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INVISIBLE WOUNDS:
HEALTH AND WELL-BEING IMPACTS OF
MENTAL DISORDER DISABILITY COMPENSATION ON VETERANS

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Working Paper 29877
<http://www.nber.org/papers/w29877>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2022, Revised September 2023

We thank Lisa Brenner, David Card, David Chan, Janet Currie, Manasi Deshpande, Mark Duggan, Liran Einav, Shari Eli, Amy Finkelstein, Kyle Greenberg, Audrey Guo, Sarah Miller, Timothy Moore, Ashley O'Donoghue, Stacey Pollack, Liam Rose, Heather Royer, Frank Schilbach, Hannes Schwandt, George Sheldon, Paul Silver, Jodie Trafton, Todd Wagner, VAGAO Health Outcomes Study group, and seminar participants at ASHEcon, Brock University, Canadian Health Economists Study Group, Carleton University, Electronic Health Economics Colloquium, European Economic Association, Indiana University, National Tax Association Conference, NBER Summer Institute (Aging, Public), Simon Fraser University, Singapore Management University, Southern Economics Association Conference, University of California Santa Barbara, University of South Carolina, and University of Toronto for helpful comments. We are especially thankful to Paul Shute, Wanmei Ou, Babatunde Oguntade, John McCarthy, Rani Hoff, Wes Kaspro, and the VA Office of Performance Analysis and Integrity and VA Debt Management Center for providing data access. The views expressed herein are those of the authors and do not necessarily reflect those of the United States Department of Veterans Affairs, the Veterans Health Administration, or the Veterans Benefits Administration. The work in this paper is part of internal VHA quality improvement and deemed non-research by the Stanford IRB. The work in this paper is part of internal VHA quality improvement and deemed non-research by the Stanford IRB. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at <http://www.nber.org/papers/w29877>

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JEL No. H51,H53,I1,I3,I38,J01

ABSTRACT

We study impacts of the US Department of Veteran Affairs (VA) Disability Compensation program on the health and well-being of the large and rapidly growing population of veterans claiming mental disorders. Our empirical strategy leverages quasi-random assignment of veterans to medical examiners who vary in their assessing tendencies. We find that an additional \$1,000 per year in transfers decreases food insecurity and homelessness by 4.1% and 1.3% over five years, while the number of collections on VA debts declines by 6.4%. Despite facing few monetary costs, healthcare utilization increases by 2.5% over the first five years, with greater engagement in preventive care and improved medication adherence. Patient satisfaction surveys suggest that transfers improve communication and trust between veterans and VA clinicians, leading to greater overall satisfaction. Apart from a reduction in self-reported pain, we estimate precise null average effects on mental and physical health, and on mortality. Lastly, those on the margin of claim denial experience worse outcomes on average than other applicants, with suggestive evidence of large treatment effects for this sub-population, highlighting the precarious positions of many marginally (dis)qualified applicants for this program.

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An online appendix is available at <http://www.nber.org/data-appendix/w29877>

1. Introduction

An estimated one in five Americans will experience a mental disorder in any given year (SAMHSA, 2016). The risks of some of the most prominent disorders, for example major depression and post-traumatic stress disorder, are linked to “invisible wounds”—experiences of trauma and loss that eventually manifest in the individual’s mood, thoughts, and behavior. Military service carries high risks of such trauma and loss, and subsequent mental disorder; nearly 20% of service members returning from Operation Enduring Freedom showed signs of major depressive or post-traumatic stress disorder (Tanielian et al., 2008).

The resulting disorders are often chronic, with recurrent and unpredictable symptoms that make it difficult for affected individuals to support themselves (Bartel and Taubman, 1986; Ettner et al., 1997; Danziger et al., 2009). Those affected experience elevated rates of poverty, homelessness, food insecurity, medical comorbidities, substance use disorders, and mortality (Frank and Glied, 2006; Tarasuk et al., 2013; Chesney et al., 2014).

Disability programs constitute a key form of support for this population. For example, the Veterans Affairs Disability Compensation (VA DC) program, which we study in this article, provides up to \$43,000 a year in untaxed, (mostly) unconditional income to veterans with service-connected mental disorders. Once granted, veterans receive a reliable and long-lasting source of income support (GAO, 2019; Murdoch et al. 2019).

At the same time, academics and policymakers, noting the decades-long growth of disability program expenditures, both for veterans and civilians, have pointed to the rapid increase in the compensation of mental disorders as a leading cause (e.g., Autor and Duggan, 2006; Autor et al., 2016). Around one third of all disability recipients, across VA DC, Social Security Disability Insurance (SSDI), and Supplemental Security Income (SSI), now receive benefits for mental disorders.¹

¹In 2022, 5.4 million veterans received compensation through VA DC, with total program payments equal \$120 billion, roughly 85% of the expenditures of SSDI. Even more so than SSDI, VA DC expenditures have been on the rise; spending on benefits increased 150% over the past decade (VBA, 2011; VBA, 2021). For comparison, SSDI growth has been significantly slower at 13% from \$131 billion to \$149 billion. VA DC growth may increase as recent legislative efforts seek to expand the program by as much as \$280 billion over the next decade, a nearly 32% increase over this period (CBO, 2021).

Because these conditions are often difficult to verify, unlike more traditionally recognized physical disabilities such as cancers and heart disease, there is concern that some applicants receive compensation beyond the underlying degree of their impairment. Taken together with the extensive evidence on the negative labor supply effects of more generous disability income (Autor and Duggan, 2003; Autor et al., 2016; French and Song, 2014; Gelber et al., 2017), these concerns raise important questions about exactly how effective this aid is among these recipients.²

Quantifying the health and well-being impacts of disability income on mental health recipients is one crucial task in speaking to these concerns. Does this income support access to necessities, such as housing and food, or is the typical recipient already able to meet these needs? Do these benefits allow individuals to invest in their health? Do they exacerbate the high rate of co-occurring substance use disorders by increasing consumption of “sin goods”? We know very little about these important questions, in large part due to a lack of data linking disability applicants to measures of their subsequent health and well-being (Chetty and Finkelstein, 2013).³ Furthermore, in the context of the VA, understanding the impacts of disability compensation is a crucial part of the overall calculus of military service, as spending on the program has increased substantially in recent decades (Greenberg et al., 2022; Bruhn et al., 2022).

This article provides the first causal evidence on the health and well-being impacts of disability compensation for the large and growing population of veterans with mental disorders. To do so, we construct a detailed dataset that combines extensive, individual-level

²Similar concerns are raised for other “difficult-to-verify” conditions such as back pain (e.g., Autor and Duggan, 2006) which have also seen rapid growth (Meara and Skinner, 2011).

³Recent work by Gelber et al. (2022); Black et al. (2018) are the only studies that we know of that provide causal estimates of disability income (SSDI) on one extreme measure of health: mortality. The former finds evidence that more generous payments along the intensive margin reduce mortality. Importantly, the authors find no evidence of such improvements for mental disabilities; if anything, their estimates suggest mortality increases among this population. The latter study finds gaining SSDI (along the extensive margin) increases mortality on average, but reduces mortality among the less healthy. As mortality is relatively rare among applicants with mental disorders, who are much younger than the average applicant, there is reason to believe that any health and well-being effects would manifest in other dimensions that the data in that article do not cover. In another paper, Börsch-Supan et al. (2020) compare those who become disabled but do not receive disability income to those who also do receive disability income, finding some improvements in measures of mental health, especially in countries with more generous programs.

data sources from across the Department of Veterans Affairs. We combine nearly twenty years of claims for mental disability compensation, the VA’s medical assessments of each veteran’s disabilities and their realized compensation, state-of-the-art electronic health records, and internal VA screens and surveys to construct a longitudinal dataset tracking key indicators of each veteran’s health and well-being in the five years following their claim. In total, our analytical sample covers over 800,000 veterans from 2004 to 2021 applying for mental disability compensation through VA DC.

As disability compensation amounts are directly tied to the evaluated severity of a veteran’s disability, simple comparisons of veterans receiving more or less compensation would tend to find that more compensation is associated with worse outcomes. To overcome this challenge and provide causal estimates, our research design leverages exogenous variation in disability ratings resulting from the quasi-random assignment of mental disability claims to medical examiners.⁴ Board-certified psychiatrists and licensed psychologists, these examiners evaluate hundreds to thousands of veterans’ claims each over our sample period. The information they recover and report on these forensic examinations is a crucial input to the VA’s determination of the *severity* of the veteran’s disability; veterans whose disorders are deemed more severe then receive higher monthly compensation for (typically) the rest of their lives.⁵

We begin by investigating the relationship between examiner assignment and veterans’ cumulative benefits. We construct a measure of each veteran’s examiner’s tendency in evaluating mental disability claims as the leave-out average VA DC compensation among all of the examiner’s other claims. We find large and permanent first-stage impacts of examiner tendencies on disability income. Conditional on geographic region and year, being randomly assigned a one standard deviation higher tendency examiner is associated with an increase of \$1,445 in annual benefits in the first year (a 10% increase over the mean), with a persistent annual impact of \$1,230 per year over 5 years, thus providing a durable and reliable extra

⁴Similar designs (“judges’ design”) have been used in a variety of empirical settings, including studies of the criminal justice system (e.g. Kling, 2006; Mueller-Smith, 2015; Aizer and Doyle Jr, 2015; Dobbie et al., 2018), bankruptcy protection (e.g., Dobbie and Song, 2015), foster care (e.g., Doyle, 2007, 2008), hospital care (e.g., Doyle et al., 2015), and physicians (e.g., Eichmeyer and Zhang, 2022).

⁵More precisely, monthly benefit amounts are an increasing function of a veteran’s Combined Disability Rating (CDR), which we discuss more in [section 2](#).

income stream for these veterans.

We then turn to estimating impacts on economic stability and financial well-being. An additional \$1,000 per year reduces rates of ever being food insecure (measured by annual primary care screens) and ever being homeless (proxied by diagnosis codes, use of homeless beds and services such as rental assistance/vouchers) over a five year period by 4.1% and 1.3%. Financial well-being, measured by the number and balance amount of delinquent debt owed to the VA,⁶ also improves significantly. Veterans use the additional income to secure basic needs such as food and housing; in contrast, we do not find any increases in use of “sin goods” such as alcohol consumption or binge drinking, despite the prevalence of substance use disorders in this population. Measures of self-reported pain improve by half a percent, suggesting that in addition to helping secure basic needs and improve financial well-being, disability income may alleviate psychosocial stress.⁷

To begin to understand potential impacts on health, we next investigate impacts on healthcare utilization and engagement. We find that an additional \$1,000 per year increases VA outpatient utilization by 2.5%, leading to more scheduled appointments, more outpatient visits, and higher take-up of preventive care such as annual flu vaccinations and Hepatitis C screens, and greater medication adherence. This utilization increase is not driven by changes to direct monetary costs as veterans in our sample face little to no cost-sharing. Instead, these increases in healthcare engagement suggest that disability benefits raise veterans’ demand for plausibly valuable care. Viewed in light of our results on improved housing and food security, these likely beneficial health investments are also consistent with the idea that scarcity (of housing, food, and other necessities) impedes decision making (e.g., [Mullainathan and Shafir, 2013](#); [Haushofer and Fehr, 2014](#)): when scarcity is alleviated, veterans seek additional,

⁶Veterans can owe VA money (e.g., for educational/employment benefits, home loans, etc.). After a certain grace period, the debt is referred to the Treasury, who can then withhold the veteran’s federal funds.

⁷The medical and psychology literature have established a link between psychological and social processes and pain ([Linton and Shaw, 2011](#)). The reduction in pain may also be driven by lowering occupation-related physical demands due to labor market effects of disability income ([Cutler et al., 2020](#)); however, the elderly experience similarly sized reductions in pain.

valuable care.⁸

Supporting evidence suggests this increased healthcare engagement partly reflects improved veteran-clinician relationships. Higher VA engagement is in contrast to non-VA care; we do not find any changes to Medicare utilization among the dual-eligible. We study VA-conducted care satisfaction surveys to investigate mechanisms, and find evidence of improved patient-clinician communication and rapport, trust, and greater veteran satisfaction in VA mental health care. Our findings suggest there are spillovers of program benefits; when the VA provides veterans with mental disabilities higher disability income, these individuals become more engaged and satisfied with their healthcare and report better relationships with their physicians.

Despite these improvements, we estimate precise null average effects of disability income on downstream physical and mental health, and mortality. Our 95% confidence intervals can rule out effect sizes larger than 0.1% for \$1,000 annually—in either direction—on incidence of major depressive disorder, alcohol and substance use disorders, and changes to body mass index, blood pressure, and glucose levels. Rare events such as overdose poisoning and suicide attempts are estimated with slightly less precision; however, we are able to reject clinically and statistically significant changes. Shifting to mortality, a 95% confidence interval implies that an extra \$1,000 in annual benefits (or roughly \$13,200 in net present value, tax-free⁹) reduces 5-year all-cause mortality by no more than 0.011pp or 0.14%. Comparing to the literature, we show that our estimates are much more precise than most other work examining the effects of income or wealth on mortality. We view our mortality findings as providing another data point in triangulating survival benefits of income; a standard meta-analysis would put a high weight on our estimates, given that our standard errors are often an order of magnitude smaller than others in the literature.

⁸Another potential explanation for positive utilization impacts hinges on the desire of veterans to qualify for Individual Unemployability (IU) status, a designation that provides veterans with compensation at the 100% rate if they have multiple service-connected disabilities and can demonstrate that they are unable to hold a job as a result of one or more of them. In theory, receiving a higher rating on the assessments we examine may push some veterans to be nearly IU eligible, in which case they may be incentivized to seek more care documenting their unemployability and/or other disabilities. For more details, see <https://www.benefits.va.gov/BENEFITS/factsheets/serviceconnected/IU.pdf>.

⁹Assuming a life expectancy from benefits receipt of 20 years and discount rate of 5%

Overall, our main results suggest important but moderate well-being improvements for veterans claiming mental disorders. For example, back-of-the-envelope calculations suggest that food insecurity could be eliminated in this population for \$24,000 per veteran per year; this amount would simultaneously reduce homelessness by about one-third (since the cost to eliminate homelessness is approximately \$78,000).¹⁰

The modest size of these average effects raises additional questions about whether disability compensation could be better targeted to those with greater needs. For instance, much of the debate about disability program growth and size centers on whether less qualified or less severe applicants ought to be on these programs at all. To explore this idea, we document that those denied benefits at their claim, on average have economic and health outcomes—up to and including mortality—that are *as* poor as those granted the *highest* compensation rates. These applicants, while not meeting criteria for compensation for their mental health claim—at least in the eyes of their assigned examiner, are severely disadvantaged in ways not accommodated or observed by VA DC rules, a fact that may limit the efficacy of the program if the sickest veterans benefit the most from compensation. We explore this idea: Estimates from a correlated random coefficients model (e.g., [Wooldridge, 2015](#)) suggest that the veterans most likely to be denied would in fact benefit *most* from additional compensation—on outcomes up to and including mortality. These auxiliary findings echo those of [Deshpande and Lockwood \(2021\)](#), who find that the value of SSDI may actually be greater for those without qualifying health disorders than for the typical applicant, and suggest that VA DC could be highly effective in helping those on the current margin of receipt.

Our paper contributes to a growing literature on policies improving mental health outcomes and supporting individuals with mental disorders. Researched policies include health insurance coverage ([Finkelstein et al., 2012](#); [Jácome, 2022](#)); medical technologies such as medication¹¹ ([Shapiro, 2022](#); [Biasi et al., 2022](#); [Bütikofer et al., 2020](#)) and cognitive behavioral therapy¹²

¹⁰We do not perform similar exercises for mortality or other health outcomes where we cannot reject the null of zero impact in the denominator.

¹¹There is a large medical literature on the efficacy of psychotropics such as antidepressants ([Cipriani et al., 2018](#)).

