Appendixes

Veterans' Health Insurance Coverage Under the Affordable Care Act and Implications of Repeal for the Department of Veterans Affairs

Michael Dworsky, Carrie M. Farmer, Mimi Shen

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Appendix A. Methods and Supplementary Results

In this appendix, we provide additional background on our data sources, detail on methods, and supplementary results referenced in the text. Where possible, methods in this study follow those developed in Eibner et al. (2015),[1] RAND's comprehensive examination of the unique health care demands of veterans.

Our primary data source for tracking veterans' health insurance coverage and U.S. Department of Veterans Affairs (VA) coverage was the 2013–2015 American Community Survey (ACS). The ACS is a mandatory federal survey collected by the U.S. Census Bureau. Approximately 1 percent of the U.S. population is sampled each year, making the ACS the largest federal household survey with information on both veteran status and respondents' sources of health insurance coverage. Because the ACS identifies respondents' states of residence and provides some substate geographic identification on the public-use microdata sample, it is also an invaluable data source for developing state-specific estimates and examining the impact of the Medicaid expansion. In this study, we worked primarily with the Integrated Public Use Microdata Series (IPUMS) ACS, an enhanced version of the ACS maintained and distributed by the IPUMS-USA.[2]

In addition to the ACS, we conducted several analyses using the National Health Interview Survey (NHIS). As with the ACS, we primarily used an enhanced and harmonized version of the NHIS prepared by IPUMS,[3] although we added a number of variables from the original NHIS files distributed by the National Center for Health Statistics (NCHS). The NHIS is a continuously fielded survey designed by the NCHS and collected by the U.S. Census Bureau. It is among the gold-standard data sources for precise identification of the source of insurance coverage and also contains rich detail on respondents' health status. We used the NHIS for several purposes in this study:

1. We used the health insurance data in the 2011–2015 NHIS to replicate our ACS analysis of changes in health insurance coverage.

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[1] Christine Eibner, Heather Krull, Kristine Brown, Matthew Cefalu, Andrew W. Mulcahy, Michael Pollard, Kanaka Shetty, David M. Adamson, Ernesto F. L. Amaral, Philip Armour, Trinidad Beleche, Olena Bogdan, Jaime L. Hastings, Kandice Kapinos, Amii Kress, Joshua Mendelsohn, Rachel Ross, Carolyn M. Rutter, Robin M. Weinick, Dulani Woods, Susan D. Hosek, and Carrie M. Farmer, *Current and Projected Characteristics and Unique Health Care Needs of the Patient Population Served by the Department of Veterans Affairs*, Santa Monica, Calif.: RAND Corporation, RR-1165/1-VA, 2015. As of June 27, 2017: https://www.rand.org/pubs/research_reports/RR1165z1.html

[2] Steven Ruggles, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek, *Integrated Public Use Microdata Series: Version 6.0* [dataset], Minneapolis: University of Minnesota, 2015, http://doi.org/10.18128/D010.V6.0.

[3] Lynn A. Blewett, Julia A. Rivera Drew, Risa Griffin, Miram L. King, and Kari Williams, *IPUMS Health Surveys: National Health Interview Survey, Version 6.2* [dataset], Minneapolis: University of Minnesota, 2016.

2. We used information on health status and diagnosed health conditions from the NHIS Sample Adult file for 2015 to estimate the proportion of nonelderly veterans with declinable preexisting conditions.
3. We used the pooled 2011–2015 NHIS data to estimate the distribution of health status by age and income among nonelderly veterans as an input into our model for the impacts of Affordable Care Act (ACA) repeal.

Finally, we used the Household Component of the 2008–2014 Medical Expenditure Panel Survey (MEPS-HC) to examine utilization of VA and all-payer health care by nonelderly veterans. The MEPS-HC is a two-year panel survey consisting of five interviews focusing on individuals' health care utilization and spending, among other topics. RAND's 2015 study on veterans and VA used the MEPS to describe VA use and reliance, leveraging the fact that the MEPS allows nationally representative estimates of health care obtained from all payers, including VA (Eibner et al., 2015). (See Table A.1.)

Table A.1. Overview of Data Sources

	Data Sources		
	ACS	**NHIS**	**MEPS**
Years of data used	2013–2015	2011–2015	2008–2014
Survey type	Repeated cross-section	Repeated cross-section	Short panel
Universe	U.S. resident population	U.S. civilian noninstitutionalized population	U.S. civilian noninstitutionalized population
State codes included?	Yes	No	No
Definition of *veteran*	Ever served on active duty in the U.S. armed forces, reserves, or National Guard	Ever served on active duty in the U.S. armed forces, reserves, or National Guard	Ever been honorably discharged from active duty in the U.S. Army, Navy, Air Force, Marine Corps, or Coast Guard
Definition of *non-VA uninsurance*	Uninsured at time of survey	Uninsured at time of survey	Uninsured for full year; in monthly estimates, uninsured for full month
Definition of *VA coverage*	Respondent indicates health insurance or health coverage from VA (including those who have ever used or enrolled for VA health care)	VA coverage variable not used	N.A. (VA not treated as insurance in MEPS)
Definition of *VA patient*	N.A.	N.A.	Respondents who had any payment by VA for services used
Unweighted sample size of noninstitutionalized, nonelderly veterans (2013)	103,984	3,529	773
Weighted total number of noninstitutionalized, nonelderly veterans (2013)	10,171,390	11,205,643	8,945,214
Role in study	Estimate ACA's effects on insurance status and VA coverage, including by Medicaid expansion status, priority group, and distance from VA facilities	Validate ACS coverage estimates, estimate health status and preexisting condition prevalence	Estimate VA use and reliance by insurance status

NOTE: N.A. = not applicable.

Identifying the Veteran Population in Federal Household Surveys

Because this study uses information from multiple survey data sets to measure the same constructs, this section provides detailed information about key questions from each survey on veteran status and VA enrollment.

The ACS is an important data source for studying the veteran population. The ACS asks respondents the following question to ascertain veteran status:

Has this person ever served on active duty in the U.S. Armed Forces, Reserves, or National Guard? Mark (X) ONE box.

- *Never served in the military ➔ SKIP to question 29a*
- *Only on active duty for training in the Reserves or National Guard ➔ SKIP to question 28a*
- *Now on active duty*
- *On active duty in the past, but not now*

To avoid comparability problems resulting from changes to the veteran status question in 2013, we limited our analysis of the ACS to 2013–2015 data.[4] The 2013 ACS captures a weighted total of 10,171,390 noninstitutionalized, nonelderly veterans (ages 19–64) in 2013.

In addition to veteran status, the ACS contains questions about service-connected disability (including service-connected disability ratings) and era of service. Service-connected disability ratings, along with other information contained in the ACS, make it possible to impute veterans into VA priority groups, as we discuss further later in this section. We grouped veterans into four service eras: post-9/11 (September 2001 or later), Gulf War (August 1990 to August 2001), post-Vietnam to Gulf War (May 1975 to July 1990), and Vietnam era (August 1964 to April 1975). Respondents whose service spanned multiple service eras were assigned to the most recent service era they mentioned, so our service-era classifications should be interpreted as reflecting the respondent's date of separation from the armed forces.

The NHIS uses a similar question to the ACS to identify veterans:

Have you ever served on active duty in the U.S. Armed Forces, military Reserves, or National Guard?

Read if necessary. Active duty does not include training for the Reserves or National Guard, but DOES include activation, for example, for service in the US or in a foreign country, in support of military or humanitarian operations.

- *Yes*
- *No*
- *Refused*
- *Don't Know*

This question was adopted in the 2011 NHIS and remained unchanged through 2015. Prior to 2011, the NHIS used a different question that asked only about honorable discharge from the military. Discharge condition is not collected by the NHIS in 2011 and later years, making it impossible to define a comparable sample of veterans between the pre-2011 and post-2010 periods, and so we limit our analysis to 2011 and later years.

The NHIS does not contain information about service-connected disabilities, but it does elicit the era of service. We view the population of veterans identified by the ACS and the NHIS to be generally comparable, and the distributions of age, service era, and basic demographics match closely across the two surveys. The NHIS produces an estimate of 11,205,643 noninstitutionalized, nonelderly veterans in 2013.

[4] Kelly Holder and David Raglin, *Evaluation of the Revised Veteran Status Question in the 2013 American Community Survey*, Washington, D.C.: U.S. Census Bureau, 2014.

The veteran status question in the MEPS identifies a narrower population of veterans: those with an honorable discharge. We used the following question from the MEPS-HC to identify veterans:

> *Have you ever been honorably discharged from active duty in the U.S. Army, Navy, Air Force, Marine Corps, or Coast Guard?*
> - *Yes*
> - *No*
> - *Refused*
> - *Don't Know*

In addition, the MEPS does not elicit era of service. The MEPS produces a slightly lower estimate for the total number of noninstitutionalized, nonelderly veterans (8,945,214) than either the ACS or the NHIS. This number is likely lower than the ACS or the NHIS in part because of the restriction to honorably discharged veterans and in part because we excluded veterans who were institutionalized anytime during the interview year from our analysis sample (whereas veterans were included in the ACS and NHIS samples if they were noninstitutionalized on the day of the survey). We also suspect that reservists who have experienced deployment or significant activations may be less likely than veterans who served in regular components to identify themselves in response to this question, but we cannot verify that this is the case.

It is important to note that none of these data sets contains all the information necessary to determine respondents' VA eligibility or priority group with certainty. The ACS has the most-complete information about respondents' military service, since it includes information about service-connected disability ratings in addition to era of service. The ACS, however, does not capture length of service or discharge condition. The NHIS, similarly, does not capture these variables, nor does it include service-connected disabilities. Meanwhile, while the MEPS does ask specifically about honorable discharge, it does not contain service era, service-connected disability, or any other questions about military service. Although we were able to impute priority group using information in the ACS, the incomplete nature of information about veterans' history of service is a limitation of the data sources used in this analysis.

In this report, all estimates of totals for the noninstitutionalized, nonelderly veteran population are derived by estimating population shares or per capita figures in our survey data sets and then calculating totals based on population estimates from VA's VetPop demographic model,[5] which provides estimates of the nonelderly veteran population at both the national and state levels. Because VetPop includes institutionalized veterans, we used the ACS to estimate that 1.36 percent of the nonelderly veteran population was institutionalized in 2015. This

[5] Our estimate of the total number of veterans in 2015 was derived from VetPop2016 estimates for the 50 states and the District of Columbia. For our analysis of state-specific impacts of ACA repeal, we also used estimates of VA patients by state as of fiscal year 2015, reported in State Summary fact sheets available from the National Center for Veterans Analysis and Statistics (NCVAS) website.
For VetPop2016, see VA NCVAS, "Table 6L: VetPop2016 Living Veterans by State, Age Group, Gender, 2015–2045," 2017. As of July 25, 2017:
http://www.va.gov/vetdata/docs/Demographics/New_Vetpop_Model/6L_VetPop2016_State.xlsx
For state summaries, see VA NCVAS, "State Summary: VA Population and Health Care as of 9/30/2015," 2015. As of July 25, 2017: http://www.va.gov/VETDATA/index.asp

estimate appears broadly consistent with prior estimates that 0.85 percent of all-ages veterans were incarcerated in 2011–2012, as incarceration rates are presumably lower for elderly veterans, and some nonelderly veterans are housed in institutions other than prison.[6] Finally, we note that homeless veterans would not be captured in any of the household surveys identified here, and so they are not included in our analysis. Scaling down VetPop's 2015 population estimate of 10,951,407 nonelderly veterans by the estimated proportion of institutionalized nonelderly veterans yields a population benchmark of 10,802,468 noninstitutionalized, nonelderly veterans in 2015.

Measurement of Health Insurance Coverage and Source of Coverage

Our primary data source for measuring health insurance coverage in this study is the ACS. The ACS relies on a single question on health insurance that is designed to elicit coverage status at the time of the survey for each person in the household. The text of the question reads:

> *Is this person CURRENTLY covered by any of the following types of health insurance or health coverage plans? Mark "Yes" or "No" for EACH type of coverage in items a–h.*

The eight possible response categories are as follows:

- employer-sponsored insurance (ESI) ("Insurance through a current or former employer or union [of this person or another family member]")
- direct-purchase insurance ("Insurance purchased directly from an insurance company [by this person or another family member]")
- Medicare ("Medicare, for people 65 and older, or people with certain disabilities")
- Medicaid ("Medicaid, Medical Assistance, or any kind of government-assistance plan for those with low incomes or a disability")
- TRICARE ("TRICARE or other military health care")
- VA ("VA [including those who have ever used or enrolled for VA health care]")
- IHS ("Indian Health Service")
- other ("Any other type of health insurance or health coverage plan").

Official statistics on the uninsured population classify individuals as insured if they report being covered by any type of insurance other than IHS. (IHS-only coverage may not be comprehensive and therefore is not treated as health insurance in federal statistics.) We also note that the ACS does not attempt to distinguish between Marketplace coverage and other direct-purchase health insurance. Changes in direct-purchase insurance thus are likely to reflect the effect of Marketplace take-up net of individuals who transitioned from the pre-ACA nongroup market to Marketplace coverage.

We constructed several additional variables to capture insurance configurations other than those directly captured in the IPUMS ACS variables. In particular, we defined a variable to identify whether respondents had a non-VA, non-IHS source of insurance coverage.

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[6] Jennifer Bronson, E. Ann Carson, Margaret Noonan, and Marcus Berzofsky, *Veterans in Prison and Jail, 2011–12*, Washington, D.C.: Bureau of Justice Statistics, 2015. As of July 25, 2017: https://www.bjs.gov/index.cfm?ty=pbdetail&iid=5479

In addition, we constructed a series of variables to identify veterans with VA coverage and a secondary source of coverage. Changes in non-VA coverage among VA enrollees are of particular interest in our analysis of VA use. The insurance types we analyze in the ACS are as follows, with indented items representing subcategories of the preceding category:

- uninsured (including VA): no insurance or IHS only
- uninsured (excluding VA): uninsured or VA-only
- VA-covered
    - VA-only: VA covered with no other non-IHS coverage
    - VA with private: VA with ESI or direct-purchased coverage
    - VA with Medicaid
- private coverage
    - employer-sponsored coverage
    - direct-purchase coverage
- Medicaid
- TRICARE.

Measurement of veterans' VA enrollee and VA patient status in household surveys can be problematic because VA is primarily an integrated health delivery system rather than a form of health insurance. Questions that are designed to measure more-typical forms of health insurance may be misunderstood by respondents, while the fact that most VA enrollees never disenroll also seems likely to lead to underreporting of enrollment by those who have not used VA services recently.

In the ACS, VA coverage is measured as a response option in the question about health insurance status. Although the VA response option on the ACS prompts respondents to answer affirmatively if they have ever used or enrolled in VA coverage, we believe that this question most likely captures those who have recently used VA, in which case the VA-covered population as measured in the ACS would correspond most closely to the *VA patient* population rather than the *VA enrollee* population. We think that this interpretation is justifiable because the ACS health insurance question explicitly focuses on health insurance status at the time of the interview ("Is this person CURRENTLY covered . . ."). Furthermore, the all-ages population of VA-covered veterans (including institutionalized veterans) in the ACS (6.2 million in 2014) undercounts the number of enrollees (9.1 million in 2014) by about one-third but is very close to the total count of veteran VA patients (6.0 million in 2014).[7] We were not able to locate any cognitive testing or validation studies with clear guidance on the interpretation of VA coverage as reported in the ACS, however, so we refrain from using the ACS to estimate either VA enrollees or VA patients. Instead, we refer to ACS respondents who select the VA option on the health insurance question as *VA-covered* individuals, a term meant to reflect this ambiguity.

[7] U.S. Department of Veterans Affairs, *2016 Congressional Submission: Volume II: Medical Programs and Information Technology Programs*, Washington, D.C., 2016.

An important limitation of the ACS as a data source on health insurance is that it relies on respondents to correctly identify their source of coverage and does not have any follow-up questions to verify the source of coverage. While the Census Bureau ACS undergoes some logical editing prior to release, misreporting of insurance source even after application of these edits is a widely recognized limitation of the ACS. Respondents are known to underreport Medicaid coverage, mistakenly reporting that they have direct-purchase coverage, while some respondents report having direct-purchase health insurance when they have only a single-service plan (e.g., dental insurance) but not a comprehensive health plan that covers a broad range of services.[8] That said, no survey data on health insurance are immune from reporting errors, and a nationwide record linkage study has shown that the ACS compares reasonably well to other federal data sources in terms of the false-negative reporting rate for public insurance (the percentage of actual Medicaid enrollees who report other coverage on the survey).[9]

We did not apply any logical edits beyond those provided by the Census Bureau or otherwise attempt to correct ACS survey responses. Instead, to assess whether our estimates might be affected by this misreporting, we compared our ACS estimates with estimates from the NHIS, which is considered the gold-standard data source for accurately identifying the source of health insurance. As discussed later, while we found differences in the baseline levels of coverage by source between the two surveys, we estimated similar adjusted changes between 2013 and 2015 and thus do not have evidence that misreporting in the ACS was responsible for our findings on trends in coverage.

NHIS Questions

Unlike the ACS, measuring the source of health insurance is among the primary functions of the NHIS. The NHIS is primarily administered as an in-person interview and includes extensive follow-up questions and logical editing to improve the accuracy of insurance type responses. We examine the following health insurance categories in the NHIS:

- uninsured (including VA): no insurance or IHS only
- uninsured (excluding VA): uninsured or VA only
- private coverage
  - employer-sponsored coverage
  - direct-purchase coverage
    - Marketplace coverage (2014 and 2015 only)
- Medicaid

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8 Victoria Lynch and Genevieve M. Kenney, "Improving the American Community Survey for Studying Health Insurance Reform," *Tenth Conference on Health Survey Research Methods*, Hyattsville, Md.: National Center for Health Statistics, 2011, pp. 87–94. As of July 25, 2017: http://www.srl.uic.edu/hsrm/hsrm10_proceedings.pdf#page=236

9 Michel H. Boudreaux, Kathleen Thiede Call, Joanna Turner, Brett Fried, and Brett O'Hara, "Measurement Error in Public Health Insurance Reporting in the American Community Survey: Evidence from Record Linkage," *Health Services Research*, Vol. 50, No. 6, 2015, pp. 1973–1995, doi:10.1111/1475-6773.12308.

- TRICARE.

Compared with the ACS, baseline levels of Medicaid and direct-purchase coverage in the NHIS are lower, while levels of uninsurance are higher. (See Table A.2.)

Table A.2. Comparison of ACS and NHIS Sources of Coverage for Nonelderly Veterans (2013)

	Uninsured	Uninsured, Excluding VA Coverage	Medicaid	Private	ESI	Direct Purchase
ACS 2013	9.40% [9.2%, 9.6%]	17.80% [17.5%, 18.1%]	7.07% [6.9%, 7.3%]	64.44% [64.1%, 64.8%]	59.48% [59.1%, 59.9%]	7.69% [7.5%, 7.9%]
NHIS 2013	11.84% [11.1%, 12.6%]	21.29% [20.3%, 22.3%]	3.29% [2.9%, 3.7%]	60.95% [59.8%, 62.1%]	56.29% [55.1%, 57.5%]	2.86% [2.5%, 3.2%]

SOURCES: Authors' calculations, 2013 IPUMS ACS and 2013 NHIS.
NOTES: Table reports unadjusted proportion of nonelderly veterans with each source of coverage as estimated in the 2013 ACS and the 2013 NHIS. 95-percent confidence intervals are in brackets.

