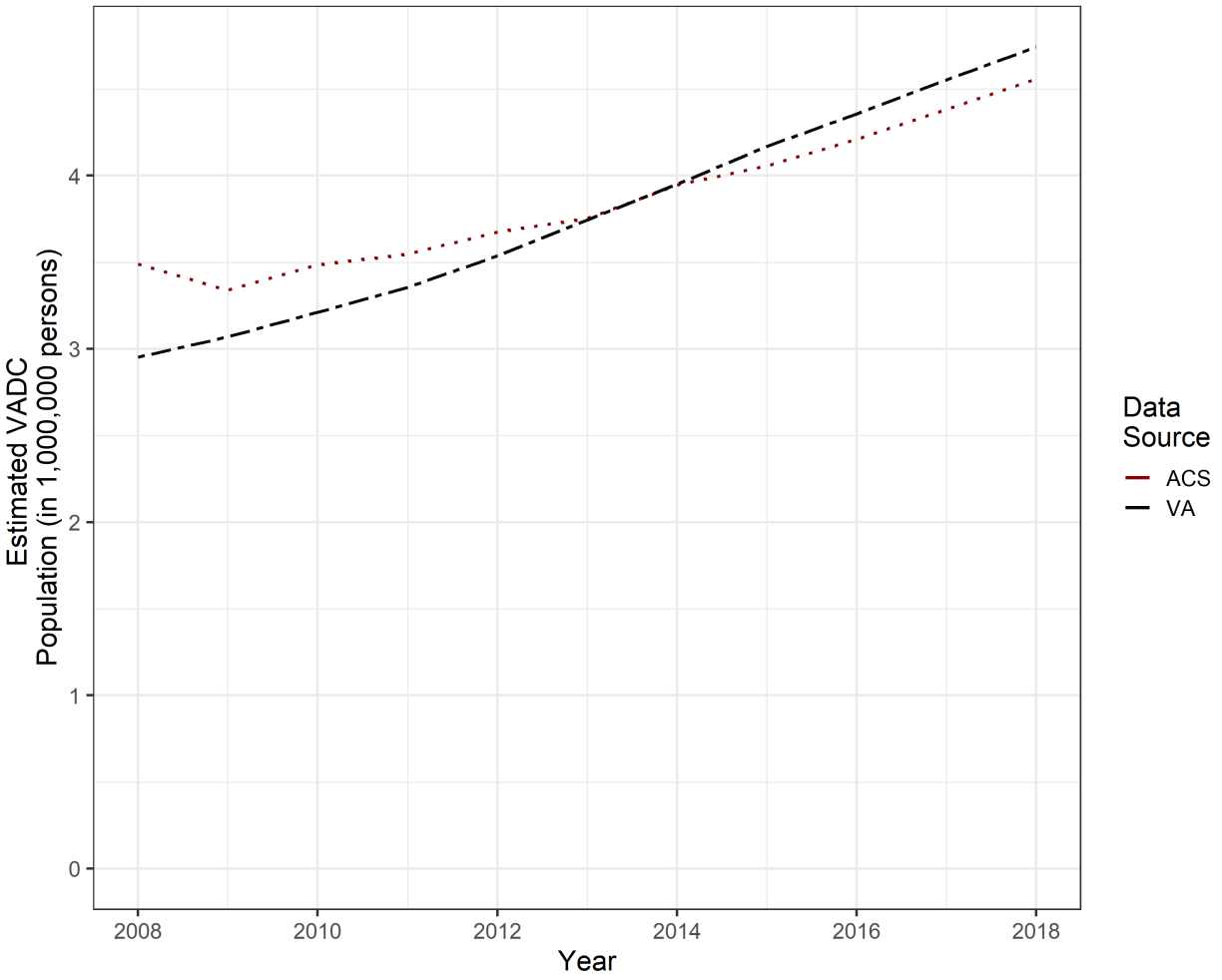
Source: https://www.va.gov/health-care/eligibility/priority-groups/

Table 2.3: Descriptive Statistics of Veteran Sample Before and After ACA Implementation, by Medicaid Expansion Status

	Pre-ACA, Non-Expansion	Post-ACA, Non-Expansion	Pre-ACA, Expansion	Post-ACA, Expansion
Demographics				
Mean Age	48.3	47.2	49.3	47.6
Female	12.1%	15.4%	9.8%	13.0%
Asian/Pacific Islander	1.7%	2.2%	3.2%	4.0%
Black	19.2%	20.9%	11.0%	11.7%
White	76.0%	72.8%	81.5%	78.8%
Other	3.1%	4.0%	4.3%	5.5%
Married	64.2%	61.3%	62.3%	59.0%
Never Married	12.7%	15.0%	15.3%	18.2%
Separated/Divorced	23.1%	23.7%	22.4%	22.9%
College Degree	26.0%	28.7%	24.5%	26.9%
Labor Force Status				
In Labor Force	80.8%	80.7%	79.6%	80.7%
Hourly Wage (2018$)	$28	$29	$30	$30
Total Income (2018$)	$58,166	$59,577	$60,006	$61,115
Wage Income (2018$)	$46,133	$48,196	$47,443	$50,592
Service Characteristics				
Post-911 Veteran	12.3%	23.8%	11.1%	22.7%
Post-Vietnam Veteran	53.6%	63.4%	49.7%	62.3%
Vietnam Veteran	33.9%	12.8%	38.9%	15.0%
Disability Status				
Any Self-Reported Disability	14.7%	15.9%	13.7%	14.8%
Self-Reported Physical Disability	7.1%	7.5%	6.6%	6.7%
Self-Reported Cognitive Disability	4.5%	5.6%	4.4%	5.4%
Any Service-Connected Disability Rating	19.7%	26.6%	16.1%	21.8%
Service-Connected Disability Rating >= 50%	6.0%	12.0%	4.6%	8.7%

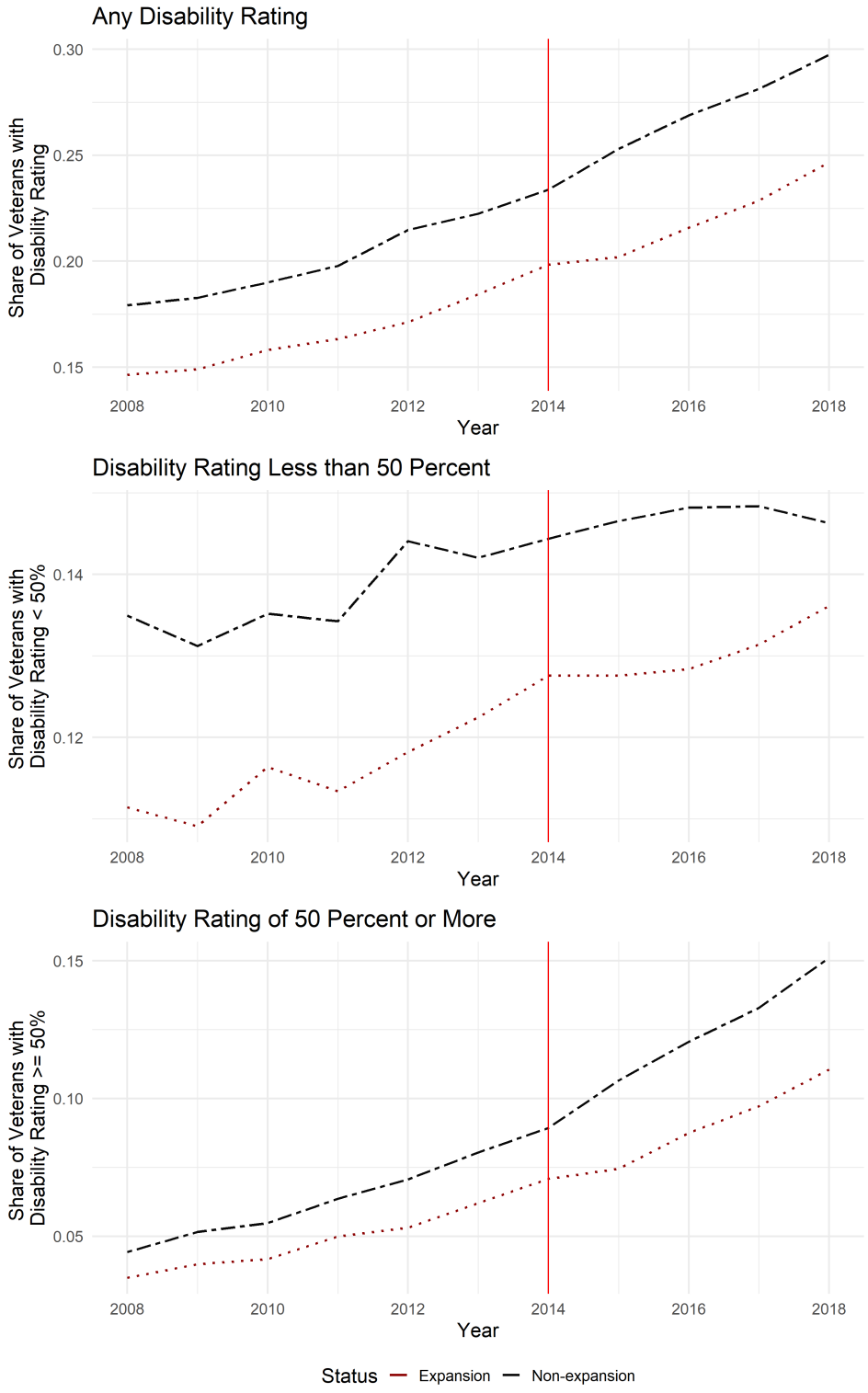
Source: ACS. Pre-ACA refers to observations in 2008 – 2013; Post-ACA includes observations from 2014 – 2018. Expansion states are those from the first column of Table 2.1. The states in column 3 of Table 2.1 are removed from these results.

Figure 2.1: VADC Population Estimate, ACS and VA, 2008 – 2018



Source: ACS, 2008-2018 and VA annual benefits reports.

Figure 2.2: Share of Veterans with Disability Ratings, 2008 – 2018



Source: ACS, 2008-2018.

Figure 2.3: Within-Cluster Sum of Squares by the Number of Clusters Estimated

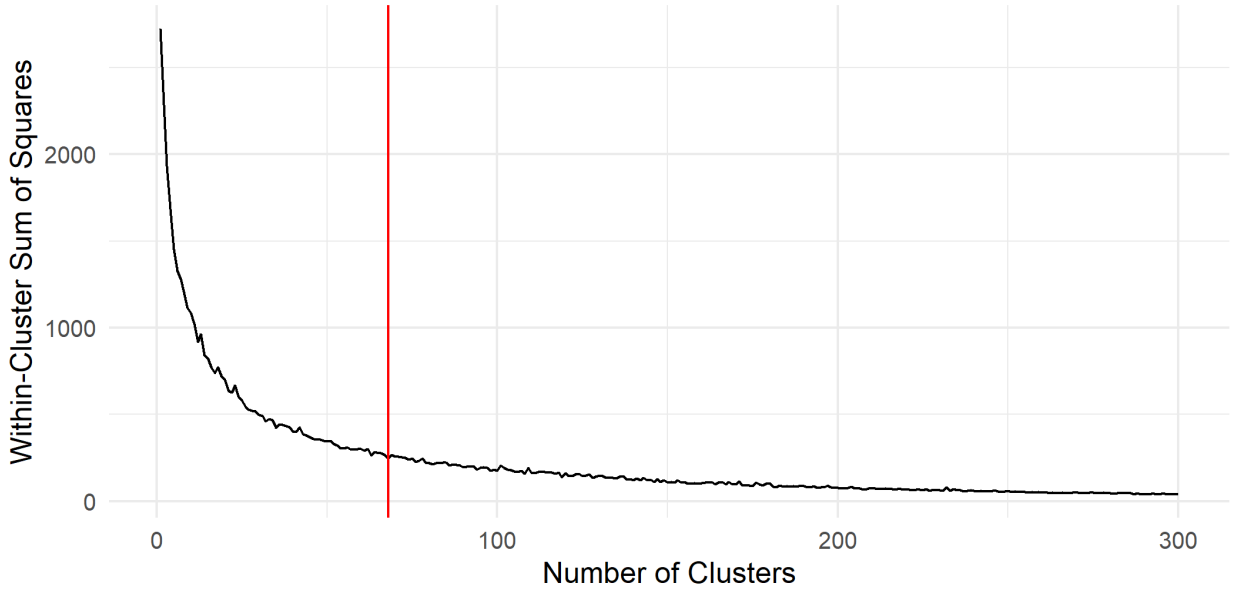
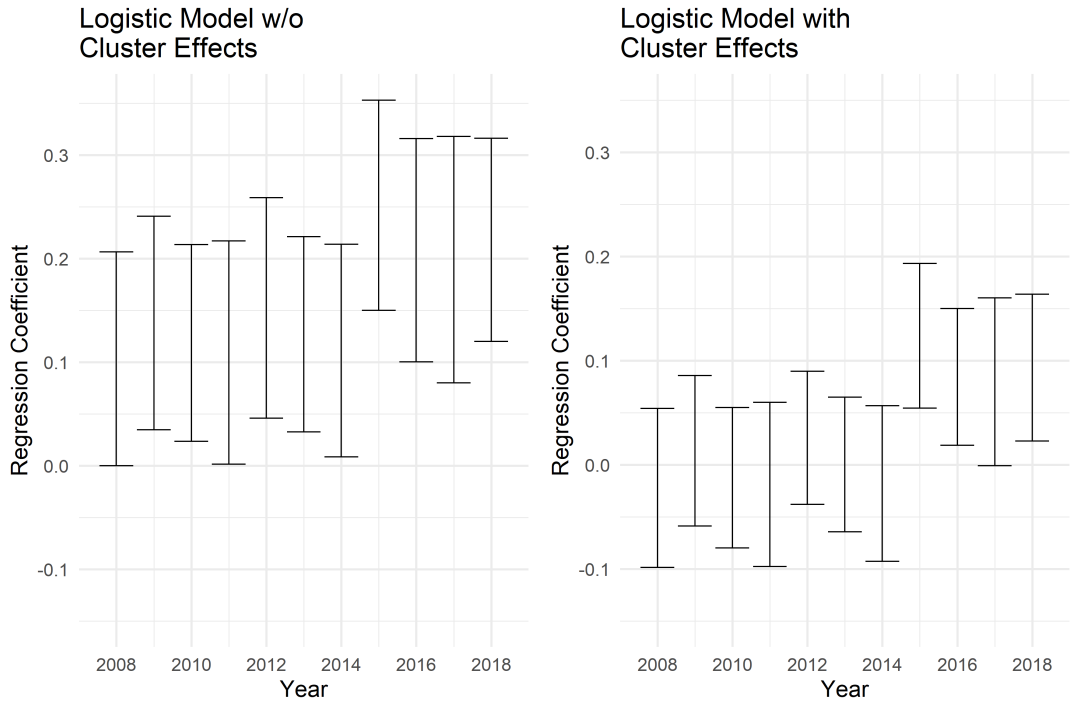