¹²Outside of mental health outcomes, [Blattman et al. \(2022\)](#); [Heller et al. \(2017\)](#) find that cognitive behavioral therapy reduces crime among at-risk and economically advantaged individuals, respectively.

(Blattman et al., 2017; Baranov et al., 2020; Angelucci and Bennett, 2022b,a; Bhat et al., 2022; Serena, 2022); and cash transfers in developing countries (see Ridley et al., 2020, for a recent review). We build on this work by studying (disability) income transfers as a policy and directly focusing on a population with mental disabilities who may benefit from a steady stream of income payments.

We also contribute to the literature on the potential benefits of disability programs.¹³ Recent studies have focused on its financial benefits: e.g., consumption smoothing and insurance value (Autor et al., 2019; Low and Pistaferri, 2015) and financial distress (Deshpande et al., 2021). Two papers estimate the causal impacts of disability insurance on mortality. Gelber et al. (2022) exploit kinks in the SSDI benefit formula and find large reductions in mortality stemming from higher compensation amounts, but with imprecise and statistically insignificant estimates for those with mental disorders as a primary disability. Black et al. (2021) use a judges' design and find that being allowed onto SSDI *increases* mortality. We build on these findings by studying a wide set of health outcomes *beyond* mortality, which are especially importance among the younger, longer-lived population with mental disorders. Also related, Chatterji and Meara (2010) study how a policy change which terminated SSDI and Medicare benefits for individuals with substance use disorders impacted hospital visits, and Trivedi et al. (2022) exploit a VA DC policy that expanded eligibility criteria and found reduced hospitalizations but no impact on mortality. Our research design and data allow us to measure precise health and mortality effects with standard errors that are up to an order of magnitude smaller than existing estimates, considerably refining our knowledge of the impacts of disability income.

Finally, there is a broader literature looking at the health impacts of cash transfers. Unconditional cash transfers typically focus on wealth shocks (e.g., lotteries and stock market fluctuations: Imbens et al., 2001; Cesarini et al., 2016; Lindqvist et al., 2020; Golosov et al., 2021; Schwandt, 2018) and cash transfer programs (e.g., Evans and Moore, 2011; Banerjee et

¹³This is in contrast to a large literature on its costs, largely in the form of additional fiscal costs driven by labor supply reductions (Autor and Duggan, 2003; Autor et al., 2016; Cesarini et al., 2017; Coile et al., 2015; Gelber et al., 2017; Maestas et al., 2013; French and Song, 2014).

al., 2020; Jones and Marinescu, 2020; Hoynes and Rothstein, 2019). There is also a larger literature looking at conditional cash transfers on a host of outcomes, with mixed results; see Lleras-Muney (2022) for a review.

It is important to note at the outset that this paper studies the impact of disability income influenced by a medical examiner’s evaluating tendencies rather than VA policies or differences in adherence to evaluating rules and guidelines. It is the variation in evaluations within VA DC guidelines among complex and subjective cases that forms the basis for the research design and the findings in this paper. Our study cannot speak to the VA’s evaluating or rating system.

The rest of this paper is structured as follows. The next section provides details on the VA DC program. Sections 3 and 4 describes our data sources and outlines our instrumental variable empirical strategy. The results are presented in section 5 and discussed in section 6. Finally, the last section concludes.

2. Veterans Affairs Disability Compensation Program

2.1 Primer

The VA DC program provides benefits to veterans for disabilities incurred during active military service. The program paid \$120 billion in benefits to 5.4 million veterans in 2022, making it almost 85% the size (in expenditures) of the Social Security Disability Insurance (SSDI) program—the primary disability program for non-veterans in the United States.

Benefits are administered as monthly, tax-free payments and, unlike the all-or-nothing SSDI and Social Security Income (SSI) programs, are an increasing function of veterans’ VA-determined degree of service-connected disability, known as their “combined disability rating” (CDR). Intended to reflect the degree to which the combination of a veteran’s

service-connected disabilities inhibit work capacity,¹⁴ CDRs range from 0% to 100%, are rounded to the nearest 10%, and are an increasing and concave function of the disabilities for which a veteran is rated (where ratings for each disability are themselves in increments of 10%). Monthly benefits for a single veteran in 2020 ranged from \$142.29 for a CDR of 10% to \$3,106.04 for a CDR of 100% (see [Table D.1](#) for the schedule).¹⁵ Benefit amounts differ slightly based on the veteran’s dependent situation; for example, each additional child dependent adds \$25.00 for a veteran with a CDR of 30% and \$86.05 for CDR of 100%. There is no income or wealth test for these benefits.¹⁶

2.2 Disability Claim and Rating Process

A veteran’s disability rating determination process for a particular disability begins with the veteran filing a claim with the Veterans Benefits Administration (VBA). A veteran must provide evidence and documentation (health records, records of their combat experiences, and so on) to substantiate both the severity of the disability and how the disability is related to their time and activities in service.

After the filing stage, a veteran’s claim is distributed to their local VBA office, at which point an examination is scheduled to independently assess the severity of the claimed disability.¹⁷ This examination is forensic and is virtually always a one-off encounter between the veteran and the examiner.¹⁸ Mutual availability plays a large role in the assignment of veterans to examiners; if the VA can only find examiners far from the veteran’s residence,

¹⁴Service-connected disabilities are broadly construed as those incurred during the veteran’s time in the military (including training), though evidence of events that caused particular disabilities is often required as well. Service-connectedness is evaluated under the evidentiary standard of equipoise, in which the benefit of the doubt goes to the veteran, as ruled in *Gilbert v. Derwinski* (1990).

¹⁵We have experimented with leveraging CDR rounding rules for a potential regression discontinuity design. However, because the majority of veterans only have 1-3 disabilities, the distribution of unrounded CDRs are highly discretized—taking 4-5 values on each side of the threshold—and lumpy, making an RDD infeasible.

¹⁶Veterans can receive “Individual Unemployability”, a dimension of disability that is separate from the CDR ratings, which generally prohibits them from “substantial gainful employment”.

¹⁷For some conditions, and in some cases, the veterans’ evidence and documentation can be treated as sufficient. This is not the case for mental disorder claims, for which the VA does not accept prior clinical evidence and requires a VA-administered examination for substantiation.

¹⁸That examiners are not supposed to administer any treatment in these exams has drawn some criticism especially in the context of mental health examinations (e.g. [Rosen, 2010](#)).

the veteran is reimbursed for their travel costs.

During the examination, the examiner reviews the veterans' medical history, assesses symptoms, and makes judgments on the severity of the veteran's disability. The reporting of this information takes place on standardized Disability Benefit Questionnaires (DBQs; discussed in more detail in [Appendix D](#)). DBQs provide room for free text but, for mental health claims in particular, also prominently feature a seven-item Likert-style assessment of the veteran's Occupational and Social Impairment (OSI). This field closely mimics the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-V; DSM-IV prior to 2014) and forces examiners to make discrete choices in evaluating similarly impaired veterans, providing us with much of the underlying variation in our examiner tendency measure described in the next section. The DBQ is then passed along to a ratings officer who ultimately assigns ratings percentages based on comparing submitted information with a rating rubric. The first page of the DBQ, the OSI section, and the rating officer's rubric can be found in [Figure D.1](#) and [Figure D.2](#).

Once a ratings determination is made, veterans can appeal, but owing to the complexity of the appeals process, initial ratings are quite persistent. From start to finish, the ratings process takes four months on average, though it can take substantially longer.¹⁹ Reexaminations are rare and ad hoc.²⁰

Mental Health Disability Claims

Mental health disabilities in VA have a few notable features that distinguish them from other types of VA DC-covered disabilities.

First, the burden of mental health disorders in the veteran population is large and rapidly growing, with substantial variation across veterans. As of 2019, 1.9 million veterans receive

¹⁹Claims averaged 154 days to decision in FY 2019. See <https://www.va.gov/disability/after-you-file-claim/>, accessed March 9, 2021.

²⁰VA can request a reexamination if the disability has improved; however, this is rare and not permitted if the disability has persisted for more than 5 years, the disability is permanent in nature (e.g., 100% disability), or if the veteran is over 55 years of age. Moreover, when "reasonable doubt arises regarding the degree of disability such doubt will be resolved in favor of the claimant" (Code of Federal Regulations §4.3). For more on the adjudication process, see VBA Manual M21-1: https://www.benefits.va.gov/WARMS/M21_1.asp.

disability compensation for a mental health-related condition, with over 1.1 million for PTSD alone, the fourth most prevalent disability.²¹ Veterans receiving VA DC for PTSD have the highest fiscal burden. [Table C.1](#) shows that PTSD recipients are among the youngest (average age 49), have low mortality rates (one-year rate of 1.0%), their disability ratings are the highest (average rating of 50.1%), and their ratings increase the most over time (+5.88% increase over five years). Moreover, mental disorders exhibit the greatest variation in their ratings compared to other disorders—two-thirds of PTSD disabilities are rated over 50%. The share of VA DC beneficiaries with a mental disability has nearly tripled in under two decades²² ([Figure 1a](#)) and mental health is now the highest-rated “body system” for the plurality of beneficiaries ([Figure 1b](#)).

Second, as mentioned above, the VA requires VA-administered mental disorder examinations and does not accept external evaluations by private providers. This greatly reduces a veteran’s ability to shop for favorable clinicians, as well as any discretion over whether the VA chooses to examine a given veteran. Exams are conducted by board-certified psychiatrists, doctorate-level psychologists, or residents of either under close supervision, which constrains the set of examiners and heightens the role of mutual availability in the examiner assignment process.

Finally, conclusions from mental health examinations, including OSI scores and other documentation, are more subjective than many physical examinations, which are often based on a single quantitative, equipment-testable metric such as the the outcome of a metabolic stress test for cardiovascular conditions, or the degree of flexion of a veteran’s joint. In combination with the wide-ranging ratings for mental-health disabilities, any systematic variation across examiners’ assessments can have substantial implications for the total dollar value of benefits received by a veteran over their lifetime, improving the power of our design.

²¹Mental disorder disabilities are also common among non-veterans, accounting for 34.5% (3.4 million) of all SSDI beneficiaries in 2019 ([Social Security Administration, 2020](#)).

²²This is partly due to a policy change in 2010 which did not require veterans to recall the exact triggering event for PTSD disabilities ([Autor et al., 2016](#)) and the change to DSM-V which removed certain criteria for PTSD.

3. Data Sources and Sample

Our analysis utilizes linked administrative microdata from the Veterans Health Administration (VHA) and Veterans Benefits Administration (VBA). Below we outline the key features of each data source; [Appendix A](#) provide a detailed description on each variable definition. Wherever possible, we follow official VA Office of Mental Health and Suicide Prevention definitions and use source data that create internal VA metrics, predictive algorithms, and clinical decision support dashboards.²³

Disability claims From the VHA, we observe information on all mental health disability examinations conducted by the VHA between 2004 and 2021.²⁴ This includes the date of the examination, the facility at which it was conducted, and the identities of the examiner and the veteran. We also have completed and digitized DBQ forms for roughly half the examinations. We link veterans’ mental health disability claims to the universe of individual disability ratings history (resulting disability of initial claims, denials, appeals, re-ratings, etc.) from the VBA.

Economic and financial well-being The VHA’s annual food insecurity screens track whether the veteran has recently “run out of food and unable to access or have money to buy more food”. These screens allow us to track rates and changes to food insecurity. For all our survey/screen outcomes, we provide bounds on our treatment effects in [Table C.2](#).

Due to its integrated nature, the VHA is also a provider of a broad range of homeless services (e.g., acute and residential homeless beds, homeless clinics and assistance centers, and housing/rental assistance vouchers) which it tracks via health records. Using these records, we construct proxies of ever being homeless over a time period following validated

²³For example, [Figure C.1](#) displays a clinical suicide prevention dashboard. Its back-end source data on homelessness, debt, appointment, and medication adherence outcomes are precisely what we use to construct our outcomes.

²⁴Examinations can also be conducted by private non-VHA contractors. We do not study these exams.

definitions.²⁵

Information on VA debt—most frequently from educational/employment benefits or home loans—from 2016 to 2021 come from the VBA’s debt management center. Delinquent VA debt are mandated by federal law to be referred to the U.S. Department of Treasury after 120 days of debt notice. The Treasury then retrieves the debt by withholding the veteran’s federal funds such as federal pay, tax refunds, social security payments, or VA benefits. Using debt referrals to the Treasury, we construct measures of (VA) debt collection analogous to Dobbie et al. (2017) and Dobkin et al. (2018) for private debt.

Health and mortality As an early adopter of electronic health records in the 1990s, the VHA maintains rich and detailed records which we use to construct a comprehensive view of health and mortality. In addition to standard encounter, diagnosis, and procedure records used to construct measures of utilization, we also have rich information on patients’ scheduled appointments, clinicians’ orders (e.g., flu vaccinations, screening devices), issued but potentially unfilled prescriptions, patient questionnaires (e.g., food insecurity screens, PHQ-9 depressive screens, Alcohol Use Disorders screens), vital signs (blood pressure, pain scores, etc.), biomarkers (weight and height), and lab test results (e.g., HbA1c glucose levels). Data on suicide events are from a congressionally-mandated VA suicide prevention network, which comprises of clinical suicide evaluations, suicide behavior and overdose reports, clinical text, current and historic reports from suicide prevention coordinators, in addition to medical records. We also observe veteran-linked Medicare claims (Parts A, B, and D) from 2011-2019, which give us a view into veterans’ non-VHA care. Finally, veteran-level data on date and cause of death come from the CDC National Death Index. Date of death is available through 2021 and cause of death is available through the end of 2018.

²⁵Similar VA homelessness measures have been used in prior studies to estimate incidence and predictors (Tsai et al., 2014), investigate gender differences (Brignone et al., 2018), and as an outcome following financial assistance (Nelson et al., 2021).

Sample Our analytic sample construction begins with 1.27M veterans filing their first disability claim for a mental health condition between 2004 and 2019.²⁶ For each veteran, we construct combined disability ratings for each calendar year which maps to yearly benefit compensation amounts. This is the sample used to construct examiner tendency discussed in the next section. Following tendency construction, we make a few additional restrictions: We drop veterans who are evaluated by examiners with fewer than 100 total exams over the study period (this step decreases sample size by 10%) and then we drop those who are not enrolled in VHA benefits prior to their disability exam. With these restrictions, our baseline sample consists of 867,016 veterans examined at 128 VHA facilities by 1,749 licensed mental health specialists. Finally, we construct outcomes at the 1-year and 5-year level relative to their examination date for veterans who remain alive during the outcome period (Table C.3 presents our main results without any restrictions on attrition).

Table 1 summarizes our sample of veterans at the time of their first mental health exam. Roughly 89% of our sample are men, 61% are non-Hispanic White, 22% Black, and 8% Hispanic. Almost half the sample are under the age of 50; this is in contrast to SSDI where 30% (41%) of SSDI (mental health) beneficiaries are under the age of 50 (Social Security Administration, 2020). Half of our sample served during the Gulf War and after. Anxiety disorders, in particular PTSD, and mood disorders make up virtually all mental health disability claims. The average claimant receives \$15,090 in disability compensation benefit in their first year, which is just over half their annual income at the time of application. Average compensation amount over the first five years is \$83,233. This gradual upward drift (in real dollars) over time reflects the fact that VA disability compensation is nearly permanent, as well as the fact that veterans are more likely to have ratings increased (via appeals, re-ratings, or worsening of conditions) than decreased.

²⁶Disability examinations can be conducted in-house by the VHA or by licensed contractors. We observe the former.