Although the NHIS asks respondents about VA coverage, we found that these data severely undercounted even the VA patient population. Only 2.9 million (all-ages) veterans in the 2014 NHIS reported VA coverage, which is a dramatic undercount compared with either the VA enrollee population or the VA patient population. As with the ACS, we were not able to locate cognitive testing or validation studies on the NHIS's VA coverage question. We suspect that the skip patterns in the NHIS health insurance question sequence are poorly suited to identification of VA enrollment or VA patients. Like the ACS, the NHIS asks a general question about health insurance coverage ("What kind of health insurance or health care coverage do you have?") and includes as an option "Military health care (TRICARE/VA/CHAMP-VA [Civilian Health and Medical Program of the Department of Veterans Affairs])." Only respondents who select "military health care" as their response are asked specifically about VA coverage in a follow-up question. NCHS researchers who have examined the military coverage variables on the NHIS agreed that the conceptual difference between VA enrollment, VA use, and more-typical sources of health insurance were likely to explain at least part of the undercount.[10]

In light of these problems, we judged the NHIS to be an unreliable data source for measuring veterans' engagement with VA, and we did not report any NHIS estimates of VA coverage in this study. However, we did compare trends in coverage by source between the NHIS and the ACS. In addition, the NHIS specifically identifies Marketplace coverage (which is not separately identified in the ACS), allowing us to characterize the proportion of nonelderly veterans with Marketplace coverage.

MEPS

The MEPS-HC is designed to be nationally representative of the civilian noninstitutionalized population. In contrast with the cross-sectional data sources we used to analyze insurance status,

[10] Personal communication with Carla Zelaya, NCHS, April 6, 2017.

the panel dimension of the MEPS adds a degree of complexity to the definition of a target population and analysis sample since individuals flow in and out of the civilian noninstitutionalized population over the course of the year. Fortunately, the MEPS provides high-frequency detail on individuals' population status and eligibility for the survey: Individuals in sampled households who are in the civilian noninstitutionalized population at a given point in time are referred to as "in-scope" for the MEPS-HC. The target population for the MEPS-HC consists of individuals who are in-scope at any time during the calendar year; final person weights deliver estimates that are representative for this population.[11] We followed RAND's VA study and defined individuals as eligible for our sample if they had a positive person weight (meaning that they were included in a sampled household at any point during the survey year) (Eibner et al., 2015).

Health insurance coverage estimates from the MEPS are far less precise than those from the NHIS and ACS due to the small sample size of nonelderly veterans, and we did not report them in this study. We did, however, use the health insurance measures in the MEPS to describe how VA use and reliance vary with non-VA insurance status. The MEPS, like the NHIS, contains detailed questions on health insurance and is subject to considerable logical editing. Because the MEPS is a panel survey, health insurance is observed at the monthly level, with individuals classified as having a given type of insurance if they are covered for at least one day in the month. Uninsurance at the monthly level, then, means that an individual was uninsured for the full month; uninsurance at the yearly level means that an individual was continually uninsured for the full year.

In sharp contrast with the ACS and NHIS, the MEPS does not treat VA as a form of health insurance. Instead, the MEPS collects self-reported event histories of health care utilization during the interview reference period (about five months on average). A separate component of the MEPS, the MEPS Medical Provider Component (MPC), involves follow-back interviews with a sample of health care providers identified by the MEPS-HC respondents. The MEPS-MPC collects the amount and source of payment from a sample of medical providers named by the respondent. After an imputation process, the MEPS produces a series of event files with detail on paid amounts for each payer for every medical event reported in the panel. A validation study showed that MEPS respondents recalled inpatient stays accurately but underreported emergency department visits and office-based visits.[12] Even so, the MEPS is unique as a nationwide data source combining all-payer health care utilization, health insurance status, and veteran status.

Rather than attempting to identify *VA enrollees* or a concept of *VA coverage* comparable to the ACS, we used the MEPS to identify *VA patients* based on their use of VA care in a given

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[11] The MEPS universe does not include persons who were previously out of scope and who either form new households or who enter existing households where they are unrelated to any individuals in the MEPS universe. As a consequence, the MEPS-HC is likely to undercount newly separated veterans.

[12] Samuel H. Zuvekas and Gary L. Olin, "Validating Household Reports of Health Care Use in the Medical Expenditure Panel Survey," *Health Services Research*, Vol. 44, No. 5, Part 1, 2009, pp. 1679–1700, doi:10.1111/j.1475-6773.2009.00995.x.

calendar year. VA patient status is defined using annual expenditure variables from the Full-Year Consolidated Data File: Veterans are classified as VA patients if they had any health care or prescriptions paid for by VA during the calendar year.

Characteristics of the Nonelderly Veteran Population

This report presents adjusted differences between coverage levels in 2013 and 2015 for nonelderly veterans. Seven in eight veterans are male, and veterans are older on average (48 years old in 2015) than other nonelderly adults. Most veterans are white and non-Hispanic; nearly half have incomes above 400 percent of the federal poverty level (FPL) (which is the level at which eligibility for exchange subsidies ends). However, nearly 40 percent of nonelderly veterans would become eligible for the ACA's advance premium tax credits, while 14 percent had incomes below 138 percent of the FPL and so fell into the income range targeted by Medicaid expansion. (See Table A.3.)

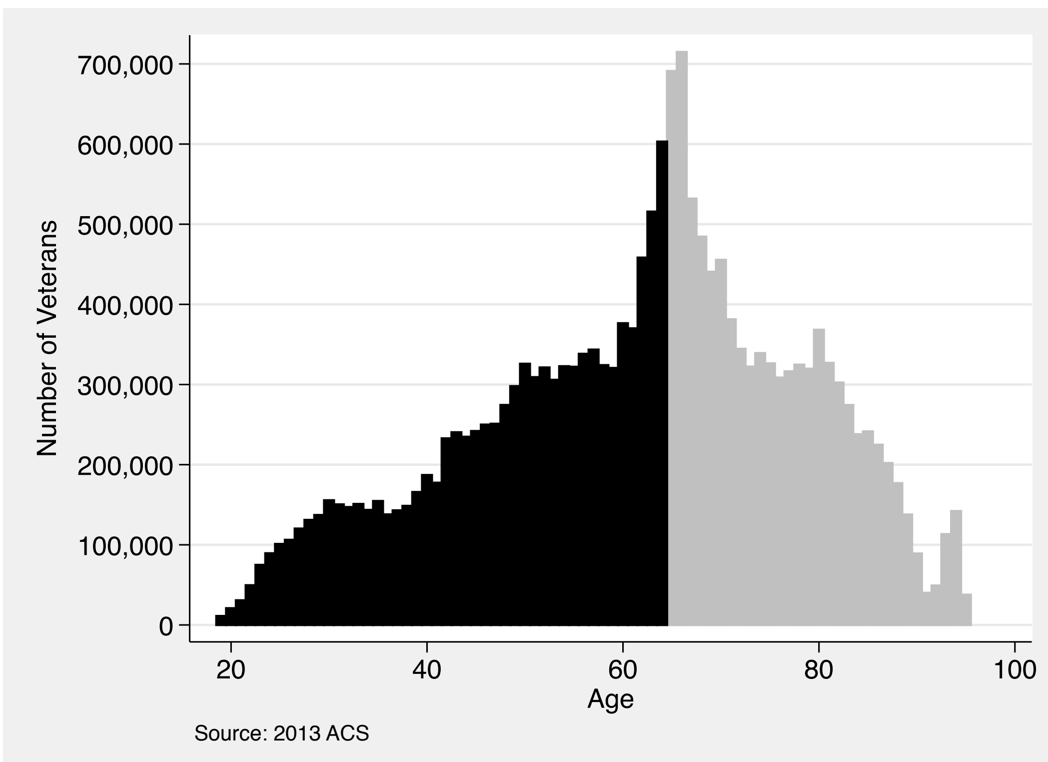
Table A.3. Characteristics of Nonelderly Veterans (2013–2015)

	Year		
	2013	**2014**	**2015**
Basic demographics			
Female	12.6%	13.3%	13.8%
Age (years)	48.7	48.1	47.9
Race/ethnicity			
White, non-Hispanic	72.0%	71.2%	70.0%
Black, non-Hispanic	15.2%	15.4%	15.8%
Other non-Hispanic	4.7%	5.0%	5.2%
White, Hispanic	5.6%	5.9%	6.4%
Other Hispanic	2.5%	2.5%	2.7%
Income range			
0%–138% FPL	14.2%	14.1%	13.9%
139%–250% FPL	17.1%	17.0%	16.3%
251%–400% FPL	23.3%	22.9%	22.8%
> 400% FPL	45.4%	46.0%	47.1%
Service era			
Post-9/11 era	26.5%	29.8%	32.8%
Gulf War	22.9%	24.1%	24.7%
Post-Vietnam and pre–Gulf War	28.6%	28.4%	29.0%
Vietnam and earlier	21.9%	17.7%	13.5%
Number of unweighted observations (ACS)	103,984	98,328	94,267

SOURCE: Authors' calculations, 2013–2015 IPUMS ACS.

Figure A.1 presents the age distribution of veterans as of 2013. The spike in the middle represents the Vietnam-era veterans: As the ACA was about to be implemented, large numbers of Vietnam-era veterans were aging into Medicare eligibility and out of our sample. Table A.3 shows that the proportion of nonelderly veterans who separated in the Vietnam era fell by nearly half, from 22 percent of nonelderly veterans in 2013 to 13.5 percent in 2015. The aging out of the Vietnam-era veterans largely explains why the average age among nonelderly veterans fell between 2013 and 2015 and why the racial and ethnic composition of the population shifted away from white non-Hispanics. These shifts in age and service era are a potentially important confounding factor for the implementation of the ACA in 2014. Younger adults and nonwhite or Hispanic adults typically have lower levels of insurance coverage. Apart from age, the different military experiences of post-9/11 veterans and other factors, such as the transition from conscription to an all-volunteer military at the end of the Vietnam era, are likely to make the younger veterans who are becoming more numerous over time very different from the older veterans who were aging out of our sample.

Figure A.1. Age Distribution of Veterans (2013)



NOTES: The number of veterans reflects ACS person weights and not the VetPop benchmark. The nonelderly veteran population is shaded in black; the elderly population is shaded in light gray.

Methods for ACS Coverage Analysis

To produce adjusted estimates of the change in insurance status after 2014, we estimated logistic regressions for insurance coverage that controlled for a full set of indicator variables for single years of age and service era (Vietnam-era, post-Vietnam and pre-9/11, and post-9/11) as well as an indicator for white non-Hispanic race/ethnicity and full interactions between female gender and age greater than or equal to 50.

Table A.4 shows adjusted baseline levels and differences between 2013 and 2015. Adjusted quantities for 2013 and 2015 are defined by setting the 2015 time effect to zero (for 2013) or one (for 2015) and taking average values of the individual predicted values for the 2015 sample of veterans. These adjusted quantities should thus be interpreted as reflecting the change in coverage that would have been observed if the 2013 nonelderly veteran population were identical to the 2015 nonelderly veteran population in terms of age, race/ethnicity, gender, and service era. Table A.6 presents regression estimates underlying Figure 3.2 in the main report (available online at www.rand.org/t/RR1955).

For reference, Table A.5 shows unadjusted levels of insurance coverage by source in the ACS and tests the significance of changes between the 2013 baseline and the levels observed in 2014 and 2015. Comparison to Table A.4, which shows adjusted estimates, indicates that adjusting for age, race/ethnicity, gender, and service era had little impact on the sign and significance of our estimated changes in coverage. Because younger adults are less likely to have insurance coverage, an increase in ESI that was insignificant in the raw data became significant after regression adjustment; other estimates of the change in coverage between 2013 and 2015 changed by only a few tenths of a percentage point.

Table A.4. Uninsurance and Coverage by Source for Nonelderly Veterans, Adjusted for Age, Race/Ethnicity, Gender, and Service Era (ACS)

	Uninsured	Uninsured, Excluding VA Coverage	Medicaid	VA	Private	Private: ESI	Private: Direct Purchase
2013	9.1%	17.2%	6.7%	27.8%	63.5%	58.8%	7.5%
	[8.84%, 9.33%]	[16.87%, 17.50%]	[6.54%, 6.93%]	[27.44%, 28.15%]	[63.06%, 63.86%]	[58.40%, 59.21%]	[7.28%, 7.67%]
2015	5.8%	13.9%	9.3%	29.1%	65.8%	59.6%	8.7%
	[5.58%, 6.01%]	[13.60%, 14.22%]	[9.06%, 9.54%]	[28.68%, 29.43%]	[65.41%, 66.22%]	[59.17%, 59.99%]	[8.50%, 8.94%]
Difference	–3.3%	–3.3%	2.6%	1.3%	2.4%	0.8%	1.2%
	[–3.61%, –2.96%]	[–3.72%, –2.83%]	[2.23%, 2.88%]	[0.75%, 1.78%]	[1.79%, 2.92%]	[0.02%, 1.35%]	[0.95%, 1.54%]
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	0.008	< 0.001

SOURCE: Authors' calculations, 2013–2015 IPUMS ACS.
NOTE: Person weights and survey design variables were used for inference. 95-percent confidence intervals are in brackets.

Table A.5. Unadjusted Coverage and Changes in Coverage for Nonelderly Veterans, 2013–2015 ACS

	Uninsured	Uninsured, Excluding VA Coverage	Medicaid	Private Coverage	ESI	Direct Purchase
2013 baseline	9.4%	17.8%	7.1%	64.4%	59.5%	7.7%
	[9.2%, 9.6%]	[17.5%, 18.1%]	[6.9%, 7.3%]	[64.0%, 64.8%]	[59.1%, 59.9%]	[7.5%, 7.9%]
2015 vs. 2013	–3.6%***	–3.9%***	2.2%***	1.4%***	0.1%	1.0%***
	[–3.9%, –3.3%]	[–4.3%, –3.4%]	[1.9%, 2.5%]	[0.8%, 1.9%]	[–0.5%, 0.7%]	[0.7%, 1.3%]

SOURCE: Authors' calculations, 2013–2015 IPUMS ACS.
NOTE: Person weights and survey design variables were used for inference. 95-percent confidence intervals are in brackets.

Table A.6. Change in VA Coverage, Adjusted by Age, Race/Ethnicity, Gender, and Service Era

		Non-VA Insurance Status for VA-Covered Veterans		
	VA Coverage	VA Only	VA and Medicaid	VA and Private
2013	27.8%	29.2%	9.2%	48.1%
	[27.44%, 28.15%]	[28.51%, 29.89%]	[8.79%, 9.60%]	[47.37%, 48.86%]
2015	29.1%	27.9%	11.9%	47.7%
	[28.68%, 29.43%]	[27.21%, 28.62%]	[11.42%, 12.34%]	[46.97%, 48.47%]
Difference	1.3%	–1.3%	2.7%	–0.4%
	[0.75%, 1.78%]	[–2.27%, –0.29%]	[2.07%, 3.30%]	[–1.45%, 0.65%]
p-value	< 0.001	0.011	< 0.001	0.456

SOURCE: Authors' calculations, 2013–2015 IPUMS ACS.
NOTE: Person weights and survey design variables were used for inference. 95-percent confidence intervals are in brackets.

NHIS Coverage Estimates

Table A.7 presents adjusted estimates for non-VA insurance coverage from the NHIS using the same logistic regression specification that we used in the ACS. The NHIS shows broadly similar decreases to the ACS in uninsurance and in non-VA uninsurance among nonelderly veterans after adjusting for age, race/ethnicity, gender, and service era. As in the ACS, Medicaid and direct-purchase coverage account for the majority of the observed reduction in uninsurance among nonelderly veterans. Adjusted changes in ESI and overall private coverage are not statistically different from zero in the NHIS, but these estimates are not very precise and do not rule out the changes in coverage estimated in the ACS. Because, as discussed previously, the NHIS does not accurately capture VA coverage, we were not able to compare our ACS estimates of increased VA coverage.

Marketplace coverage was defined only in 2014 and later years, and so we report the level of Marketplace coverage rather than the change; the estimate of Marketplace coverage is not adjusted for covariates. Table A.8 presents unadjusted levels of Marketplace coverage by service era. We found that Marketplace coverage was higher for older veteran groups, ranging from 1.1 percent for post-9/11 veterans to 4.7 percent for Vietnam-era veterans.

Table A.7. Changes in Uninsurance and Coverage by Source for Nonelderly Veterans, Adjusted for Age, Race/Ethnicity, Gender, and Service Era (NHIS)

	Uninsured	Uninsured, Excluding VA Coverage	Medicaid	Private Coverage	ESI	Direct Purchase	Marketplace†
2015 vs. 2013	–4.5%***	–3.6%***	2.9%***	0.5%	–1.3%	2.0%***	2.4%***
	[–5.8%, –3.3%]	[–5.4%, –1.8%]	[1.8%, 4.0%]	[–2.0%, 3.0%]	[–3.7%, 1.2%]	[1.1%, 2.9%]	[1.9%, 3.0%]

SOURCE: Authors' calculations, 2013–2015 NHIS.
NOTES: Final person weights and survey design variables were used for inference. 95-percent confidence intervals are in brackets.
† Marketplace coverage was not defined in 2013, so this estimate represents the unadjusted proportion of nonelderly veterans with marketplace coverage in 2015.

Table A.8. Nonelderly Veterans with Marketplace Coverage by Service Era (2015)

	Proportion of Veterans
Post-9/11	1.1%***
	[0.4%, 1.8%]
Gulf War	3.4%***
	[1.9%, 4.9%]
Post-Vietnam, pre–Gulf War	2.1%***
	[1.0%, 3.1%]
Vietnam era	4.7%***
	[2.3%, 7.0%]

SOURCE: Authors' calculations, 2015 NHIS.
NOTES: Final person weights and survey design variables were used for inference. 95-percent confidence intervals are in brackets.

Analysis of Medicaid Expansion in the ACS

We estimated the effect of state Medicaid expansion decisions on coverage using a differences-in-differences approach that treats nonelderly veterans in states that did not implement the ACA Medicaid expansion (*nonexpansion states*) as a control group for nonelderly veterans in states that had implemented the expansion in 2015 or earlier (*expansion states*). As before, we used logistic regressions that control for age, race/ethnicity, gender, and service era in addition to calendar year effects and state fixed effects. The variable of primary interest is a differences-in-differences treatment indicator equal to one in expansion states in the year 2015 and zero otherwise. We included a similar differences-in-differences treatment indicator for the year 2014 so that the year 2015 treatment indicator captured the difference between 2015 and the

2013 baseline. Because this model relies on state identifiers, we could not estimate it in the NHIS.

We reported average marginal effects for the 2015 Medicaid expansion treatment variable where the average effect was calculated for all veterans in 2015. This isolates the effect of Medicaid expansion decisions (relative to coverage levels observed in the nonexpansion states), holding state effects, time effects, age, race/ethnicity, gender, and service era constant. We note that our analysis is limited to the most recently available ACS data and that estimates including the 2016 ACS or later years may be better able to capture the long-run effects of Medicaid expansion on insurance coverage.

Because the ACS does not report interview dates, we used Medicaid expansion status as of July 1, 2015, to classify states as expansion or nonexpansion when analyzing 2015 ACS data. Three states (Montana, Alaska, and Louisiana) implemented the Medicaid expansion between July 1, 2015, and the time of our analysis (August 2017): Medicaid expansion in Montana and Louisiana did not take effect until 2016, while Alaska's Medicaid expansion took effect on September 1, 2015. We used pre-ACA income limits to impute Medicaid eligibility in these states, and these states are treated as nonexpansion states in our empirical analysis of ACS data. When modeling the state-specific impact of ACA repeal, however, we treated Louisiana as an expansion state when assigning the change in non-VA uninsurance, effectively assuming that the uninsurance rate for nonelderly veterans in Louisiana will more closely resemble other Medicaid expansion states than other nonexpansion states by 2020. We did not produce state-specific estimates for Montana or Alaska due to the small number of nonelderly veterans in our ACS samples for those states.