Figure 2.4: Event-Study Regression Coefficients with k-Means Cluster Fixed Effects



Note: Error bands show 95-percent confidence intervals of logistic regression coefficients shown in columns 4 of Tables 2.4 and 2.5.

Table 2.4: Event-Study Regression Models

	CDR >= 50%	CDR >= 50%	CDR >= 50%	CDR >= 50%
2008 * Nonexpansion	0.2459	0.2458	0.1721	0.1032
	[0.0001]***	[0.0001]***	[0.0043]**	[0.0501]
2009 * Nonexpansion	0.2683	0.2778	0.2103	0.1377
	[0.0000]***	[0.0000]***	[0.0005]***	[0.0088]**
2010 * Nonexpansion	0.2866	0.2762	0.2039	0.1184
	[0.0000]***	[0.0000]***	[0.0005]***	[0.0144]*
2011 * Nonexpansion	0.2568	0.2548	0.1843	0.1091
	[0.0000]***	[0.0001]***	[0.0043]**	[0.0471]*
2012 * Nonexpansion	0.3035	0.2994	0.2285	0.1523
	[0.0000]***	[0.0000]***	[0.0008]***	[0.0051]**
2013 * Nonexpansion	0.2804	0.2815	0.2148	0.1268
	[0.0000]***	[0.0000]***	[0.0002]***	[0.0083]**
2014 * Nonexpansion	0.2518	0.2665	0.2014	0.1111
	[0.0001]***	[0.0000]***	[0.0014]**	[0.0339]*
2015 * Nonexpansion	0.3932	0.3962	0.3315	0.2514
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
2016 * Nonexpansion	0.3576	0.3629	0.2914	0.208
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0002]***
2017 * Nonexpansion	0.3532	0.3559	0.2893	0.1989
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0010]**
2018 * Nonexpansion	0.36	0.3671	0.2953	0.218
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Self-reported disability controls		X	X	X
Demographic Controls			X	X
Veteran cohort controls				X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.5: Event-Study Regression Models with Cluster Fixed Effects

	CDR >= 50%	CDR >= 50%	CDR >= 50%	CDR >= 50%
2008 * Nonexpansion	0.0707	0.0786	0.0068	-0.0224
	[0.0513]	[0.0384]*	[0.8535]	[0.5660]
2009 * Nonexpansion	0.0973	0.1131	0.0465	0.0134
	[0.0101]*	[0.0063]**	[0.2474]	[0.7173]
2010 * Nonexpansion	0.1087	0.1053	0.0338	-0.0125
	[0.0006]***	[0.0016]**	[0.3261]	[0.7168]
2011 * Nonexpansion	0.0812	0.0872	0.0177	-0.019
	[0.0322]*	[0.0343]*	[0.6610]	[0.6375]
2012 * Nonexpansion	0.1291	0.1311	0.0632	0.0257
	[0.0001]***	[0.0006]***	[0.0886]	[0.4307]
2013 * Nonexpansion	0.1046	0.1101	0.0454	0.0003
	[0.0005]***	[0.0008]***	[0.1499]	[0.9930]
2014 * Nonexpansion	0.0722	0.091	0.0279	-0.0181
	[0.0685]	[0.0276]*	[0.4695]	[0.6339]
2015 * Nonexpansion	0.2159	0.2244	0.1626	0.1237
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0005]***
2016 * Nonexpansion	0.1851	0.1952	0.1263	0.0842
	[0.0000]***	[0.0000]***	[0.0004]***	[0.0120]*
2017 * Nonexpansion	0.1844	0.1932	0.1289	0.0795
	[0.0000]***	[0.0000]***	[0.0019]**	[0.0532]
2018 * Nonexpansion	0.1881	0.1989	0.1292	0.0932
	[0.0000]***	[0.0000]***	[0.0003]***	[0.0094]**
Self-reported disability controls		X	X	X
Demographic Controls			X	X
Veteran cohort controls				X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Figure 2.5: Share of Veterans with CDR >= 50 Percent, Observed and Synthetic Control, 2008 – 2018

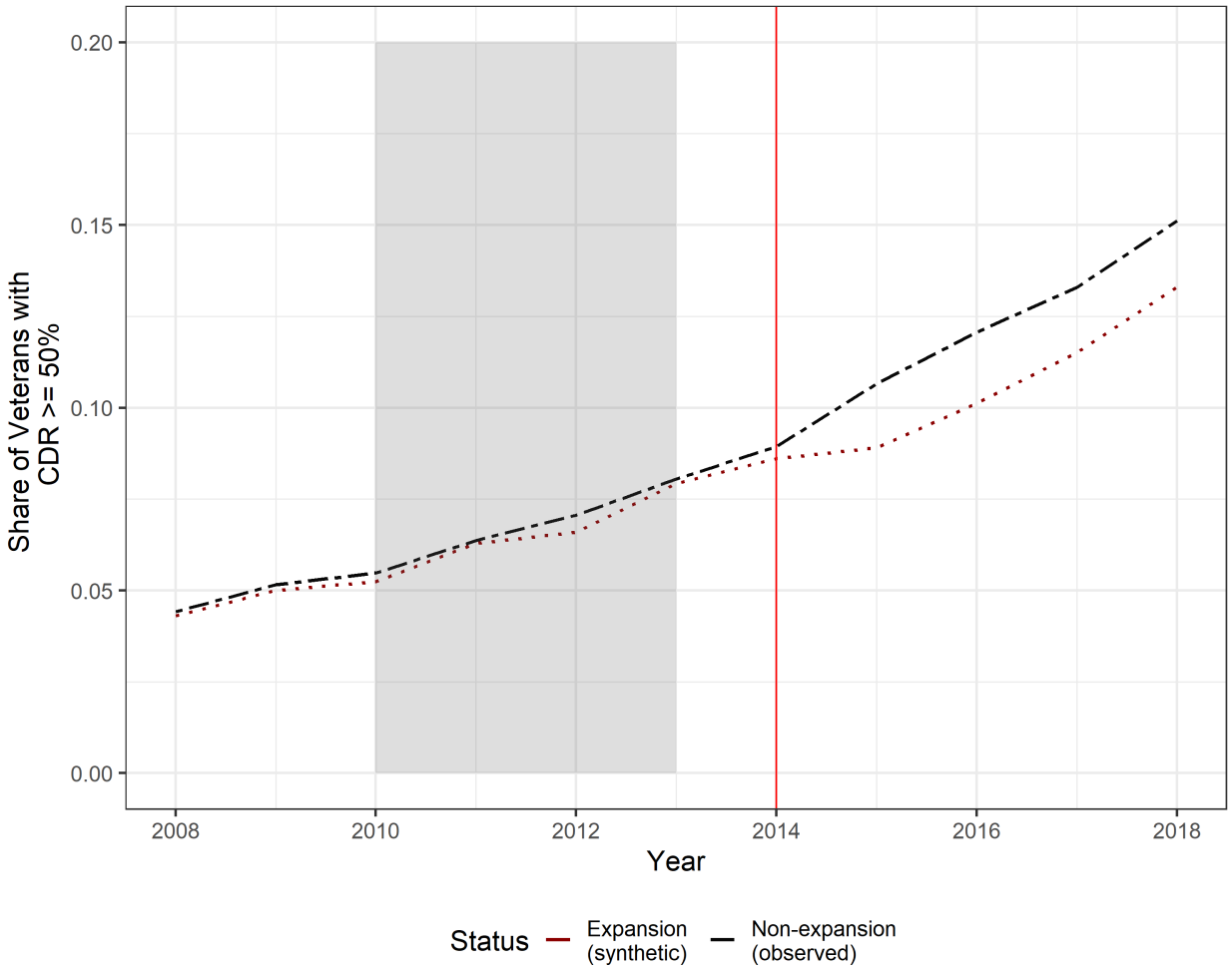


Figure 2.6: Difference Between Treatment and Synthetic Control, 2008 – 2018

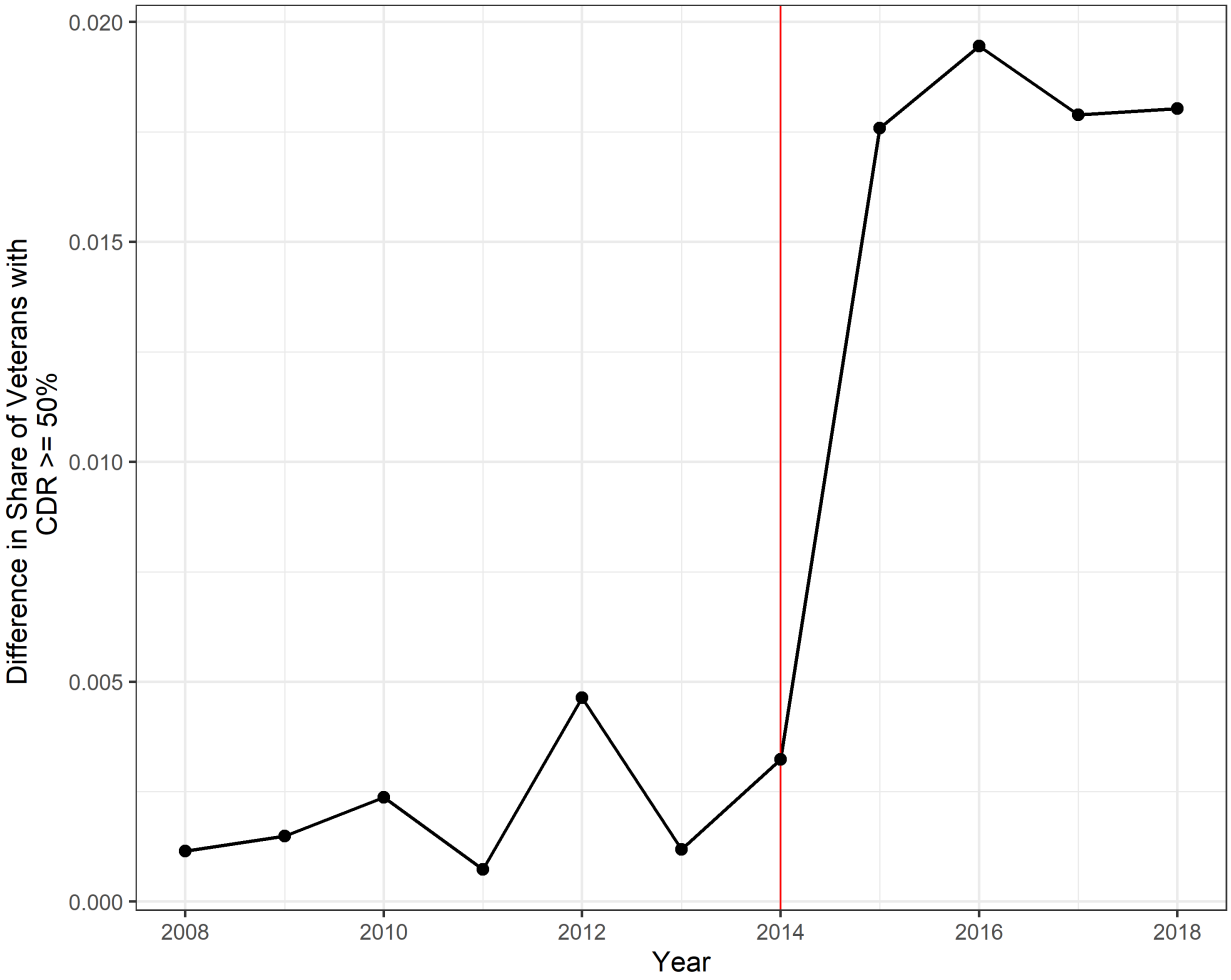


Figure 2.7: Distribution of MSPE Ratio from 1,000 Simulations Randomly Assigning States to Non-Expansion Status