4. Empirical Strategy

Consider a model relating veteran i 's outcomes to their annualized VA disability benefits, $Benefits_i$:

$$Y_i = \beta_0 + \beta_1 Benefits_i + \beta_2 \mathbf{X}'_i + \varepsilon_i \quad (1)$$

where Y_i is a specific outcome of interest (e.g., any homeless episode within five years), \mathbf{X}_i is a vector of veteran-level control variables, and ε_i is an error term. Ordinary least squares estimates of β_1 in [Equation 1](#) likely reflect both the causal effects of benefits and the correlation between benefits and unobserved determinants of veterans' outcomes. As the VA DC program intends to provide more generous benefits to more disabled veterans, we would expect such estimates to be biased towards finding that benefits are detrimental to veteran health.²⁷

To circumvent this issue, we use a measure of the tendency of the veteran's examiner in evaluating mental health disabilities in ways that lead to higher compensation amounts as an instrument for the the veteran's annual disability compensation amount. These estimates identify an average causal response of veteran outcomes to additional benefits, among veterans whose exact degree of disability and impairment is ambiguous to examiners.

4.1 Instrument Construction

We construct our benefits instrument as the average first-year compensation amounts of other veterans examined by the focal veteran's examiner, following [Dahl et al. \(2014\)](#). In constructing this measure, we leave out the veteran him/herself (i.e., we use the "jack-knife" mean); we also focus attention on examinations occurring in the same facility-year (our data cover 128 facilities across 16 years). Constructing the measure this way circumvents potential concerns around non-random examiner assignment across space or time: for example, sicker veterans may live near VA facilities with higher-tendency examiners, or the composition

²⁷See [Table C.4](#) for the ordinary least squares regressions. As expected, estimated coefficients are biased towards benefits appearing to be detrimental to veteran health.

of claimants and examiners may be evolving together over time. This choice focuses our comparisons on veterans at risk of being assigned to the same set of mental health examiners within the *same VA facility in the same year*.

Specifically, to summarize mental health examiners’ tendencies, we link details on the disability examination (location, time, examiner) with the veteran’s first-year disability benefit compensation, $Benefits_i$.²⁸ Next, we construct residualized benefit amounts of veteran i , denoted as b_i^* :

$$b_i^* \equiv Benefits_i - \gamma \mathbf{X}_i = Z_{ij} + \varepsilon_i \quad (2)$$

where \mathbf{X}_i contains facility-by-year fixed effects, as well as other veteran characteristics predictive of benefit amounts. The veteran characteristics in \mathbf{X}_i —which we show later are *not* essential for quasi-random assignment, but are included for statistical precision—include five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent Orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran’s Elixhauser comorbidity score based on a one-year look-back period. Note that this residual b_i^* contains our measure of examiner tendency Z_{ij} as well as an idiosyncratic veteran-level error term ε_i .

Finally, for each veteran, we construct the leave-out average tendency of examiner j across all of j ’s examinations, denoted by $\mathbb{K}(j)$, as:

$$Z_{ij} = \frac{1}{N_j - 1} \sum_{i' \in \{\mathbb{K}(j) \setminus i\}} b_{i'}^* \quad (3)$$

where N_j is the total number of examinations performed by examiner j . We use this leave-out measure of tendency because regressing outcomes on examiner tendency constructed *without* leaving out veteran i would introduce bias, as the same estimation error would appear on

²⁸We use the historical individual disability records to construct annual CDRs that we then map to dollar amounts. Since we do not observe veteran dependent information, we impute veterans’ compensation amount as if they were single. Dependent information plays a much smaller role than CDR in determining compensation.

both sides of the regression. We then use this predicted examiner tendency measure Z_{ij} as an instrument for $Benefits_i$.

4.2 Variation in Examiner Tendency and First-Stage Estimates

Figure 2 presents a histogram of examiner tendencies. The average number of cases per examiner is 648, with the top 10% of examiners evaluating over 1,600 examinations. The 5th to 95th percentile of our measure of examiner tendency ranges from -\$2,335 to +\$2,352, with a standard deviation (SD) of \$1,447, suggesting large differences in examiners' perceptions of disability and impairment.

The local-linear relationship between our examiner tendency measure and realized one-year benefits is also presented in Figure 2, where we find strong predictive power of our instrument for realized benefits. To compactly summarize this relationship, we estimate a linear first-stage regression of benefits on examiner tendency. Estimates of this model imply that being assigned to an examiner with a one standard deviation (SD) higher tendency measure is associated with a \$1,445 increase in first-year VA DC benefits for these veteran, a 10% increase over average annual disability compensation benefits and 5% increase over total annual income. This coefficient is highly significant, with a facility-level clustered standard error of \$20 and a first stage F -statistic of 5,386, well above conventional rule-of-thumb levels for valid inference (e.g. Lee et al., 2021). Figure C.2 demonstrates that the examiner also has sticky, permanent impacts on cumulative benefits (and thus veteran wealth). A one SD increase in tendency increases five-year cumulative benefits by \$6,151; the first-stage impacts dissipate over time because veterans can appeal, re-rate, and file claims for new disabilities.²⁹

²⁹In Table C.5, we investigate how being quasi-randomly assigned a higher-tendency examiner impacts subsequent appeals and increase requests on the same claim, as well as filing for new disability claims. We find that veterans assigned to higher-tendency examiners are less likely to appeal and file for increases in the long-term but no more likely to file new disability claims (mental health and non-mental health) in the long-term.

4.3 Instrument Validity

So far, we have established that examiner variation in tendency is both substantial and predictive of realized benefits of veterans. For examiner tendency to serve as a valid IV for identifying average causal responses of health and well-being requires two further assumptions. First, examiner tendency must satisfy an *exclusion restriction*, such that examiner assignment is only related to veteran outcomes through its causal effect on veteran’s benefits. Second, examiner tendency must satisfy a *monotonicity condition*, such that the effects on compensation amounts of being assigned to a higher tendency examiner are weakly positive for all veterans. We discuss these in turn below.

Quasi-Random Assignment and the Exclusion Restriction For the exclusion restriction to hold, we require (a) that examiner assignment is uncorrelated with veterans’ potential outcomes, and (b) that an examiner’s influence on a veteran’s outcomes operates solely through the channel of increased benefits.

To begin, we consider whether examiner assignment is correlated with veterans’ potential outcomes. This could be the case if the VA internally assigned examiners based on the details of veterans’ claims. In reality, the assignment process is based largely on which providers are available to administer a mental disorder examination within a reasonable time frame. This lends support to the idea that veterans and examiners are quasi-randomly paired, and thus that a veteran’s potential outcomes should be unrelated to the type of examiner assigned to the case.

To put this idea to the test, [Figure 3a](#) examines the relationship between a detailed set of veterans’ observable characteristics, their determined benefit amounts (left panel) and the tendency of their assigned examiner (right panel). Not surprisingly, these characteristics—including demographics, period of service, exposure to Agent Orange and radiation, and prior-year diagnoses and health events—are highly correlated with realized benefit amounts. The right panel of [Figure 3a](#) assesses whether these veteran characteristics are predictive of examiner assignment along a “bare” leave-out tendency measure, which residualizes *only* for

facility-by-year fixed effects and *not* the veteran characteristics in [Equation 2](#). In contrast to the left panel, we do not find correlations between observable veteran characteristics and the measured tendency of the assigned examiner. [Figure 3b](#) summarizes this balance table by showing that *predicted* benefit compensation is not meaningfully correlated with examiner tendency.³⁰ Examiners whom we measure to have higher and lower tendencies examine observably similar veterans within a facility-year, consistent with quasi-random assignment.

What remains to discuss regarding the exclusion restriction is whether examiners with a higher tendency measure interact with their assigned veterans in ways that could impact veteran outcomes through channels other than their impact on realized disability compensation. For instance, if higher tendency examiners also recommend follow-up treatment for veterans during their examinations, or have better “bedside manner,” our estimates would capture not only the effects of higher benefits, but also correlated examiner behaviors on veterans’ outcomes. In our setting, the scope for these forms of interactions is relatively limited: examinations are strictly forensic, and there is usually no pre- or post-exam contact between veterans and examiners ([Sripada et al., 2018](#)).

Nevertheless, it is worth considering how such correlated behaviors might impact our IV estimates. If higher tendency examiners tend to provide more welcoming experiences, veterans may think more highly of VA personnel in general, with potential positive downstream effects on health outcomes. Viewed in this light, our IV estimates would place an upper bound on the health improvements resulting from additional benefits in isolation. To the extent such exclusion-restriction violations influence our results, reduced-form estimates demonstrating the net impacts of being assigned to a higher tendency examiner are still valid and could be useful for evaluating examiners’ impacts more generally. We present these reduced-form impacts in [Table C.6](#). Additionally, in robustness checks and in [Appendix D](#), we attempt to further explore our exclusion restriction using examiner-completed DBQs; none of this

³⁰We predict first-year benefit amount using the full set of veteran characteristics in [Figure 3a](#), controlling for facility-by-year fixed effects and split veterans into twenty equally-sized bins based on their assigned examiner tendency. We then plot the mean actual and predict benefit compensation amounts against the examiner ventiles. Consistent with the first stage and balance figures, examiner tendency linearly predicts actual benefit amount almost one-for-one; however, does not predict predicted benefit amount (roughly 0.3% of the first stage explanatory power and not statistically significant).

evidence suggests any obvious violations.

Monotonicity In our setting, the monotonicity condition rests on the assumption that any veteran seen by a higher-tendency examiner would end up with a weakly higher benefit amount than had they been seen by an examiner with a lower tendency.

We probe whether violations of monotonicity are likely using three approaches. The first is a joint test of monotonicity and exclusion assumptions proposed in Frandsen et al. (2023).³¹ This test hinges on the observation that for the identification assumptions to hold, outcomes averaged at the examiner-level must be a continuous function of the examiner-level instrument, with bounded slope. We implement this test in Table C.7 using five-year mortality as the outcome and various binary treatment thresholds, and fail to reject the null hypothesis.

Another standard test in examiner-design settings estimates various first stages for a series of subgroups. Frandsen et al. (2023) provide formal rationale for such an exercise, which tests a weaker “average monotonicity” assumption that still preserves well-behaved LATE weights. Table C.8 estimates first-stage models for a series of subgroups (sex, race, age, mental disorder type, and predicted first-year benefits).

Perhaps most germane to this discussion, the final three rows of Table C.8 demonstrate that, across the distribution of veteran severity, as measured by the benefits the veteran is predicted to receive based on observables, examiner tendencies have strong positive impacts on realized benefits. For instance, we estimate that veterans in the lowest tercile of predicted benefits based on their pre-examination observables receive \$1,326 (*s.e.* = 43.9) more in their first year of benefits if they are assigned a one-SD higher tendency examiner. The comparable figure for veterans in the highest tercile is \$1,525 (*s.e.* = 24.9). All of the estimates in this table are positive and highly statistically significant (with *t* statistics typically over 50), suggesting that examiners with high tendencies on average have high tendencies in their examinations across the distribution of veteran types.

Lastly, given the salience of the OSI section of the DBQ in determining benefit amounts

³¹New work by Sigstad (2023) shows that in three different judge IV settings, violations of average monotonicity result in minimal bias (small negative IV weights for small sub-samples).

and its multi-valued structure, one could be concerned that examiners have non-monotonic tendencies across the OSI—or disability impairment—spectrum. Monotonicity implies that examiners who have a greater overall tendency have a greater tendency in every part of the impairment spectrum. We test this by constructing six complementary measures of examiner tendency, one at each threshold value of OSI, by replacing $Benefits_i$ in [Equation 2](#) with an indicator for being above an OSI threshold. [Figure D.4](#) demonstrates that our baseline measure of tendency is highly correlated with each of these six threshold-tendency measures. The highest correlations are for thresholds at the middle of the OSI spectrum, with a correlation of 0.65 for the third and fourth OSI box thresholds, but even at the top (bottom) threshold, where there is less data and thus noisier estimates, our continuous tendency measure is still correlated at 0.39 (0.53). Examiners with higher overall tendencies have consistently greater tendencies across the disability severity spectrum. This evidence, while not exhaustive, aligns with the idea that higher tendency examiners provide uniformly higher degrees of OSI assessments, providing some support for our monotonicity assumption.

5. Results

The previous section established the strong and persistent influence of our examiner instrument on veteran benefits. In this section, we use our examiner tendency instrument to investigate the one- and five-year effects of higher VA DC benefits, framed in terms of an additional \$1,000 per year. We begin by studying measures of economic stability and well-being, before turning to healthcare utilization and engagement, and downstream health outcomes and mortality. Recall that some of our outcomes are measured from surveys and are thus not complete; however, we show that response rates are not meaningfully correlated with provider tendency and provide bounds on the treatment effects in [Table C.2](#).

5.1 Economic stability and financial well-being

A primary goal of cash transfers is to improve economic stability. While prior studies have found that cash transfers can reduce rates of poverty (Hoynes and Patel, 2018; Miller et al., 2018), it is unclear whether they impact more tangible non-income-based measures such as fulfilling basic needs. We track measures of economic well-being by taking advantage of the richness of the VHA’s administrative health records and its broad range of health and social services provided due to its highly integrated nature.

Table 2 presents 2SLS estimates of an extra \$1,000 per year in benefits on measures of one-year (panel A) and five-year (panel B) economic stability and financial well-being. Food insecurity—tracked by the VA via annual primary care screens mandated since 2017—improves by 0.06 percentage points (pp) in the first year on a base of 2.2% and 0.10pp over five years on a base of 2.4%. Column 2 reports the impact of VA DC benefits on ever being homeless over one and five years. Homelessness is proxied in the VA using a variety of administratively monitored sources including diagnoses, use of homeless beds, and other homeless services such as rental assistance and vouchers.³² Ever being homeless in the first year decreases by 0.072 percentage points (1.0%) over a mean of 7.8%. The five-year effect size is 0.184pp, or 1.3% over the baseline mean of 14.3%. The high homelessness rate reflects the fact that this proxy is a measure of ever being homeless (“interval prevalence”) as opposed to point-in-time; prior studies of veterans receiving mental healthcare have found similar rates (Tsai et al., 2014). It is important to note that while this proxy of homelessness is imperfect, to the extent that we see increases in utilization for veterans receiving higher benefits—and we do in the next section—we would expect to see increases in services and codes that indicate homelessness. Thus, we view our estimates as providing a lower bound on the decrease in homelessness from higher disability income. Taken together, we find strong evidence that veterans with mental disabilities, who are significantly more likely to be homeless (Tsai and Rosenheck, 2015), food insecure (Dubowitz, 2021), and near the federal poverty level (Murdoch et al., 2011), are first securing basic needs like food and shelter with higher cash transfers. In the discussion we

³²See Appendix A for more details.

contextualize our estimates and benchmark our effect sizes against related policies.

Next, we examine measures of financial well-being via debt veterans owe to the VA. A non-trivial fraction of veterans have significant VA debt. Approximately 1.7% of our sample have any collections over five years and the median balance among these collections is \$8,229, with a quarter owing over \$17,800; see [Table C.9](#) for breakdowns by source of debt. As previously mentioned, we construct two measures of Treasury debt referrals (or “collections”) analogous to the prior literature ([Dobbie et al., 2017](#); [Dobkin et al., 2018](#)): the number of debt collections (column 3) and inverse hyperbolic sine of total collection balance amounts (column 4). We find that the number of collections decline by 0.11 (6.4%) over five-years and the collection balances decline by two-thirds of a percent. These findings imply that disability income significantly improve economic stability and financial well-being among individuals with mental disabilities.³³

5.2 Healthcare utilization and engagement

Individuals who are low income and/or housing or food insecure and more likely to postpone preventive care, medication, and rely on emergency services ([Kushel et al., 2006](#)). In this section, we study whether disability income—which improves housing and food insecurity—also changes utilization patterns and improve healthcare engagement and preventive care.