Table A.9 reports differences-in-differences effects of Medicaid expansion on VA coverage and VA dual enrollment. We did not find evidence that Medicaid expansion reduced VA coverage. However, we did find that Medicaid expansion led to a significant reduction in the proportion of veterans with only VA coverage, a change that was mirrored by a corresponding increase in the share of veterans with VA coverage and Medicaid. These patterns were much more pronounced among the sample of families with income below 138 percent of the FPL.

Table A.9. Effects of Medicaid Expansion (Differences-in-Differences) on VA Coverage and Dual Enrollment

	VA Coverage	VA Only	VA and Medicaid	VA and Private
All nonelderly veterans				
2015 Medicaid expansion effect	0.05%	–0.9%**	0.8%***	0.1%
	[–0.9%, 1.0%]	[–1.6%, –0.2%]	[–0.4%, 1.2%]	[–0.5%, 0.6%]
Veterans with family income ≤ 138% FPL				
2015 Medicaid expansion effect	–1.6%	–3.5%***	2.4%***	–0.9%
	[–5.2%, 2.0%]	[–6.2%, –0.9%]	[0.6%, 4.2%]	[–2.2%, 0.4%]

SOURCE: Authors' calculations, 2013–2015 IPUMS ACS.
NOTES: This table reports marginal effects of state Medicaid expansion from logistic regressions controlling for service era, age, state fixed effects, and year fixed effects. VA-only and VA dual enrollment regressions were estimated for the full sample (i.e., they were not limited to the subsample with VA coverage). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 95-percent confidence intervals are in brackets.

To examine whether increases in Medicaid coverage were driven by newly eligible or previously eligible veterans, we imputed Medicaid eligibility on the basis of family structure and income variables reported in the ACS. We used the State Health Access Data Assistance Center–created health insurance unit (HIU) variables on the IPUMS ACS to calculate the poverty ratio for veterans at the HIU level. We classified veterans as parents if there were any children age 18 or younger in the HIU. A small number of children age 18 or younger are identified as the head of household in the ACS. Heads of household age 18 or younger are not counted as children unless their father or mother lives in the household; we also classified children age 18 or younger who were married to the head of household as adults.

To impute pre-ACA eligibility, we compared the HIU-level poverty ratio with the upper income limit reported for the applicable family type (parents or childless adults) in each state's modified adjusted gross income (MAGI) conversion plans. In theory, the MAGI income limits calculated for 2013 were intended to approximate the population-wide eligibility rate achieved under the states' pre-ACA eligibility procedures. To the extent that this is true, the MAGI conversion income limits can be used to approximate the states' Medicaid eligibility determinations using data on total family income without attempting to replicate the states' more complex pre-ACA income counting rules. Additional discussion of the MAGI income limits is documented in a previous RAND study on the ACA Medicaid expansion.[13] In addition to imputing income-based eligibility, veterans receiving Supplemental Security Income are coded as Medicaid-eligible in all years, abstracting from state differences in the income limit for SSI. (See Table A.10.)

[13] Michael Dworsky and Christine Eibner, *The Effect of the 2014 Medicaid Expansion on Insurance Coverage for Newly Eligible Childless Adults*, Santa Monica, Calif.: RAND Corporation, RR-1736-RWJ, 2016. As of July 25, 2017: http://www.rand.org/pubs/research_reports/RR1736.html

Table A.10. Medicaid Eligibility of Nonelderly Veterans by 2015 State Expansion Status

	All States	Expansion States	Nonexpansion States
HIU income < 138% FPL	17.82%	17.78%	17.86%
Received SSI income	2.78%	3.05%	2.49%
Medicaid-eligible in 2015	11.92%	19.22%	3.95%
Previously eligible	6.91%	10.00%	3.53%
Newly eligible	5.01%	9.22%	0.43%

SOURCE: Authors' calculations, 2013–2015 IPUMS ACS.

As discussed in the main report, Medicaid eligibility among nonelderly veterans nearly doubled between 2013 and 2015 in Medicaid expansion states. While only about 14 percent of nonelderly veterans had family income below 138 percent of the FPL, a larger share of HIUs had income low enough to qualify for Medicaid. Estimates that focus on the subsample of veterans below 138 percent of the FPL should be interpreted as capturing a group more likely to be exposed to the Medicaid expansion but not necessarily capturing the entire Medicaid expansion population.

We note that there was also a slight increase in eligibility in the nonexpansion states. Eligibility for comprehensive Medicaid benefits in nonexpansion states was largely limited to parents and caretakers of dependent children and generally did not change by much in 2014. However, the reopening of Wisconsin's Badgercare program to new enrollees effectively expanded Medicaid eligibility to childless adults with incomes up to 100 percent of the FPL. Our imputation also accounts for the addition of a 5-percent standard disregard (applied in 2014) implemented under the ACA, which marginally increased the Medicaid income limit for existing eligibility groups in nonexpansion states.

We then stratified the sample by state expansion status and used logistic regression to estimate adjusted changes in coverage between 2013 and 2015 for previously eligible and newly eligible veterans. The models controlled for eligibility group (previously or newly eligible) and interactions between newly eligible and separate year indicators for 2014 and 2015, in addition to age, race/ethnicity, gender, and service-era controls and state and year fixed effects. This specification allowed us to test for differences in coverage changes between the newly and previously eligible subgroups. (We estimated the same model in nonexpansion states, but the coefficients for newly eligible adults were imprecisely estimated due to the very small change in eligibility for nonexpansion states, and we do not report them here.)

Table A.11 reports marginal effects from these models, which underlie our discussion in the text of changes for previously and newly eligible adults. We note that the estimates of coverage changes for newly and previously eligible adults in this table represent before-after changes in coverage, rather than differences-in-differences estimates that leverage cross-state differences in Medicaid expansion decisions. The reported difference in before-after changes between newly and previously eligible adults could be viewed as a differences-in-differences estimate, but it compares changes between groups of Medicaid-eligible adults in expansion states and thus is not comparable to estimates of differences-in-differences Medicaid expansion effects elsewhere in this report.

Table A.11. Changes in Coverage by State Expansion Status and Pre-ACA Medicaid Eligibility (2013–2015)

	Uninsured	Uninsured, Excluding VA	Medicaid	Private Coverage	VA Coverage
Expansion states					
Newly eligible	–11.77%	–15.82%	14.45%	2.21%	–0.25%
	[–13.9%, –9.7%]	[–18.4%, –13.2%]	[12.2%, 16.7%]	[–0.3%, 4.7%]	[–2.7%, 2.3%]
Previously eligible	–7.63%	–9.48%	10.26%	2.23%	1.08%
	[–9.2%, –6.0%]	[–11.7%, –7.3%]	[7.8%, 12.7%]	[0.1%, 4.6%]	[–1.3%, 3.5%]
Difference (newly eligible minus previously eligible)	–4.10%	–6.30%	4.20%	0.02%	–1.32%
	[–6.8%, –1.5%]	[–9.7%, –3.0%]	[0.9%, 7.5%]	[–3.5%, 3.4%]	[–4.7%, 2.2%]
Nonexpansion states					
Previously eligible	–3.32%	–4.70%	4.80%	3.68%	1.04%
	[–6.1%, –0.5%]	[–8.0%, –1.3%]	[0.7%, 8.9%]	[–0.9%, 8.1%]	[–3.3%, 5.4%]

SOURCE: Authors’ calculations, 2013–2015 IPUMS ACS.

Changes in Insurance by Priority Group

The priority group system determines eligibility and level of cost-sharing for VA health care services based on veterans’ service-connected disability rating, income, and other factors. Using the ACS data, we used a priority group–sorting algorithm previously developed by RAND to categorize nonelderly veteran ACS respondents into VA enrollment priority groups. Many of the factors used to determine priority group are directly measured in the ACS, including service-connected disability rating, VA health service use, family and household income, family and household size, individual income, area of residence, and Medicaid use. Using the 2013, 2014, and 2015 ACS data and demographic adjustment factors drawn from VA administrative records, the algorithm assigns a priority group to each veteran eligible for priority group assignment that mimics that veteran’s likely priority group assignment if he or she enrolled in VA. Generally, all veterans with two or more years of service who are discharged as honorable, general, or uncharacterized can be assigned to a priority group, although only those assigned to priority groups 1–8d are eligible to use VA services, with exceptions made under certain conditions for veterans assigned to priority group 8e.

The algorithm is applied on an inflated count of veterans captured by the ACS, using a set of frequency weights developed to correct misreporting by respondents and limitations of the ACS in reaching individuals not living in housing units or group quarters. In the first step, the algorithm sequentially sorts veterans into potential priority groups based on disability rating, household income, family size, and area of residence. In the second step, the algorithm reassigns unassigned veterans who reported VA coverage to priority groups 1–5 in accordance with actuarial adjustments used to match administrative benchmarks for VA patient counts in each category. The algorithm then assigns remaining veterans to priority groups 6–8 status, using both self-reported data and actuarial adjustments. Because discharge condition is not observed in the

ACS, our actuarial adjustments incorporated previously reported Department of Defense estimates that about 94 percent of veterans discharged between 2000 and 2013 had an other-than-dishonorable discharge. Further details on this algorithm are presented in Appendix D of Eibner et al. (2015). Administrative benchmarks and income limits used in the original development of this algorithm were updated for 2014 and 2015 data using information from the VA website.[14]

As a validation exercise, Table A.12 compares the results of the priority group–sorting algorithm for all-ages veterans with VA coverage to administrative estimates reported for VA patients by NCVAS for fiscal year 2014. The reasonably close correspondence between the two distributions shows that the priority group–sorting algorithm was successfully calibrated and produces a distribution similar to that reported by VA. We do note that the use of actuarial adjustments may lead to biased estimates of averages by priority group. In general, classification errors arising from randomly assigning veterans to priority groups will bias priority group averages toward the population-wide average and will bias differences between groups toward zero.

Table A.12. Comparison of RAND-Imputed ACS Priority Groups to VA Administrative Estimates

	Proportion of 2014 VA Patients	
Priority Group	**NCVAS**	**ACS (RAND Algorithm)**
1	27.3%	26.5%
2	8.4%	8.1%
3	12.7%	12.4%
4	3.3%	1.7%
5	22.5%	21.9%
6	4.7%	5.1%
7	3.0%	3.3%
8a–8d	17.8%	20.4%
8e, 8g users	0.4%	0.5%

SOURCE: Authors' calculations, 2014 ACS and Department of Veterans Affairs, Veterans Health Administration Office of Policy and Planning, "Number of Veteran Patients by Healthcare Priority Group: FY2000 to FY2014," last updated June 18, 2015. As of September 5, 2017: https://www.va.gov/vetdata/docs/Utilization/Number_of_Veteran_Patients_by_HC_Priority_Groups_2000_2014.xls
NOTE: This table includes all-ages VA patients, including institutionalized patients.

[14] Annual geographic means thresholds for priority groups 7–8 were obtained from the VA website. For example, 2014 geographic means thresholds for priority group 7 are available from U.S. Department of Veterans Affairs, "2014 GMT Tables Priority Group Level 7," undated. As of September 5, 2017: http://nationalincomelimits.vaftl.us/LegacyGMTThresholds/?FiscalYear=2014&PGLevel=7

Counts of VA patients by priority group were obtained from the National Center for Veterans Analysis and Statistics: Department of Veterans Affairs, Veterans Health Administration Office of Policy and Planning, "Number of Veteran Patients by Healthcare Priority Group: FY2000 to FY2014," last updated June 18, 2015. As of September 5, 2017:
https://www.va.gov/vetdata/docs/Utilization/Number_of_Veteran_Patients_by_HC_Priority_Groups_2000_2014.xls

Table A.13 presents the distribution of nonelderly veterans across the priority group categories discussed in the text.

Table A.13. Nonelderly Veterans by Potential Priority Group, 2015

Group Name	Priority Groups	Nonelderly Veterans (2015)	Proportion of Nonelderly Veterans
High priority, service-connected disability	1–4, 6	3,421,839	29.8%
High priority, low income	5	1,871,677	16.3%
Low priority	7–8d	1,228,647	10.7%
Ineligible veterans	8e, 8g, and other ineligible	4,960,519	43.2%

SOURCE: Authors' calculations, 2015 ACS.
NOTE: This table classifies nonelderly, noninstitutionalized veterans by potential priority group based on information reported in the ACS.

Distance from VA Facilities

As mentioned in the main report, the lowest level of geography reported in the ACS public-use microdata samples is substate areas containing roughly 100,000 to 200,000 people known as Public Use Microdata Areas (PUMAs). There are more than 2,000 PUMAs in the United States. RAND obtained geocodes for all VA Medical Centers (VAMCs) (140 VAMCs) and outpatient facilities (761 community-based outpatient clinics [CBOCs] and 180 outpatient clinics) and calculated the distance from the centroid (i.e., the geographic center) of each PUMA to the nearest VAMC and the nearest outpatient clinic. We note that this is a rough approximation to the distance between individual veterans and VA facilities since veterans are distributed broadly throughout PUMAs rather than living at the centroid.

We originally defined *high-distance veterans* as those in PUMAs with centroids more than 40 miles from the nearest VAMC *and* more than 40 miles from the nearest CBOC. The 40-mile threshold was chosen to match the definitions used in the VA Choice Act of 2014.[15] However, just under 5 percent of veterans live in such PUMAs, and the resulting estimates were too imprecise to draw meaningful conclusions. Instead, we used a broader definition of *high-distance veterans*, which included veterans living in PUMAs with centroids more than the median distance to a VAMC (greater than 12 miles) *and* more than the median distance to an outpatient facility (more than 25 miles).

We were interested in comparing the experiences of high-distance veterans and low-distance veterans. Nationwide changes between 2013 and 2015 were not significantly different for these two groups, and we do not report them here. However, we also hypothesized that the Medicaid expansion might result in larger changes in non-VA coverage (and, potentially, in VA coverage) for high-distance veterans, on the assumption that these veterans find it more costly to access VA care due to higher travel times. We thus estimated a logistic regression using a triple-difference specification allowing the effect of the Medicaid expansion to differ freely between high-income

[15] Veterans Access, Choice, and Accountability Act of 2014, Public Law 113-146.

and low-income veterans while controlling for all two-way interactions between state, distance to VA facility, and time (in addition to age, race/ethnicity, gender, and service era). We calculated the marginal effect of Medicaid expansion for low-distance and high-distance veterans using the 2015 sample of veterans. The significance of the difference in Medicaid expansion effects between the two groups was assessed with a t-test for the coefficient on the interaction term between Medicaid expansion, 2015, and high distance. Table A.14 presents estimates of this model for the sample of low-income veterans with family income below 138 percent of the FPL.

Table A.14. Effect of Medicaid Expansion by Distance from VA Facilities, Nonelderly Veterans with Income ≤ 138% FPL

	Uninsured	Uninsured, Excluding VA	Medicaid	VA	VA-Enrolled with Medicaid
Low distance	–3.72%	–5.72%	7.06%	–0.44%	2.62%
	[–5.86%, –1.59%]	[–8.52%, –2.91%]	[3.66%, 10.46%]	[–4.13%, 3.25%]	[0.76%, 4.49%]
High distance	–6.15%	–11.31%	12.21%	–4.01%	2.01%
	[–8.75%, –3.55%]	[–14.40%, –8.21%]	[8.66%, 15.76%]	[–8.53%, 0.50%]	[–0.13%, 4.15%]
Difference in Medicaid expansion effects	–2.42%	–5.60%***	5.15%***	–3.57%**	–0.62%
	[–5.03%, 0.48%]	[–8.36%, –2.83%]	[2.01%, 8.30%]	[–7.08%, –0.06%]	[–2.11%, 0.88%]
p-value of difference	0.17	< 0.01	< 0.01	0.07	0.73

NOTES: Veterans are “high-distance” if they live in a PUMA with centroid above the median distance from the nearest VAMC (> 25 miles) and the nearest CBOC (> 12 miles).
Table reports logistic regression marginal effects of 2015 × Medicaid expansion state interaction term.
The model allows separate Medicaid expansion effects for low-distance and high-distance veterans.
The model controls for age, service era, and year fixed effects; state interacted with distance from VA; and distance from VA interacted with year.
p-values for difference are based on the interaction coefficient for Medicaid expansion state × 2015 × high-distance.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Preexisting Conditions

We replicated an algorithm developed by researchers at the Kaiser Family Foundation (KFF) for identifying NHIS respondents likely to face difficulty in obtaining nongroup insurance in a market with medical underwriting.[16] The KFF researchers drew on past research and conducted a review of insurance underwriting manuals from the pre-ACA individual market to identify a list of medical conditions (e.g., diabetes) and personal characteristics (e.g., severe obesity) likely to result in denial of coverage or other unfavorable underwriting outcomes. They then identified 24 of these conditions in the NHIS (primarily on the Sample Adult questionnaire, which is a more detailed survey administered to one randomly chosen adult per household) and estimated that at

[16] Gary Claxton, Cynthia Cox, Anthony Damico, Larry Levitt, and Karen Pollitz, “Pre-Existing Conditions and Medical Underwriting in the Individual Insurance Market Prior to the ACA,” Menlo Park, Calif.: Kaiser Family Foundation, 2016.

least 27 percent of the nonelderly adult population in 2015 had a declinable preexisting condition; the algorithm likely represents a lower bound since the NHIS only asks about a specified set of health problems. (See Table A.15.)

Table A.15. Prevalence of Declinable Preexisting Conditions Among Nonelderly Veterans (2015)

Percentage with Declinable Preexisting Conditions	Veterans	Nonveterans	Difference (Veterans Minus Nonveterans)
Unadjusted	34.47%	27.24%	7.23%
Adjusted (at population average age/gender distribution)	31.06%	27.43%	3.63%

SOURCE: Authors' calculations, 2015 NHIS.

We programmed this algorithm, replicated Kaiser's estimate as a programming check, and then compared the prevalence of declinable preexisting conditions between veterans and the general population. These results are presented in Table A.16. We used logistic regression with controls for age and gender to obtain a more meaningful comparison between veterans and nonveterans but still found that veterans are significantly and meaningfully (4 percentage points, or roughly 10 percent) more likely than nonveterans to have a declinable preexisting condition. This is not surprising in light of previous research indicating higher morbidity among veterans than among comparable nonveterans (Eibner et al., 2015).

Table A.16. Sources of Insurance by Declinable Preexisting Condition Status, Nonelderly Veterans (2015)

Non-VA Insurance Status (2015)	Declinable Condition	No Declinable Conditions	*p*-value
Uninsured (including VA)	5.58%	6.69%	0.49
Medicaid	9.91%	5.42%	0.017**
Private coverage	48.38%	60.92%	0.001***
ESI	42.97%	54.35%	0.047**
Marketplace coverage	1.75%	3.52%	0.1422

SOURCE: Authors' calculations, 2015 NHIS.
NOTES: Table reports unadjusted proportion of nonelderly veterans with insurance from each source by declinable preexisting status. Statistical significance of difference in coverage rates between veterans with and without preexisting conditions assessed using a chi-squared test. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also compared insurance status between veterans with and without declinable preexisting conditions to gain further insight into the potential exposure of each group to medical underwriting in the event of ACA repeal. We found no significant differences in uninsurance between the two groups, but we found that those with declinable preexisting conditions were significantly less likely to have ESI and were significantly more likely to have Medicaid coverage. There was no significant difference between the groups in the proportion with Marketplace coverage.

Measurement of Health Care Utilization in the MEPS

As discussed above, the MEPS-HC comprises a number of Event Files that contain each respondent's detailed history of health care utilization over the two-year panel. Because each event has detailed and accurate information on payments by all payers and, for certain events, the place of service, the MEPS can be used to measure the quantity of care consumed within and outside the VA system in a number of categories. The VA study by Eibner et al. (2015) carried out an extensive analysis of patterns of VA use and VA reliance, and we adopted those methods in defining outcome variables and coding the Event Files.