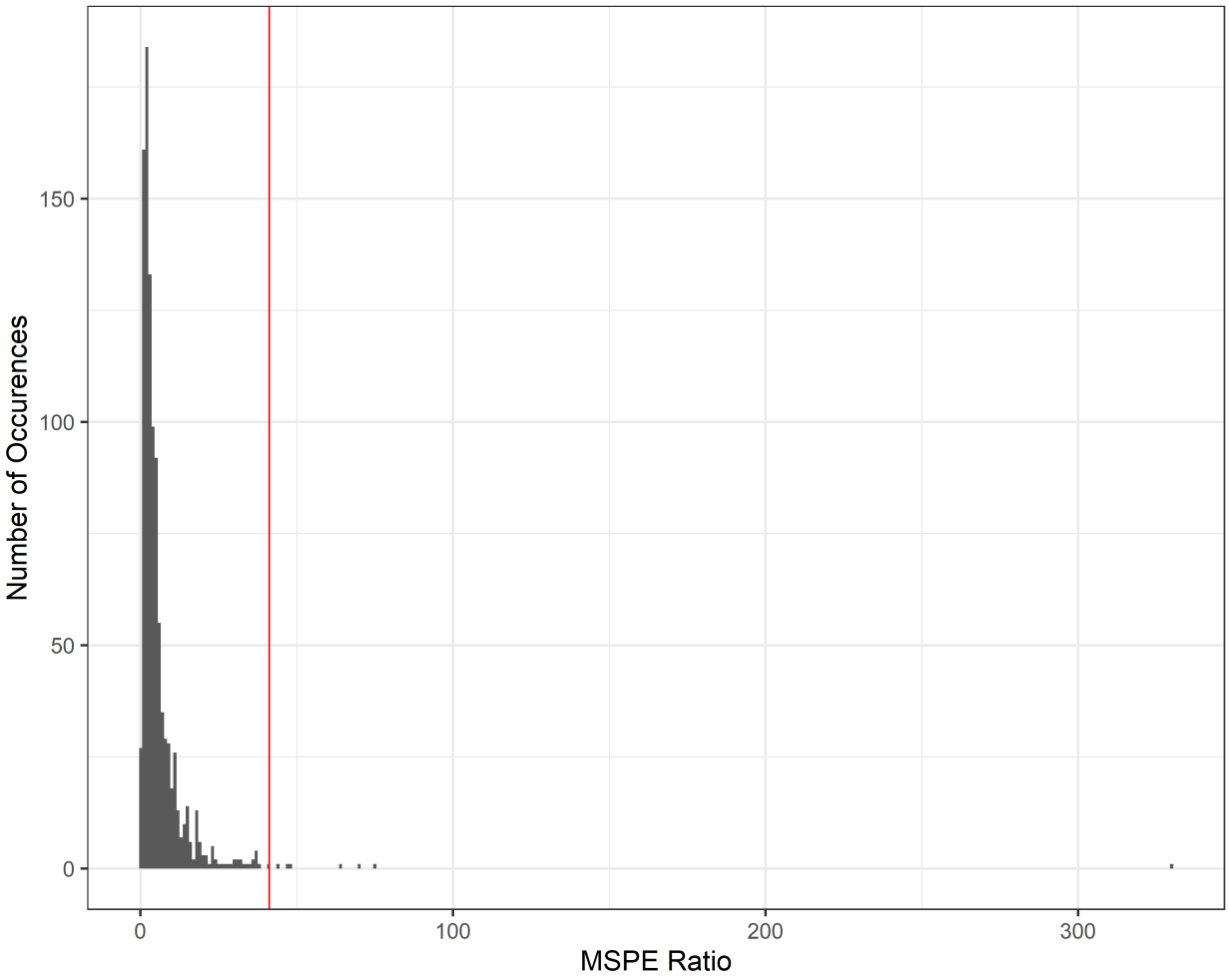


Table 2.6: Difference-in-Difference Estimates, CDR of 50 Percent or More

	2015	2016	2017	2018
Post-ACA	0.1245	0.2664	0.3786	0.5127
	[0.0001]***	[0.0000]***	[0.0000]***	[0.0000]***
NONEXPANSION	0.0017	-0.011	-0.0113	-0.0104
	[0.9563]	[0.7127]	[0.7173]	[0.7337]
Post-ACA * NONEXPANSION	0.1297	0.0894	0.0863	0.1018
	[0.0046]**	[0.0427]*	[0.0880]	[0.0281]*
Self-reported disability controls	X	X	X	X
Demographic Controls	X	X	X	X
Cluster fixed effects	X	X	X	X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.7: Difference-in-Difference Estimates, CDR of 50 Percent or More by Medicaid Eligibility Status

	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible
	2015	2015	2016	2016	2017	2017	2018	2018
Post-ACA	0.1301	0.0679	0.2825	0.1232	0.387	0.3259	0.5353	0.32
	[0.0001]***	[0.4639]	[0.0000]***	[0.1555]	[0.0000]***	[0.0010]**	[0.0000]***	[0.0013]**
NONEXPANSION	0.0388	-0.2293	0.0236	-0.232	0.0233	-0.2175	0.0284	-0.25
	[0.1941]	[0.0204]*	[0.4454]	[0.0198]*	[0.4715]	[0.0284]*	[0.3549]	[0.0110]*
Post-ACA * NONEXPANSION	0.106	0.2931	0.0552	0.3406	0.0635	0.2134	0.0572	0.4151
	[0.0199]*	[0.0334]*	[0.2268]	[0.0080]**	[0.2272]	[0.1217]	[0.2191]	[0.0025]**
Self-reported disability controls	X	X	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X	X	X
Cluster fixed effects	X	X	X	X	X	X	X	X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.8: Difference-in-Difference Estimates, Any CDR

	2015	2016	2017	2018
Post-ACA	0.0498	0.1017	0.1668	0.2572
	[0.0123]*	[0.0000]***	[0.0000]***	[0.0000]***
NONEXPANSION	0.027	0.0053	-0.0014	0.0057
	[0.2829]	[0.8274]	[0.9575]	[0.8264]
Post-ACA * NONEXPANSION	0.0679	0.0607	0.0534	0.037
	[0.0157]*	[0.0367]*	[0.0947]	[0.2094]
Self-reported disability controls	X	X	X	X
Demographic Controls	X	X	X	X
Cluster fixed effects	X	X	X	X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.9: Difference-in-Difference Estimates by Medicaid Eligibility Status, Any CDR

	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible
	2015	2015	2016	2016	2017	2017	2018	2018
Post-ACA	0.0413	0.0947	0.0971	0.1102	0.1591	0.2036	0.2595	0.2091
	[0.0537]	[0.1527]	[0.0000]***	[0.0860]	[0.0000]***	[0.0025]**	[0.0000]***	[0.0014]**
NONEXPANSION	0.0349	-0.0357	0.0097	-0.0343	0.005	-0.0503	0.0135	-0.0488
	[0.1850]	[0.5673]	[0.7077]	[0.5686]	[0.8610]	[0.4171]	[0.6197]	[0.4406]
Post-ACA * NONEXPANSION	0.0707	0.06	0.0535	0.1276	0.0545	0.056	0.025	0.1203
	[0.0161]*	[0.5168]	[0.0909]	[0.1442]	[0.1275]	[0.5621]	[0.4056]	[0.1846]
Self-reported disability controls	X	X	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X	X	X
Cluster fixed effects	X	X	X	X	X	X	X	X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.10: Difference-in-Difference Estimates, Labor Force Participation

	2015	2016	2017	2018
Post-ACA	0.0176	-0.0047	0.0042	-0.0007
	[0.4413]	[0.8550]	[0.8387]	[0.9804]
NONEXPANSION	0.1252	0.1282	0.1254	0.1159
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0001]***
Post-ACA * NONEXPANSION	-0.055	-0.0857	-0.1386	-0.1234
	[0.0828]	[0.0074]**	[0.0000]***	[0.0004]***
Self-reported disability controls	X	X	X	X
Demographic Controls	X	X	X	X
Cluster fixed effects	X	X	X	X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.11: Difference-in-Difference Estimates by Medicaid Eligibility Status, Labor Force Participation

	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible
	2015	2015	2016	2016	2017	2017	2018	2018
Post-ACA	0.0409	-0.1154	0.0098	-0.188	0.0153	-0.2083	-0.0157	-0.1569
	[0.1079]	[0.0262]*	[0.7038]	[0.0003]***	[0.5270]	[0.0002]***	[0.5843]	[0.0089]**
NONEXPANSION	0.1309	0.1712	0.1349	0.1751	0.1249	0.1963	0.1141	0.1921
	[0.0000]***	[0.0007]***	[0.0000]***	[0.0004]***	[0.0001]***	[0.0001]***	[0.0003]***	[0.0002]***
Post-ACA * NONEXPANSION	-0.0646	-0.0515	-0.0957	-0.0233	-0.1305	-0.1527	-0.1198	-0.189
	[0.0772]	[0.4519]	[0.0063]**	[0.7531]	[0.0003]***	[0.0445]*	[0.0012]**	[0.0194]*
Self-reported disability controls	X	X	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X	X	X
Cluster fixed effects	X	X	X	X	X	X	X	X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.12: Difference-in-Difference Estimates, VA Health Insurance

	2015	2016	2017	2018
Post-ACA	0.0794	0.1321	0.1888	0.2602
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
NONEXPANSION	-0.0207	-0.0434	-0.0401	-0.0298
	[0.5553]	[0.2185]	[0.2666]	[0.4166]
Post-ACA * NONEXPANSION	0.0098	0.0462	0.0388	0.043
	[0.7056]	[0.1134]	[0.2238]	[0.1601]
Self-reported disability controls	X	X	X	X
Demographic Controls	X	X	X	X
Cluster fixed effects	X	X	X	X

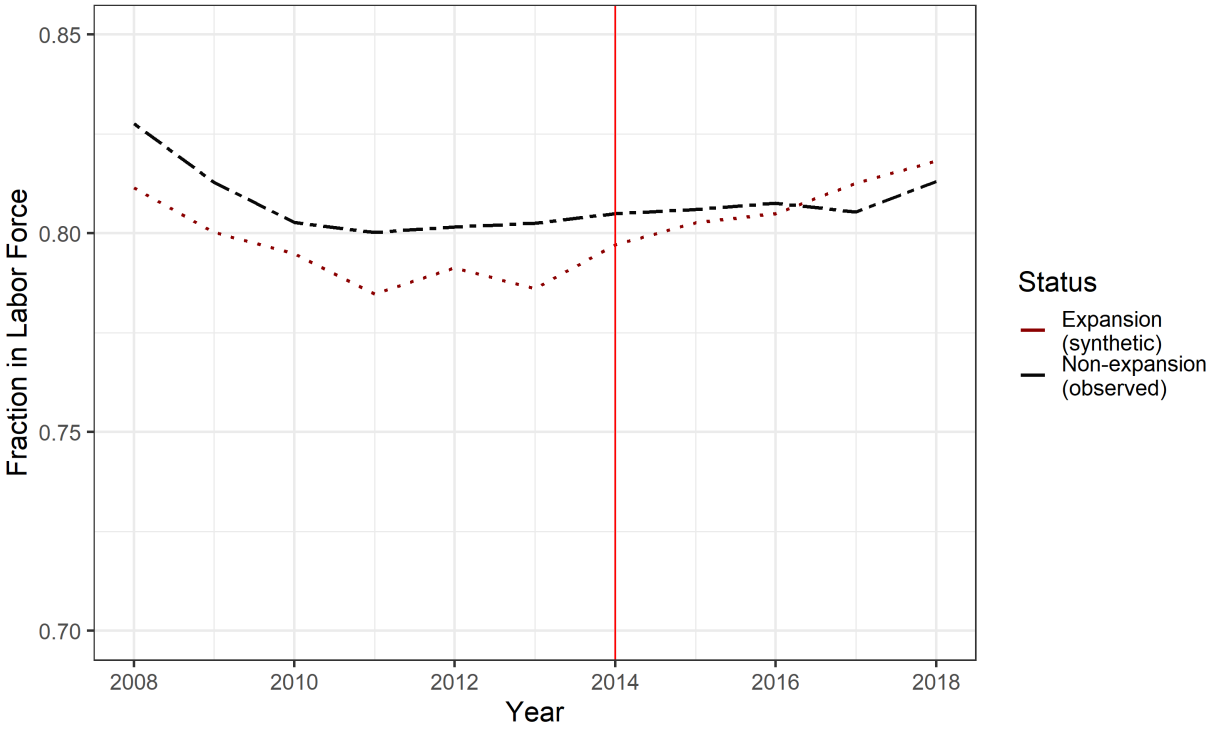
Note: P-values are shown in brackets. Models are run as logistic regressions.