Utilization [Table 3](#) reports 2SLS estimates of an additional \$1,000 in VA DC benefits on one-year and five-year healthcare utilization and engagement in panels A and B, respectively. Total utilization—measured by “average cost” computed by the VA to reflect healthcare utilization using Medicare reimbursement rates ([Wagner et al., 2003](#))—increases by roughly a constant 2.6% over \$10,169 in the first year and \$40,234 over the first five years. This increase is entirely driven by outpatient utilization (column 2) and we do not find any statistically

³³These results are similar to those from a recent randomized trial in Vancouver, Canada, which gave a one-time lump-sum payment to homeless individuals ([Dwyer and Zhao, 2021](#)). One key difference is that the Vancouver experiment screened out individuals on the basis of poor mental health, as well as alcohol and substance use disorders, due to general concerns over whether cash transfers could harm these individuals, whereas our sample is composed entirely of individuals with claimed mental disorders.

significant effect on inpatient utilization (column 3), suggesting an increase in engagement as opposed to a worsening of health. Mental health outpatient utilization increases by the same amount as overall outpatient utilization (column 4).

These utilization estimates allow us to calculate the income elasticity of demand for healthcare, a rather elusive elasticity in the literature, perhaps due to the lack of data linking exogenous changes to income with healthcare spending. Our preferred elasticity estimate is 0.90 after accounting for labor supply impacts of VA DC (Table C.10 displays estimated elasticities without accounting for labor supply).³⁴ To the best of our knowledge, we are among the first to estimate this elasticity at the individual-level. Our estimate is in-line with Acemoglu et al. (2013), which estimates an elasticity of 0.7 using area-level shocks to oil prices and Moran and Simon (2006), which estimates an income elasticity of prescription drug use of 1.3 using Social Security notches.

Engagement Columns 5 to 9 of Table 3 shows that veterans are not simply increasing utilization, but they are engaging in preventive care and in ways that may improve health. They schedule 0.12 and 0.86 additional VHA appointments over one and five years for every additional \$1,000 per year. Next, we examine adherence to VHA preventive care recommendations: flu vaccinations, Hepatitis C screens, and colorectal cancer screens. We find that annual flu vaccination rates increase by 0.15pp and the likelihood of having any Hepatitis C screen increases by 0.31pp over five years; effects on annual colon screens are positive but statistically insignificant. Finally, rates of medication adherence measured using medication possession ratios increase. Improvements in medication adherence are primarily concentrated in cardiovascular drugs (statins, hypertensive drugs) as opposed to psychotropics (Table C.11), highlighting the broad potential improvements in health behaviors—beyond mental health—stemming from disability transfers. Taken together, our

³⁴We take Autor et al. (2016)'s 2SLS estimates of the causal impact of every \$1,000 (in 2001 dollars) on the probability of having positive income from Table 8, and calculate the change in probability of being employed for every \$1,000 (in 2020 dollars). By assuming no intensive margin labor responses we compute a change in total income—net of labor market effects of disability income—which we use along with our utilization effects to calculate our preferred elasticity.

findings show that higher compensation leads to increased healthcare utilization, often in ways that are considered high value such as increased scheduling of appointments, takeup of preventive care, and greater rates of medication adherence.

Mechanisms Healthcare utilization increases with cash transfers despite low out-of-pocket cost of care for our sample.³⁵ However, there are non-monetary barriers to healthcare access (“ordeals”) especially since a quarter of our sample live in rural areas. Cash transfers may alleviate these barriers by allowing veterans to transition to self- or part-time employment (Coile et al., 2015), or by making transportation (e.g., gas, bus ticket, etc.) more affordable. We find some suggestive evidence for this hypothesis in [Table C.13](#); utilization effects are 1.2-1.5pp (60-90%) larger for veterans who live more than 10 miles from the nearest VHA primary care clinic.

Increased engagement and take-up of preventive care may be indicative of improved patient-clinician communication and trust (Alsan et al., 2019; Koulayev et al., 2017; Simeonova et al., 2020). We have multiple pieces of evidence to support this interpretation. First, VA DC benefits specifically increases VHA (outpatient) utilization. We do not find any economically or statistically significant change in Medicare utilization among the 65+ population ([Table C.14](#)). Second, individuals facing household and financial stressors are less likely to engage in preventive health behaviors (Kushel et al., 2006; Gunja et al., 2022), and we find improvements in food security, housing, financial well-being, and preventive care.

Finally, we directly test this hypothesis using the Veteran Satisfaction Survey, a VA-conducted survey on randomly selected veterans receiving mental healthcare in the VHA (see [Appendix A](#) for details). Despite a small sample size—only 1,401 of our sample were surveyed and responded within 5 years of first claiming disability³⁶—some clear patterns emerge in [Table 4](#). An additional \$1000 in disability compensation per year increases i) overall

³⁵All mental health services are free for VHA-enrolled veterans and all medical care are free if the veteran has any service-connected disability. In [Table C.12](#), we show that our utilization findings persist even among veterans with no copayments (ex post) or no expected copayments (ex ante).

³⁶Our precision despite the small sample size speaks to the power of our research design: we are able to precisely measure the annuity-like impact of medical examiners on compensation.

satisfaction with VA healthcare; ii) perceived collaborative medication management; and iii) communication, trust, and rapport each by 0.03 standard deviations (the measures are composite averaged z -scores; [Figure C.4](#) displays both the composite groupings and individual response outcomes). The latter two include questions on education and communication about medications and treatment options (e.g., “*My mental health provider(s) are more likely to talk with me about my concerns than to suggest or prescribe medication*”) and overall communication (e.g., “*My mental health provider(s) and I developed my treatment plan together*”) and trust (e.g., “*My mental health provider(s) have taken my personal preferences and goals into consideration during my treatment*”).³⁷ It is also reassuring—for our exclusion restriction—that veterans do not report better access and availability (the coefficients are smaller and statistically insignificant), but of course, cash transfers may change veterans’ *perception* of access.

Another potential explanation could be that some veterans may believe that certain utilization and medical records may increase their chances of increasing their disability compensation. While this may be possible with short-term mental health utilization, it is unlikely to explain long-term preventive care and cardiovascular medication adherence outcomes. Moreover, assignment to a higher tendency examiner does not lead to increases in additional claims or increases over the next five years ([Table C.5](#)). It is also worth noting that program incentives may even operate in the opposite direction: there are longstanding concerns that compensation for mental health conditions “create obstacles and disincentives for therapy or treatment”. ([National Research Council, 2007](#)).³⁸ Finally, in the discussion section, we find that veterans who receive lower than expected ratings, experience positive

³⁷Investigating treatment practices, we find suggestive evidence consistent with the trust angle in [Table C.15](#): veterans are more likely to complete prolonged exposure therapy, an evidence-based form of PTSD treatment that requires a higher degree of vulnerability and trust ([Powers et al., 2010](#)).

³⁸This belief dates back to a 2005 Office of Inspector General report that found in a small case review of 100% PTSD-rated veterans, 39% of them began decreasing their mental health visits following award date [VA Office of Inspector General \(2005\)](#). This might be due to incorrect beliefs that compensation for their PTSD is tied to VHA mental health treatment or that some veterans have low treatment outlook moral (“feel hopeless”) and primarily seek compensation “to validate that they had indeed been harmed by their wartime experience” ([Black et al., 2018](#)). Since the OIG report, ([Sripada et al., 2018](#)) found that it is not that utilization decreased but rather baseline mental health utilization among PTSD awardees is low.

treatment effects along a wide set of outcomes including survival, despite constant utilization effects.

5.3 Physical and Mental Health Outcomes

So far we have documented substantial improvements in intermediate health measures, alongside signs of improved communication and trust in healthcare providers. The natural next question, especially in light of the perennial debate over the relationship between income and health, is whether these improvements translate into downstream physical and mental health outcomes for the average beneficiary.

Table 5 reports 2SLS estimates of the average effect of disability income on prevalence of major depressive disorder (MDD), alcohol and substance use disorders (AUD/SUD), overdose poisoning, and suicide events, body mass index (BMI), pain score, HbA1c glucose levels, and blood pressure. Outside of overdose and suicide events which are standard indicator variables, the other measures are constructed conditional on having at least one observation over the study period. Table C.2 provides bounds on the effect sizes for these outcomes. Across virtually all health outcomes, we estimate precise average null effects: 95% confidence intervals can rule out effect sizes of more than 0.1%—in either direction—over the baseline mean. Overdose and suicide events are less precise since they are rare events.³⁹ Figure C.3 leverages our rich panel data and investigates the impact of an extra \$1,000 per year on annual measures of alcohol consumption, binge drinking (proxied by responding weekly or more frequent to the following question: “*How often did you have six or more drinks on one occasion in the past year?*”), and depression—measured via clinical questionnaire screens—and find similarly precise null effects.

The one exception is self-reported (physical) pain scores taken in primary care settings in column 6, which decreases by 0.3–0.5%. This effect may be driven by a combination of improved psychosocial factors such as a reduction in stress (e.g., improvement in basic needs

³⁹Across all our outcomes, we can benchmark how the utilization effect impacts our ability to observe the variable, except for overdose and suicide events because they are constructed unconditionally. This means that the utilization effects create an upward bias on these two outcomes.

and reduction in financial debt; Edwards et al., 2016) or changes to physical occupational demands due to labor market outcomes (Cutler et al., 2020). We note that we do not detect changes in other potential non-self-reported proxies for stress including BMI, blood glucose levels, or blood pressure; we also detect similar reductions in pain among the elderly who are unlikely to experience changes to physical demands at work.

5.4 Mortality

Column 10 of Table 5 reports impacts of additional benefits on mortality. Consistent with our findings on other downstream health outcomes, excluding pain, we find no evidence of improved survival associated with more generous benefits. Our 95% confidence interval rules out 5-year mortality reductions greater than 0.011 percentage points, or 0.14%. This conclusion is virtually unchanged when, instead of clustering standard errors at the facility level, we cluster by examiner, or by facility-year.⁴⁰

Unlike our other health indicators and outcomes, there are a handful of recent estimates of mortality impacts of government income assistance (Gelber et al., 2022; Black et al., 2021; Berman, 2021; Trivedi et al., 2022), and wealth more generally (e.g., Cesarini et al., 2016; Schwandt, 2018). These estimates provide a useful opportunity to situate our findings in the broader literature on the mortality effects of income and wealth shocks.⁴¹

Figure 4 provides these comparisons. We plot estimates and confidence intervals from 6 papers (11 estimates in total, excluding ours) examining mortality and income/wealth shocks. To put these coefficients on the same scale (the effect of an additional \$1,000 per year on annual mortality rates), we perform back-of-envelope calculations for each paper that is not already in these terms, as detailed in the notes to the figure. Panel (a) plots all 11 estimates, while panel (b) zooms in on estimates with the narrowest confidence intervals.

There are a few features of this figure that stand out. First is that our data and design

⁴⁰We investigate specific causes of death (top three disease-related causes along with external causes) in Table C.16 and do not find strong patterns.

⁴¹There is also a vast correlational literature on income-mortality gradients, but we do not compare to those studies here. For discussions of these gradients, see, for example, Cesarini et al. (2016) and Chetty et al. (2016).

yield the most precise estimates among these studies. We attribute this to the strong variation in examiner tendencies in our setting, combined with our large sample size. For example, our standard errors are over an order of magnitude smaller than those from Gelber et al. (2022), reflecting in part the high variance of the regression kink design employed in that paper; our standard errors are also at most half as large as any article on government support in this list.⁴² Second, the most precise estimates, including ours, tend to be the closest to zero. If we assumed homogeneous effects, a meta-analysis of these estimates would put substantially more weight on estimates from panel (b) of Figure 4 than those that only appear in panel (a).

An important caveat to this second point is that there are many other differences in terms of sample populations, periods of study, and forms of assistance may be driving some of the observed differences across studies. Subsample analyses and tests of heterogeneity are helpful in illustrating this point. For example, while Gelber et al. (2022) find that additional disability income decreases mortality for low-income beneficiaries, it *increases* mortality—albeit insignificantly—for the subsample with mental disabilities, perhaps the most comparable sample to ours. However, this result is quite noisy and not statistically different from 0. Those authors also find null results for higher-income beneficiaries (those at the “upper bend point”).

Taken together, the point estimates suggest that income transfers can improve survival for especially disadvantaged individuals (e.g., the very poor, those requiring expensive medical treatment, and/or the elderly over 75). However, in settings with more generous and comprehensive safety nets such as in Sweden (the setting in Cesarini et al., 2016) or the VA (our paper, as well as Trivedi et al., 2022), income transfers may play less of a role in reducing mortality. In these settings, the potential health benefits of additional income are likely only to come through less extreme health outcomes than death, such as those we have studied above.

⁴²The one exception is Cesarini et al. (2016), whose standard errors are 20% larger than ours.

6. Discussion

Our results point to significant average impacts of VA mental health disability compensation on economic well-being and healthy behaviors, with negligible impacts on more extreme outcomes, including overdoses, suicides, or all-cause mortality. To further contextualize these results and shed light on whether more generous compensation policies would pass cost-benefit considerations, it is useful and illustrative to benchmark our estimates against other figures from the literature. As a first step, our point estimates and sample means can be used in back-of-envelope extrapolations to shed light on the implied cost of eliminating food insecurity or homelessness in our sample. Noting at the outset that these extrapolations are quite large and should be taken as suggestive only, the estimates in [Table 2](#) suggest that an extra \$1000 per year over 5 years reduces food insecurity by 0.09 percentage points, while food insecurity affects 2.41 percent of our sample over this horizon, implying a cost to fully eliminate food insecurity of about \$24,000 per veteran per year. Providing cash benefits at that level would simultaneously reduce homelessness by $0.184 \times 24 = 4.42$ percentage points, relative to a baseline of 14.33 percentage points—a reduction of 31%.⁴³

These estimates provide an average impact of additional compensation, but it is important from a policy perspective to understand how those impacts are distributed across applicants. As one way of understanding such heterogeneity, we present results stratified by veteran characteristics in [Table C.17](#). While the results for most subsamples are relatively consistent with our overall results, one notable and logical pattern is that economic well-being indicators are only weakly impacted for those whose baseline income exceeds \$30,000.

Of particular interest are the potential impacts among those who are on the margin of qualifying for the program. For instance, recent evidence from the SSDI program ([Deshpande and Lockwood, 2021](#)) suggests that many who apply without an obvious health issue suffer from other hardships that make it plausible that impacts of allowance would be even greater for

⁴³One point of reference for the cost effectiveness of this aid for reducing homelessness comes from [Evans et al. \(2016\)](#), who estimate the cost of avoiding a veteran homeless spell of \$10,300. Our estimates speak to the costs of reducing the prevalence of homelessness altogether, rather than reducing the number of spells, so arguably our estimated costs should be higher; how much higher is unclear.

them. Our data provide an intriguing parallel: applicants who are deemed ineligible experience some of the worst subsequent economic and health outcomes. In [Table C.18](#), measures of homelessness, food insecurity, and mortality rates among those denied compensation are strikingly similar to those receiving the highest compensation rates in our sample. For example, the five year mortality rate for those denied compensation is 9.9%, compared to 6.5-6.8% for those receive positive ratings below 100% and 12.8% for those deemed 100% disabled. This may suggest potentially high returns to compensation among those who, under current rules, are being screened out.

To further explore this idea in a final analysis, we estimate a correlated random coefficients model (e.g., [Garen, 1984](#); [Wooldridge, 2015](#)) to estimate heterogeneous impacts for veterans with differing latent benefit levels. Note that this analysis comes with additional assumptions—for details, see [Appendix B](#). Results are summarized in [Figure 5](#), where we find evidence consistent with the hypothesis that those on the margin of eligibility (and who have poor average outcomes) stand to benefit more than the average applicant from more generous disability compensation along many key outcomes, exhibiting higher reductions in homelessness, overdoses, suicide attempts, and overall mortality. Taken together with the evidence on this population’s vulnerability in [Table C.18](#), these results suggest that, while VA DC may not be the appropriate form of support for this population by law, policies that opt to include more of these applicants, e.g., policies that make certain mental health conditions presumptively service-connected, may have substantial economic and well-being implications for this marginal population. Future work more carefully exploring this question in the VA DC context is crucial for understanding the implications of such policy changes.