VA use is defined as receipt of care provided in a VA facility or paid for by VA. We examined binary measures of any VA use as well as the average number of events paid for by VA or occurring at a VA facility in three categories that were studied by Eibner et al. (2015):

- office-based visits
- inpatient surgery
- prescription drugs.

To avoid the complexity of assigning uniform prices to VA and non-VA care, we chose not to analyze costs or expenditures and instead focused on visit counts or prescription counts—i.e., the number of VA-paid events in a given span of time. In each of these event categories, we also examined all-payer use of care (including VA care). Table A.17 presents descriptive statistics characterizing the distribution of nonelderly veterans' VA and total health care use as measured in the 2008–2014 MEPS. Many nonelderly veterans use no health care in the specified categories in the average year: The proportions of nonelderly veterans with any health care use in an average year are 76.4 percent for office-based visits, 70.9 percent for prescription drugs, and 4.3 percent for inpatient surgery.

We estimate that 30 percent of nonelderly veterans use VA care at least once or have at least one prescription dispensed by VA in an average year. The proportion of nonelderly veterans using VA care was 25.2 percent for office-based visits, 14.6 percent for prescription drugs, and 1.4 percent for inpatient surgery. We note that, because the MEPS does not allow us to observe VA enrollment or eligibility, our analysis of VA use in the MEPS is limited to examining patterns of use among all nonelderly veterans rather than focusing on VA enrollees. Finally, it is worth recalling that the population of veterans identified in the MEPS may differ from the population of veterans captured in the ACS and NHIS; the MEPS asks respondents if they have ever been honorably discharged from active duty, whereas the ACS and NHIS do not ask about discharge condition. It is possible that our MEPS estimates slightly overestimate VA use for the full population of veterans with any discharge condition. Unfortunately, we are not aware of another nationally representative data source with high-quality data on VA use that would allow us to determine how large an issue this is likely to be.

Table A.17. Detailed Summary Statistics on VA and Total Health Care Use, All Nonelderly Veterans, 2008–2014 MEPS

	Proportion with Any Use in Year	Average Annual Use	Standard Deviation	Skewness	25th Percentile	Median	75th Percentile	Maximum
Office-Based Visits								
VA	25.2%	1.125	4.426	14.540	0	0	1	159
	[23.7%, 26.7%]	[0.991, 1.259]						
Total	76.4%	5.453	9.788	5.426	1	2	6	186
	[74.9%, 77.9%]	[5.120, 5.787]						
Inpatient Surgery								
VA	1.4%	0.016	0.140	9.714	0	0	0	2
	[1.0%, 1.8%]	[0.011, 0.021]						
Total	4.3%	0.050	0.257	6.087	0	0	0	3
	[3.7%, 4.9%]	[0.042, 0.059]						
Prescription Drugs								
VA	14.6%	3.095	13.451	7.974	0	0	0	228
	[13.2%, 16.0%]	[2.513, 3.678]						
Total	70.9%	14.309	23.729	3.187	0	5	18	231
	[69.2%, 72.5%]	[13.299, 15.320]						
VA Patient (Any VA Care or Prescriptions)								
VA	31.10%							
	[29.38%, 32.72%]							

SOURCE: Authors' calculations, 2008–2014 MEPS-HC Full-Year Consolidated Files and Event Files.
NOTES: Unweighted *N* = 6,502. All calculations use MEPS person-level weights rescaled so that the nonelderly veteran population in each year from 2008 to 2014 is equally weighted in all calculations. 95-percent confidence intervals are calculated using MEPS survey design variables.

Table A.17 also reports detailed distributional statistics on the annual count of health care events per nonelderly veteran. As is typical of data on health care utilization, these data are fairly skewed. Because our analysis includes nonenrolled veterans, our data are also characterized by a large proportion of zero counts. As we will discuss, we used count regression models to adjust utilization measures for insurance status and other individual characteristics.

While we originally had planned to compare VA use and reliance in 2014 with levels observed prior to ACA expansion, the sample size in the MEPS proved too small to obtain informative one-year estimates of use and reliance. Similarly, estimated differences in out-of-pocket spending between 2014 and earlier years were imprecisely estimated and insignificant after essential control variables (such as age) were added to our models. The fact that 2014 was the first year of implementation for the ACA's major coverage provisions also means that annual averages for 2014 are likely to understate the steady-state impact of the ACA, since coverage ramped up over the course of 2014. It will be valuable to revisit these before-after comparisons after release of the 2015 MEPS in late summer 2017.

Reliance

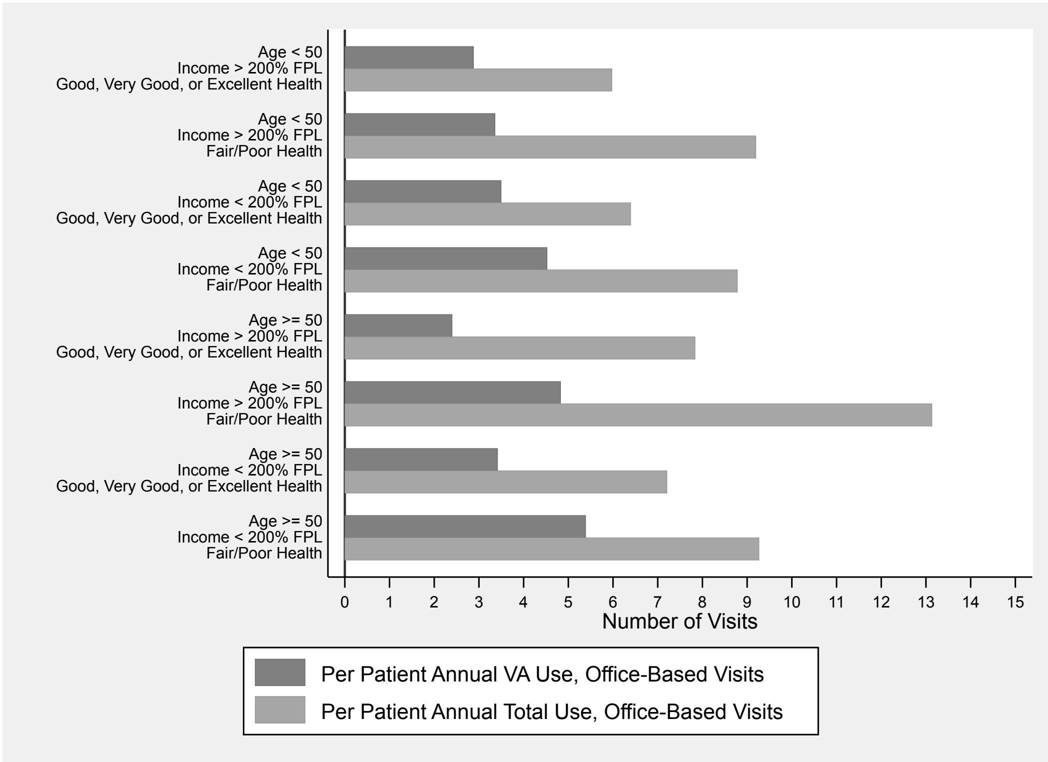
VA reliance refers to the fraction of an individual's total health care use that is obtained within the VA system. Reliance is an important concept for studying veterans' health care use because most veterans, even most VA enrollees, also obtain care outside VA. Eibner et al. (2015) reported on a comprehensive examination of patterns of reliance for the all-ages veteran population.

In this study, we define reliance at the population level rather than the individual level. In previous research on VA, including Eibner et al. (2015) and the Survey of Enrollees,[17] it is more common to define reliance at the individual level. The key difference is that individual-level reliance is not defined for people who do not use any health care while under observation. We report the unadjusted average of individual-level reliance for comparability with these other studies, but otherwise we prefer to focus on *average* reliance (the ratio of population-average VA use to population-average total use) or *adjusted* reliance (the ratio of adjusted VA use to adjusted total use). We have two motivations for our focus on average reliance. First, our analysis of ACA repeal involves regression-adjusted estimates, and it is much more tractable to analyze average reliance in a regression framework than it is to analyze individual reliance. Second, individual-level reliance is not defined for individuals who consume no health care, but the policies analyzed in this study are likely to change the set of individuals who consume health care. Average health care use is nonzero for all sufficiently large populations, and so the sample included in adjusted reliance calculations remains constant when working with average reliance.

Our analysis of ACA repeal's impacts on VA care is driven by differences in total and VA health care use across cells of veterans with different levels of exposure to loss of insurance under ACA repeal. Figure 4.2 in the main report illustrated systematic differences across these subgroups in the proportion of veterans who were VA patients. To more fully describe patterns of use and reliance across these groups of veterans, Figures A.2–A.4 present the average levels of VA and total health care use in the categories we examine stratified by age, income, and health status. There are two noteworthy features of these data. First, VA use and total use by VA patients vary widely across these groups, particularly for inpatient surgery and prescription drugs. Second, groups of VA patients with very high VA use still have substantial non-VA use. This is consistent with the patterns of reliance documented by Eibner et al. (2015). These estimates are not regression-adjusted for other covariates or health insurance status, so we include them in this appendix primarily to familiarize readers with the degree of variation in VA use across groups of veterans. The high levels of non-VA use observed among even subpopulations of VA patients with high VA use highlight the scope for substitution between VA and non-VA care when insurance status or other factors change.

[17] Joseph Gasper, Helen Liu, Sharon Kim, and Laurie May, *2015 Survey of Veteran Enrollees' Health and Use of Health Care*, Washington, D.C.: U.S. Department of Veterans Affairs, 2015. As of June 27, 2017: https://www.va.gov/HEALTHPOLICYPLANNING/SoE2015/2015_VHA_SoE_Full_Findings_Report.pdf

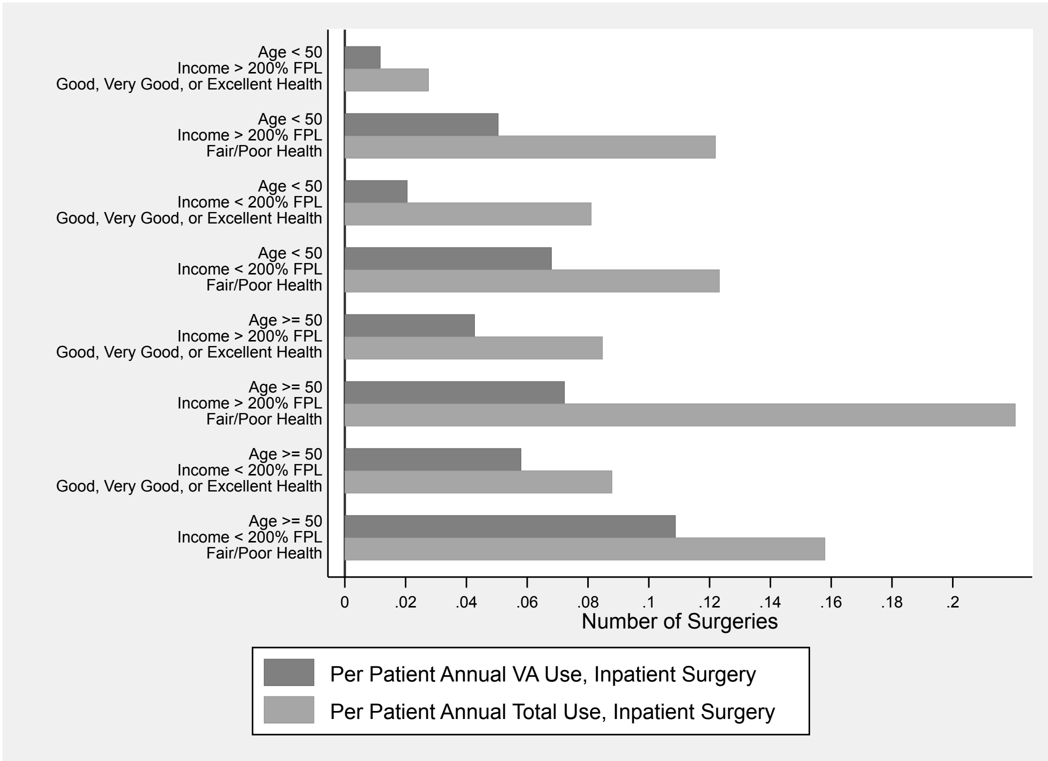
Figure A.2. VA and Total Health Care Use for VA Patients, by Age, Income, and Health Status, Office-Based Visits



SOURCE: Authors' calculations, 2008–2014 MEPS.

NOTE: Sample consists of nonelderly, noninstitutionalized VA patients.

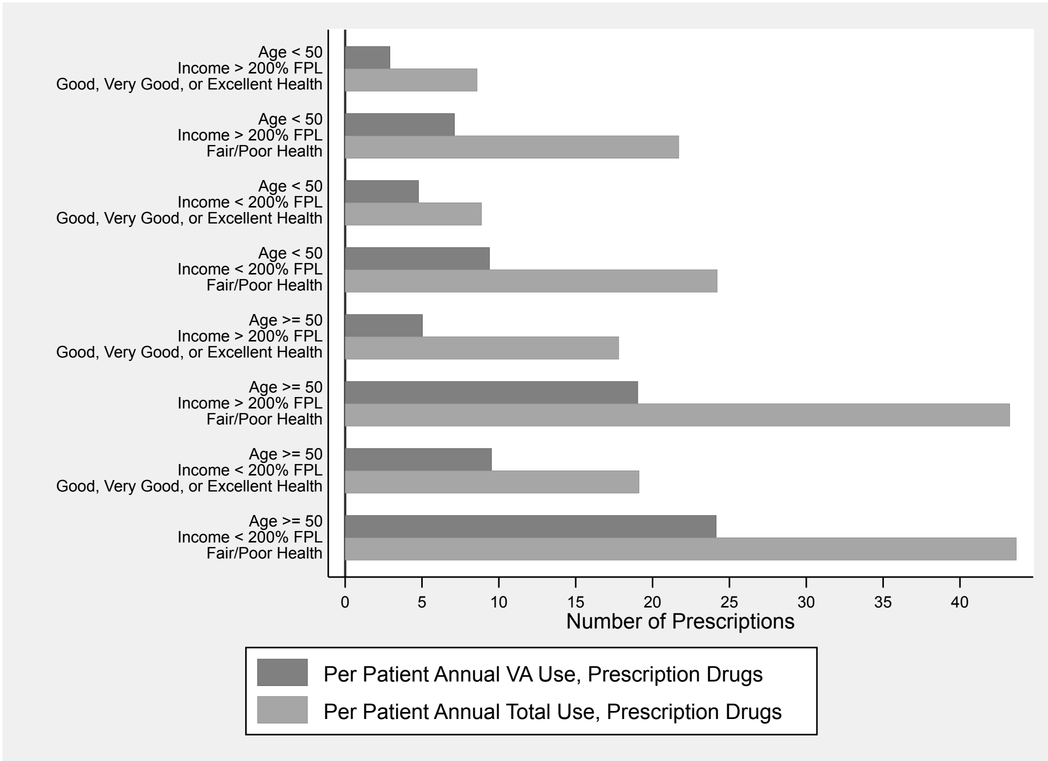
Figure A.3. VA and Total Health Care Use for VA Patients, by Age, Income, and Health Status, Inpatient Surgery



SOURCE: Authors' calculations, 2008–2014 MEPS.

NOTE: Sample consists of nonelderly, noninstitutionalized VA patients.

Figure A.4. VA and Total Health Care Use for VA Patients, by Age, Income, and Health Status, Prescription Drugs



SOURCE: Authors' calculations, 2008–2014 MEPS.

NOTE: Sample consists of nonelderly, noninstitutionalized VA patients.

Modeling Effects of Uninsurance on VA and All-Payer Health Care Use

As discussed in the report, we analyzed the effects of ACA repeal on VA use and reliance by using a statistical model to estimate how demand for VA and total health care varies with veterans' individual characteristics and non-VA insurance status. We used estimates from this model to calculate the expected level of VA and total use for demographic subgroups if individuals have non-VA insurance coverage. We assume that the conditional mean of individual utilization (both VA utilization and total utilization) is an exponential function of insurance status and control variables:

$$E(\mathrm{VA} \mid X) = \exp(X\pi_j^{\mathrm{VA}} + \beta^{\mathrm{VA}}U)$$

$$E(\mathrm{T} \mid X) = \exp(X\pi_j^{\mathrm{T}} + \beta^{\mathrm{T}}U)$$

where X denotes individual characteristics other than insurance and contextual variables such as year fixed effects, U denotes an indicator variable for being without non-VA insurance, and VA and T denote the quantities of VA care and total health care demanded. Since all our control variables are binary or categorical, this assumption amounts to the proposition that insurance and all personal characteristics have a constant multiplicative effect on utilization of VA care and on total care. An econometric model consistent with this specification of the conditional mean of health care use is the Poisson regression model, which can be written (focusing on VA care) for observation *i* as

$$\mathrm{VA}_i = \exp(X_i \pi_j^{\mathrm{VA}} + \beta^{\mathrm{VA}} U_i)\eta_i$$

where η_i is an error term with mean 1 that is conditionally independent of the explanatory variables. Under the exponential conditional mean assumption, Poisson pseudomaximum likelihood estimation is consistent for the effect of covariates on expected VA use while controlling for insurance status.[18] We emphasize that, even though our outcome variables are counts, we do not need to rely on correct specification of the full distribution of VA use to obtain consistent estimates of the regression coefficients.[19] Our analysis of ACA repeal requires information about only the average level of utilization.

Tables A.18, A.19, and A.20 report Poisson regression coefficients from our models for VA and total use of office-based visits, inpatient surgery, and prescription drugs. Because inpatient surgery is a less common event, we had to use a coarser set of controls for age in our model for inpatient surgery; other explanatory variables are identical to those used in the models for office-based visits and prescription drugs. We estimated separate models for each outcome, both for the overall nonelderly veteran population and specifically for the population of VA patients. We note that respondents were included in our VA patient sample if they used any VA care in the calendar year of the survey; some of these patients may not use any care in the specific category that is the focus of each regression model, so restriction to VA patients does not truncate the outcome distribution at zero. In addition, our indicator variable for being uninsured is taken from the annual insurance status variable on the MEPS-HC Full Year Consolidated File, which classifies individuals as uninsured if they are uninsured for the full calendar year. This is a more stringent definition of uninsurance than that captured by the point-in-time measures in the ACS and the NHIS. However, we estimated cross-sectional count models at the monthly level and obtained very similar estimates.

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[18] J. M. C. Santos Silva and Silvana Tenreyro, "The Log of Gravity," *Review of Economics and Statistics*, Vol. 88, November 2006, pp. 641–658.

[19] Jeffrey M. Wooldridge, *Econometric Analysis of Cross Section and Panel Data*, Cambridge, Mass.: MIT Press, 2002.