Table 2.13: Difference-in-Difference Estimates by Medicaid Eligibility Status, VA Health Insurance

	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible	Not Medicaid Eligible	Medicaid Eligible
	2015	2015	2016	2016	2017	2017	2018	2018
Post-ACA	0.0815	0.0786	0.1503	0.066	0.2048	0.1405	0.2995	0.0651
	[0.0001]***	[0.0884]	[0.0000]***	[0.1675]	[0.0000]***	[0.0010]***	[0.0000]***	[0.2305]
NONEXPANSION	-0.016	-0.0737	-0.0429	-0.0744	-0.0401	-0.0541	-0.0268	-0.0602
	[0.6554]	[0.1882]	[0.2344]	[0.1987]	[0.2793]	[0.3260]	[0.4726]	[0.3003]
Post-ACA * NONEXPANSION	0.0053	0.0611	0.0333	0.1243	0.0196	0.1499	0.0117	0.2706
	[0.8537]	[0.3721]	[0.3194]	[0.0579]	[0.5802]	[0.0335]*	[0.7160]	[0.0002]***
Self-reported disability controls	X	X	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X	X	X
Cluster fixed effects	X	X	X	X	X	X	X	X

Note: P-values are shown in brackets. Models are run as logistic regressions.

Figure 2.8: Labor Force Participation Rate of Veterans, 2008 – 2018



Source: ACS 2008-2018.

Chapter 3: Effects of the 2011 Expansion of the Work Opportunity Tax Credit on Veteran Employment

Summary

In this chapter I explore the effects of the 2011 expansion of the Work Opportunity Tax Credit (WOTC), a federal policy intended to increase hiring of targeted groups, including some veterans. Previous work has found that credits targeted at service-disabled veterans raise employment levels by as many as 2 percentage points, with effects concentrated among older veterans (Heaton, 2012). This analysis will build on those findings, with two important distinctions. First, Heaton studied the 2007 expansion of the WOTC, which coincided with the end of a long economic boom and the beginning of the Great Recession. In contrast, the late-2011 WOTC expansion was enacted during a period of high veteran unemployment at the beginning of several years of continuous job growth. Second, the 2011 expansion applied to a broader set of veterans than the 2007 law, and I will compare the differential responses of veterans across eligibility levels. Results show moderate effects of the WOTC on employment for some groups, but no positive effect for long-term unemployed or service-disabled veterans.

Background

In recent years, Congress and several states have expanded employer subsides for eligible veterans with the intention of raising employment levels for those groups. These subsidies typically allow employers who hire qualified veterans to claim a tax credit proportional to the new hire's wages. The largest of these programs, the Work Opportunity Tax Credit (WOTC), first established in 1996, has been modified several times since 2007 to expand eligibility and the size of the credit for veterans with a history of unemployment, and especially veterans with service-connected disabilities.

Wage subsidies have a long and somewhat checkered history as a policy tool to boost employment for unemployed or otherwise disadvantaged people. While some scholars have argued for the superiority of these policies relative to other options, such as federally-funded job guarantees (Kaldor, 1936; Phelps, 1997), empirical evidence of their effectiveness has been mixed (Crepon & van den Berg, 2016; Hamersma, 2008, 2011; Heaton, 2012; Katz, 1996; Lombardi, Skans, & Vikström, 2018; Neumark & Grijalva, 2017; Sjögren & Vikström, 2015). Interestingly, the only paper to-date to estimate the effects of the WOTC for disabled veterans found relatively large effects, which some observers have attributed to reduced stigma for this group (Heaton, 2012; Neumark, 2016). Specifically, Heaton estimated that a 2007 expansion of

the WOTC targeted at veterans with service-connected disabilities increased employment of that population by 2 percentage points, corresponding to approximately 32,000 additional jobs in each year the credit was available at a cost of $10,000 per full-time job.

The economic justification for hiring credits is straightforward: by reducing their net cost, the policy boosts demand for credit-eligible workers relative to other groups. The actual mechanism of this effect, however, is somewhat contested. In a Coasian world without transaction costs, subsidies should have identical effects on equilibrium employment and wages whether they are given to employers or employees, ignoring the financing of the subsidy (Dickert-Conlin & Holtz-Eakin, 2000). This is because in a frictionless world the surplus of the credit is bargained between the worker and the firm according to their relative bargaining power, not the incidence of the credit. This may not hold in the real world, however, due to hiring frictions, asymmetric information, and stigma. In fact, firm-directed hiring credits are sometimes compared unfavorably to worker-directed subsidies, such as the Earned Income Tax Credit (EITC), for these reasons (Bartik, 2001).

Stigma has been identified as a significant barrier to the effectiveness of firm-side hiring credits. In a randomized study of a hiring credit in the 1970s, Burtless found that those eligible for the credit had lower employment rates and earnings than the control group, raising concerns that eligibility for the credit sent a negative signal to employers about worker quality (Burtless, 1985). The policy Burtless studied probably exacerbated potential stigma: recipients had to bring coupons proving their eligibility to potential employers, thereby directly advertising their "otherness" in the interview process.[15] The literature has debated whether these stigma effects are more or less pronounced during recessions, with some arguing that the negative signal of quality is weaker when being unemployed is less rare (Cahuc, Carcillo, & Barbanchon, 2014; Neumark, 2013).

The literature on hiring credits intersects with a literature on veteran experiences in the labor market more broadly. Studies on the potential wage and employment premiums of military service have produced conflicting results depending on the nature of the comparison group and the veteran cohorts used in the analysis. Studies of World War I and World War II veterans have found modest, positive wage and education premiums (Bound & Turner, 2002; Gabriel, 2016; Rosen & Taubman, 1982) or no statistical effect (Angrist & Krueger, 1994), while studies of Vietnam veterans have found negative effects (Angrist, 1990; Berger & Hirsch, 1983). Studies of post-9/11 veterans have found that differences in unemployment rates between veterans and non-veterans can largely be explained by the unique experience of transitioning from military to civilian employment and not persistent skill gaps or negative attitudes towards former servicemembers among employers (Loughran, 2014).

[15] While these forms of coupons have been eliminated, the WOTC still requires job applicants to inform firms of their eligibility.

Mirroring these economic studies, a sociological literature has attempted to identify the effects of military service throughout the life course, including in the civilian economy (MacLean & Elder Jr, 2007). This literature explicitly examines how characteristics of military service, such as combat experience, interact with individual characteristics, such as race and pre-service socioeconomic status. For example, a veteran's ability to manage and recover from a service-related health condition, and by extension perform effectively in the civilian economy, may be influenced by racial disparities in access to health care (Nayback, 2008). One longitudinal analysis of veterans across several service periods found that combat experience is associated with lower employment and earnings, and that disabilities sustained during combat are a stronger predictor of this difference than pre-service socioeconomic status (MacLean, 2010). Military service may also convey benefits in the labor market. An audit study using resumes randomly classified as veteran and non-veteran found that Black veterans with transferable skills had higher callback rates than Black non-veterans, while callback rates for whites were comparable across veteran and non-veteran groups (Kleykamp, 2009). This may reflect the higher concentration of Black veterans in military jobs with transferable skills, but also suggests a possible positive stigma conferred on veterans from groups otherwise subject to employer discrimination (Gaddis, 2015).

Policy Background and Variation

The WOTC is a provision of the IRS code that allows employers to claim a tax credit for hiring eligible workers. Eligible classes have changed over time but have included some veterans, ex-felons, SNAP and SSI recipients, and the long-term unemployed, among others. Certifying eligibility is coordinated by state workforce agencies alongside other federal agencies where additional information is required; certification of service-connected disability status is handled by the VA.

The credit applies to a specified portion of worker wages in their first year of employment, up to a specified maximum, which varies by eligibility group. In most cases, this is 40 percent of wages if the employee worked at least 400 hours during the first year of employment; 25 percent if between 120 and 400 hours; and zero percent if fewer than 120 hours. Only employers with a tax liability can claim the credit, but employers can claim the credit back one year or forward up to 20 years if they have insufficient tax liability in the present year.

The WOTC has been expanded several times in recent years. The initial eligibility standard for veterans was fairly limiting, requiring that they had received SNAP benefits for three months in the previous year or AFDC/TANF benefits for nine of the twelve months prior to the hiring date. In 2007, it was expanded to include veterans with service-connected disabilities who were either recently discharged from service or out of work for at least six months in the previous year. In 2009, as part of the American Recovery and Reinvestment Act (ARRA), non-disabled veterans who separated within the previous five years and were experiencing long-term

unemployment were made eligible. This expansion, however, only applied to hires in 2009 and 2010. The current analysis focuses on the VOW to Hire Heroes Act, passed in November 2011, which established the following eligibility criteria:

- Veterans who were members of a family receiving SNAP benefits for at least 3 months in the previous year, or who were unemployed (and receiving unemployment compensation) for at least four weeks and less than six months in the previous 12 months could claim a maximum credit of $2,400;
- Veterans with service-connected disabilities within one year of release from active duty could claim a maximum credit of $4,800;
- Veterans who had been unemployed (and receiving unemployment compensation) for at least six months in the previous 12 months could claim a maximum credit of $5,600; and
- Service-disabled veterans who had been unemployed (and receiving unemployment compensation) for at least six months in the previous 12 months could claim a maximum credit of $9,600.

These eligibility categories are represented in Figure 1. As the figure shows, there is considerable variation across eligibility groups in the share of wages being replaced by the credit, and in the position of the kink where these replacement rates begin to fall. It is important to note, however, that variation in the replacement rate does not necessarily reflect the "value" of the credit to the employer, since that value is determined by the difference between the prevailing market wage and the prospective employee's productivity at the firm, which is unobserved.

Since the VOW Act, the WOTC has been periodically updated, and the number of veterans receiving the credit appears to be growing, though changes in the classification of certifications over time might explain some of this trend. According to the Department of Labor, more than 120,000 veterans were certified as WOTC-eligible hires in each year between 2015 and 2017, representing between 6 and 8 percent of all WOTC certifications (Collins & Donovan, 2018). This represents a dramatic increase from 2009, when fewer than 10,000 veterans were reported as being WOTC certified.

Conceptual Issues

While the underlying economic logic of employer tax credits is straightforward, their potential effects are not. Consider, for example, the effect of stigma on the take-up rate of the credit. An eligible veteran will "claim" the credit (i.e., will inform potential employers of their eligibility and perform the paperwork needed to certify that eligibility) if doing so provides a meaningful benefit, either in terms of the probability of receiving a job offer or the wage

received. If they are concerned that advertising their eligibility will send a negative signal to the employer about their quality, they will only claim the credit when its value exceeds the strength of the signal. We can formalize this discussion by slightly modifying Spence's model of labor market signaling (Spence, 1973).

In the classic signaling model, workers are assumed be one of two types, denoted by $\theta \in \{L, H\}$, where types represent productivity in the labor market. Workers know their own type and employers only know the distribution of types in the population. Employers are assumed to operate in an environment of perfect competition so that zero profits are expected in equilibrium. Workers can send costly signals to employers in order to reveal their true type but cannot otherwise credibly communicate their underlying ability. Spence's version of this model presented years of education as such a signal, since, by assumption, one's ability to complete additional years of schooling is correlated with ability. In this section I suggest work experience, by which I mean the completeness of the worker's recent work record, as a plausible signal of ability. Since workers of low ability—where ability is viewed from the employer's perspective, and can include factors such as timeliness or conformity in addition to skill—are, on average more likely to be fired and less likely to be promoted, these workers will find it harder to maintain a complete work record. I represent work experience by e and in this analysis focus on a simplification where e is binary: e_0 indicates an incomplete record of experience and e_1 a complete one.

For workers to maintain a full experience record, they must exert some effort, and therefore expend a cost, represented by $c(\theta, \mu)$, where $c(L,\ \mu) > c(H,\ \mu)$ by assumption. (For simplicity I assume achieving an incomplete work history, e_0, is costless for both groups.) μ is an indicator of overall labor market conditions (analogous to the unemployment rate) such that $c_\mu > 0\ \forall\theta$. Allowing the cost function to vary with μ captures the intuition that in worse economic environments the cost of maintaining a full employment record will be higher. In addition, I assume that worsening economic conditions have the effect of closing the gap between high and low types in the cost of maintaining a complete employment record, or: $\frac{\partial(c(L,\mu)-c(H,\mu))}{\partial\mu} < 0$. This builds into the model the intuition that an incomplete employment record is a stronger signal of low ability in good economic conditions.