7. Conclusion

Individuals with mental disabilities are highly disadvantaged and rely on government programs and cash transfers as a key form of support ([Frank et al., 2019](#)). In 2021, 29% of Social Security Disability Insurance and 37% of VA Disability Compensation recipients were on the

rolls for mental disabilities; mental disabilities have also been responsible for much of the growth in disability program expenditures, both for SSDI and VA DC (Autor and Duggan, 2006; Autor et al., 2016).

In this paper we provide evidence on the broad economic and health impacts of cash transfers to veterans claiming mental disabilities. We make novel data linkages between benefits administration and highly granular electronic health records to study a host of economic and health outcomes, many of which are rarely observed by researchers. Leveraging quasi-random assignment of disability claim cases to mental health disability examiners, we find that being assigned a higher-tendency examiner is effectively like winning an annuities lottery: permanently higher tax-free benefits.

Permanent cash transfers significantly improve economic stability among veterans with mental disabilities by reducing food insecurity, homelessness, and the likelihood of having financial debt. These are among our strongest effect sizes, which implies that veterans are first attending to their basic needs. In contrast, we find no changes to alcohol consumption or likelihood of developing alcohol or substance use disorders.

Higher disability compensation increases healthcare utilization and engagement. We also find higher rates of take-up in preventive care, scheduled appointments, and greater medication adherence. These engagement measures, along with findings from VA-conducted satisfaction surveys on trust and communication imply that cash transfers increase care satisfaction and improve patient-clinician relationships.

Despite their impacts on preventive care, improved engagement, and clinician trust, we estimate precise null effects of more generous benefits on a wide array of downstream physical and mental health outcomes, including mortality. However, we find evidence that those on the margin of eligibility—and are typically denied benefits—are among the most disadvantaged yet have the largest potential treatment effects of benefits on homelessness, overdoses, suicide attempts, and overall mortality. This suggests that there may be large health benefits in providing compensation for marginally qualified veterans applying for mental disability compensation, but the VA DC program as presently constructed, may not be designed to

target recipients based on their potential gains.

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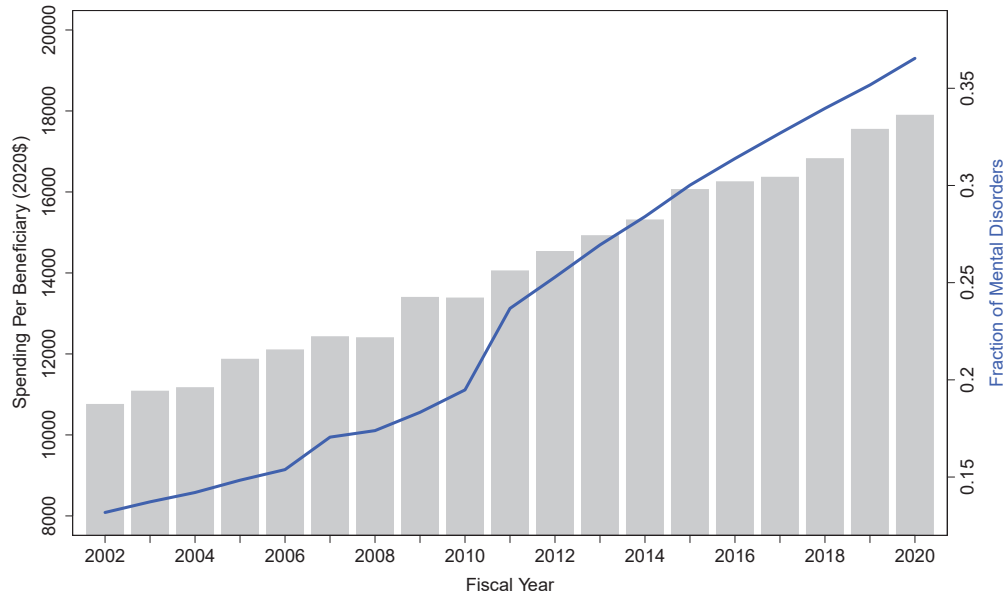
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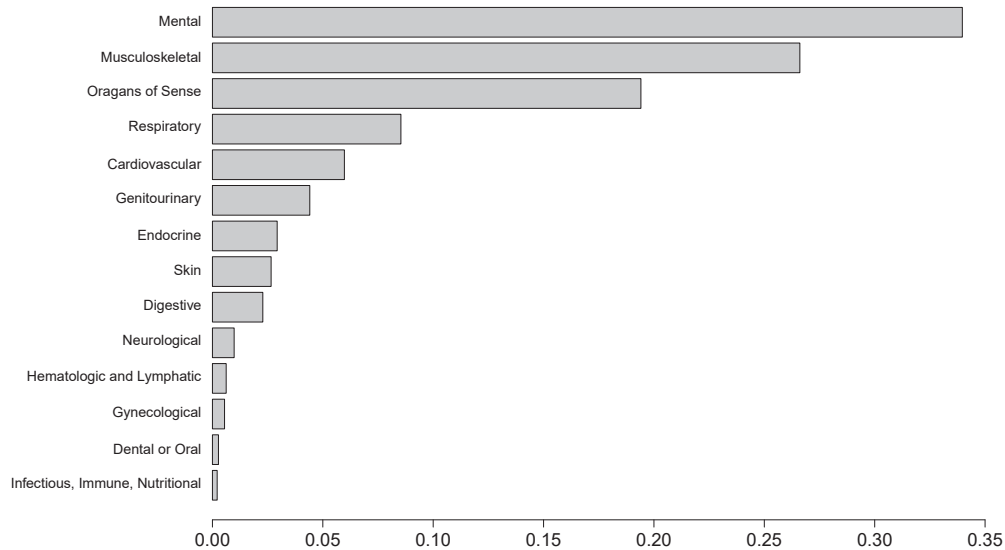
Figures and Tables

Figure 1: VA Disability Compensation Growth and Mental Disabilities

(a) Growth in VA DC spending per beneficiary and mental disorder share, FY2002–2020

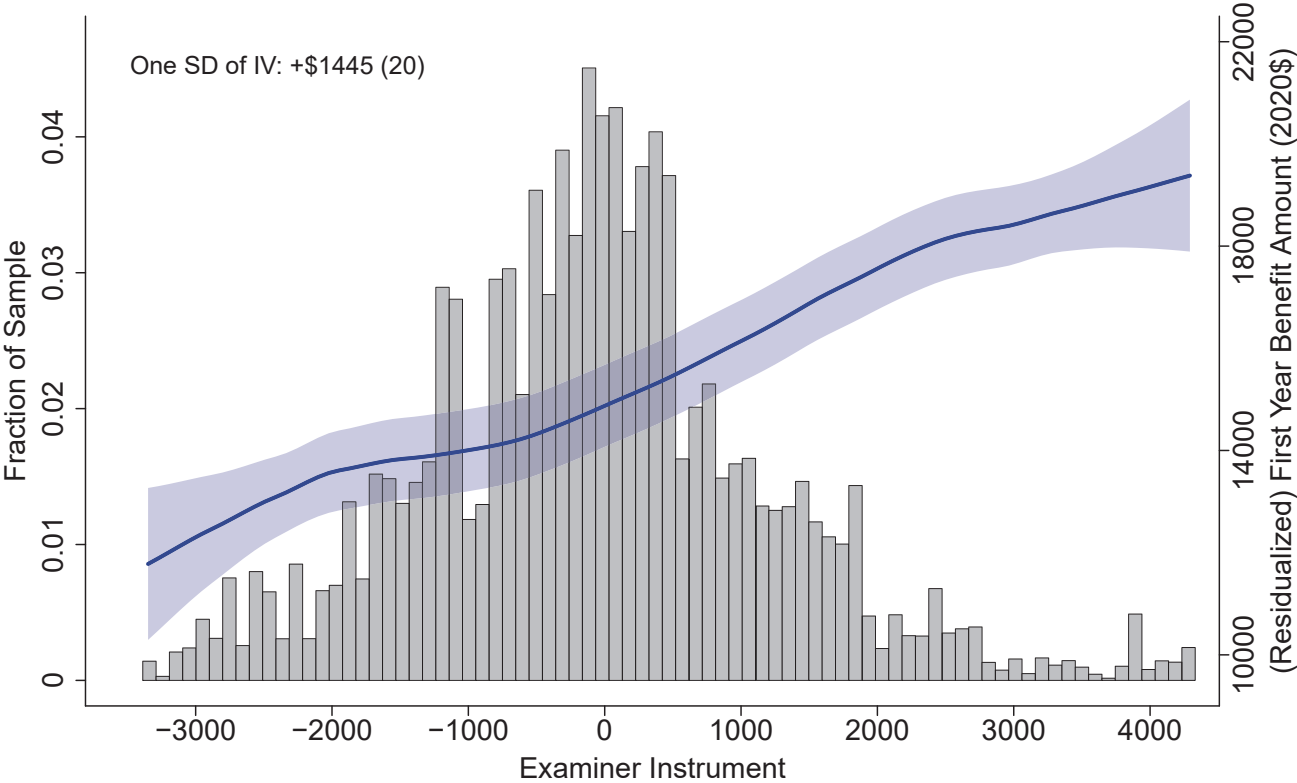


(b) Fraction of beneficiaries with each body system as their highest rated disability, 2020



Notes: Panel a displays the growth in VA DC spending per beneficiary and the share of all beneficiaries with a mental disorder disability between fiscal year 2002 and 2020. The gray histogram (left y-axis) displays the average spending per VA DC beneficiary in 2020 dollars. The blue line graph (right y-axis) displays the fraction of beneficiaries with a mental disorder disability. Panel b displays the fraction of VA DC beneficiaries on January 1, 2020 with each body system as their highest rated disability. If multiple body systems are tied, they are all included as the highest; hence the bars sum to 109%.

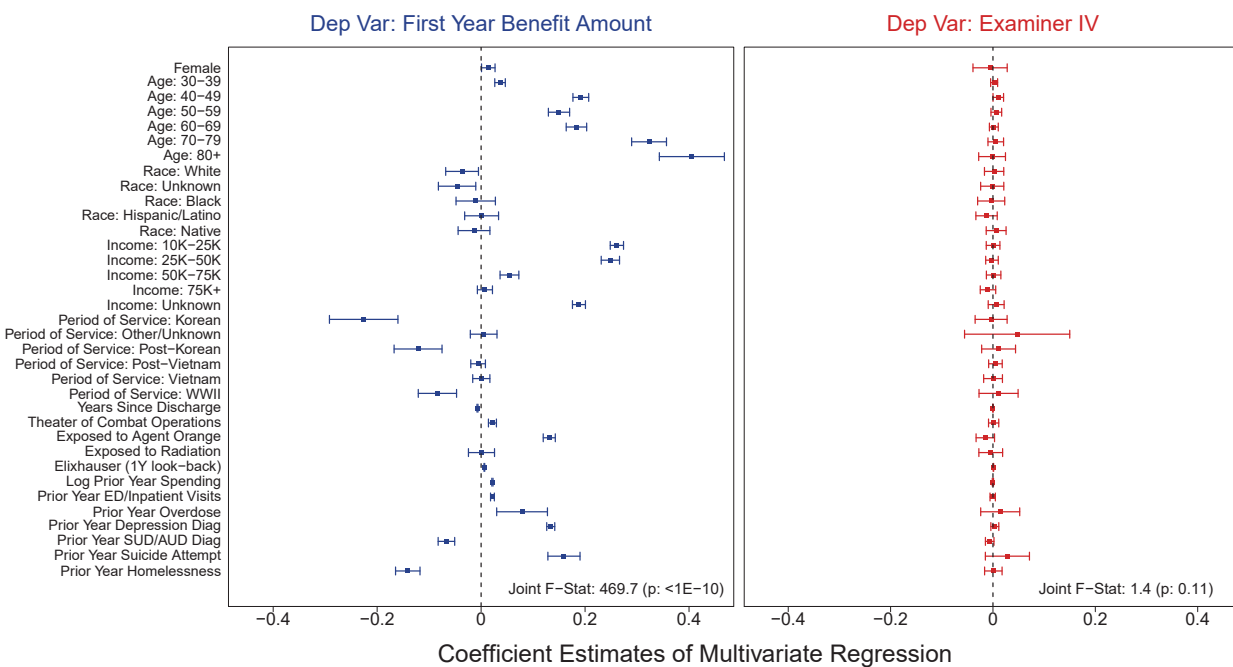
Figure 2: Distribution of Examiner Tendency IV and Annual Compensation (First Stage)



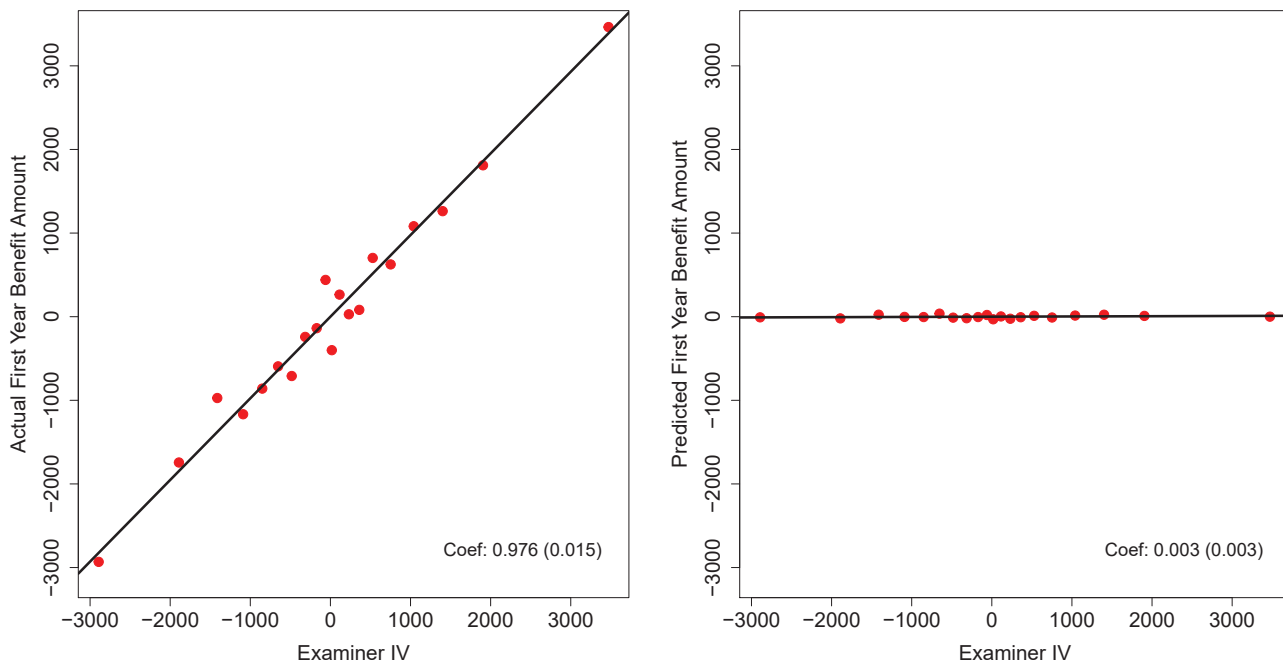
Notes: This figure displays the distribution of examiner tendency instrument as defined in Equation 2 and Equation 3, and its impact on first year disability compensation benefit, residualized for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran’s Elixhauser comorbidity score based on a one-year look-back period. Overlaid on top of the histogram of examiner tendency (left y-axis) is a local linear regressions of first year benefit on examiner instrument; 95% confidence bands are also displayed. The estimated linear first stage coefficient (and its standard error) of a standardized IV on first year disability compensation benefit are displayed at the top of the figure.