Table A.18. Poisson Regression Coefficients for VA and Total Office-Based Visits

	Nonelderly Veterans		Nonelderly VA Patients	
Variables	**VA**	**Total**	**VA**	**Total**
Uninsured (full year, excluding VA)	0.4161***	–0.3285***	0.3025***	–0.1263
	(0.1392)	(0.1155)	(0.1127)	(0.1010)
Ever in fair/poor SRH this year?	1.1607***	0.7163***	0.5230***	0.4421***
	(0.0977)	(0.0572)	(0.0965)	(0.0781)
Annual family income < 200% FPL?	0.4455***	–0.1060	0.1405	–0.1461
	(0.1209)	(0.0743)	(0.1076)	(0.0981)
Age 25–29	0.3884	0.7103**	–0.2525	0.2878
	(0.5278)	(0.3232)	(0.4108)	(0.4083)
Age 30–34	0.0988	0.5976**	–0.4484	0.0395
	(0.5302)	(0.2912)	(0.4007)	(0.3714)
Age 35–39	0.1997	0.8646***	–0.2480	0.3873
	(0.5346)	(0.2928)	(0.4155)	(0.3782)
Age 40–44	0.2206	0.9921***	–0.1708	0.4723
	(0.5645)	(0.2917)	(0.4439)	(0.3917)
Age 45–49	0.4406	1.2628***	–0.1215	0.8013**
	(0.5501)	(0.2859)	(0.4158)	(0.3687)
Age 50–54	0.2924	1.3537***	–0.3220	0.7968**
	(0.5228)	(0.2951)	(0.3940)	(0.3884)
Age 55–59	0.2572	1.3954***	–0.4441	0.5259
	(0.5192)	(0.2839)	(0.3849)	(0.3661)
Age 60–64	0.8462*	1.5918***	0.0272	0.8366**
	(0.5059)	(0.2860)	(0.3736)	(0.3533)
Female, age < 50	–0.0233	0.5056***	–0.2339	0.2447
	(0.1937)	(0.1055)	(0.1975)	(0.1661)
Female, age 50–64	0.2890	0.4495***	0.2414	0.3734**
	(0.1803)	(0.1187)	(0.1562)	(0.1478)
Non-Hispanic white only	–0.3511**	0.0424	–0.2323*	0.0949
	(0.1532)	(0.1029)	(0.1382)	(0.1321)
Non-Hispanic black only	0.0629	-0.1911	0.0360	–0.0384
	(0.1970)	(0.1163)	(0.1764)	(0.1530)
Non-Hispanic Asian only	–0.6924*	–0.1529	–0.1535	0.1294
	(0.3824)	(0.2175)	(0.3310)	(0.3331)

Variables	Nonelderly Veterans VA	Nonelderly Veterans Total	Nonelderly VA Patients VA	Nonelderly VA Patients Total
Non-Hispanic other race or multiple race	–0.4214	0.0362	–0.2590	–0.1123
	(0.2811)	(0.1836)	(0.2495)	(0.2056)
Year 2009	0.1381	–0.0304	0.0828	–0.0834
	(0.1115)	(0.0669)	(0.1052)	(0.1098)
Year 2010	0.1349	0.0037	0.2012	0.0265
	(0.1493)	(0.0913)	(0.1370)	(0.1308)
Year 2011	0.3394*	0.0933	0.3652**	0.1081
	(0.1768)	(0.0788)	(0.1748)	(0.1214)
Year 2012	0.2694*	–0.0087	0.2872**	0.0280
	(0.1439)	(0.0877)	(0.1313)	(0.1346)
Year 2013	–0.0326	–0.0020	–0.0372	–0.1040
	(0.1535)	(0.0753)	(0.1440)	(0.1096)
Year 2014	0.2766	0.1779*	0.3651*	–0.0184
	(0.2182)	(0.0942)	(0.2106)	(0.1560)
Constant	–0.9030*	0.1239	1.0830***	1.2517***
	(0.5239)	(0.3045)	(0.4106)	(0.3746)
Number of observations	6,502	6,502	2,147	2,147

SOURCE: Authors' calculations, 2008–2014 MEPS-HC.
NOTES: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports coefficients from Poisson regression of yearly count of office-based visits on full-year uninsurance status, self-reported health status, family income, age, gender, race/ethnicity, and year. Excluded category for age contains persons ages 19–39. Excluded category for female indicators is male. Excluded category for race/ethnicity is Hispanic. Excluded category for year is 2008. Robust standard errors estimated using MEPS survey design variables are reported in parentheses. Poisson regression coefficients should be interpreted as the natural log of the proportional change in the outcome associated with a variable holding other variables constant. SRH = self-reported health.

Table A.19. Poisson Regression Coefficients for VA and Total Inpatient Surgery

Variable	Nonelderly Veterans		Nonelderly VA Patients	
	VA	**Total**	**VA**	**Total**
Uninsured (full year, excluding VA)	0.0136	–0.7463***	–0.1337	–0.6764**
	(0.3111)	(0.2458)	(0.2932)	(0.2604)
Ever in fair/poor SRH this year?	1.3776***	1.5311***	0.7329***	0.9361***
	(0.2626)	(0.1523)	(0.2686)	(0.2314)
Annual family income < 200% FPL?	0.7296**	0.2346	0.4143	0.0368
	(0.3036)	(0.1887)	(0.2926)	(0.2577)
Age 40–54	0.8879*	0.7275***	0.9123*	0.7304**
	(0.4863)	(0.2534)	(0.4991)	(0.3155)
Age 55–64	1.4857***	1.4704***	1.2720**	1.1297***
	(0.5134)	(0.2556)	(0.5208)	(0.3307)
Female, age < 50	1.2074***	1.0400***	1.1988***	1.0118***
	(0.4392)	(0.2406)	(0.4317)	(0.2978)
Female, age 50–64	–0.4166	0.0203	–0.4446	0.1520
	(0.4822)	(0.4031)	(0.4841)	(0.4219)
Non-Hispanic white only	0.6017	0.5413*	0.7307	0.9007**
	(0.6799)	(0.3073)	(0.6638)	(0.4241)
Non-Hispanic black only	0.8922	0.3997	0.8581	0.7189
	(0.7085)	(0.3348)	(0.7001)	(0.4463)
Non-Hispanic Asian only	–20.8205***	–0.2374	–20.8545***	–22.0748***
	(0.7164)	(0.6429)	(0.7949)	(0.5799)
Non-Hispanic other race or multiple race	0.7875	0.7658*	0.8941	0.6980
	(0.7436)	(0.3943)	(0.7230)	(0.4888)
Year 2009	0.4302	0.1518	0.4129	0.2770
	(0.4015)	(0.2552)	(0.3918)	(0.3127)
Year 2010	–0.1513	0.1671	–0.0481	0.3815
	(0.4451)	(0.2484)	(0.4358)	(0.3018)
Year 2011	–0.7730	0.1475	–0.6293	0.1180
	(0.6192)	(0.2729)	(0.6125)	(0.3952)
Year 2012	0.4630	0.3416	0.5653	0.5691
	(0.5314)	(0.3128)	(0.5180)	(0.3868)
Year 2013	–0.1409	–0.0357	–0.0886	–0.0125
	(0.5337)	(0.3151)	(0.5341)	(0.4115)

Variable	Nonelderly Veterans VA	Nonelderly Veterans Total	Nonelderly VA Patients VA	Nonelderly VA Patients Total
Year 2014	–0.0884	–0.1612	0.0526	–0.0890
	(0.4848)	(0.2693)	(0.4896)	(0.3400)
Constant	–6.7758***	–5.3539***	–5.3840***	–4.5899***
	(0.8271)	(0.4071)	(0.8425)	(0.5849)
Observations	6,502	6,502	2,147	2,147

SOURCE: Authors' calculations, 2008–2014 MEPS-HC.
NOTES: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports coefficients from Poisson regression of yearly count of inpatient surgeries on full-year uninsurance status, self-reported health status, family income, age, gender, race/ethnicity, and year. Excluded category for age contains persons ages 19–39. Excluded category for female indicators is male. Excluded category for race/ethnicity is Hispanic. Excluded category for year is 2008. Standard errors were estimated using MEPS survey design variables reported in parentheses. Poisson regression coefficients should be interpreted as the natural log of the proportional change in the outcome associated with a variable, holding other variables constant.

Table A.20. Poisson Regression Coefficients for VA and Total Prescription Drugs

	Nonelderly Veterans		Nonelderly VA Patients	
Variables	**VA**	**Total**	**VA**	**Total**
Uninsured (full year excluding VA)	0.4783***	–0.3048***	0.3579**	–0.0723
	(0.1801)	(0.0861)	(0.1427)	(0.0931)
Ever in fair/poor SRH this year?	1.7635***	1.1233***	1.1289***	0.8975***
	(0.1446)	(0.0567)	(0.1195)	(0.0648)
Annual family income < 200% FPL?	0.6299***	0.1377**	0.3181**	0.0829
	(0.1568)	(0.0546)	(0.1355)	(0.0713)
Age 25–29	1.4384**	1.3796***	1.0163	1.1743**
	(0.6595)	(0.3947)	(0.6796)	(0.4617)
Age 30–34	1.4779**	1.2397***	1.0700	1.0186***
	(0.6874)	(0.3134)	(0.6916)	(0.3737)
Age 35–39	1.2485*	1.5526***	0.9866	1.2520***
	(0.6751)	(0.3054)	(0.6933)	(0.3627)
Age 40–44	1.2619*	1.8393***	1.0469	1.3075***
	(0.6673)	(0.3067)	(0.6645)	(0.3650)
Age 45–49	1.1855*	2.0351***	0.8880	1.6289***
	(0.6609)	(0.3003)	(0.6609)	(0.3574)
Age 50–54	1.8183***	2.2575***	1.4543**	1.6940***
	(0.6370)	(0.3018)	(0.6557)	(0.3367)
Age 55–59	2.2730***	2.5687***	1.8405***	2.0015***
	(0.6494)	(0.2990)	(0.6780)	(0.3471)
Age 60–64	2.4280***	2.7090***	1.8811***	2.0899***
	(0.6370)	(0.2961)	(0.6425)	(0.3345)
Female, age < 50	–0.3772	0.1229	–0.4890*	–0.1792
	(0.2809)	(0.1351)	(0.2732)	(0.1474)
Female, age 50–64	–0.4839*	0.1445	–0.4219	0.1444
	(0.2848)	(0.1223)	(0.2776)	(0.1793)
Non-Hispanic white only	–0.0942	0.1213	0.0164	0.2376**
	(0.1909)	(0.0837)	(0.1909)	(0.1140)
Non-Hispanic black only	0.1889	–0.0466	0.1304	0.0555
	(0.1958)	(0.0923)	(0.1887)	(0.1241)
Non-Hispanic Asian only	–2.7230***	–0.2206	–2.0249*	–0.4866

	Nonelderly Veterans		Nonelderly VA Patients	
Variables	**VA**	**Total**	**VA**	**Total**
	(1.0334)	(0.1949)	(1.0350)	(0.3484)
Non-Hispanic other race or multiple race	0.0660	0.1551	0.2131	0.1805
	(0.3216)	(0.1693)	(0.3090)	(0.1912)
Year 2009	–0.1058	–0.0116	–0.1342	–0.0371
	(0.1476)	(0.0600)	(0.1449)	(0.0804)
Year 2010	0.0165	0.1039	0.0838	0.0972
	(0.2037)	(0.0676)	(0.1915)	(0.0971)
Year 2011	0.1327	0.1290*	0.2286	0.1172
	(0.1781)	(0.0772)	(0.1616)	(0.0879)
Year 2012	–0.3485*	0.0603	–0.3032*	0.0188
	(0.1797)	(0.0763)	(0.1731)	(0.1133)
Year 2013	0.3592	0.0609	0.4320**	0.1361
	(0.2292)	(0.0727)	(0.2106)	(0.1088)
Year 2014	0.3227	0.0814	0.4813*	0.0889
	(0.3087)	(0.0841)	(0.2882)	(0.1530)
Constant	–1.9414***	–0.2357	–0.2234	0.6231*
	(0.6536)	(0.3046)	(0.6732)	(0.3627)
Number of observations	6,502	6,502	2,147	2,147

SOURCE: Authors' calculations, 2008–2014 MEPS-HC.
NOTES: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports coefficients from Poisson regression of yearly count of prescriptions received on full-year uninsurance status, self-reported health status, family income, age, gender, race/ethnicity, and year. Excluded category for age contains persons ages 19–39. Excluded category for female indicators is male. Excluded category for race/ethnicity is Hispanic. Excluded category for year is 2008. Robust standard errors were estimated using MEPS survey design variables reported in parentheses. Poisson regression coefficients should be interpreted as the natural log of the proportional change in the outcome associated with a variable holding other variables constant.

VA patients' adjusted levels of VA and total use by non-VA insurance status are calculated from these models and reported in Table 3.4 of the main report: Adjusted average reliance as reported in that table is calculated as the ratio of predicted VA use to predicted total use.

Of course, uninsurance and VA use may both be determined by unobserved factors, including VA eligibility. We assume that this is the case, and so in our view the regression coefficients estimated above do not have a causal interpretation. Nevertheless, the coefficients on the control variables are informative about the association between individual characteristics and health care use while controlling for uninsurance. We did not use the coefficients on uninsurance to predict the impact of losing insurance on VA use, but we did rely on the coefficients on demographic characteristics to predict levels of health care use if insured as an input into our analysis of ACA repeal.

Model Selection

One might have several concerns about the use of Poisson regression to model the data we analyzed here: Data for several outcomes are fairly skewed with large outliers, and all categories of health care use are characterized by a large proportion of zeros. Both of these issues are more acute for VA health care use than for total health care use. While our use of these estimates requires only that the exponential conditional mean assumption hold (and not that the data actually be Poisson-distributed), either of these issues could lead to a poor model fit.

To assess the importance of these issues, we estimated two alternative statistical models for each of our six health care use outcomes. All models used the same set of covariates.[20] First, to account for skewness and outliers, we estimated a Gamma regression, which also uses an exponential conditional mean function but is more robust to large outliers than Poisson regression due to a different assumption about how the variance of the outcome increases with the conditional mean.[21] Second, to account for excess zeros, we estimated a log-linear hurdle model in which the process determining zeros was a probit model and the process for positive outcomes was a log-linear normal regression; this model specified the log variance of the error term as a linear function of the explanatory variables. We chose a hurdle model over a zero-inflated count model because hurdle models are more theoretically appropriate for situations in which one process governs whether a zero outcome occurs and a different process governs the value of positive outcomes. In this setting, this binary part of the model would be interpreted as capturing the VA enrollment margin and VA use decisions, while the part for positive outcomes would be interpreted as capturing VA use among those using one or more service in each category.

We used tenfold cross-validation to compare these models to Poisson regression. Cross-validation is a procedure that can be used to compare model fit across different models for the same data while making minimal assumptions on the data-generating process. By evaluating out-of-sample fit for a model estimated on a subsample of the data, cross-validation reduces the risk of choosing a model on the basis of overfitting. Table A.21 compares our cross-validation results between the Poisson, Gamma, and log-linear hurdle models. In general, Poisson regression achieves a better model fit than the alternatives. While Gamma regression outperforms Poisson for total office-based visits in terms of mean absolute prediction error, Poisson outperforms Gamma in terms of mean squared error. We also note that Gamma regression was not an

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[20] We had difficulty using more-flexible specifications of our explanatory variables due to the somewhat limited sample size of nonelderly veterans available in the MEPS and the large number of zero observations; inclusion of additional variables beyond those used here often led to convergence problems. We used a more parsimonious specification of age effects for inpatient surgery than for prescription drugs and office-based visits.

[21] David K. Blough, Carolyn W. Madden, and Mark C. Hornbrook, "Modeling Risk Using Generalized Linear Models," *Journal of Health Economics*, Vol. 18, 1999, pp. 153–171.

appropriate choice for inpatient surgery since there not substantial outliers, and we failed to achieve convergence in some cross-validation subsamples.

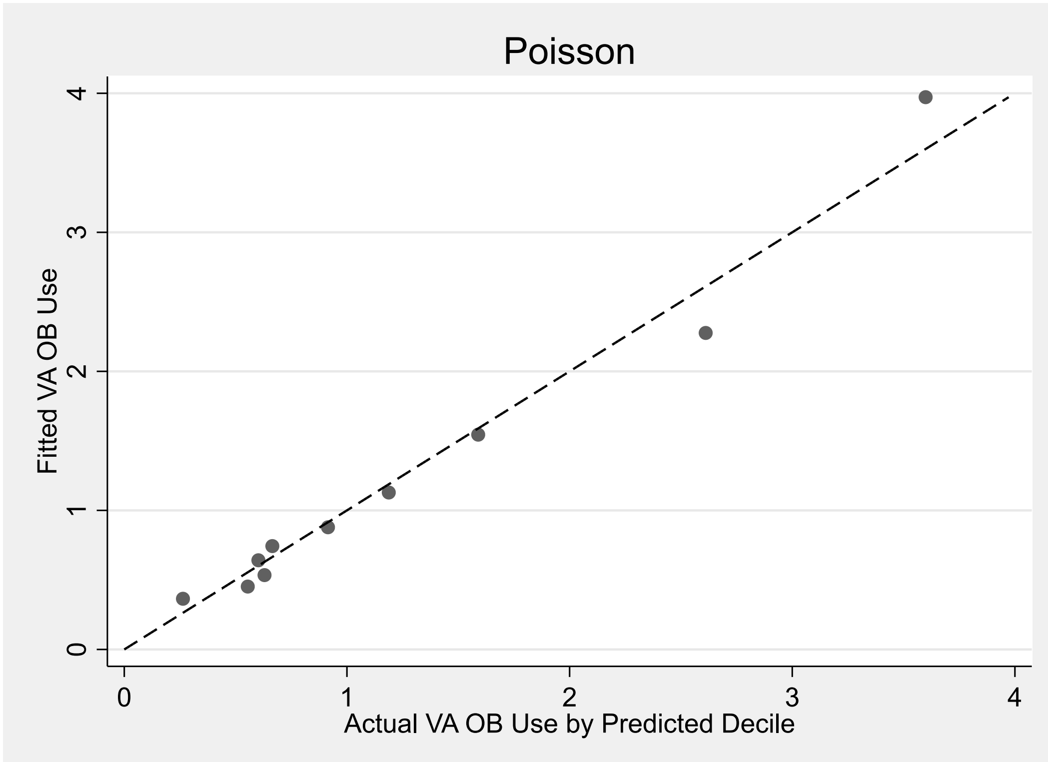
Table A.21. Cross-Validation Results: Poisson, Gamma, and Hurdle Models for VA and Total Use

	VA Use			Total Use		
	Poisson	**Gamma**	**Hurdle**	**Poisson**	**Gamma**	**Hurdle**
Office-based visits						
Mean absolute prediction error	1.782	1.827	1.850	5.068	5.056	5.134
Mean squared error	20.933	21.181	21.043	92.995	93.053	92.978
Inpatient surgery						
Mean absolute prediction error	0.033	Convergence	0.036	0.090	Convergence	0.096
Mean squared error	0.020	Not achieved	0.020	0.059	Not achieved	0.059
Prescription drugs						
Mean absolute prediction error	168.044	181.373	170.162	454.899	457.926	476.135
Mean squared error	5.155	5.573	5.504	13.494	13.602	14.483

NOTES: This table reports goodness-of-fit measures from tenfold cross-validation for Poisson regression, Gamma regression, and exponential hurdle models. Smaller numbers indicate better model fit. The same subsamples were used for each model. Hurdle models for office-based visits and prescription drugs allow for heteroskedasticity of the error term in the continuous part of the model, with the log of the variance specified as a linear function of the explanatory variables in the model. The hurdle model for inpatient visits is homoskedastic because we were not able to achieve convergence of the heteroskedastic model for inpatient surgery. Gamma regression for inpatient surgery also failed to converge in some subsamples, so cross-validation results are not reported.