To link this model to the WOTC, I assume some fraction of job seekers, indexed by group identity, g_k, are potentially eligible for a wage subsidy paid to their prospective employer upon being hired. In order to be eligible, a job seeker must send a message to the employer with two pieces of information: that they belong to a subsidy-eligible group, and that their employment record is incomplete. This mirrors eligibility for the WOTC, which is based on being in a targeted group and having an extended absence from the labor market. Qualifying job seekers who send this message and are eventually hired will receive some fraction of the wage subsidy, αs, in their compensation, where $\alpha \in [0, 1]$ and $s > 0$. The worker share of the subsidy is, by

assumption, negotiated between the worker and employer. The signaling game consists of the following steps:

1. Nature assigns each worker a type.
2. Given these types, and knowledge of c and s, workers choose a level of work experience, e. For those who are eligible for the credit, workers also choose whether to claim the credit, which involves sending an additional signal to the employer of their group identity.
3. Firms make wage offers based on the signals they receive.

There are three types of equilibria in this game: separating, in which signals are perfectly informative of types; pooling, in which signals provide no information about types; and mixed, in which signals are sometimes informative. I will focus on the first two, which highlight the key dynamics of policy interest. In particular, the analysis reveals trade-offs between the overall program participation rate (measured here in terms of whether all, no, or some eligible job seekers claim the credit) and the size of the credit, prior beliefs about worker types, and external conditions.

Separating equilibrium

In a separating equilibrium, group identity is irrelevant since the work experience signal perfectly identifies underlying abilities and wages are set exactly to the ability level. It is simple to show that no equilibrium in which only the high types claim the credit can be sustainable. In that case, low types could easily achieve a better outcome by claiming the credit. Thus, the only feasible separating equilibrium is one in which the low types claim the credit and the high types do not. For that equilibrium to obtain, the following conditions must hold:

1. $L + \alpha s \geq H - c(L, \mu)$
2. $H - c(H, \mu) \geq L + \alpha s$

The first condition says low types are better off claiming the credit than pretending to be high-types and signaling a complete experience record to employers. The second condition says high types are better off not claiming the credit and signaling to employers that they are of high ability. These two conditions imply that a separating equilibrium will only occur when the value of the subsidy claimed by the job seeker, αs, is in the interval $[H - L - c(L, \mu), H - L - c(H, \mu)]$. This range has an intuitive interpretation: its lower boundary is the difference between a low type's wages when pretending to be a high type and the baseline wage of a low type without the subsidy; and its upper boundary is the difference between a high-type's wages when not claiming the credit and the wage available if they pretend to be a low type.

A few observations can be made about this equilibrium. First, since in this case employers are paying wages equal to worker productivity—plus a modest benefit for those who claim the credit—we do not need to worry about the employer's incentive compatibility. Second, and relatedly, the amount of subsidy workers receive in this equilibrium will depend on market structure—but will tend towards the low end of the interval in settings characterized by high amounts of market power and firm concentration, as are many sectors today (Naidu, Posner, & Weyl, 2018). Finally, an increase in μ, such as that caused by the Great Recession, will tend to make this equilibrium less likely, since increased costs and narrowed differences in costs between low and high type workers will tend to induce high types to claim the credit, producing a pooling equilibrium.

Pooling equilibrium

In a pooling equilibrium, all job seekers send the same signal so signals no longer become informative about type. There are two potential pooling equilibria in this setting: one in which all members of the credit-eligible group claim the credit (and therefore reveal their group identity); and one in which no one claims the credit. I will focus on the first equilibrium, which will obtain under the following conditions:

1. $\mathbb{E}[\theta|Claim] + \alpha s \geq L - c(L, \mu)$
2. $\mathbb{E}[\theta|Claim] + \alpha s \geq H - c(H, \mu)$

The first condition says that the expected wage when receiving the credit is at least as much as the cost-adjusted wage when not claiming the credit (and in this case producing a separating equilibrium in which only the high types claim the credit). Since by assumption the lowest wage a worker can receive in this economy is L, the first condition will always hold. The second condition ensures that high types are incentivized to claim the credit by requiring that the worker's portion of the credit is at least as large as the difference between cost-adjusted earnings in a separating equilibrium and the base wage in the pooling equilibrium.

Note that since s is in theory unbounded, there will exist some value of the credit such that these conditions will always hold. This captures the obvious point that if the government were sufficiently generous in subsidizing wages, the participation rate of eligible people would eventually reach one. Relatedly, the employer's incentive to increase the share of the credit paid to the worker increases with s. In reality, of course, though the size of the WOTC has varied across eligibility groups and over time, it is fairly small relative to average wages. Also, since claiming the credit involves sending a two-part message to the employer that includes group identity, g_k, and work experience, e_o, and since $\mathbb{E}[\theta|Claim]$ is calculated over a mixture of types, employers' prior beliefs about the distribution of abilities among groups becomes relevant. In other words, since all job seekers are sending the same work experience signal, $\mathbb{E}[\theta|Claim]$

will reduce to $\mathbb{E}[\theta|g_k]$. If group identity is a positive signal to employers, as has been suggested to be the case for veterans, then the second condition of this equilibrium will be more likely to hold. If, however, group identity is a negative signal, which may be the case with ex-felons or some veterans with observable disabilities, high types may be incentivized to balk. It is important to note that in the long run employer beliefs must accurately reflect underlying abilities, and wage offers will depend on how employers update their beliefs and the number of WOTC hires relative to total hires. But it is reasonable to think prior beliefs that are not grounded in empirical experience could meaningfully affect the effectiveness of the WOTC in cases where WOTC hires are rare and employer priors differ significantly across eligibility groups.

Research Approach

Following Heaton, I use a two-way fixed effects framework to explore the effects of the 2011 WOTC expansion on employment levels of eligible veterans. In short, I identify groups of veterans and non-veterans whose employment histories and self-reported SNAP receipt would make them eligible for the WOTC and follow their employment rates over time. Since the VOW expansions of the WOTC only applied to veterans, a comparison between plausibly-eligible veterans to similar non-veterans, both before and after the expansion, should identify the effect of the policy. Due to the tiered nature of the eligibility rules, I conduct two sets of analyses: one on people who report working fewer than 48 and more than 27 weeks in the previous year; and another on people who worked fewer than 27 weeks in the previous year. Throughout the analysis these groups are referred to as being eligible for the small and large credit, respectively, since the maximum credit is larger for people with more time unemployed and receiving unemployment compensation. Note that I will sometimes refer to both veterans and non-veterans as being eligible—this just means that their work history and/or receipt of SNAP benefits indicates they would plausibly be eligible *if they were a veteran*, not that they were actually certified as eligible.

Sample Construction

My data source for this analysis is the 2009 – 2013 American Community Survey (Ruggles et al., 2020). I limit the sample to individuals aged 19 – 64 (veteran and non-veteran) who are not in school, are not self-employed or employed in the family or governmental sectors, who did not move in the previous year, and who report being in the labor force at the time of the survey. I exclude recent movers because my identification of WOTC eligibility depends on the number of weeks worked in the previous year. People who have recently moved, and especially veterans, may be experiencing time out of employment for reasons other than unemployment, and their inclusion in the sample could contaminate the comparison between veterans and non-veterans. In a sensitivity analysis, I only restrict the sample to people who made cross-state moves, keep those who moved within a state. Restricting the sample to non-movers has the unfortunate

consequence of removing recently-separated veterans from the sample. This limits the policy relevance of the analysis since one of the key goals of the WOTC was to target recently separated veterans.[16] In the conclusion of this dissertation I will discuss research designs using other data sources that could estimate the effects of the WOTC for the recently separated population. My restriction on being in the labor force at the time of the survey is one of necessity: since people out of the labor force when surveyed are by definition not employed, their inclusion would contaminate the comparison in employment rates between credit-eligible and non-credit-eligible people. In theory, the WOTC could induce workers out of the labor force to re-enter employment, but my cross-sectional data does not enable analysis of those dynamics.

Identifying WOTC Eligibility

Table 3.1 shows eligibility criteria for the 2011 WOTC and accompanying variables in the ACS. SNAP receipt, but not its duration, is well-identified at the family level. By necessity, I assume individuals who report some SNAP receipt in the ACS did so for the three months required to qualify for the WOTC. Similarly, receipt of a service-connected disability rating is cleanly identified in the data. The ACS contains information about income from several sources, such as business income, wage income, and Social Security income, but does not report income from unemployment insurance. One possible way to identify people who received unemployment income is to compare total income to income from all other delineated sources. If total income is less than or equal to income from all other sources, then it may be possible to infer that a person did not receive unemployment income, and the duration of unemployment could be partially bounded by the this difference using state-specific unemployment maximums. However, since unemployment income may be classified as wage income in the ACS, I do not use this method to restrict the sample. Rather, to identify the duration of unemployment, I use the number of weeks individuals report working in the previous year. Specifically, I classify individuals who report working fewer than 27 weeks as being unemployed for at least 6 months in the previous year, and those who report working fewer than 48 weeks as being unemployed for at least four weeks in the previous year. Coupled with the sample restrictions removing self-employed and family workers, movers, and people no longer in the labor force, it seems reasonable to expect much of the observed time out of the labor market is due to unemployment, but this is an assumption of the analysis. Since the ACS contains no reliable information on the separation date from active duty, I make efforts to exclude recently separated veterans from the analysis by excluding movers, as discussed above.

[16] Needs citation.

Weighting

My baseline comparison is between veterans and non-veterans who plausibly meet eligibility criteria for the WOTC before and after the VOW Act. As an efficient method to achieve balanced comparisons, I construct weights based on the inverse of the estimated probability each observation belongs to the target group, which I define as eligible veterans in the post-VOW period (Stuart et al., 2014). The justification for this weighting approach is that it reduces to a single number the observable differences between the four groups, and defines four samples whose differences in outcomes are mostly driven by unobserved group-specific characteristics. An intuitive motivation for this approach is that it increases the weight of observations that are similar to the target group but dissimilar to their own group. To construct these weights, I first define groups consisting of the following categories: the target; eligible veterans in 2009 – 2011; eligible non-veterans in 2012 – 2013; and eligible non-veterans in 2009 – 2011. Then I estimate a multinomial logistic regression model with this as the dependent variable and independent variables including age, education, gender, race, disability, and state of residence. The coefficients from this model are shown in Table 3.2. For each group, weights are defined as follows:

$$w_{i,g} = \frac{p_{i,1}}{p_{i,g}}$$

where $p_{i,1}$ is the predicted probability individual i belongs to group 1 and $p_{i,g}$ is the probability of belonging to group g. Because of this structure, I refer to these weights as propensity scores, though they are not identical to the conventional meaning of that term. Final weights are defined by interacting $w_{i,g}$ with the ACS sampling weight.

Results

Graphical Evidence

Figure 3.2 shows the estimated share employed at the time of the survey for two groups: veterans and non-veterans classified as being eligible for the small version of the WOTC. Those eligible for the larger credit (i.e., people who worked fewer than 27 weeks in the previous year), are excluded from the sample. The figure shows the effects of the weighting scheme described above: in the first panel, observations are weighted using the ACS sampling weights, while in the second panel, these weights are interacted with the propensity score weights. While the veteran and non-veteran eligible groups clearly exhibit differential trends using sampling weights, the propensity score-weighted sample shows roughly parallel trends through 2011. In 2009, approximately 72.7 percent of non-veterans who met the eligibility criteria were employed at the

time of the ACS survey, compared to 72.3 percent of veterans. In 2013, 81.6 percent of such veterans were employed, compared to 80.6 percent of non-veterans. This implies a change in the differential employment rates of veterans and non-veterans of 1.4 percentage points over this period.

Figure 3.3 replicates Figure 3.2 for those potentially eligible for the larger version of the credit (i.e., those with at least six months out of work in the previous year). The employment rate for this sample is significantly lower than for the sample shown in Figure 3.2, though the business cycle dynamics are similar. Again, the propensity score weights seem to successfully balance the groups in the pre-intervention period, with the exception of 2011. In 2009, approximately 49.4 percent of non-veterans meeting the eligibility standard were employed at the date of the survey, compared to 50.2 percent of veterans. In 2013, 63.1 percent of non-veterans and 63.4 percent of veterans reported being employed. The plots show no evidence of a WOTC effect.

To check the validity of the comparison between veterans and non-veterans, Figure 3.4 replicates the previous figures for people who report working at least 48 weeks in the previous year. These groups exhibit approximately similar trends using both sets of weights; their employment rates differ by less than half a percentage point in all periods. This suggests that the weighting procedure described above is sufficient to balance the veteran and non-veteran samples.

Regression Evidence

In this section I translate the figures above into regression models. For these models I drop observations in 2011 because the VOW Act was passed in November of that year, and since the ACS is fielded throughout the year I cannot determine whether observations were collected before or after the implementation of the credit. Results are similar in sensitivity estimates where 2011 is included (not shown). For the main models below, the key indicator of interest is the $Post - 2011 * Veteran$ variable, which captures the difference in the differential employment between veterans and non-veterans who meet the eligibility standard after WOTC implementation. Results are shown using linear probability models, which have the advantage of being easy to interpret in terms of marginal effects, and logistic models, which may be more appropriate in domains where the outcome is close to zero or one. When interpreting results here I refer to linear probability models for simplicity. Results are also shown for both sets of weights, and the propensity score weights are my preferred version. In a separate set of regression models, not shown, I include an additional comparison group—veterans and non-veterans who are not eligible for the WOTC credit—in order to address the possibility of differential trends between the veteran and non-veteran populations. As implied by the very close trends shown in Figure 3.4, these results are qualitatively very similar to those shown here.