Figure 3: Balance and First Stage

(a) Balance: Veteran Observables Do Not Predict Examiner IV

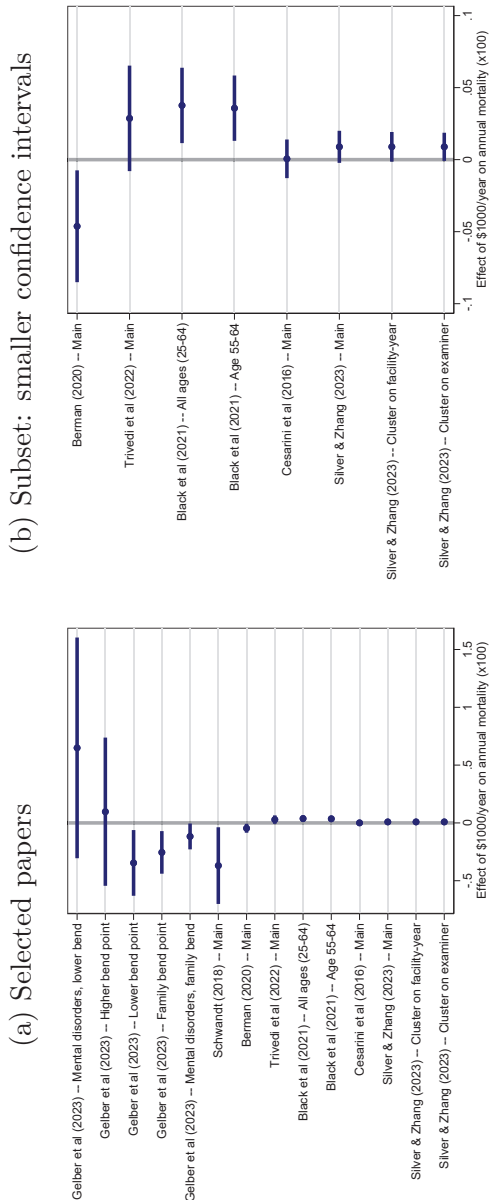


(b) Effect of Examiner IV on Actual and Predicted Benefit Compensation



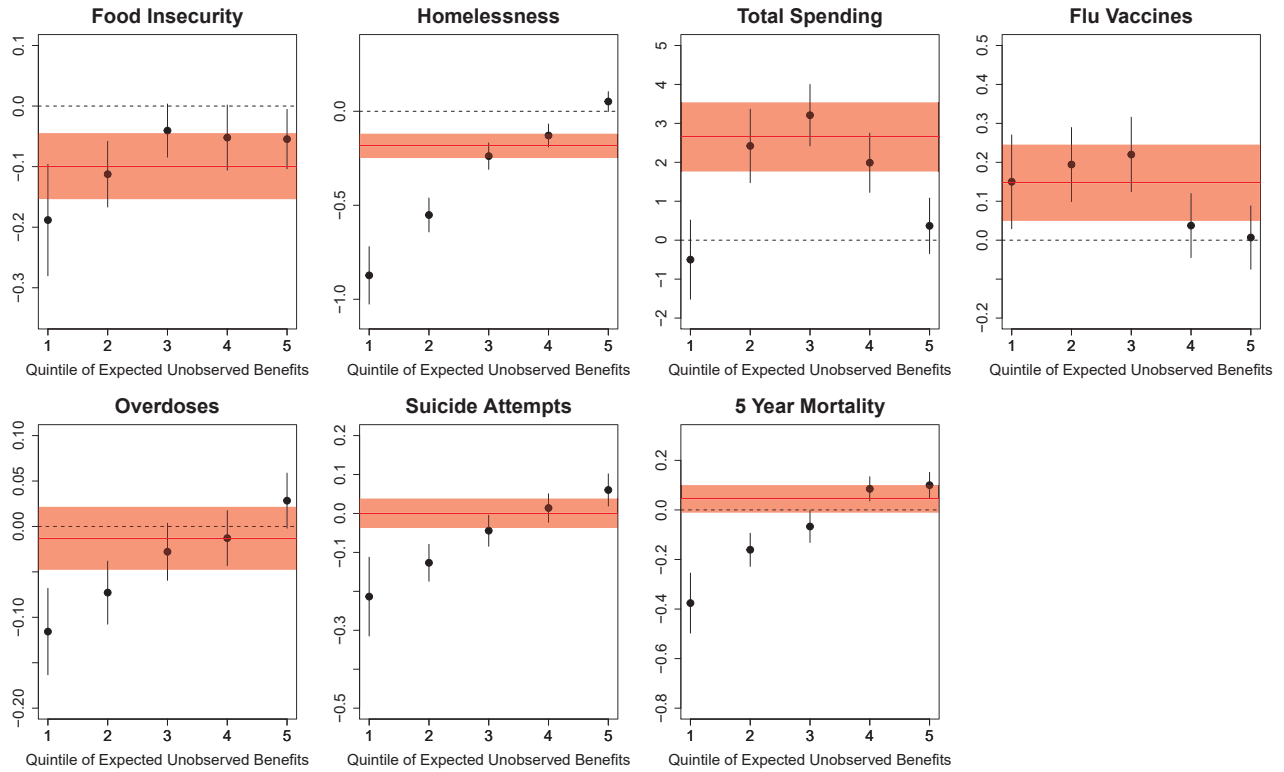
Notes: This figure tests our conditional independence assumption of quasi-random assignment conditional on facility-by-year fixed effects. In Figure 3a, the left panel plots the estimated coefficients of a multivariate regression of *standardized* first-year compensation benefits on pre-disability exam observables: veteran demographics and prior medical history, controlling for facility-by-year fixed effects. The right panel plot the estimated coefficients from a regression of *standardized* examiner tendency the same set of covariates. The examiner tendency only residualizes for facility-by-year fixed effects in Equation 2 and *does not* include veteran observables as controls. Robust standard errors are clustered at the facility-level. The F-statistic and p-value corresponding to a joint F-test on the displayed set of covariates are displayed; the F-test degrees of freedom are 38 and 864,193. Figure 3b plots actual and predicted benefit compensation against examiner tendency ventiles. The left panel plots actual first-year benefit amounts, residualized for facility-by-year fixed effects against twenty equally-spaced examiner IV bins. The right panel plots predicted first-year benefits amounts using veteran characteristics (from the right-hand side of Figure 3a), residualized for facility-by-year fixed effects against the same bins. The R-squared on the prediction regression using veteran characteristics is 0.097. The linear relationship between the dependent variable and examiner tendency using the underlying non-binned data are summarized at the bottom right corner of each panel.

Figure 4: Comparing Mortality Impacts to Selected Recent Literature



Notes: Figure displays estimates and confidence intervals from the literature. Panel (a) shows 14 estimates from 7 papers (including ours), while panel (b) zooms in on the 5 papers (also including ours) with the smallest standard errors. For comparability, where necessary, we scale coefficients and standard errors from each paper to reflect the implied impacts of \$1000 per year on annual mortality. From our own work, we display annualized coefficients from our 5-year models, with different levels of clustering standard errors. For Gelber et al. (2022), who leverage kinks in Social Security Income with respect to individuals earning histories, we take coefficients from Table 2, which directly represent said effects. For Black et al. (2021), who leverage quasi-random assignment of SSDI applications to appeals we take coefficients from Table 4 (instrumental-variable impacts of disability allowance on mortality) and Table 6 (regression-adjusted differences in cash benefits by allowance status). For Trivedi et al. (2022), we use estimates from Table 2 (difference-in-differences impacts of a VA policy on cash benefits through VA DC) and from Table 3 (difference-in-differences impacts of the policy on mortality). For Cesarini et al. (2016), the treatment is a one million SEK (\approx \$140,000 USD) lottery prize, which we annuitize using an interest rate of 3.125% and a life expectancy at winning of 20 years. This yields an annual annuity payment of \approx \$9500. We take estimates from Table AVIII of the effect of winning such a lottery on 5-year mortality, and scale them by dividing by 9.5 (to be in thousands of dollars per year), and then dividing by 5 to put into annualized terms. For Berman (2021), who studies annual discontinuities in Social Security Income by birthdate, we use numbers reported in the text on mortality rates, as well as information from Table 2 (on annual payment amounts) and Table 7 (impacts on log 6-year mortality). Schwandt (2018) examines the effects of a 10% wealth shock from stock market shocks on health outcomes including mortality. We annuitize this 10% wealth shock using the average wealth of individuals in Schwandt's sample (\$1.1 million in the most recent wave of their data), an interest rate of 3.125%, and a life expectancy of 10 years from the time of the shock. Under these assumptions, a 10% wealth shock for these individuals adds up to about \$13,000 per year. We use this calculation to scale the impacts on mortality (reported as survival) in Table 3, column 2.

Figure 5: Heterogeneous Impacts of Disability Compensation: Correlated Random Coefficients Model



Notes: This figure investigates heterogeneous impacts of disability compensation on our main outcomes, using a control function approach. First, we run a regression of first year mental health benefits on the examiner tendency instrument and the baseline set of controls and fixed effects. We obtain the residuals from this first stage regression and bin individuals into five quintiles. Then, in the second stage we regress each individual five year outcome on first year mental health benefits interacted with the residual bins (along with the main effects). The coefficients on the interaction term are displayed; the horizontal red line corresponds to the baseline IV estimate presented in the paper. See the text for more details.

Table 1: Summary Statistics

	Mean	S.D.	Q1	Median	Q3
Female	0.11				
Asian/Pacific Islander	0.03				
Black	0.22				
Hispanic	0.08				
Native	0.01				
White (Non-Hispanic)	0.61				
Age	50.6	16.3	35.9	52.1	63.2
Period of Service: WWII (1941-46)	0.02				
Period of Service: Korean (1950-55)	0.02				
Period of Service: Vietnam (1961-75)	0.33				
Period of Service: Gulf (1990-)	0.50				
Peacetime Era (Other)	0.12				
Combined Disability Rating	56.0	32.3	30	60	80
Benefit Amount: 1 Year (2020\$)	\$15,090	\$11,761	\$5,228	\$13,580	\$19,894
Benefit Amount: 5 Years (2020\$)	\$83,233	\$58,073	\$37,657	\$78,344	\$111,778
N= 867,016					
Disability Category:					
Anxiety Disorders	0.75				
Post Traumatic Stress Disorder	0.65				
Mood Disorders	0.25				
Major Depressive Disorder	0.18				
Bipolar Disorder	0.02				
Chronic Adjustment Disorder	0.05				
Delirium, Dementia, Amnestic/Cogn. Dis.	0.03				
Schizophrenia and Psychotic Disorders	0.02				
Dissociative Disorders	0.02				
Number of Examiners	1,749				
Cases per Examiner	496	644	123	230	603

Notes: This table displays summary statistics of veteran demographics, military service, disability benefit compensation, and disability claim variables for our sample veterans with first disability compensation claims. All variables are calculated at time of the disability claim and financial amounts are in 2020 dollars. Disability categories are not mutually exclusive as a veteran may claim multiple mental health disabilities at once.

Table 2: Economic Security and Financial Well-Being

Panel A. 1-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>			
	Food Insecurity (1)	Homeless-ness (2)	# Debt Collection (3)	Debt Balance Collection (4)
\$1,000 per year	-0.060* (0.034)	-0.072*** (0.016)	-0.039** (0.017)	-0.259** (0.126)
Mean Dep Var ($\times 100$)	2.17	7.75	1.56	16.6
N=	64,060	855,264	276,121	276,121

Panel B. 5-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>			
	Food Insecurity (1)	Homeless-ness (2)	# Debt Collection (3)	Debt Balance Collection (4)
\$1,000 per year	-0.099*** (0.028)	-0.184*** (0.033)	-0.107*** (0.020)	-0.658*** (0.133)
Mean Dep Var ($\times 100$)	2.41	14.33	1.68	13.05
N=	124,224	576,677	261,448	261,448

Notes: This table reports estimated 2SLS coefficients from [Equation 1](#) for measures of economic and financial well-being. One-year and five-year outcomes are displayed in panels A and B, respectively. Benefit compensation amounts are scaled to units of an additional \$1,000 per year and the coefficients and mean dependent variables are scaled by 100 for interpretability and readability. Food insecurity is an indicator for ever reporting a survey response of “food shortage and no money to buy food or access to food” given to all non-institutionalized veterans starting in 2017. See [Table C.2](#) for bounds on the effect sizes after accounting for potential response biases correlated with the IV. Homelessness is proxied with an indicator for any of the following within the outcome period: diagnosis for lack of housing/inadequate housing, outreach by or use of VA homeless and/or shelter programs and services; see [Appendix A](#). Columns 3 and 4 are number of delinquent debts owed to the VA sent to the Department of Treasury and the inverse hyperbolic sine of total collection balances on delinquent debt. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran’s Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: Healthcare Utilization, Engagement, Preventive Care, and Medication Adherence

Panel A. 1-Year Outcomes

		<i>Dependent variable: ($\times 100$)</i>								
Total	Output	Input	MH OP.	Scheduled	Annual Flu	Any Hep C	Annual Colon	Medication		
Util \$	Util \$	Util \$	Util \$	Appts	Vaccination	Screen	FOBT	Adherence		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
\$1,000 per year	2.63*** (0.40)	2.63*** (0.38)	0.36 (0.46)	2.69*** (0.43)	11.75*** (2.99)	0.14*** (0.04)	0.15*** (0.03)	0.06 (0.11)	0.07*** (0.02)	
Mean Dep Var ($\times 100$)	783.66	773.44	89.80	462.62	2,232.10	33.26	16.35	27.03	73.44	
N=	854,873	854,873	854,873	854,873	854,873	854,873	825,740	409,588	503,532	

Panel B. 5-Year Outcomes

		<i>Dependent variable: ($\times 100$)</i>								
Total	Output	Input	MH OP.	Scheduled	Annual Flu	Any Hep C	Annual Colon	Medication		
Util \$	Util \$	Util \$	Util \$	Appts	Vaccination	Screen	FOBT	Adherence		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
\$1,000 per year	2.65*** (0.45)	2.66*** (0.40)	1.56 (1.23)	2.67*** (0.63)	85.64*** (19.96)	0.15*** (0.05)	0.31*** (0.07)	0.07 (0.11)	0.05** (0.02)	
Mean Dep Var ($\times 100$)	1,028.43	1,014.23	261.03	732.55	10,784.44	36.51	45.81	24.85	75.35	
N=	576,677	576,677	576,677	576,677	576,677	576,677	562,950	285,427	455,673	

Notes: This table reports estimated 2SLS coefficients from Equation 1 for healthcare utilization and related outcomes. One-year and five-year outcomes are displayed in panels A and B, respectively. Benefit compensation amounts are scaled to units of an additional \$1,000 per year and the coefficients are scaled by 100 for interpretability and readability. Columns 1-4 correspond to regressions with inverse hyperbolic sine of total, outpatient, inpatient, and mental health outpatient average cost as the dependent variable; average cost is computed by the VA to reflect healthcare utilization and is available until FY2019 (Wagner et al., 2003). Column 5 displays the number of scheduled appointments. Columns 6-8 displays all VHA preventive care recommendations that apply to the majority of our sample; the fraction of years with an annual flu vaccination (a value of 0.8 for the 5-year horizon would mean the veteran receives a flu vaccination for 4 of the 5 years), whether the veteran has received any hepatitis C screen (recommended for all adult veterans under the age of 79 and hence only estimated on this sample), and the fraction of years with an annual colon cancer screen via a fecal occult blood test (recommended for all adult veterans ages 50 to 75 and only estimated on this sample). Column 9 displays medication adherence rates proxied by drug episode duration-weighted average medication possession ratio (MPR) calculated only for veterans with any prescriptions. See Table C.2 for bounds on the effect sizes after accounting for potential response biases correlated with the IV. All regressions are estimated on samples of veterans that are alive for the entire outcome period. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. * p<0.1; ** p<0.05; *** p<0.01.