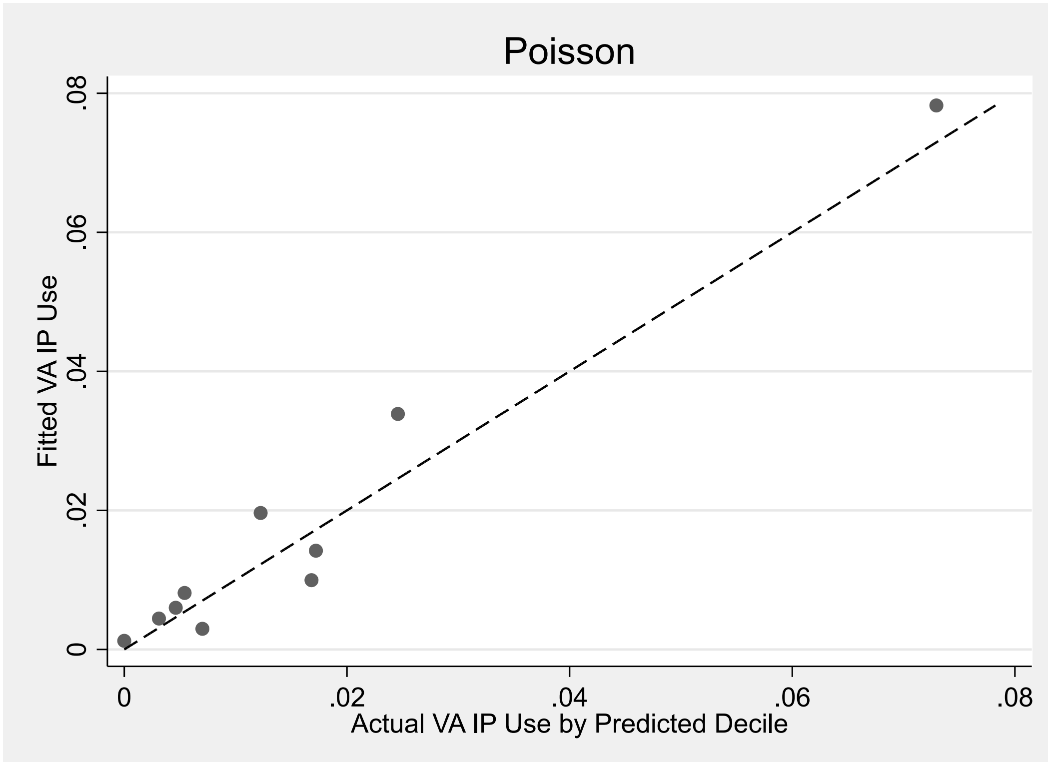
To illustrate that we achieved an acceptable in-sample model fit with Poisson regression, we binned observations into deciles of the predicted value of VA use for each of our three outcomes. Figures A.5–A.7 compare actual VA use with predicted VA use across deciles. A perfect model fit would yield a plot where all values fall on the 45-degree line, which is plotted for reference. For all three categories of use, model predictions and actual values are reasonably close to each other. Inpatient surgery was, in general, more difficult to model because there were relatively few surgeries in the sample, limiting the degree of flexibility we could include in our model specification. Even so, these figures clearly indicate that our models are capturing a meaningful amount of the variation across veterans in patterns of VA use.

Figure A.5. Predicted Versus Actual VA Office-Based Visits by Predicted Decile



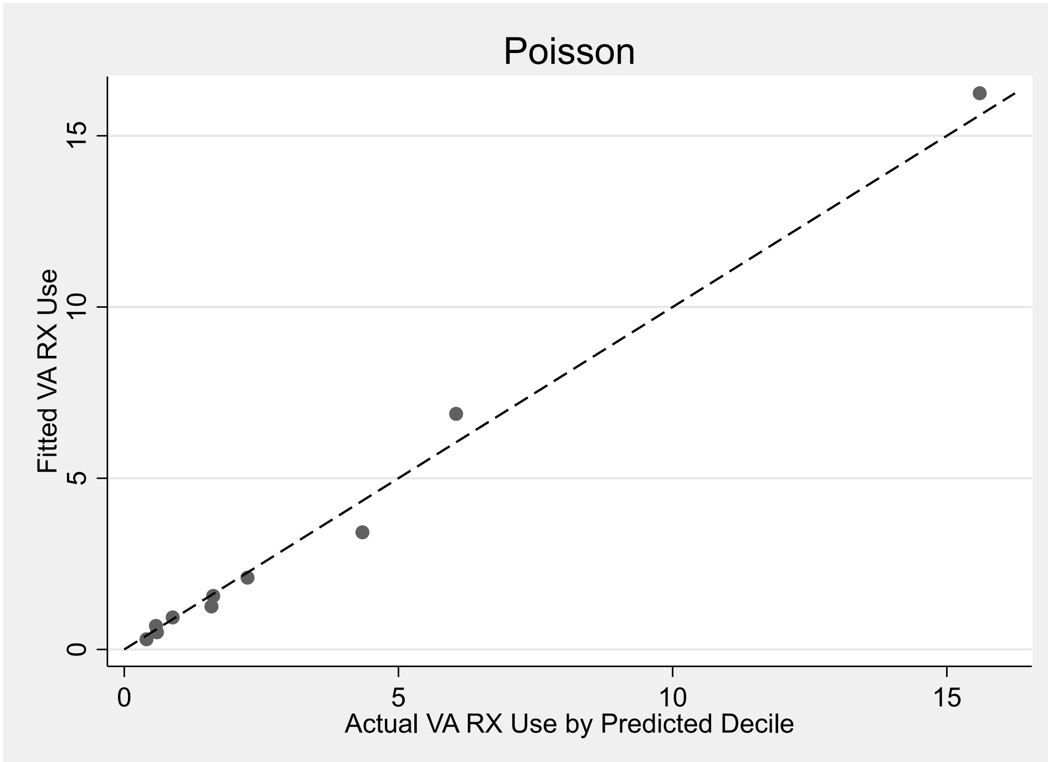
NOTE: OB = office-based.

Figure A.6. Predicted Versus Actual VA Inpatient Surgeries by Predicted Decile



NOTE: IP = inpatient surgery.

Figure A.7. Predicted Versus Actual VA Prescriptions Received by Predicted Decile



NOTE: RX = prescription.

Effects of Losing Insurance on VA Demand: Fixed-Effects Estimates

The core of our policy analysis involves modeling how veterans' demand for VA and non-VA health care would change if we changed their insurance status while holding both observable and unobservable individual characteristics constant. Observable characteristics include information captured in our survey data sources, such as demographics or self-reported health status. Unobservable characteristics include a potentially vast range of personal characteristics not included in our models that might affect health care utilization. Although the MEPS contains rich detail on individual health conditions and patterns of health care utilization during the panel, the limited sample size of veterans available for our analysis makes it infeasible to control for these variables in our cross-sectional regression models without sacrificing the precision of our estimates. Even with a large sample size, however, it still would be difficult to argue that controlling for observed health status fully eliminates the potential for selection bias in a cross-sectional regression of health care demand on uninsurance.

For policy analysis, we would ideally have experimental or quasi-experimental estimates of the effect of health insurance on VA and non-VA health care utilization either estimated for a representative sample of nonelderly veterans or estimated on another population but with external validity for nonelderly veterans; random assignment of insurance status could be relied upon to avoid selection bias due to unobservable differences in health care demand between the insured and uninsured populations. While several well-known experimental studies have been conducted to estimate the effect of health insurance on the general public (the RAND Health Insurance Experiment) or low-income adults (the Oregon Health Study), there are no truly experimental studies of the effect of non-VA health insurance on veterans' health care utilization.

Because individual demand for health insurance coverage is driven in large part by health status and the need for health services, cross-sectional regressions of VA and total health care use on uninsurance generally cannot deliver consistent estimates of the causal effect of uninsurance on the use for health care. Because individuals with greater health care needs value health insurance more highly, cross-sectional estimates of the effect of insurance coverage on total (all-payer) health care utilization will typically be biased *upward*: If we observe that people with insurance use more health care than those who are uninsured, self-selection into health coverage suggests that some portion of this gap in utilization is explained by individual health status rather than the causal effect of insurance on individual behavior. Conversely, cross-sectional approaches will tend to underestimate the reduction in health care use caused by a lack of health insurance because some of those without insurance choose to go without coverage because they are healthy.

Similar arguments suggest that the effect of non-VA coverage on VA utilization would also be biased upward (compared with the true causal effect of non-VA coverage on VA utilization); holding individual characteristics (such as Medicaid eligibility or observable measure of health status) constant, we might expect VA enrollees who also purchase or enroll in non-VA insurance to be those with greater needs for care. Shen et al. (2008) investigated the nature of this selection bias using a large cross-sectional survey of veterans fielded in 1999.[22] Importantly, that study used a valid instrumental variables strategy to circumvent selection bias; we rely on these estimates in our policy analysis, so we discuss that study in greater detail later. Shen et al. was consistent with the theory that nonelderly veterans with private health insurance coverage had greater health care needs, on average, than those who were uninsured. As a consequence, cross-sectional estimates of the effect of non-VA private insurance on VA health care utilization were biased upward.

Given the clear potential for bias in cross-sectional estimates of the effect of non-VA insurance on VA use, we attempted to leverage the panel aspect of the MEPS to examine changes in VA use for veterans who gained or lost insurance while under observation during the two-year MEPS panel. Insurance status, inpatient stays, and office-based visits are all captured at the monthly or higher frequency in the MEPS, so we constructed an analytic data set with observations at the person-month level capturing health insurance coverage and the number and

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[22] Yujing Shen, Ann Hendricks, Fenghua Wang, John Gardner, and Lewis E. Kazis, "The Impact of Private Insurance Coverage on Veterans' Use of VA Care: Insurance and Selection Effects," *Health Services Research*, Vol. 43, No. 1p1, 2008, pp. 267–286. As of August 9, 2017: http://dx.doi.org/10.1111/j.1475-6773.2007.00743.x

payer (VA versus non-VA) of inpatient stays and office-based visits.[23] Pooling 2008–2014 data, there were 660 nonelderly veterans who switched insurance status during the MEPS.

We also hypothesized that the effects on VA demand of changes in insurance status might be asymmetric between veterans who gain and veterans who lose insurance. For example, those who lose insurance may be receiving regular treatment that they would seek to continue after the loss of insurance, resulting in substitution of VA care for non-VA care. Such asymmetries are potentially important for analyzing ACA repeal because most of the anticipated changes in coverage would involve losing rather than gaining non-VA insurance. In our sample, 318 veterans transitioned from being uninsured to being insured (gained insurance), and 342 transitioned from being insured to being uninsured (lost insurance). About one-third of the sample (unweighted) experienced more than one insurance transition in the panel; we classified individuals as insurance gainers or losers based on the direction of their first insurance transition.

We used fixed-effects Poisson regression and fixed-effects linear regression to isolate within-person variation in insurance status—i.e., switches from insured to uninsured and vice versa. For statistical inference, we used the survey bootstrap of Rao and Wu (which resamples primary sampling units within strata rather than individuals) with 200 resamples, as implemented in Stata by Kolenikov (2011).[24] As elsewhere in this study, we prefer Poisson regression due to the skewed distribution of health care use. However, a challenge with fixed-effects Poisson regression for studying inpatient use is that individuals who have zero outcomes in all time periods must be dropped from the sample to ensure convergence. Inpatient surgery was rare enough that our samples were extremely small after stratifying on type of insurance switch. There were only 18 inpatient surgeries at the VA in the panel for individuals who switched insurance, leaving sample sizes in the teens or single digits when we narrowed attention to individuals gaining or losing insurance. We reported fixed-effects linear regression (ordinary least squares [OLS]) estimates of all models to address possible concerns that Poisson regression estimates with so few individuals in the sample would be uninformative. In this appendix, we report models with fixed effects but no other covariates. We estimated models that control for time trends, which are theoretically appropriate to account for the fact that individuals consume more care over the course of the panel as they age. However, these models were not estimable for inpatient surgery due to the small sample sizes available, so we report models with individual fixed effects but no other covariates. The fixed effects control for all time-invariant individual characteristics, including VA eligibility and demographics.

When insurance losers and insurance gainers are pooled together, both our OLS and Poisson estimates indicate that uninsurance is associated with lower use of total health care but do not indicate any significant effects on VA care. Based on the fixed-effects Poisson estimates, the

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[23] Prescription drug purchases are not recorded at the monthly frequency and were instead aggregated to the survey-round frequency. However, our estimates for prescription drug purchases were not precise enough to be informative and are not reported here.

[24] J. N. K. Rao and C. F. J. Wu, "Resampling Inference with Complex Survey Data," *Journal of the American Statistical Association*, Vol. 83, No. 401, 1988, pp. 231–241; Stanislav Kolenikov, "Resampling Variance Estimation for Complex Survey Data," *The Stata Journal*, No. 2, 2010, pp. 165–199.

predicted percentage reduction in total care associated with uninsurance is estimated to be 32 percent for office-based visits and 54 percent for inpatient surgery. (See Table A.22.)

Table A.22. Effect of Insurance Gain and Insurance Loss on VA and Total Health Care Use, Fixed-Effects Linear Regression and Poisson Regression Estimates

	Office-Based Visits				Inpatient Surgery			
	Fixed-Effects OLS		Fixed-Effects Poisson		Fixed-Effects OLS		Fixed-Effects Poisson	
	VA	Total	VA	Total	VA	Total	VA	Total
All veterans with change in insurance (*N* = 660)								
Regression coefficient	–0.0031	–0.1267**	–0.0261	–0.3803**	–0.0001	–0.0058**	–0.0214	–0.7781**
	(0.0334)	(0.0544)	(0.2849)	(0.1565)	(0.0012)	(0.0024)	(0.4303)	(0.3316)
N (switch and 1+ event)	660	660	265	517	660	660	18	51
Veterans losing insurance (*N* = 342)								
Regression coefficient	0.0384**	–0.1077***	0.3990**	–0.3698**	0.0010	–0.0049*	–0.4139	–0.8642*
	(0.0164)	(0.0416)	(0.1578)	(0.1449)	(0.0017)	(0.0027)	(0.6337)	(0.4746)
N (switch and 1+ event)	342	342	128	280	342	342	6	22
Veterans gaining insurance (*N* = 318)								
Regression coefficient	–0.0484	–0.1475	–0.3358	–0.3888	–0.0012	–0.0068*	0.3175	–0.6875
	(0.0687)	(0.1022)	(0.4558)	(0.2602)	(0.0018)	(0.0041)	(0.6652)	(0.4820)
N (switch and 1+ event)	318	318	137	237	318	318	12	29

NOTES: This table reports regression coefficients on a dummy variable for being uninsured from OLS and Poisson regressions with individual-level fixed effects. Unit of observation is the person-month. The number of persons in the sample is reported in rows labeled "*N*." Most individuals contributed 24 monthly observations. Some individuals in 2008 and 2014 files contributed 12 monthly observations. Individuals who did not use any care in the panel did not contribute to fixed-effects Poisson estimation and were dropped from the sample. OLS regression coefficients reflect the change in the expected number of health events per month associated with switching insurance status, holding constant the individual fixed effect. Poisson regression coefficients should be interpreted as the natural log of the proportional change in the outcome associated with a variable holding constant the individual fixed effect.

To explore this possibility, we stratified our sample of veterans who switched insurance status according to their insurance status at the time they entered the MEPS panel. Veterans who were uninsured at the start of the panel and subsequently switched thus gained insurance at least once during the panel, while those who were insured at the start of the panel and switched insurance thus lost insurance at least once during the panel. We report fixed-effects OLS and fixed-effects Poisson regression coefficients for office-based visits and inpatient surgery.

However, when we stratified the sample by direction of insurance switch and estimated separate models for insurance losers and insurance gainers, we found strong evidence of an asymmetric response for office-based visits. Veterans who were insured at the start of the panel increased their VA utilization after losing insurance. The percentage increase suggested by the

Poisson regression coefficient is significant at the 5-percent level and is quite large (49 percent); the OLS estimate is also significant and suggests a similar proportional change (42-percent increase) relative to the sample mean of 0.092 visits per month. Total office-based visits fell by 32 percent.

Utilization changes look very different for veterans who were uninsured at the start of the panel and subsequently gained insurance. The insurance gainers did not have significantly different utilization after gaining insurance. While some point estimates suggest that gaining insurance may have increased both VA and total utilization, these are imprecisely estimated and are not significantly different from zero.

We used the same fixed-effects regression framework to estimate the effect of within-person changes in insurance status on VA-paid inpatient stays and total inpatient stays. We found no significant changes in inpatient VA stays associated with within-person changes in insurance status: The point estimate was close to zero but was very imprecisely estimated. There may not be enough inpatient surgery use in this subsample of the MEPS (about 10 percent of our main analytic sample) to obtain informative estimates of how insurance switching affects veterans' VA use.

We view these estimates as suggestive evidence that the response of VA use to non-VA health insurance is asymmetric: Veterans use more office-based VA care after losing insurance but may not change their use of VA care after gaining insurance. These findings are particularly interesting in light of a newly published study that uses VA records linked to CMS claims data to estimate changes in VA use for a cohort of about 20,000 VA enrollees who transition to Medicaid.[25] This study clearly documented that veterans gaining Medicaid coverage did not reduce their use of VA office-based or inpatient care in the first year after enrollment. While the researchers' analysis did not include individual fixed effects, it controlled for a much richer set of covariates than we were able to include in models here, and the study is well executed and convincing.

That said, the research design employed by Yoon et al. (2017) is unlikely to capture the causal effect of insurance on VA use since the study is not able to leverage any experimental or quasi-experimental variation in health insurance status. Panel data and fixed-effects estimation are not a panacea for the challenges created by self-selection into health insurance coverage; at least some transitions in coverage may well be driven by changes in circumstances that also directly drive demand for health care. As with the fixed-effects estimates presented here, Yoon et al. were not able to determine whether individuals were entering Medicaid because of their health status for reasons unrelated to health (such as an expansion of eligibility) or because of a change in economic circumstances (such as job loss) or a deterioration in health status that caused them to seek out additional care. The evidence presented here that the effect of non-VA

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[25] Jean Yoon, Megan E. Vanneman, Sharon K. Dally, Amal N. Trivedi, and Ciaran S. Phibbs, "Use of Veterans Affairs and Medicaid Services for Dually Enrolled Veterans," *Health Services Research*, June 13, 2017, doi:10.1111/1475-6773.12727.

insurance on VA use is asymmetric between insurance gain and insurance loss also suggests that the estimates reported in Yoon et al. may not capture the most-relevant parameters for our policy analysis.

Because we were not able to implement a valid experimental or quasi-experimental research design in the public-use MEPS, we relied on parameter estimates drawn from the literature for our baseline empirical analysis. In the future, data similar to those used by Yoon et al. (2017) should be used to study the effect of insurance loss on VA demand.

Analysis of ACA Repeal

As in our empirical model, we assumed an exponential conditional mean model for per capita use of each type of service. Substantively, this assumption means that being uninsured has a constant multiplicative effect on demand for VA care and total health care. While we did not have sufficient data in the MEPS to develop a microsimulation model of health care demand for veterans, we were able to use the MEPS to estimate the parameters π^{VA} and π^{T} that characterize the effect of individual characteristics on health care demand. β^{VA} and β^{T} are the crucial parameters that capture the percentage changes in VA use and all-payer use that result when an individual's insurance status changes from being insured to being uninsured.

We partitioned the population of nonelderly veterans into eight cells defined by a small set of sociodemographic and health characteristics that affect baseline insurance status, exposure to ACA repeal and replacement, and health care demand. In order to facilitate use of estimates from the recent Comprehensive Assessment of Reform Efforts (COMPARE) analysis of the AHCA, we used the subgroups reported in that analysis (age, income, and self-reported health status). For cell *k*, we let x_k denote the covariates associated with the cell, potentially including the distribution of covariates not used in the cell definition (e.g., race/ethnicity and gender). We also let p_k denote the fraction of the nonelderly veteran population in cell *k*, while VA denotes the count of VA care in some category (e.g., the yearly number of office visits). Then the overall per capita level of VA care demanded is

$$E(\mathrm{VA}) = \sum_k p_k E(\mathrm{VA} \mid x_k)$$

And, if *N* is the total number of veterans and N_k is the number of veterans in cell *k*, the total volume of VA demand is $NE(\mathrm{VA})$.