Table 3.3 shows the main two-way fixed effect estimates for the group eligible for the small credit. The coefficient on $Post - 2011$ captures the business cycle effects over this period: both groups were 5.5 percentage points more likely to be employed in 2012 and 2013 compared to 2009 and 2010. As shown in Figure 3.2, veterans were slightly less likely to be employed than non-veterans in the pre-2011 period, and slightly more likely after the tax credit. The linear probability model implies an average treatment effect of the WOTC of 1.2 percentage points, with a 95 percent confidence interval of [0.0006, 0.0243]. In a sensitivity analysis where people who moved within their state of residence are included in the sample I estimate an average treatment effect of 0.9 percentage points, with a 95 percent confidence interval of [-0.0015, 0.02].

Table 3.4 extends Table 3.3 by showing how the DD treatment effect shown above varies by subgroups. Each row in the table shows the coefficient on $Post - 2011 * Veteran$ for a model restricted to individuals in the subgroup. The results strongly suggest that SNAP receipt is the eligibility category driving the results in Table 3.3. The estimated average treatment effect for this sample is nearly 2.5 percentage points and is statistically significant at the 95 percent level. In fact, in a regression model in which SNAP receipt is interacted with the model in Table 3.3 (not shown), the coefficient on $Post - 2011 * Veteran$ becomes indistinguishable from zero, suggesting the effect shown in Table 3.3 is an average of a relatively large effect on the SNAP sample and a null effect on the non-SNAP sample. Estimated treatment effects are also large and statistically significant for the cohort in their 40s, and there is suggestive evidence that individuals with self-reported cognitive and physical disabilities, as well as females and people in the services sector, are more responsive to the tax credit, though these estimates are not significantly different from zero.

Table 3.5 reproduces Table 3.3 for people who met the eligibility standards for the larger WOTC credit (i.e., those with at least six months out of the labor market in the previous year). As in the previous table, there is strong evidence of a business cycle in the data—this group was 9.3 percentage points more likely to be employed in the post-2011 period than in 2009 and 2010. In contrast to Table 3.3, however, there is no evidence that the WOTC increased employment rates for veterans with long-term unemployment when using propensity score weights. Further, the subgroup analyses in Table 3.6 show no evidence that the credit was effective for any of the subgroups analyzed. When using ACS sampling weights along there is evidence of a treatment effect, though this is likely confounded by pre-trend differences between the veteran and non-veteran groups, as shown in Figure 3.3.

One important subgroup not shown in Tables 3.4 or 3.6 is veterans with service-connected disabilities. The VOW Act authorized a $9,600 credit for service-disabled veterans with six or more months of unemployment in the previous year. To examine whether this larger credit influenced employment, I interact the model in Table 3.5 with service-connected disability status. Since non-veterans cannot by definition have a service-connected disability, this essentially divides veteran estimates into two groups. These results are shown in Table 3.7. The

net effect of the post-2011 period for non-veterans is 0.0927, compared to 0.0897 for service-disabled veterans and 0.0866 for non-service-disabled veterans, and the differences between these groups are not statistically significant.

Discussion

The results presented in the previous section are mixed: the 2011 expansion of the WOTC appears to have raised employment levels by approximately 1.24 percentage points for veterans with more than one month but less than six months out of work in the previous year, with nearly all of the effect occurring among veterans made eligible for the credit through family SNAP receipt. There is no evidence that the credit raised employment levels for people with six months or more out of work or for veterans with a service-connected disability. A valuable metric for evaluating job creation programs is the ratio of jobs created to jobs funded. This measure captures the fact that some WOTC certifications are linked to hires that would have occurred in the absence of the policy and therefore do not produce net job gains. To produce this estimate, I assume that the only jobs created by the 2011 expansion of the WOTC were those linked to SNAP receipt. I estimate from the ACS that in the 2012 – 2013 period, approximately 790,000 veterans would have been eligible for the WOTC due to their family's SNAP receipt. Given an estimated average treatment effect of 0.0249, this corresponds to 19,671 jobs created. There is only limited evidence available on the total number of WOTC certifications made in each year, but a 2013 Congressional Research Service (CRS) report estimates that 15,183 WOTC certifications were made in 2012 for veterans receiving SNAP benefits (Scott, 2013). Assuming an equal number of certifications in 2013, this implies that 65 percent of WOTC certifications issued to SNAP-receiving veterans were job creating. The same CRS report estimates that a total of 33,361 WOTC certifications were issued to all veterans through the VOW expansions in 2012. Again assuming an equal distribution of certifications in 2012 and 2013, this implies that 29 percent of all VOW WOTC certifications were job creating.

These results are less optimistic about the WOTC than those presented by Heaton (2012), but nonetheless suggest the policy is somewhat effective, at least for certain groups. My finding that the WOTC raised employment rates for the SNAP population but not for those with extended periods out of work may be explained in part by the conceptual model described above. Unlike all other eligible veterans, veterans in families receiving SNAP benefits did not need to be unemployed in the previous year to be eligible for the credit. As the model suggests, a veteran's work history can be an informative signal of underlying ability, and long periods out of work can signal to employers that the worker is of low quality (i.e., employers might expect high-quality job seekers to be induced into work by numerous attractive opportunities). As the model suggests, a hiring incentive must be large enough to counterbalance this "stigmatizing" eligibility criterion in order to effectively induce eligible workers to claim the credit. One interpretation of these results is that the WOTC—even the expanded version authorized by the VOW Act—was

too small to do so for long-term unemployed and service-disabled veterans. Policymakers interested in boosting the employment prospects of these groups may want to explore alternative policies that focus on removing direct barriers to employment for these groups, rather than policies operating purely through hiring incentives.

Chapter 3 Figures and Tables

Figure 3.1: WOTC as a Share of Wages, VOW to Hire Heroes Act

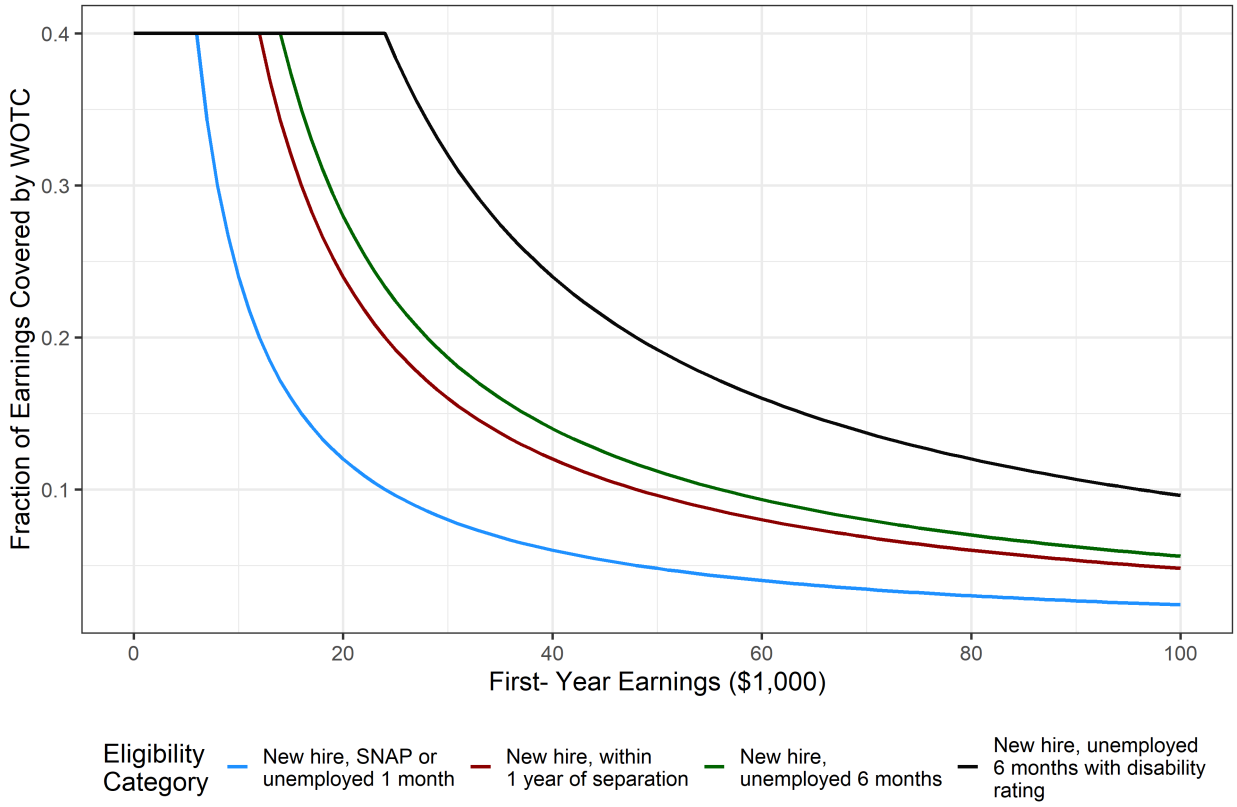


Table 3.1: ACS Analogues for WOTC Eligibility Criteria

Eligibility Criterion	ACS Variable
Family receipt of SNAP benefits for at least 3 months in previous year.	"In the past 12 months, did you or any member of this household receive benefits from the Food Stamp Program or SNAP (the Supplemental Nutrition Assistance Program)?" Indicator for receipt of SNAP benefits in the previous year (no duration given).
Months unemployed in previous year.	"How many weeks did this person work, even for a few hours, including paid vacation, paid sick leave, and military service?" None or missing; 1 – 13; 14 – 26; 27 – 39; 40 – 47; 48 – 49; 50 – 52.
Service-connected disability receipt.	"Does this person have a VA service-connected disability rating?"
Separation date from active duty.	N/A

Source: https://usa.ipums.org/usa-action/variables/group

Table 3.2: Multinomial Logistic Regression Coefficients by Sample Group

	Post-VOW Veteran	Pre-VOW Veteran	Pre-VOW Nonveteran
Age = 25 – 29	0.5127	0.5316	0.0352
	[0.0000]***	[0.0000]***	[0.0014]**
Age = 30 – 34	0.767	0.6958	-0.0238
	[0.0000]***	[0.0000]***	[0.0349]*
Age = 35 – 39	0.8518	0.9765	0.0149
	[0.0000]***	[0.0000]***	[0.2028]
Age = 40 – 44	1.1857	1.3161	0.024
	[0.0000]***	[0.0000]***	[0.0419]*
Age = 45 – 49	1.5707	1.6368	0.0795
	[0.0000]***	[0.0000]***	[0.0000]***
Age = 50 – 54	1.7481	1.6938	-0.0131
	[0.0000]***	[0.0000]***	[0.2755]
Age = 55 – 59	1.8647	1.9253	-0.1031
	[0.0000]***	[0.0000]***	[0.0000]***
Age = 60 – 64	2.4044	2.6283	-0.1397
	[0.0000]***	[0.0000]***	[0.0000]***
Some College	0.7884	0.7488	-0.0735
	[0.0000]***	[0.0000]***	[0.0000]***
College	0.2677	0.1315	-0.0379
	[0.0000]***	[0.0000]***	[0.0001]***
Masters	0.2862	0.1419	-0.0199
	[0.0000]***	[0.0009]***	[0.1660]
Doctorate	-0.0459	-0.4321	0.0206
	[0.7400]	[0.0060]**	[0.6287]
Female	-2.0874	-2.2016	-0.024
	[0.0000]***	[0.0000]***	[0.0001]***

Black	0.1096	0.0116	-0.1195
	[0.0000]***	[0.6568]	[0.0000]***
Asian/Pacific Islander	-0.7519	-0.9337	-0.0951
	[0.0000]***	[0.0000]***	[0.0000]***
Multiple/Other	-0.6333	-0.7298	-0.0533
	[0.0000]***	[0.0000]***	[0.0000]***
Cognitive Impairment	0.1338	0.1458	-0.0224
	[0.0054]**	[0.0035]**	[0.2136]
Physical Impairment	0.2636	0.2887	0.1202
	[0.0000]***	[0.0000]***	[0.0000]***
Mobility Limitation	-0.2481	-0.2493	-0.0389
	[0.0003]***	[0.0007]***	[0.1223]
Difficulty with Self-Care	0.0268	-0.0347	0.0143
	[0.7581]	[0.7166]	[0.6960]
Visual Impairment	-0.0839	-0.2545	-0.0716
	[0.1702]	[0.0000]***	[0.0017]**
Hearing Impairment	0.5435	0.5487	0.0577
	[0.0000]***	[0.0000]***	[0.0110]*
Constant	-3.4793	-3.3146	-0.0085
	[0.0000]***	[0.0000]***	[0.7414]
State Fixed Effects	X	X	X

Note: Pre-VOW veteran is comparison group.