Table 4: Satisfaction, Access, Trust, and Communication (Veteran Satisfaction Survey)

	<i>Dependent variable: (Standardized)</i>			
	Satisfaction with VA care (1)	Access and Availability (2)	Collaborative Medication Management (3)	Communication, Trust, & Rapport (4)
\$1,000 per year	0.032** (0.013)	0.013 (0.013)	0.028** (0.012)	0.027** (0.013)
N=	1,401	1,401	1,390	1,401

Notes: This table reports estimated 2SLS coefficients from Equation 1 for composite measures of satisfaction, access, trust, and communication from the Veteran Satisfaction Survey (VSS). Composite measures are constructed as average Z-scores of individual questions from the VSS; see Figure C.4 for groupings and Appendix A for details on the VSS. Veterans who are not selected for the survey, do not complete the survey, or skip the question are dropped. The impact of \$1,000 on completing the survey (response bias) is 0.00017 (SE=0.00011) and statistically insignificant at the 10% level. The sample size reflects the randomly selected veterans from 2017-2020 who completed the survey within five years of first claiming mental disorder disability. Regression coefficients and 95% confidence intervals (robust standard errors are clustered at the facility-level) are graphed. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Mental and Physical Health Outcomes

Panel A. 1-Year Outcomes

		<i>Dependent variable: ($\times 100$)</i>									
MDD	AUD/ SUD	Overdose Poisoning	Suicide Event	BMI	Pain Score	HbA1c (%)	Systolic BP	Diastolic BP	All-Cause Mortality		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		
\$1,000 per year	0.002 (0.052)	-0.001 (0.004)	-0.004 (0.007)	0.116 (0.525)	-1.036** (0.415)	0.025 (0.188)	2.495 (1.879)	-0.856 (1.764)	0.0022 (0.0091)		
Mean Dep Var ($\times 100$)	68.37	0.30	0.91	3,017.19	301.07	621.47	12,841.28	7,753.25	1.42		
N=	561,229	855,264	655,186	665,745	639,000	353,971	646,487	646,487	867,416		

Panel B. 5-Year Outcomes

		<i>Dependent variable: ($\times 100$)</i>									
MDD	AUD/ SUD	Overdose Poisoning	Suicide Event	BMI	Pain Score	HbA1c (%)	Systolic BP	Diastolic BP	All-Cause Mortality		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		
\$1,000 per year	-0.050 (0.063)	-0.068 (0.086)	0.0001 (0.019)	-0.298 (0.971)	-1.456*** (0.396)	0.028 (0.176)	0.660 (2.163)	-2.537 (2.273)	0.0445 (0.0284)		
Mean Dep Var ($\times 100$)	74.98	54.78	2.89	3,054.29	297.81	604.31	12,849.35	7,768.07	8.07		
N=	529,759	529,356	522,089	441,691	529,111	423,239	530,362	530,362	626,523		

Notes: This table reports estimated 2SLS coefficients from Equation 1 for physical and mental health outcomes, and mortality. One-year and five-year outcomes are displayed in panels A and B, respectively. Benefit compensation amounts are scaled to units of an additional \$1,000 per year and the coefficients are scaled by 100 for interpretability and readability. Columns 1 and 2 are measures of major depressive disorder (MDD) and alcohol/substance use disorder constructed from annual mental health screens (mandated since 2008) in primary care. The indicator takes on the value of one if the veteran ever has a diagnosis of MDD or AUD/SUD or screens positive via annual mental health screening tools, and zero if the veteran never screens positive and is never diagnosed. Overdose poisonings are indicators for whether the veteran has been diagnosed with an overdose. Suicide events are indicators for ever attempting suicide from VA Office of Mental Health and Suicide Prevention's national surveillance dataset starting in 2010; see Appendix A for more details. BMI is calculated as the average in the first year and the average in the fifth year. Pain score and hemoglobin A1c variables are averages across the entire time period. Blood pressure are averaged first at the encounter-day level and then averaged across the entire time period. Only pain scores and blood pressure measurements taken in outpatient primary care clinic settings are used. See Table C.2 for bounds on the effect sizes after accounting for potential response biases correlated with the IV. With the exception of all-cause mortality, all regressions are estimated on samples of veterans that are alive for the entire outcome period. All regressions include station-by-year fixed effects and baseline controls in the text; standard errors are clustered at the station-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix (For Online Publication Only)

A. Variable Definitions

In this appendix we describe the source and construction of our variables, grouped by outcome type. Note that wherever possible, we use official VA definitions and measures, sourcing our data from the Office of Mental Health and Suicide Prevention. For example, see [Figure C.1](#) for an example of a clinical dashboard which uses the same definitions on homelessness, VA debt, medication adherence, and appointments.

A.1 Utilization and Average Cost

Our “log utilization” outcomes are based on VA’s average cost computed by the Health Economics and Resource Center (HERC). It uses CMS relative value weights to assign national-level VA cost to encounter-level VA utilization. It is average cost in the sense that two encounters with the same characteristics (e.g., procedures, diagnoses, length of stay, etc.) will have the same average cost. It does *not* reflect veteran out-of-pocket spending. Outpatient costs do not include prescription costs. Inpatient costs include acute inpatient hospital, nursing home, and inpatient domiciliary and rehabilitation care. See [Wagner et al. \(2003\)](#) for more details.¹ We also compute the number of days the veteran has any encounter of that type of care or care setting: the number of days with any mental health outpatient encounter or the number of days with any emergency department or acute inpatient hospital visit.

A.2 Preventive Care

We calculate the number of days the veteran receives any preventive care, calculated from CPT procedure codes: 4000F-4320F; 90750-90759, 90762-90764, 90778, 99381-99429, G0438,

¹For an overview: <https://www.herc.research.va.gov/include/page.asp?id=average-cost>.

G0439. There is likely to be under-use of procedure codes in the VHA as providers are salaried and do not bill insurers.

We also evaluate whether veterans' preventive care follows the VA's official preventive care guidelines (VHA, 2021). Of all the preventive care guideline recommendations, three apply broadly to the majority of our sample and can be measured at (roughly) annual frequencies²: annual flu immunization for all adults, annual colorectal cancer screen via fecal occult blood test (FOBT) among all adults ages 45-75, and hepatitis C screen at least once among all adults ages 18-79. Based off of these recommendations, we construct the fraction of years where the veteran has a flu immunization (takes on 0 or 1 for the 1-year outcome and 0, 0.2, 0.4, 0.6, 0.8, or 1 for the 5-year outcome), fraction of years they have a FOBT colon cancer screen, and an indicator for whether the veteran receives any hepatitis C screen in 1 or 5 years. All three measures are constructed from procedure codes, lab results, and clinician ordered items in a computerized system.

A.3 Food Insecurity

The VA started screening for food insecurity in primary care starting in October 2017. This is done in primary care via VA's EHR clinical reminder system. An annual reminder automatically pops up on all primary care provider's computer screen as an alert. The screen asks "In the past three months did you ever run out of food and you were not able to access more food or have money to buy more food?". A binary yes/no response is required on the screen, entered, and automatically recorded. Our indicator is derived from the recorded data and takes a value of one if the veteran answers yes and zero if they answer no. Veterans who are not screened (within the 1-year or 5-year time period) are coded as zero and thus dropped from the regressions with food insecurity as an outcome. By late 2019, nearly 5 million veterans have been screened and approximately 74,000 have screened positive (Cohen et al., 2020).

²Other recommendations either do not apply to the majority of our sample (e.g., breast and cervical cancer screens, syphilis screens, etc.), are recommended without guidance on frequency, (e.g., high blood pressure screen), or are not easily measured in the data (e.g., overweight and obesity counseling).

A.4 Homelessness

Homelessness is measured from three sources: medical diagnosis codes, inpatient hospital bed sections, and utilization of homeless and employment services. Our definition of homelessness is the official VA Office of Mental Health and Suicide Prevention definition which appears on multiple patient dashboards used to assist clinicians in decision making, and used in various predictive algorithms (e.g., for suicide risk). Similar VA measures of homelessness have been used in (Brignone et al., 2018; Tsai et al., 2014; Nelson et al., 2021). Below we describe the three sources.

1. Diagnosis codes

- Homelessness (ICD-9: Z59.0; ICD-10: V60.0) across all care settings/modalities
- Inadequate housing (ICD-9: Z59.1; ICD-10: V60.1) across all care settings/modalities

2. Inpatient hospital bed sections

- Acute inpatient hospital beds for homeless veterans
- Residential Domiciliary Care for Homeless Veterans (DCHV³)

3. Outpatient homeless and employment services:

- Health Care for Homeless Veterans (HCHV) at VA medical outpatient clinics, contracted community centers.⁴
- U.S. Department of Housing and Urban Development-VA Supportive Housing (HUD-VASH) Program: use of HUD-VASH services (in-person or telephone) such as residential assistance, vouchers, counseling, and others.⁵

³The VA defines DCHV as a setting that “provides a residential level of care for a homeless Veteran population. DCHVs provide a 24/7 structured and supportive residential environment as a part of the rehabilitative treatment regime.” See <https://www.va.gov/homeless/dchv.asp>.

⁴This also includes non-medical care (e.g., housing services, social work, etc.) at non-medical facilities; see <https://www.va.gov/homeless/hchv.asp>.

⁵See <https://www.va.gov/homeless/hud-vash.asp>.

- Homeless Veteran Community Employment Services (HVCEs) “provides vocational assistance, job development and placement, and ongoing supports to improve employment outcomes among homeless veterans and veterans at-risk of homelessness. Formerly homeless veterans who have been trained as Vocational Rehabilitation Specialists provide these services.”⁶
- Compensated Work Therapy (CWT) and vocational assistance for homeless veterans are vocational programs such as paid vocational programs, on-the-job-training, apprenticeships, and non-paid work experiences
- Community outreach to homeless veterans by VA staff via telephone
- Use of community homeless services awarded by the VA’s Homeless Veterans Grant and Per Diem (GPD) program to fund contracted community non-profit agencies⁷

A.5 Medication Adherence-Related Variables

We construct five medication-related outcomes. The first, is the number of new drugs the patient starts and refills at least once during the 1 or 5 year period. A drug is formulation without dosage and not the brand name. The second outcome is the ratio of prescriptions that are dispensed and released to the patient divided by the number of new prescriptions written for the patient. The underlying data comes from the universe of prescriptions written by a VA provider that get entered electronically and prescriptions filled and released at VA pharmacies.

Drug episode-level medication possession ratio (MPR) is constructed by the VA for all veterans who are alive and fill a prescription after January 1, 2017. A drug episode is a “trial” of a drug (formulation without dosage). A patient may have multiple episodes for the same drug if i) a new drug is released more than 300 days from the previous release; or ii) if a new

⁶See https://www.va.gov/homeless/employment_programs.asp.

⁷These agencies may provide supportive housing or services such as case management, education, crisis intervention, counseling, and targeted services for specialized under-served populations; see <https://www.va.gov/homeless/gpd.asp>.

release is more than 180 days from the previous and under a different prescription; or iii) if a new release is more than twice the days supply since the previous release and is under a different prescription and the previous prescription was discontinued. The VA computes MPR for a drug episode as:

$$MPR_{episode} = \frac{\text{Days Supply Dispensed}}{\text{Drug Episode Duration}}$$

$MPR_{episode}$ is mechanically only defined for drug episodes that get refilled at least once; it is top-coded at one. Using drug episode MPR, we construct 1-year and 5-year patient MPR as the episode duration weighted average MPR for all *non-opioid* drug episodes that start in that time period (regardless of when they end). This is our average MPR measure. We also construct the fraction of drug episodes with $MPR_{episode}$ greater than 0.8, a commonly used adherence threshold that has been found to be predictive of reduced mortality (Rodriguez et al., 2019).

We also calculate average MPRs for five drug classes using VA drug class codes: *antidepressants* (tricyclic antidepressants, monamine oxidase inhibitor antidepressants, and other antidepressants), *antipsychotics* (phenothiazine/related antipsychotics and other antipsychotics), *sedatives/hypnotics* (barbituric acid derivatives, benzodiazepine derivatives, and other sedatives/hypnotics), *statins* (antilipemic agents), and *hypertensive drugs* (angiotensinconverting enzyme inhibitors, angiotensin II receptor blockers, direct renin inhibitors, antiadrenergic antihypertensives, betablockers, diuretics, and calciumchannel blockers).

A.6 VA Debt

Data on debt owed to the VA and debt progression (debt notification letters, referral to Treasury Offset Program letters) between 2016 and 2021 are from the VBA Debt Management Center (DMC). VA debt can accrue on VA benefits such as disability and pension benefits, home loans, and GI Bill education, vocational, and employment benefits. This typically happens when veterans no longer meet eligibility requirements such as being a full-time

student (and thus have to repay portions of tuition, books and fees, school housing, etc.), or dependent situation changes (child dependent is no longer under 18 and this has resulted in months of disability benefit overpayment), or inability to make mortgage payments on VA home loans. In some cases veterans may also incur medical debt, although the amounts are generally small and we observe no instances of debt collection on medical debt in our baseline sample (who all receive nearly free healthcare).

When a debt is first established, the DMC sends an initial letter of notification to the veteran. If within 30 days of the initial letter, the veteran has not made debt arrangements, the DMC will send a second letter of notification. If no arrangements have been made within 120 days (including applications for debt waiver and forgiveness), the DMC is required to refer the debt to the U.S. Treasury which may i) add fees and interest; ii) keep part or all of your federal or state payments to pay down your debt (known as offsetting in the Treasury Offset Program); iii) refer your account to a private collection agency. At this stage—which we consider “debt collection”—the VBA can no longer waive or forgive the debt.⁸

With the debt referrals to Treasury, we follow Dobbie et al. (2017) and Dobkin et al. (2018) and construct variables on the number of debt collections (that get referred to Treasury) and the collection amount on all such debt within one and five years of the disability claim. Although we do not observe non-VA debt, the amount of VA debt is substantial; 2.6% of our baseline sample have any collections within five years and the median balance among these collections is \$8,229 with a quarter owing over \$17,500.

A.7 Physical and Mental Health Outcomes

Physical and mental health outcomes are measured from electronic health records. Major depression disorder (MDD) is an indicator variable that takes the value of one when the veteran (*i*) **ever** screens positive on the 2-item or 9-item Patient Health Questionnaire (PHQ-2 ≥ 3 , PHQ-9 ≥ 5) over the time frame **or** (*ii*) is diagnosed with MDD over the

⁸For more details on the life-cycle of VA debt, see <https://www.va.gov/resources/va-debt-management>.

time frame. Veterans who score negative on all PHQs and are never diagnosed with MDD receive a value of zero. All other veterans (including those who are never screened) are coded as missing. AUD/SUD is constructed analogously replacing PHQs with the Alcohol Use Disorders Identification Test-Concise ($AUDIT-C \geq 3$) and MDD diagnosis with AUD or SUD diagnosis. The AUDIT-C and PHQ questionnaires can be found on the [NIDA website](#). Question 3 of the AUDIT-C (*"How often did you have six or more drinks on one occasion in the past year?"*) is used to construct proxy for binge drinking in [Figure C.3](#); the proxy takes a value of one for responses of "weekly" or "daily or almost daily". Overdose poisonings is a binary variable constructed only using poisoning diagnosis codes. See [subsection A.8](#) for description on the data behind the suicide variable.

Average body mass index, pain score, HbA1c glucose levels, and blood pressure are constructed at the one-year and five-year level only for individuals with at least one measurement during the time period. Pain scores are self-reported responses to (some variant) of the following question: *"On a scale of zero to ten, where zero means no pain and ten equals the worst possible pain, what is your current pain level?"* Since BMI and blood pressure are often measured multiple times within a single encounter to improve precision, we first obtain encounter day-level averages before taking averages again at the one-year or five-year level. Only measurements of pain and blood pressure taken in primary care settings are used.