This framework gives us a way of modeling how the impact of a particular change in the distribution of insurance coverage across subgroups would affect per capita and total VA use. (We used the same methods to predict changes in all-payer use among veterans.)

We define a scenario *S* as a vector of changes in the probability that veterans in each population cell *k* are uninsured:

$$S = (\Delta P(U|x_k))_{k=1}^{K} \equiv (\Delta U_k)_{k=1}^{K}$$

where ΔU_k is the proportion of veterans in group *k* losing insurance.

We emphasize that ΔU_k is defined in *percentage points* (i.e., units of probability) and not percentages (i.e., not proportionally). Then the change in per capita demand for VA care under scenario S is

$$\Delta_S E(\mathrm{VA}) = \sum_{k=1}^{K} p_k \Delta U_k (\exp(X_k \pi^{VA} + \beta^{VA}) - \exp(\pi^{VA} X_k))$$

$$= \sum_{k=1}^{K} p_k \Delta U_k \exp(\pi^{VA} X_k)(\exp(\beta^{VA}) - 1)$$

$$= (\exp(\beta^{VA}) - 1) \times \sum_{k=1}^{K} p_k \Delta U_k \exp(\pi^{VA} X_k)$$

The first term in the third row of the equation $(\exp(\beta^{VA}) - 1)$ is the percentage change in utilization resulting from the loss of insurance, all else constant. The second term $(\sum_{k=1}^{K} p_k \Delta U_k \exp(\pi^{VA} X_k))$ is the average utilization of those losing insurance under scenario S when they are insured.

Empirical Implementation of ACA Repeal Model

To model the effects of ACA repeal on VA use, we need the following objects:

- β^{VA}, the semi-elasticity of VA use with respect to uninsurance
- p_k, the population shares of the demographic cells $k = 1 \ldots K$
- $S = (\Delta U_k)$, the scenario—i.e., the set of percentage-point reductions in insurance coverage due to a policy change
- $\exp(\pi^{VA} X_k)$, the average utilization when insured for individuals in cell k.

We used the pooled 2008–2014 MEPS data to estimate the cross-sectional associations between individual characteristics, uninsurance, and use of VA and all-payer health care using separate Poisson regression models. Setting $U = 0$ for all observations and constructing individual predicted values gives us $\exp(\pi^{VA} X_i)$, the expected per capita level of health care use when insured for MEPS respondent i. Because the 2008–2014 MEPS data do not match the composition of the target population for our analysis (which is the 2015 nonelderly veteran population), we needed to reweight the MEPS to match the target population.

To reweight for post-estimation, we calculated p_{ayh} (2015 probability for one-year age, poverty ratio, and health status cell) using data on nonelderly veterans from the 2015 ACS (for the age and income distributions) and the 2015 NHIS (for health status conditional on age and family income). It is necessary to combine estimates from the two data sets because the ACS does not ask respondents for their self-rated health status, but the ACS is a better data source for the age and income distributions due to its larger sample size and more-detailed income questions.

This would be important even if we were using MEPS data from our target population because the limited sample size of veterans can lead the observed distributions of veteran characteristics to diverge slightly from the corresponding estimates derived from the ACS. All our repeal analysis estimates are accordingly reweighted to match the joint distribution of age, income, and health status p_{ayh} estimated from the more reliable ACS and NHIS. Specifically, after estimating our baseline model of health care use using pooled 2008–2014 MEPS data, we reweighted the respondents in the estimation sample to match the characteristics of the 2015 nonelderly veteran population. To do so, we constructed new sample weights for the MEPS as follows:

$$w_i^{2015}(a,y,h) = \overbrace{w_i}^{\text{MEPS weight}} \times \overbrace{\frac{\sum_{\text{Full MEPS}} w_i}{\sum_{i:a(i)=a,y(i)=y,h(i)=h} w_i}}^{\text{1 / proportion total MEPS weight in cell}} \times \overbrace{p_{ayh}}^{\text{2015 proportion of veterans in cell}}$$

Evidence on Non-VA Insurance Status and Demand for VA Care

We searched for high-quality peer-reviewed evidence on the causal effect of non-VA insurance on VA use for nonelderly veterans. While there are a number of studies on dual VA-Medicare enrollment among the elderly population, these studies tend to focus on studying how care fragmentation or differences in reliance affect quality of care, patient outcomes, or costs. These studies tend not to focus on not on isolating the effect of gaining or losing insurance on VA use, which is not surprising since the essentially universal nature of Medicare coverage for elderly adults leaves very little variation in coverage.

Among studies focusing on insurance coverage and VA use by the nonelderly veteran population, we found two studies with strong research designs. We consider Frakt, Hanchate, and Pizer (2015) to be the more convincing study of the two that we deemed to have appropriate research designs.[26] The authors leveraged state-level Medicaid expansions occurring between 2002 and 2008 to estimate the causal effect of population-level Medicaid eligibility on aggregate state-level measures of cumulative VA enrollment and VA use drawn from nationwide administrative VA data. They used a well-established research design to isolate the effect of Medicaid eligibility changes driven by policy from changes in eligibility driven by potentially endogenous changes in income and family structure.

Frakt, Hanchate, and Pizer (2015) found significant effects of predicted Medicaid eligibility on VA enrollment and demand for inpatient days and clinic visits, with all three outcomes declining in response to increases in Medicaid eligibility. Specifically, they estimated statistically significant elasticities with respect to Medicaid eligibility of –0.11 for VA enrollment, –0.065 for inpatient days, and –0.14 for outpatient clinic stops. Because they used data from a period prior to the ACA Medicaid expansion, when Medicaid eligibility in most states was fairly limited (sample average 8.9 percent) for the overwhelmingly male veteran population, these elasticities actually imply fairly large responses of VA enrollment and VA use to Medicaid eligibility: An increase in Medicaid eligibility of 10 percent, which would represent an increase of 0.89 percentage points in the population studied by Frakt, Hanchate, and Pizer,

[26] Austin B. Frakt, Amresh Hanchate, and Steven D. Pizer, "The Effect of Medicaid Expansions on Demand for Care from the Veterans Health Administration," *Healthcare*, Vol. 3, No. 3, 2015, pp. 123–128.

reduced enrollment by 1.1 percent, reduced inpatient surgeries by 0.6 percent, and reduced outpatient clinic stops by 1.4 percent.

These estimates imply very strong behavioral responses to health insurance at the individual level, particularly when we consider that these estimates capture the effect of eligibility rather than insurance coverage. If we assumed that the only mechanism through which Medicaid expansion affects VA use is by increasing insurance coverage, then we would need to scale the estimates from Frakt, Hanchate, and Pizer up by the inverse of the take-up rate to reflect the effect of increased insurance coverage (rather than Medicaid eligibility) on VA use. Realistic Medicaid take-up rates (typically below 20 percent for adults) would lead to far larger estimates for the semi-elasticity of VA demand with respect to uninsurance.[27] In spite of the compelling research design, we ultimately decided not to use the Frakt, Hanchate, and Pizer estimates in our policy analysis because of the uncertainties involved in backing out estimates of the effect of health insurance from estimates of the effect of Medicaid eligibility. Even so, this article is noteworthy for firmly demonstrating the causal pathway from Medicaid eligibility to reduced VA demand.

Instead, we adapted our central scenario elasticities from Shen et al. (2008) because that study also had a valid research design for causal inference and contained estimates of the effect of insurance coverage. Shen et al. also reported estimates that were specific to several of the types of utilization that we analyzed here (inpatient care and prescriptions). The study used data on a large sample of VA enrollees to estimate a two-part model for VA health care spending as a function of private (non-VA) insurance coverage and an extremely rich set of individual covariates, including detailed controls for health status. Recognizing the potential for self-selection of enrollees into non-VA insurance, Shen et al. used the private insurance coverage rate in each veteran's metropolitan area as an instrumental variable for private insurance coverage and then estimated selection-corrected versions of their two-part models. Shen et al. found that the effect of private insurance on VA spending (among enrollees), inpatient spending, and pharmaceutical spending was statistically significant and negative—i.e., that non-VA insurance reduced spending.

The two-part model used by Shen et al. does not have readily interpretable parameters. They accordingly reported predicted values from their model under two values of their private insurance variable. The resulting predictions allowed us to calculate a semi-elasticity of health care use with respect to the probability of uninsurance by dividing the predicted percentage change in utilization resulting from an increase in the probability of uninsurance coverage by the magnitude (in percentage points) of the increase in uninsurance. To reduce dependence on the endpoints of the change and to obtain a more conservative elasticity estimate, we used the midpoint of the utilization measures rather than the endpoint to calculate the percentage change in use.

[27] Susan H. Busch and Noelia Duchovny, "Family Coverage Expansions: Impact on Insurance Coverage and Health Care Utilization of Parents," *Journal of Health Economics*, Vol. 24, No. 5, 2005, pp. 876–890, doi:10.1016/j.jhealeco.2005.03.007.

To illustrate this calculation, we walk through the derivation of our semi-elasticity for inpatient surgery. Shen et al. calculated predicted values from their model associated at two probabilities of insurance coverage (38 percent and 34 percent). Holding all else constant, they report that predicted VA inpatient spending per enrollee would be $9,872 if 34 percent of enrollees had private insurance, compared with $9,769 if 38 percent of enrollees had insurance. A reduction of 4 percentage points in the uninsurance rate reduced VA spending on surgery by $103, a reduction of approximately 1 percent in spending per enrollee as a percentage of the midpoint of the two spending levels. This yields a semi-elasticity of VA care with respect to being uninsured of 26.2 percent, implying a value for β^{VA} of ln(1+0.262) = 0.233.

By way of comparison, Frakt, Hanchate, and Pizer (2015) estimated a Poisson regression coefficient on Medicaid eligibility for inpatient days of –0.73, which implies a semi-elasticity of inpatient use with respect to Medicaid eligibility of –52 percent. This estimate suggests that changing the Medicaid eligibility rate for a population of veterans from 0 percent to 100 percent would cut that population's use of VA inpatient care in half. Comparison to Shen et al. is complicated by the fact that Frakt, Hanchate, and Pizer (2015) used aggregate data on VA use at the VA sector-year level rather than individual-level data. However, Frakt, Hanchate, and Pizer (2015) included the veteran population as an exposure term (in addition to sector fixed effects), which means that their Medicaid eligibility coefficients should be interpreted as reflecting semi-elasticities of per-person rates with respect to Medicaid eligibility. A one-unit change in Medicaid eligibility (corresponding to a shift from 0-percent to 100-percent Medicaid eligibility) would be far outside the observed range of variation for Frakt, Hanchate, and Pizer, and so it is possible that the large elasticities implied by their estimates are an artifact of extrapolating out of sample.

Further assumptions had to be made to apply the Shen et al. parameters to our analysis, most notably that the proportional effects estimated by Shen et al. for changes in VA spending were indicative of proportional changes in the number of health care events. We also applied Shen et al.'s elasticity for total spending to the office visit category of care because the study did not separately estimate office visits.

Finally, we had to assume that there was no response of VA enrollment to the loss of non-VA insurance. We might expect there to be such an effect, but evidence on this point is, surprisingly, mixed. (Shen et al. studied a sample of enrollees and so did not examine enrollment decisions.) Again, we note that Frakt, Hanchate, and Pizer (2015) found a significant and economically meaningful reduction in new VA enrollment as a causal effect of expanded Medicaid eligibility. However, other studies have obtained different results. A pair of studies using the natural experiment created by Massachusetts health care reform found no effect on VA enrollment or VA patient status within the population of veterans.[28] Similarly, our analysis of the ACS did not

[28] S. H. Chan, J. F. Burgess, J. A. Clark, and M. F. Mayo-Smith, "Experience of the Veterans Health Administration in Massachusetts After State Health Care Reform," *Military Medicine*, Vol. 179, No. 11, 2014, pp. 1288–1292, https://doi.org/10.7205/MILMED-D-14-00093; E. S. Wong, M. L. Maciejewski, P. L. Hebert, C. L. Bryson, and C. Liu, "Massachusetts Health Reform and Veterans Affairs Health System Enrollment," *American Journal of Managed Care*, Vol. 20, No. 8, 2014, pp. 629–636.

find a statistically significant change in VA coverage as a consequence of the ACA Medicaid expansion, though this may be explained in part by the fact that the ACS captures the stock of VA patients rather than the flow of new enrollees. A study by VA researchers using data from two VA regional networks in the Midwest did not show a sharp divergence in new enrollee rates between Medicaid expansion and nonexpansion states either.[29] Meanwhile, our estimate of the before-after change in VA coverage following ACA implementation indicates a nationwide increase in VA coverage, though there is no way to tell whether this is the result of access to non-VA insurance or the individual mandate or simply the continuation of the long-term trend toward increased VA use. To sum up, our review of the literature did not provide overwhelming evidence that non-VA insurance coverage reduces VA enrollment, even though the study that we consider to have the strongest research design (Frakt, Hanchate, and Pizer, 2015) did find such an effect. In our view, it is not clearly unrealistic to assume no enrollment response to non-VA coverage.

The reason we needed to assume there was no enrollment response to non-VA coverage is that we needed to extrapolate from the Shen et al. elasticities (which are valid for enrollees) to the health care use of the entire veteran population (which is what we observe in the MEPS).

Let E denote VA enrollment. Then we have (extrapolating linearly from the marginal effect of predicted probability of U:

$$\frac{\mathrm{d}\mathbb{E}(VA|E)}{\mathrm{d}P(U)} = \mathbb{E}(\text{VA}|E, U=1) - \mathbb{E}(\text{VA}|E, U=0)$$

Enrollment is a partition of veterans, and nonenrollees cannot use VA, so

$$\mathbb{E}(VA) = \mathbb{E}(VA|E=1)P(E) + \mathbb{E}(VA|E=0)(1-P(E)) = \mathbb{E}(VA|E=1)P(E)$$

$$\frac{\mathrm{d}\mathbb{E}(VA)}{\mathrm{d}P(U)} = \frac{\mathrm{d}\mathbb{E}(VA|E)}{\mathrm{d}P(U)}P(E) + \frac{\mathrm{d}P(E)}{\mathrm{d}P(U)}\mathbb{E}(VA|E)$$

We made two additional assumptions in order to apply the Shen et al. semi-elasticities to our MEPS-based model of VA and non-VA demand, which does not contain information on VA enrollment.

First, we assumed that loss of insurance had no effect on VA enrollment. This assumption was necessary in order to shut down changes in demand coming from VA enrollment. However, Frakt, Hanchate, and Pizer (2015) found that enrollment was responsive to non-VA coverage options. If further research finds that there are enrollment effects of the ACA, this assumption could make our central estimates somewhat conservative in terms of the total impact on VA demand.

Second, we assumed that the probability that an individual's insurance status changed as a result of ACA repeal was identical for VA-enrolled and non-VA-enrolled veterans within each of the age, income, and health status demographic cells used in our repeal analysis. For example, if a group of veterans with a VA enrollment rate of 40 percent experienced a 10-percentage-point

[29] Abigail Silva, Elizabeth Tarlov, Dustin D. French, Zhiping Huo, Rachael N. Martinez, and Kevin T. Stroupe, "Veterans Affairs Health System Enrollment and Health Care Utilization After the Affordable Care Act: Initial Insights," *Military Medicine*, Vol. 181, No. 5, 2016, pp. 469–475, doi:10.7205/MILMED-D-15-00094.

increase in non-VA uninsurance, we would assume that 40 percent of the veterans losing insurance were VA enrollees and 60 percent were nonenrollees. This assumption was necessary for us to combine the semi-elasticities derived from Shen et al. with estimates of per capita VA use (including nonenrollees in the denominator) and scenarios for changes in the number of uninsured veterans that are also defined as shares of the total nonelderly veteran population (also including nonenrollees in the denominator).

Although it might seem inconsistent to use elasticities estimated from a sample of VA enrollees to predict changes in per capita use for a population that includes nonenrollees, such a calculation is appropriate as long as the proportion of veterans losing insurance coverage is uniform between enrollees and nonenrollees. This is because, by definition, nonenrolled veterans do not use VA health care. As long as the baseline level of VA use is defined on a per capita basis for the full veteran population (including both enrollees and nonenrollees), the level of VA use by the enrollees will be scaled down to account for the presence of nonenrolled veterans. Under our assumption of uniform coverage changes between enrollees and nonenrollees, the semi-elasticity of VA use with respect to non-VA insurance for the full population is identical to the semi-elasticity for enrollees only; the semi-elasticity for enrollees is the parameter we derived from the estimates of Shen et al (2008).

Since this is an important assumption, it is worthwhile to consider a numerical example. Suppose that there is a population of 100 veterans, 40 of whom are VA-enrolled and 60 of whom are nonenrolled. For simplicity, assume that all veterans in both groups have non-VA insurance at baseline. Assume that, at the baseline distribution of insurance status, the average enrollee has ten office visits a year at VA, so the population total number of VA office visits is 400, and the per capita number of VA office visits for all veterans is four. Finally, assume that an uninsured veteran makes 50 percent more VA office visits than an insured veteran.

Then, consider a 10-percentage-point increase in non-VA uninsurance, meaning that ten of our 100 veterans become uninsured. Under our assumption of uniform coverage changes between enrollees and nonenrollees, four VA enrollees lose coverage, and six nonenrollees lose coverage. The nonenrollees have no change in VA utilization under the assumption that VA enrollment does not respond to non-VA insurance. The four enrollees who became uninsured increase their VA utilization to 15 office visits per year, increasing the total number of office visits to 420. The change in office visits for the enrollees can be calculated as

$$\begin{aligned}\text{Change in volume of care} =& \text{Number of enrollees}\\ &\times \text{Proportion of enrollees losing insurance (percentage points)}\\ &\times \text{Utilization per enrollee} \times (\exp(\beta^{\text{VA}}) - 1)\\ =& 40 \times 0.1 \times 10 \times 0.5 = 20\end{aligned}$$

Assuming that the percentage-point change in uninsurance is uniform between enrolled and nonenrolled veterans, this effect can also be calculated by applying the elasticity for enrollees to per capita levels of use:

$$\begin{aligned}\text{Change in volume of care} =& \text{Number of veterans}\\ &\times \text{Proportion of veterans losing insurance (percentage points)}\\ &\times \text{Utilization per veteran} \times (\exp(\beta^{\text{VA}}) - 1)\\ =& 100 \times 0.1 \times 4 \times 0.5 = 20\end{aligned}$$

This assumption is also likely to result in estimates that are conservative in terms of the total impact on VA demand insofar as VA enrollees have a lower willingness to pay for non-VA coverage. Holding health status, income, and age constant, we might expect this to be the case since VA enrollment should allow these veterans to maintain greater access to care without non-VA insurance as compared with nonenrolled veterans. However, a critical unknown factor determining whether VA-enrolled or nonenrolled veterans are more likely to lose non-VA coverage under ACA repeal is the allocation of any reductions in Medicaid eligibility between disabled and nondisabled populations. VA-enrolled veterans within a given age, income, and health status cell may be more likely to qualify for Medicaid through a disability-related pathway than nonenrolled veterans since disability status affects eligibility for both Medicaid and VA.

Definition of Repeal Scenarios

We described three scenarios in the report: reversal of ACA coverage gains, American Health Care Act (AHCA) (2020), and AHCA (2026). Here we briefly describe how our baseline scenario and insurance changes in these scenarios were derived.

Baseline Scenario

We used the 2015 NHIS (with imputed income files) to estimate the probability of uninsurance for nonelderly veterans in the eight age, income, and health status cells used to define our scenarios for ACA repeal. Because the NHIS yields a slightly higher overall uninsurance rate than the ACS (by about 1 percentage point), we scaled down the NHIS uninsurance rate estimates to match the 2015 ACS uninsurance rate for the corresponding age-income cell in order to ensure consistency with our main estimates of coverage changes between 2013 and 2015.