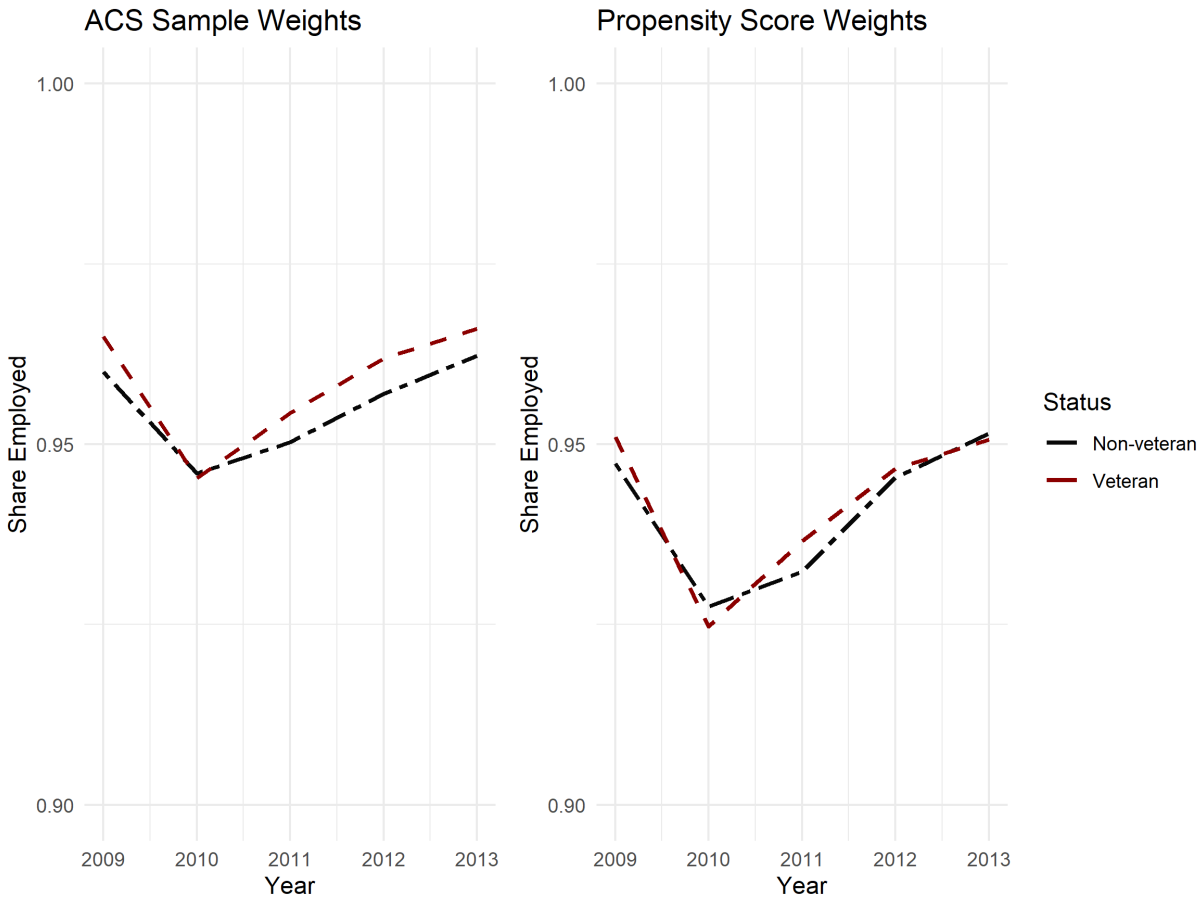
Figure 3.2: Employment Shares by Veteran Status and Eligibility Group (Small WOTC)

Source: ACS, 2009-2013.

Figure 3.3: Employment Shares by Veteran Status and Eligibility Group (Large WOTC)

Source: ACS, 2009-2013.

Figure 3.4: Employment Shares by Veteran Status and Eligibility Group (Not Eligible)



Source: ACS, 2009-2013.

Table 3.3: Difference-in-Difference Estimates for Small WOTC

	Linear Probability Model		Logistic Regression Model	
	P(emp)	P(emp)	P(emp)	P(emp)
Post-2011	0.0406	0.0546	0.2419	0.3104
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Veteran	-0.0309	-0.008	-0.1653	-0.0417
	[0.0000]***	[0.0705]	[0.0000]***	[0.0687]
Post-2011 * Veteran	0.0271	0.0124	0.1407	0.0689
	[0.0000]***	[0.0384]*	[0.0000]***	[0.0430]*
SAMPLE WEIGHTS	X		X	
PROPENSITY SCORE WEIGHTS		X		X

Note: P-values shown in brackets.

Table 3.4: Subgroup Difference-in-Difference Estimates for Small WOTC

	Linear Probability Model		Logistic Regression Model	
	P(emp)	P(emp)	P(emp)	P(emp)
SNAP Receipt	0.0307	0.0249	0.187	0.153
	[0.0001]***	[0.0039]**	[0.0001]***	[0.0024]**
Cognitive Disability	0.033	0.0248	0.1425	0.1062
	[0.2907]	[0.4619]	[0.2914]	[0.4686]
Physical Disability	0.0415	0.0394	0.1893	0.1769
	[0.1288]	[0.1818]	[0.1316]	[0.1909]
Age = 19 – 29	0.0454	0.0278	0.2757	0.1839
	[0.0178]*	[0.1525]	[0.0127]*	[0.1012]
Age = 30 – 39	0.0227	0.0069	0.1247	0.0412
	[0.1217]	[0.6488]	[0.1602]	[0.6502]
Age = 40 – 49	0.0446	0.0283	0.2152	0.1507
	[0.0001]***	[0.0185]*	[0.0008]***	[0.0241]*
Age = 50 – 64	0.0143	0.0028	0.0534	0.0101
	[0.0627]	[0.7433]	[0.2273]	[0.8322]
College	-0.003	-0.0213	-0.0774	-0.1369
	[0.8281]	[0.1468]	[0.3992]	[0.1570]
Female	0.0229	0.0226	0.1641	0.1498
	[0.0992]	[0.1094]	[0.0832]	[0.1186]
Management/Professional	0.0229	0.0051	0.0664	0.0262
	[0.0513]	[0.6891]	[0.3600]	[0.7361]
Clerical/Retail	0.0261	0.0148	0.1421	0.0706
	[0.0790]	[0.3467]	[0.1150]	[0.4591]
Services	0.0219	0.0241	0.1456	0.1708
	[0.1030]	[0.0912]	[0.1180]	[0.0831]
Production	0.0026	-0.0248	-0.0535	-0.1826
	[0.9242]	[0.3996]	[0.7416]	[0.2893]
Operations	0.0053	-0.0023	0.0117	-0.0224
	[0.7900]	[0.9124]	[0.9186]	[0.8525]
Transportation/Mechanics	-0.0005	0.0006	-0.0145	-0.0009
	[0.9556]	[0.9538]	[0.7860]	[0.9879]
SAMPLE WEIGHTS	X		X	
PROPENSITY SCORE WEIGHTS		X		X

Note: P-values shown in brackets.

Table 3.5: Difference-in-Difference Estimates for Large WOTC

	Linear Probability Model		Logistic Regression Model	
	P(emp)	P(emp)	P(emp)	P(emp)
Post-2011	0.0761	0.0927	0.3254	0.381
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Veteran	-0.0575	0.01	-0.2333	0.0401
	[0.0000]***	[0.1893]	[0.0000]***	[0.1898]
Post-2011 * Veteran	0.0233	-0.0054	0.084	-0.0206
	[0.0188]*	[0.6187]	[0.0425]*	[0.6481]
SAMPLE WEIGHTS	X		X	
PROPENSITY SCORE WEIGHTS		X		X

Note: P-values shown in brackets.

Table 3.6: Subgroup Difference-in-Difference Estimates for Large WOTC

	Linear Probability Model		Logistic Regression Model	
	P(emp)	P(emp)	P(emp)	P(emp)
SNAP Receipt	-0.0018	-0.0133	-0.013	-0.0541
	[0.9362]	[0.5903]	[0.8875]	[0.5860]
Cognitive Disability	-0.0307	-0.081	-0.1242	-0.3257
	[0.4948]	[0.0980]	[0.4914]	[0.0974]
Physical Disability	-0.0112	-0.0368	-0.0498	-0.1493
	[0.7774]	[0.4053]	[0.7589]	[0.4104]
Age = 19 – 29	0.0229	0.0018	0.1003	0.0211
	[0.4503]	[0.9531]	[0.4473]	[0.8759]
Age = 30 – 39	0.0253	-0.0067	0.0952	-0.0223
	[0.3702]	[0.8211]	[0.4235]	[0.8584]
Age = 40 – 49	0.0244	0.0034	0.088	0.0163
	[0.2507]	[0.8794]	[0.3217]	[0.8613]
Age = 50 – 64	0.0001	-0.0098	-0.0112	-0.0422
	[0.9947]	[0.5132]	[0.8419]	[0.4956]
College	0.0136	-0.0072	0.0244	-0.0245
	[0.5558]	[0.7718]	[0.8050]	[0.8177]
Female	-0.0317	-0.0461	-0.1385	-0.2015
	[0.2279]	[0.0893]	[0.2725]	[0.1229]
Management/Professional	-0.0091	-0.0393	-0.0649	-0.1594
	[0.6684]	[0.0945]	[0.4596]	[0.0972]
Clerical/Retail	0.024	-0.0108	0.0904	-0.0394
	[0.3074]	[0.6735]	[0.3637]	[0.7152]
Services	-0.0051	0.0019	-0.0302	0.0086
	[0.8389]	[0.9442]	[0.7846]	[0.9435]
Production	0.093	0.0406	0.3704	0.174
	[0.0875]	[0.4885]	[0.1095]	[0.4811]
Operations	0.0237	-0.0087	0.0991	-0.0298
	[0.5253]	[0.8311]	[0.5217]	[0.8594]
Transportation/Mechanics	0.0306	0.0108	0.1244	0.0446
	[0.0728]	[0.5592]	[0.0771]	[0.5570]
SAMPLE WEIGHTS	X		X	
PROPENSITY SCORE WEIGHTS		X		X

Note: P-values shown in brackets.

Table 3.7: Triple Difference Estimates for Service-Disabled Veterans

	Linear Probability Model		Logistic Regression Model	
	P(emp)	P(emp)	P(emp)	P(emp)
Post-2011	0.0761	0.0927	0.3254	0.381
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Veteran	-0.0583	0.0086	-0.2363	0.0347
	[0.0000]***	[0.2810]	[0.0000]***	[0.2814]
Post-2011 * Veteran	0.022	-0.0061	0.0781	-0.0241
	[0.0375]*	[0.5932]	[0.0761]	[0.6139]
Has Service-Connected Disability	0.0068	0.0116	0.0275	0.0466
	[0.7330]	[0.5893]	[0.7332]	[0.5899]
Post * Has Service-Connected Disability	0.0078	0.0031	0.0357	0.0165
	[0.7867]	[0.9172]	[0.7681]	[0.8948]
SAMPLE WEIGHTS	X		X	
PROPENSITY SCORE WEIGHTS		X		X

Note: P-values shown in brackets.

Conclusion

A 2007 National Academy of Medicine evaluation of VADC—and specifically the Veterans Affairs Schedule for Rating Disabilities—began with the following observation: that "it is impossible to undertake any responsible assessment of a veterans assistance program without…an understanding and acknowledgement that these programs are but one way (and, sometimes, an inadequate way) that a 'grateful nation' attempts to repay its indebtedness to those that serve in the military" (Barnes et al., 2007). In this dissertation I have emphasized the economic functions of VADC and have briefly compared it to other social insurance institutions such as SSDI. This narrow focus, however, ignores significant social and political differences between VADC and related, non-veteran programs. As just one example: if VADC is seen by the public as a benefit justly earned through service, then concerns about moral hazard that are central to policy discussions of other disability programs become less relevant—the deservingness of the beneficiary is taken for granted, and is not considered to be something about which designers of the program, acting on behalf of a "grateful nation," should be primarily concerned.

Nonetheless, the rapid growth of VADC in recent years raises questions about the appropriate role of the program in veterans' lives. As I discuss in this dissertation, several explanations of this growth have been proposed, including changes to the way the program is administered, changes to evidentiary standards, and external factors, such as the weak labor market following the Great Recession of 2007 – 2009 and the incomplete expansion of Medicaid under the ACA. Integrating this evidence into a coherent narrative about how the program has changed in recent years can aid policymakers in determining an appropriate response.

A pessimistic interpretation of the available evidence is that changes to the administration of VADC since 2001 have made it easier for veterans to receive compensation, potentially reducing the labor supply of veterans with capacity to work and diverting scarce resources away from the most needy towards those with more moderate functional limitations. Prior work exploiting a natural experiment induced by the 2001 Agent Orange diabetes presumption for Vietnam veterans with "boots on the ground" experience has found that veterans who entered VADC significantly reduced their labor supply (Coile, Duggan, & Guo, 2020). While these results are specific to the Vietnam cohort and may not generalize, they are consistent with my finding in Chapter 2 that the labor force participation rate among veterans grew more slowly in states that did not expand Medicaid in 2014, while participation in VADC grew more rapidly in those states. To the extent that policymakers have an interest in preserving veterans' connections to the labor force, these results provide somewhat troubling evidence that the VADC program may weaken labor market ties by providing an alternative to wage income. It is important to note,

however, that this is not necessarily a policy failure: supplemental, regular income that allows some veterans with severe impairments to reduce their labor supply may be welfare-enhancing.