Scenario 1: Reversal of ACA Coverage Gains

We estimated a logistic regression for non-VA uninsurance in the 2013–2015 ACS that controlled for age, service era, state, and full interactions between the age and income categories used in our repeal analysis and indicators for the years 2014 and 2015. This specification allows us to calculate the adjusted percentage change in the probability of being uninsured between 2013 and 2015—i.e., the semi-elasticity of non-VA uninsurance with respect to the 2015 year effect, where this effect was fully flexible across the four combinations of age and income included in the regression.

We multiplied the age- and income-specific semi-elasticities by these baseline uninsurance rates to produce a predicted percentage change in non-VA uninsurance attributable to the before-after effect of the ACA (i.e., going from 2013 to 2015) for each age, income, and health status cell. Our first scenario was defined as *increasing* uninsurance by the magnitude of the estimated cell-specific reductions. (Recall that the single-year NHIS is too small to allow precise estimation of changes in insurance status for small subgroups of veterans.)

Scenarios 2 and 3: Reversal of ACA Coverage Gains

For these scenarios, we also started with the baseline non-VA uninsurance rates estimated from the NHIS. To calculate percentage changes in uninsurance, we used a person-level output file from the COMPARE microsimulation model, which contained predicted insurance status in 2020 and 2026 under current law and under AHCA. This file is based on the Survey of Income and Program Participation (SIPP) and contains model predictions of insurance coverage under current law and AHCA for the entire SIPP sample. To develop predicted coverage changes that could be applied to veterans, we reweighted the COMPARE-SIPP file to match the distribution of age, gender, income, and health status estimated for veterans in the ACS and NHIS. For each of the eight demographic cells in our model, we calculated the predicted percentage change in insurance coverage relative to current law resulting from each AHCA scenario and then multiplied this percentage change in insurance by the baseline level of non-VA insurance coverage to obtain a percentage-point change in insurance coverage that was applicable to the 2015 population.

Discussion and Sensitivity Analyses

Our analysis does not attempt to incorporate anticipated changes in the veteran population. Instead, our baseline for all scenarios is the 2015 veteran population and the observed levels of non-VA uninsurance and VA use. We defined our scenarios as reflecting the percentage changes in insurance coverage anticipated under various changes to the ACA. Specifically, we applied the percentage change in uninsurance estimated in the ACS to the baseline level of uninsurance estimated in the NHIS. Throughout this analysis, we used measures of uninsurance that include VA coverage as insurance.

As we discussed in the main report, a major assumption involved in developing our repeal scenarios is that coverage changes resulting from a policy change are identical (in percentage terms) between veterans and nonveterans of the same age, gender, income, and health status. To validate this assumption, we used 2013–2015 ACS data to investigate whether this assumption was plausible for changes between 2015 and 2013. To approximate our analysis of ACA repeal as closely as possible, we used 2015 as the baseline year and attempted to predict the percentage difference between the uninsurance rate in 2013 and the uninsurance rate in 2015. We estimated a logistic regression model for uninsurance among the nonveteran population using 2015 as the base year and with flexible time effects across age/gender/income cells. The model included all covariates used in our ACS analysis except service era, which is not defined for nonveterans. We then used estimates for the nonveteran population to calculate the percentage change in uninsurance associated with going from 2015 coverage levels to 2013 coverage levels, averaged over the values of covariates in the 2015 veteran population. This regression-adjustment procedure is similar in spirit to the reweighting procedure we used to adapt the COMPARE microsimulation results to the veteran population.

For reference, Table A.23 reports the population shares in each cell for the veteran and nonveteran populations as of 2015, highlighting the differences in demographic structure between the two. Our results show that the model fit has some discrepancies but that overall predicted coverage changes for each age and income cell are within 10 percent to 20 percent of the changes we observe for veterans. For some cells, regression adjustment makes the coverage changes more similar between veterans and nonveterans, but for other cells, it makes the changes slightly further apart.

As an alternative to our assumption of identical proportional changes in uninsurance for veterans and nonveterans, we might have chosen to assume identical percentage-point changes in uninsurance between veterans and nonveterans. We used this assumption in one of the sensitivity analyses reported below and obtained extremely similar estimates to our main analysis. We conclude that the differences in coverage changes across groups are large enough that our analysis is robust to minor changes in how changes observed in the general COMPARE population are mapped into the veteran population.

Table A.23. Comparison of Veteran to Nonveteran Demographic Structure and Differences in Coverage Between 2015 and 2013

		Veterans		Nonveterans			
Age	Income	Share of Nonelderly Population in Demographic Cell	Adjusted % Increase in Uninsurance (2015 to 2013)	Share of Nonelderly Population in Demographic Cell	Adjusted % Increase in Uninsurance (2015 to 2013)	Predicted % Increase in Uninsurance for Veterans (2015 to 2013)	Ratio of Predicted to Actual Change in Veteran Uninsurance
Under 50	200% FPL or over	37.53%	46.10% [33.7%, 59.6%]	45.43%	54.50% [41.5%, 68.8%]	53.40% [51.0%, 55.8%]	115.84%
Under 50	Under 200% FPL	10.85%	61.80% [48.4%, 76.3%]	22.77%	69.10% [55.4%, 84.1%]	49.20% [47.4%, 50.9%]	79.61%
50 or over	200% FPL or over	40.29%	60.70% [46.2%, 76.6%]	24.02%	67.90% [52.8%, 84.5%]	59.90% [55.7%, 64.2%]	98.68%
50 or over	Under 200% FPL	11.33%	60.70% [46.7%, 76.0%]	7.78%	66.10% [51.7%, 81.8%]	68.10% [64.2%, 72.2%]	112.19%

NOTES: Adjusted percentage increase in uninsurance for veterans is derived from logistic regression for uninsurance with 2015 specified as the base year and time effects for 2013 and 2014. Adjusted changes are calculated for the 2015 veteran population. The time effects, which capture the adjusted difference in uninsurance between 2013 and 2015, are allowed to vary freely by age (over/under 50), family income (over/under 200% FPL), and gender. The model also controls for age, income, race/ethnicity, and gender. Service era is omitted to allow comparison to nonveteran population (for whom service era is not defined). Adjusted percentage increase in uninsurance for nonveterans is calculated from the same regression model estimated on a sample of nonveterans. Predicted percentage increase in uninsurance for veterans is derived from out-of-sample predicted values and average marginal effects calculated for the nonelderly veteran population rather than the nonelderly nonveteran population.

Table A.24 presents estimates of the effects of AHCA (2026 provisions) on VA and total health care use under alternative modeling assumptions. Our best estimates ("Central Parameters") are those reported in Table 4.2 of the report. Effects under the low-reliance model use semi-elasticities that are 50 percent the size of those in our central scenario. Effects in the high-reliance model use semi-elasticities that are twice as large as those in our central scenario.

The 2026 percentage-point-changes model takes percentage-point changes in uninsurance for each population cell directly from the reweighted COMPARE microsimulation output, whereas our main AHCA scenario converted policy effects from COMPARE into percentage changes in uninsurance and multiplied those percentage changes by the baseline scenario uninsurance rate to obtain predicted changes in the 2015 uninsurance rate.

The final column ("Omit Differences in Use Across Groups") estimates changes in health care use without modeling differences in baseline health care use across groups. This is equivalent to assuming that all groups experience an identical percentage-point change in uninsurance. We included these results to illustrate the importance of modeling how health care use varies across groups of veterans. Compared with the model that omits differences in use, our best estimates for the increase in VA use that would result from AHCA are roughly 40 percent larger for office-based visits and roughly 75 percent larger for inpatient surgery and prescription drugs.

Table A.24. Sensitivity Analysis: Change in VA Use and Reliance Due to AHCA (2026) Under Alternative Parameters

		Change from Baseline				
	2015 Baseline	Central Parameters	Low-Reliance Parameters	High-Reliance Parameters	2026 Percentage-Point Changes	Omit Differences in Use Across Groups
Office-based visits						
VA visits	10,698,205	+243,384	+112,872	+568,789	+309,375	+171,095
(% change)		+2.28%	+1.06%	+5.32%	+2.89%	+1.60%
All-payer visits	56,169,585	–939,353	–516,371	–1,569,659	–1,249,186	–932,157
(% change)		–1.67%	–0.92%	–2.79%	–2.22%	–1.66%
Reliance	19.05%	19.81%	19.43%	20.64%	20.04%	19.68%
(change in percentage points)		+0.76%	+0.38%	+1.59%	+1.00%	+0.63%
Inpatient surgery						
VA surgeries	157,579	+3,525	+1,660	+7,974	+4,334	+2,033
(% change)		+2.24%	+1.05%	+5.06%	+2.75%	+1.29%
All-payer surgeries	528,851	–9,310	–5,003	–16,208	–11,559	–7,026
(% change)		–1.76%	–0.95%	–3.06%	–2.19%	–1.33%
Reliance	29.80%	31.01%	30.40%	32.29%	31.30%	30.59%
(change in percentage points)		+1.21%	+0.60%	+2.50%	+1.50%	+0.79%
Prescription drugs						
VA prescriptions	28,410,071	+911,238	+418,275	+2,176,947	+860,225	+522,650
(% change)		+3.21%	+1.47%	+7.66%	+3.03%	+1.84%
All-payer prescriptions	145,225,712	–2,444,801	–1,317,547	–4,234,395	–2,416,303	–1,976,704
(% change)		–1.68%	–0.91%	–2.92%	–1.66%	–1.36%
Change in reliance	19.56%	20.54%	20.03%	21.69%	20.50%	20.20%
(change in percentage points)		+0.97%	+0.47%	+2.13%	+0.93%	+0.63%

NOTE: This table reports estimates of changes in VA and total health care use. See text for details.

Appendix B. Methods for State-Specific Estimates

In supplementary online materials accompanying this report, we report two types of state-specific estimates. First, we provide a set of empirical estimates of state-specific changes in coverage between 2013 and 2015. Second, we predict the state-level impact of the coverage changes anticipated under AHCA on the overall level of VA demand.

We report state-specific estimates of post-ACA changes in coverage for 30 states with sufficiently large populations of nonelderly veterans. Following the Urban Institute's state-specific analysis of changes in uninsurance rates,[30] we limited attention to states where the ACS contains a sample of at least 1,000 nonelderly veterans in 2015. This set of states includes 19 Medicaid expansion states and 11 nonexpansion states. Because our analysis of the coverage and VA use impacts of AHCA relies more heavily on VetPop2016 population estimates, we were able to produce estimates for all 50 states, but with additional assumptions needed to analyze states with smaller populations.

State-Specific Coverage Estimates

For states with sufficiently large samples, the spreadsheet "RR1955 State-Specific Estimates.xlsx" (available online at www.rand.org/t/RR1955) presents state-specific estimates of the number and proportion of nonelderly veterans with coverage from specific sources in 2013 and 2015. Coverage rates are based on estimates of population proportions from the ACS. To derive numbers of nonelderly veterans, we used state-level VetPop2016 estimates of the total and elderly veteran populations to calculate the number of nonelderly veterans by state in 2015. As noted in Appendix A, VetPop estimates must be scaled down by approximately 1.4 percent to account for the proportion of nonelderly veterans living in institutions. We applied this national estimate of the proportion of institutionalized veterans to the VetPop estimate for each state to obtain a target population count for 2015. We then calculated the ratio of this VetPop-derived population to the ACS population estimate of nonelderly, noninstitutionalized veterans for each state to derive a state-specific VetPop inflation factor, which we then multiplied by both the 2015 and 2013 ACS population totals for each state and insurance source to produce our state-specific population counts. The unweighted average VetPop inflation factor across states is 1.218, which is in line with the size of the nationwide veteran undercount in the ACS. We report totals and coverage rates for the following coverage configurations:

- uninsured (including VA): no insurance or IHS only
- uninsured (excluding VA): uninsured or VA-only
- private coverage
- Medicaid

[30] Jennifer Haley, Genevieve Kenney, and Jason Gates, "Veterans Saw Broad Coverage Gains Between 2013 and 2015," Washington, D.C.: Urban Institute, April 2017.

- VA-covered
    - VA-only: VA-covered with no other coverage
    - VA with private: VA with ESI or direct-purchased coverage
    - VA with Medicaid.

As discussed in Appendix A, we caution that ACS sources of insurance data are prone to reporting errors, and we caution data users that these estimates should be interpreted with the knowledge that such errors are likely. In particular, it is likely that the levels of Medicaid coverage and direct-purchase coverage may be overstated. As discussed in Appendix A, however, we place more confidence in estimated *changes* in coverage between 2013 and 2015 due to the general concordance between estimated trends in the ACS and the NHIS.

In addition to unadjusted estimates of the 2013 and 2015 numbers and proportions of veterans with each of these coverage types, we used logistic regression to estimate changes in coverage adjusted by age, race/ethnicity, gender, and service era. We modified the logistic regression model that we used to estimate adjusted nationwide changes between 2013 and 2015 to allow the coefficient on the year 2015 effect to vary freely across states. For each state, we then calculated the average marginal effect on coverage associated with the year 2015 for the nationwide veteran population with the state indicators set equal to one for the state of interest and zero for all other states. These marginal effect estimates capture what the state-specific change in coverage between 2013 and 2015 would have been if each state's nonelderly veteran population matched the nationwide distribution of age, race/ethnicity, gender, and service era. Ninety-five percent confidence intervals are presented in brackets in our spreadsheets. We reported adjusted changes in ESI and direct-purchase coverage because we were less concerned about bias in the changes due to reporting error than in the overall levels.

State-Specific VA Use Estimates

Analyzing state-specific changes in VA use that might result from AHCA requires numerous additional assumptions because of data limitations: The ACS has small samples for many states, the MEPS lacks state codes, and VA reports relatively few figures on state-level VA use by the nonelderly population. We chose an approach designed to match certain benchmark features of those data points that are available and to produce state-specific estimates of changes in VA use that are consistent with the nationwide estimates reported in Table 4.2. This modeling effort is somewhat less sophisticated than the methods used in our nationwide estimate. However, as discussed in the report, our analysis should be adequate to capture the basic intuition that both VA use and exposure to loss of insurance under AHCA or similar proposals may be positively correlated across subgroups of veterans. As with our nationwide estimates, these state-specific estimates attempt to capture differences across states in the age structure and economic status of the veteran population. Whereas our nationwide analysis modeled health status, we omitted health status from this analysis and did not rely on regression adjustment due to a lack of sufficient state-specific data about all relevant covariates. Instead, we modeled differences between Medicaid expansion and nonexpansion states in the exposure of different age and income groups to loss of coverage under the 2020 and 2026 provisions of AHCA.

To develop a state-specific baseline scenario, we began with VetPop2016 estimates of the age distribution by state (aggregated to five-year bins) as of September 30, 2015, as our starting point. We used the 2015 ACS to estimate the proportion of veterans in each five-year age cell living in families with incomes below 200 percent of the FPL and then multiplied these proportions by the VetPop2016 age distribution to obtain an age-income distribution for each state's (all-ages) veteran population as of 2015. Because some states had small samples, we used state-specific ACS estimates only for states with an unweighted sample size of 1,000 or more nonelderly veterans in 2015; to calculate the age-specific income distribution for the 21 states (including Washington, D.C.) with small samples of veterans, we grouped these states by Medicaid expansion status and used the expansion (or nonexpansion) state average among small states to calculate the age-income distribution.

Rather than analyzing VA use per capita, as in our nationwide analysis, we leveraged counts of VA patients by state for 2015 published by the VA in State Summary fact sheets.[31] To allocate these VA patients across the age and income distribution, we estimated the probability of being a VA patient by age and income for all noninstitutionalized veterans in the 2008–2014 MEPS. We then multiplied these estimated probabilities of being a VA patient by the state-specific age-income distributions derived from VetPop2016 and the ACS to obtain the age and income structure of the VA patient population for each state. To calibrate these populations to the state patient totals reported by VA, we rescaled the entire distribution to match the total. This method effectively assumes that the ratio of VA patients per capita between any two age and income groups is identical within each state, but that the overall probability that veterans are VA patients varies across states.

As we discussed in the report and documented in Appendix A, levels of VA use among VA patients also vary with age and income. We used a similar calibration strategy to define the baseline scenario, using the 2008–2014 MEPS to calculate nationwide rates of VA use per patient by age and income and then multiplying these use rates by the number of VA patients allocated to each state-age-income cell to obtain a total volume of VA care for each cell. This procedure resulted in slightly higher levels of VA use than in our nationwide estimates, so we scaled down all nationwide estimates to match the baseline scenario reported in Table 4.2.

Further assumptions were needed to develop state-specific predictions of changes in uninsurance that might result from the AHCA. As in our main analysis, we reweighted microsimulation output from RAND's COMPARE model to match the age, income, gender, and health status distribution of the veteran population. We then stratified these data by state Medicaid expansion status as of July 1, 2017 (Louisiana, Montana, and Alaska were modeled as Medicaid expansion states in the COMPARE analysis used here), and calculated the reweighted proportion of uninsured adults for each of the age-income bins used to define our state-specific baseline scenario. In contrast with our main estimates, we did not attempt to base our ACHA scenarios on information about the 2015 baseline level of uninsurance because we had

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[31] U.S. Department of Veterans Affairs, "State Summary: VA Population and Health Care as of 9/30/2015," 2015. As of August 9, 2017: https://www.va.gov/vetdata/stateSummaries.asp

insufficient data to estimate this for age-income groups within states. Instead, we assigned the predicted percentage-point change in uninsurance due to AHCA to each age-income-expansion status group, assuming that adults age 65 and over would continue to be covered by Medicare and thus would experience no change in insurance status. These model inputs and assumptions defined the full distribution of baseline VA use and changes in insurance status across age and income groups in each state. We then used the central parameters from the analysis presented in the report to calculate the predicted change in VA use implied for each state-age-income cell in response to each cell's predicted change in uninsurance rates under AHCA. Aggregating these changes in coverage led to a slight overestimate of coverage changes forecast in our main, nationwide analysis, and so we scaled down all state VA use changes so that the nationwide changes were consistent with Table 4.2.

In the spreadsheet "RR1955 State Repeal Estimates.xlsx" (available online at www.rand.org/t/RR1955), we reported three measures of VA use for each type of VA care under both the 2020 provisions and the 2026 provisions of the AHCA. Besides reporting our predicted changes in VA use as a number of health care events, we also reported these figures as a percentage of use by nonelderly veterans and as a percentage of overall use (including elderly veterans in the denominator). This latter figure may be of interest because, as noted in the report, the proportion of all-ages veterans who are elderly varies widely across states. Under the strong assumptions necessary to produce these estimates, our model can thus provide insight into which states are more or less likely to experience additional strain on VA capacity as a result of ACA repeal.

In addition to reporting changes in VA use, we reported the predicted change in uninsurance rates for nonelderly veterans in each state. We caution, again, that COMPARE does not explicitly model health insurance choice for veterans, and so these estimates are better viewed as very rough indications of how exposed each state's nonelderly veteran population is to coverage loss under the AHCA. A key assumption here is that veterans and nonveterans with the same age, gender, income, and health status would experience similar changes in insurance coverage as a result of the AHCA; actual changes in coverage might be larger or smaller. In light of the multiple layers of calibration involved in this modeling effort, we would caution against using our estimates of the absolute level of VA utilization for comparison to administrative data on VA use or as an input for further calculations, such as estimating budgetary impacts. As we discussed in Appendix A, the MEPS appears to undercount VA prescriptions by a substantial margin, and our assumptions that the rates of VA enrollment and eligibility are identical (up to a scaling constant) across all states is likely too strong to be realistic. Internal VA data most likely could allow significant refinement of this analysis, but we did not seek to access such data for this study.