My findings also point to other linkages between the labor market and VADC. In Chapter 1, I show that changes in VADC expenditures are positively associated with lagged unemployment rates, and that a key mechanism for this association appears to be an increase in the number of veterans with CDRs of 50 percent or more in weaker labor markets. Interestingly, my results suggest that this relationship strengthens up to at least the third-year lag, which cannot be fully explained by the time to process new VADC claims, which rarely exceeded 180 days at its slowest and was usually less than 120 days. At least two of the many plausible explanations for this finding are consistent with the pessimistic narrative: first, that negative economic shocks have induced veterans to file marginal disability claims in order to replace lost earnings or become eligible for IU[17]; and second, that negative economic shocks have aggravated underlying service-related health conditions, but that the earnings losses associated with these conditions are temporary. This may not be the case—in fact, it is equally plausible that negative economic shocks will aggravate health conditions that become permanent, and therefore payments from the VADC program compensating for earnings losses related to those conditions would be fully consistent with the intent of the program. Nonetheless, this highlight the possibility that the VADC program may be seen by some veterans as a way to solve short-term economic problems, and that veterans' reliance on the program will vary with economic conditions. To the extent this is the case, the program as currently implemented, in which disability benefits are often paid for life, may not accurately reflect the dynamics of earnings losses experienced by service-disabled veterans and may lead some veterans to rely on income from VADC when their health conditions have resolved.

My results also provide support for a more optimistic narrative. According to this view, efforts to ease the burden of applying for VADC and greater knowledge and understanding of the program among veterans may have increased the program participation rate, measured as the fraction of *eligible* veterans who actually claim a benefit, thereby compensating for earnings losses due to service-connected health conditions that would otherwise be borne entirely by the veteran and their family. The conceptual model of benefit claiming I present in Chapter 1 assumes that veterans will choose to apply for VADC if the expected value from doing so exceeds the costs of applying, where costs are defined broadly to include the burden of completing and filing an application, feelings of stigma associated with participating in the program, and the informational costs of learning about the program. If these costs were null, then this model would predict a complete participation rate, provided the expected benefits of the program are positive; since they are very unlikely to be null, it is reasonable to expect some amount of under-participation. In this context, the rapid increase in the share of veterans who

[17] Here, I am mostly referring to veterans with existing disability ratings who may file an additional claim for a relatively minor impairment in order to claim a higher CDR.

claim disability benefits in the last two decades, from roughly 9 percent in 2000 to nearly 25 percent in 2019, can be interpreted as one of the anticipated consequences of efforts made during this period to lower the cost of participation in the program. These efforts may also have raised the participation rate by increasing the expected benefit from receiving a service-connected disability rating, either because of changes in evidentiary standards (e.g., presumptions) that make receiving a higher rating less costly, by easing the application process for receiving initial or follow-on ratings, or by better communicating to veterans about which of their health conditions are eligible for compensation. Future work should attempt to disentangle the effects of these procedural and behavioral factors on the share of veterans participating in VADC from the significant changes in the composition of veteran population that have occurred in recent years.

My finding in Chapter 2 that VADC grew faster in states that did not expand Medicaid is also partially consistent with the optimistic narrative. Prior to the implementation of the ACA in 2014, nearly 10 percent of veterans were uninsured and likely had little contact with the health system. The ACA led some of these uninsured veterans to seek out insurance from the VA, which plausibly led them to learn about their eligibility for VADC and begin receiving benefits compensating for their service-related functional impairments. That the same increase in VADC is not observed in expansion states suggests that some of the costs of service-related health conditions in those states have been passed on from veterans to the Medicaid system. While policymakers should continue to monitor and assess the magnitude of these spillovers, it is reasonable to interpret this result as a success of the ACA: both through the individual mandate and by establishing a norm of universal coverage, it brought previously unobserved service-related health conditions into the view of the formal health system and enabled veterans with those conditions to receive compensation.

To further place this evidence into context, it is necessary to introduce criteria for evaluating disability systems. Drawing on a long tradition, I consider three aspects of performance: *adequacy*, which refers to the extent to which benefits compensate for the losses the program intends to offset; *equity*, which refers to the distribution of outcomes in the system; and *administrative efficiency*, which refers to the ability of both benefit seekers and beneficiaries to move through the system without significant delays or contortions. Equity can be further disaggregated as *horizontal equity*—the similarity of benefits among people with similar conditions—and *vertical equity*—the dissimilarity of benefits among people with divergent diagnoses.

As I mention in the Introduction, the current benchmark for measuring adequacy of VADC benefits is the relationship between average benefits and average earnings losses. While measuring benefit adequacy is outside the scope of my dissertation, my results have implications for how policymakers should understand it. Note that earnings loss is an inherently statistical concept, and measuring it requires making analytical assumptions, gathering data, and interpreting results. Consider, for example, the difficulty of disentangling *observed* from *potential* (i.e., counterfactual) earnings of a service-disabled veteran. Observed earnings may be

reduced because of lowered productivity or limited labor supply due to the veteran's service-related health condition, but also because of voluntary reductions of labor supply due to the availability of a cash benefit. Measures of earnings loss will be highly sensitive to assumptions about the importance and magnitude of these various factors. Congress partially acknowledges these challenges by saying that VADC benefits must only compensate for average earnings losses "as far as can practicably be determined," leaving to the VA and others the task of determining how to measure earnings loss.[18] But the point remains that the aim of ensuring adequacy of benefits at least in part relies on building consensus around an analytical approach to measurement and developing the analytical capacity to implement that approach. Put another way, in order for the average earnings loss standard to be a useful benchmark, it must be applied in a routine and consistent manner over time.

The pessimistic and optimistic narratives presented above intersect in conflicting ways with the concepts of adequacy and equity. According to the pessimistic view, changes that have enabled more veterans to receive disability ratings of 50 percent or more may have eroded adequacy and equity by offering benefits to some veterans that exceed their earnings loss, by inflating observed earnings losses through reductions in labor supply induced by the generosity of the benefit, or by changing the distribution of outcomes across impairment types in ways that may not correspond to actual earnings losses. According to the optimistic view, the recent growth in the program has likely brought into view service-related health conditions that otherwise would have been unobserved and unmeasured in an evaluation of the adequacy or equity of VADC benefits.

Though divergent, these perspectives lead to similar policy conclusions. First, since the primary outcomes of the VADC program are measurable under certain analytic assumptions, favorable outcomes can be achieved by investing in analytic capacity. In other words, if the pessimistic view is true and recent changes to the program have made benefits too generous, then this imbalance can be brought to equilibrium by updating the VASRD according to more recent measures of earnings loss by impairment type, which may also account for behavioral responses among veterans and variation in losses over the business and life cycles. If the optimistic view is true, then evaluations of benefit adequacy should conclude that recent efforts to increase program participation have reduced the share of earnings losses that are uncompensated but that the adequacy and equity of benefits have not significantly changed. Thus, the **VA should engage in as close to real-time monitoring of the earnings losses of service-disabled veterans as is possible**. Such studies should take a holistic view of earnings losses, and in particular should attempt to measure at each point in time the extent of losses undiagnosed due to incomplete participation. One way to measure undiagnosed losses would be to **conduct regular qualitative needs assessments on random samples of veterans**. Such assessments should not only attempt to survey the distribution of health conditions in the veteran population, but also changes in

[18] See: 38 CFR § 4.1.

veterans' attitudes towards VADC and other veteran benefits to determine whether, for example, changing social norms regarding disability can explain trends in participation. Further, a needs assessment would be useful in identifying the extent to which veterans rely on other social services, including SSDI, Medicare, and Medicaid, and whether those programs absorb some of the costs that would be more appropriately covered by VADC and the VA health system.

Further, my results in Chapter 2, and to a lesser extent those in Chapter 3, indicate that a study of earnings losses of service-disabled veterans should not exclusively focus on the cash benefit, but also on fringe benefits linked to certain service-connected disability ratings, such as priority group status for VA health care and eligibility for the WOTC. My results are consistent with the view that these benefits may have material value to eligible veterans. For example, even though I do not find that the WOTC increased the employment rate of service-disabled veterans, their eligibility for the credit may have enabled some to achieve higher earnings from employers willing to pass some of the value of the credit on to their employees. More directly, the results in Chapter 2 suggest priority group status may be an incentive to claim a VA disability rating. Assessing the material value of other benefits, such as federal hiring preferences, should be the focus of future research. Concurrent with this research, the **VA should assess its eligibility criteria for these benefits** and should, wherever possible, establish an objective standard for their eligibility. Where such a standard is not possible, the VA should consider making these benefits universally available. One program that warrants reconsideration is Veteran Readiness and Employment (VR&E), which provides job counseling for service-disabled veterans looking to enter or return to the workforce. As currently constituted, this program is only available to veterans with a service-connected disability rating of 20 percent (or 10 percent if it is accompanied by a serious employment handicap) within 12 years of separation from military service or the date they first notified the VA of their service-connected disability. My results point to two potential problems with these criteria. First, VR&E benefits may be most valuable in close proximity to acute shocks, such as job losses, that aggravate underlying health conditions. Requiring a veteran to receive a disability rating before becoming eligible for VR&E may limit their access to the program when they most need it. Second, the 12-year time limit on VR&E benefits may lead some veterans who experience such shocks years after they first receive a disability rating to turn to programs such as IU rather than returning to the workforce.

Relatedly, the **VA should explore opportunities to integrate alternatives to the average earnings loss standard into the VADC program**. As discussed, my results in Chapters 1 and 2 are consistent with the possibility that veterans may turn to VADC to solve short-term problems. While these may in most cases be appropriate uses of the program, they may also conflict with a key aim of administrative efficiency—that interacting with the program should not significantly interfere with the normal decisionmaking of prospective or current recipients. For example, a veteran recently separated from their civilian job may decide to remain out of work for an extended period in order to increase their chances of receiving a higher disability rating from the VA or becoming eligible for IU benefits. Veterans may also be reluctant to seek out health

services from the VA after a condition has resolved if they fear doing so will affect their disability rating. The VA should consider piloting a temporary disability program that would provide short-term VR&E assistance, as well as cash compensation, regardless of whether a veteran has already obtained a disability rating. Such a program would bear some similarity to unemployment insurance but would explicitly acknowledge the relationship between underlying health conditions and transitions in the labor market. While this program would increase short-term costs, it may reduce long-term expenditures by ensuring strong connections between veterans and the labor market.

My results also have implications for federal policymakers interested in using hiring credits to boost the employment levels of certain groups. I find that the 2011 expansion of the WOTC was effective at raising the employment rate of veterans in families receiving SNAP benefits, but did not raise the employment rate of service-disabled veterans or veterans with extended time out of work. If Congress is interested in expanding employment opportunities for these groups, **reauthorizing the WOTC for SNAP recipients but not for people with longer gaps in work** may be an effective way to achieve this goal. Additional research would be valuable to better understand the WOTC and to identify other policies that may be effective for veterans with more significant barriers to employment. For example, one current unknown is the extent to which firm knowledge of the WOTC varies by industry, and how this may affect the policy's effectiveness, especially as it relates to veterans. A comprehensive, well-powered survey of firms would be extremely valuable for identifying the mechanisms underlying the policy's effects. Key topics to address in such a study would be firms' overall awareness of the WOTC, and how this varies by industry; whether firms are wary of hiring veterans with extended periods out of work; how firms perceive service-disabled disability status when considering hiring veterans, and specifically whether they expect additional accommodation costs when hiring such veterans; how firms first became aware of the credit; the occupations firms are most likely to hire through the credit; and whether the administration of the credit is seen as burdensome.

Another research priority should be evaluating the WOTC for recently-separated servicemembers, which was infeasible with the data available for this dissertation. In a previous prospectus, I sketched a feasible research design to study this population using the Longitudinal Employer-Household Dynamics (LEHD) earnings data linked to administrative records managed by the Defense Manpower Data Center (DMDC). The advantage of this linkage is that the DMDC data reports servicemember's date of separation with plausible accuracy, and also includes rich detail about the nature of service, including military occupation and potentially combat experience. Since eligibility for the WOTC typically depends on the time between the hiring date and the date separated from service, it should be possibly to conduct a regression discontinuity analysis using the separation date as a run variable and individual-level information in the DMDC records to make balanced comparisons between groups eligible for the credit and those who are not. The treatment group in this analysis would be ex-servicemembers who were eligible for the WOTC at the time it was authorized, and the counterfactual control group would

be those who missed the eligibility standard by a small period (say, one or two quarters). An advantage of this research design is that would use within-person variation in employment rates over time, and would not rely on the I assumption I make here that compositional changes in the treatment and control groups over time can be mitigated with the weighting scheme I use in Chapter 3.

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