A.8 Suicide Surveillance Data

Data on suicide attempts come from the VA Office of Mental Health and Suicide Prevention's Suicide Prevention Applications Network (SPAN; [US Department of Veteran Affairs, 2021b](#)). SPAN was established following the passage of the Joshua Omvig Veterans Suicide Prevention Act in 2007 as a national surveillance database to better inform suicide prevention. It is comprised of clinically mandated suicide evaluations, suicide behavior and overdose reports, clinical texts, current and historic reports from clinical and suicide prevention coordinators, in addition to medical records. This data is used to inform national suicide prevention efforts (e.g., displayed on clinical dashboards, used as a feature in predictive algorithms of veteran

suicide risk, and used to construct reports on veteran suicide to congress). It captures data that would not normally be available in patient health records, for example, if a patient reveals to a clinician of a suicide attempt that occurred last year, this would not appear in diagnosis data, but would in SPAN. Roughly two-thirds of suicide attempts in SPAN had no data in recorded medical records (Hoffmire et al., 2016). From this data we code an indicator for whether the veteran had a suicide attempt in the 1 year or 5 year period.

A.9 Veteran Satisfaction Survey (VSS)

Starting in fiscal year 2018, the VA Office of Mental Health started conducting VHA mental health satisfaction surveys (VSS) to veterans currently receiving mental health outpatient treatment. Each year since 2018, veterans receiving mental health outpatient treatment are randomly (phone) called a set of roughly 36 questions relating to their satisfaction in VHA mental health care. Veterans are drawn and contacted until roughly 10,000 veterans respond and complete the survey each year.

We have three waves of the VSS (FY2018, 2019, 2020), covering 26,879 unique veterans receiving VHA mental health care. We merge these survey responses to our analysis sample starting in 2014 (to allow a five-year response period), resulting in a sample size of 1,401. For the few veterans who were surveyed more than once, their responses are averaged. We only focus on the 27 questions that were consistent over the three years. We group the 27 questions into four categories: i) satisfaction with VA care; ii) access and availability; iii) collaborative medication management; and iv) communication, trust, and rapport. See [Figure C.4](#) for the grouping categories. For each category, we calculate equally-weighted averages of Z-scores as our main outcome variable. In [Figure C.4](#), we also study the raw response on a 1-5 scale (1: disagree strongly; 2: disagree; 3: neither disagree or agree; 4: agree; 5: agree strongly); and an indicator for agree or agree strongly. The impact of \$1,000 on completing the survey (response bias) is 0.00017 (s.e.=0.00011) and statistically insignificant at the 10% level.

B. Correlated Random Coefficients Model

This appendix section provides details on the estimation strategy underlying [Figure 5](#). In that figure, we show estimates from a control-function implementation of a correlated random coefficients model ([Garen, 1984](#); [Wooldridge, 2015](#)).

The standard model begins with the following heterogenous treatment effect equation:

$$y_i = \delta z_{i1} + g_{i1}x_i + u_i \tag{1}$$

where y_i is the outcome of interest, z_{i1} is a vector of included exogenous variables, and x_i is the endogenous explanatory variable of interest. The treatment effect g_{i1} is individual-specific. In our setting, the causal impact of VA DC benefits (x_i) on wellbeing (y_i) may differ from veteran to veteran. One can rewrite the individual-specific treatment effect as the sum of a population treatment effect and an idiosyncratic term:

$$g_{i1} = \gamma_1 + v_{i1}, \quad \text{where } E[v_{i1}] = 0 \tag{2}$$

Suppose there is an excluded exogenous variable z_{i2} with the following first stage relationship:

$$x_i = \pi z_{i2} + v_{i2}. \tag{3}$$

Now assume that all unobservables are independent of exogenous variables z_{i1} and z_{i2} , and that u_i and v_{i1} can be expressed linearly in v_{i2}

$$E[u_i|v_{i2}] = \eta v_{i2}, \quad E[v_{i1}|v_{i2}] = \psi v_{i2} \tag{4}$$

Therefore, the estimating equation is then:

$$E[y_i|z_{i1}, z_{i2}] = \delta_1 z_{i1} + \gamma_1 x_i + \psi v_{i2} x_i + \eta v_{i2}. \tag{5}$$

[Equation 5](#) can be estimated by an OLS regression of y_i on z_{i1} , x_i , \hat{v}_{i2} , and $\hat{v}_{i2}x_i$ where

\hat{v}_{i2} is the residual from the first stage. The interaction term is the random coefficient on x_i . There is also an additional assumption that the covariance between endogenous variable and its idiosyncratic impact are independent of the exogenous instruments.

Of course, one cannot recover individual-specific treatment effects g_{i1} , but its relationship with the endogenous variable x_i can be estimated (e.g., its sign). We adapt this extend this linear model by splitting veteran's first stage residual into quantiles. Operationally, we first regress veteran benefits on examiner propensity and the standard controls from our baseline analyses. Next, we bin residuals into five quintiles. Finally, we regress veteran outcomes on benefits, residual quintile bins, the interaction of the two, and controls. The estimated coefficients on the interaction terms are plotted in [Figure 5](#) along with the baseline 2SLS estimate. In [Figure C.6](#), we also estimate a related correlated random coefficients model following [Masten and Torgovitsky \(2016\)](#).

C. Additional Exhibits

Figure C.1: Example of VA clinical dashboard (with patient with no PHI/PII) utilizing the same data we use

VA SPPRITE Report
Suicide Prevention Population Risk Identification and Tracking for Exigentcies

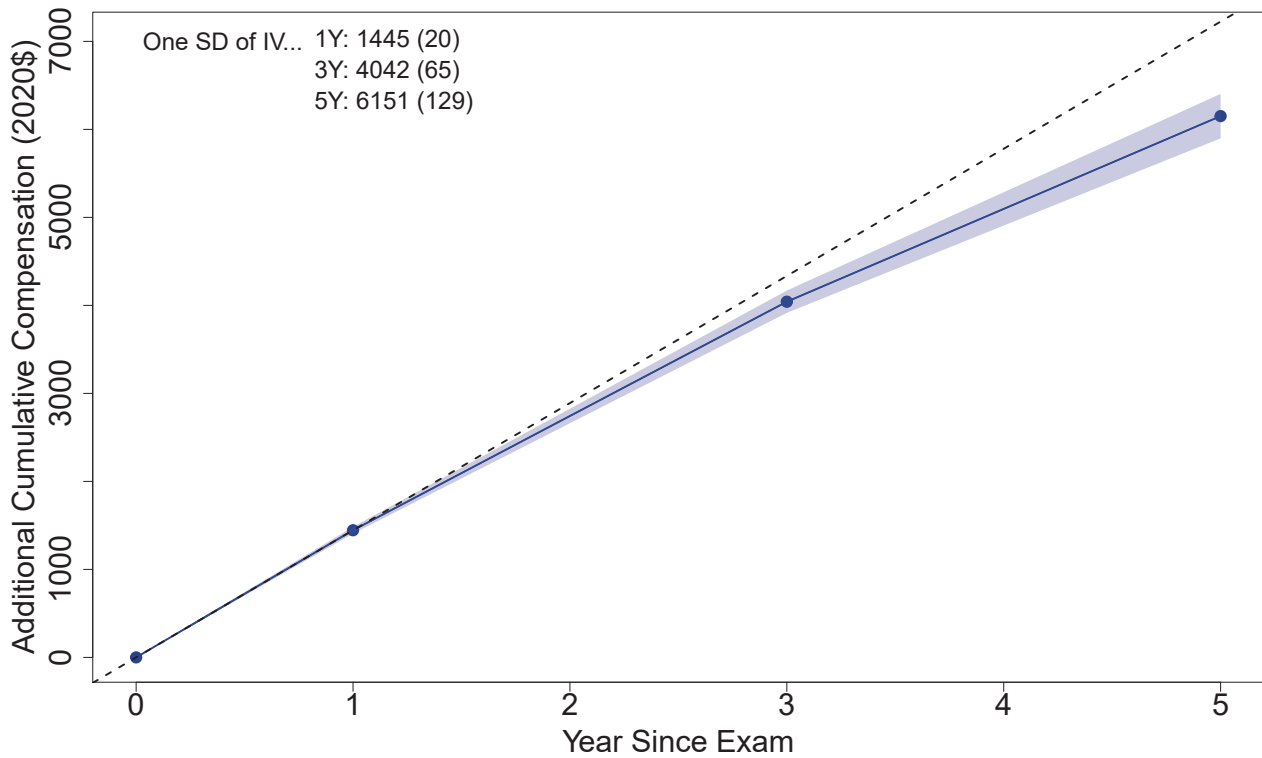
* Data displayed has a 1-2 day lag from OHS entry. This report is to be used along with the electronic medical record and direct discussion with the patient to help facilitate decision making.

Home | SPPRITE & COVID19 | Suicide Risk Management Outreach & COVID19 | FAQ | Export this Data | Obtain Dashboard Access | Patient Look-Up (CRISTAL) | STORM 90-Day Guide | CPG: Pts at Risk for Suicide | Contact Us

Patient Info	COVID-19				Debt to VSA (DMC Debt)	Most Recent Safety Plan	Recent Rx Discontinuations	Current Care & Providers		
Patient Name (9999) (Age 60, MF) Homeless Status? Medication Adherence? Date: 01/01/1910 Phone:	Positive Screen Most Recent Positive Screen: 01/01/1910 San Francisco, CA HCS Earliest Positive Screen: 01/01/1910 N. California HCS	Lab Test or Diagnosis Most Recent: Negative 01/01/1910 San Francisco, CA HCS	HHS COVID-19 Outreach Date of Eligibility: 01/01/1910 HHS - COVID Outreach Status: Successful 01/01/1910	Vaccine COVID-19 (MODERNA) Dose 1: 01/05/1910 Dose 2: 01/01/1910 San Francisco, CA HCS	Total DMC debt: \$1,501.00 among 2 debts Most Recent DMC Letter: 3/11/2020 (Notified Account Referred to Cross Services (CS)). Encourage Veteran to call DMC to discuss if they have not addressed their debt: 1-800-827-0648 (8:30 a.m. to 6:00 p.m. CT Mon-Fri) or by visiting https://vsa.com/vsa.us/assess55/	01/01/1910	Drug Category Days Since Pills Antidepressant 60	PHTC: Provider Name Patient has assigned MPHIC at other facility.	Mental Health Care Last MH Appt: 01/01/1910 TELEPHONE MH San Francisco, CA HCS Next MH Appt: 01/01/1910 San Francisco, CA HCS	Primary Care Last PC Appt: 01/01/1910

Notes: This figure displays part of the VA SPPRITE dashboard (for a fake patient with PHI/PII removed) used by clinicians and mental health specialists for suicide prevention. The boxed red regions highlight patient information that use the same definition and data as we do in our paper. Moving from left to right: homelessness, VA debt, medication adherence, and appointments. Note that this is not the only dashboard where our outcomes share data with (for example, medication possession ratios are used in 12 different dashboards). Moreover, many of our variables also feed official VA metrics and predictive algorithms (such as a suicide risk prediction algorithm).

Figure C.2: Impact of Examiner Tendency on Cumulative Compensation and its Persistence

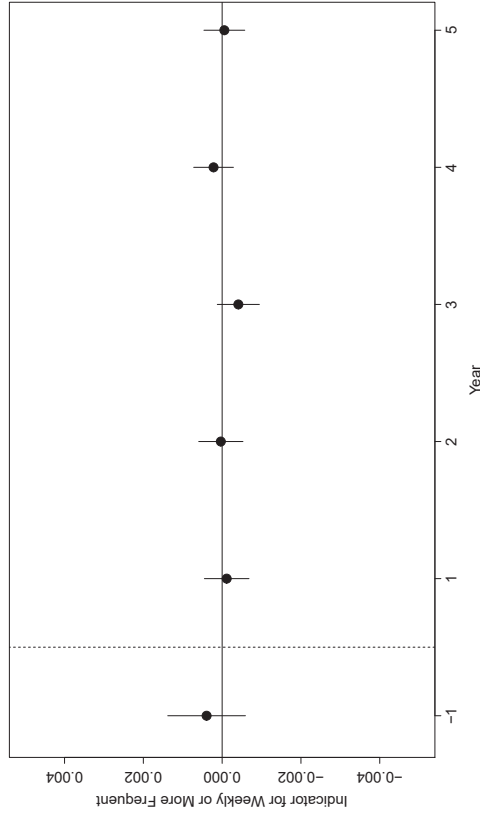
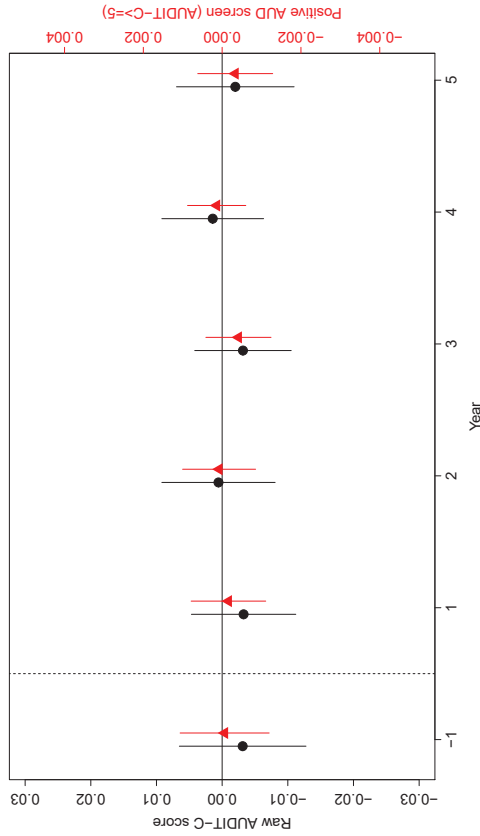


Notes: This figure displays the impact of one standard deviation higher-tendency examiner on total cumulative VA DC compensation over different time horizons (e.g., 1, 3, and 5 year post-exam). The displayed coefficients and 95% confidence intervals are from first stage regressions of cumulative compensation on standardized IV and controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran’s Elixhauser comorbidity score based on a one-year look-back period. The mean 1, 3, and 5 year cumulative compensation amounts are 15,090; 48,060; and 83,182, and the first stage F-statistics are 5,386; 3,922; and 2,288, respectively. Robust standard errors are clustered at the facility-level.

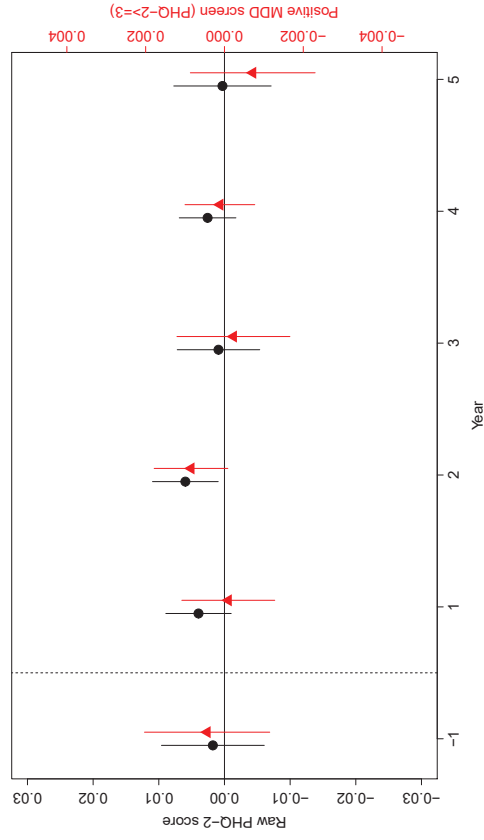
Figure C.3: Panel Mental Health Outcomes: Alcohol use disorder, alcohol consumption, and depression

(b) Binge Drinking: How often did you have six or more drinks on one occasion in the past year? (weekly or almost daily)

(a) Alcohol Use Disorder Screen

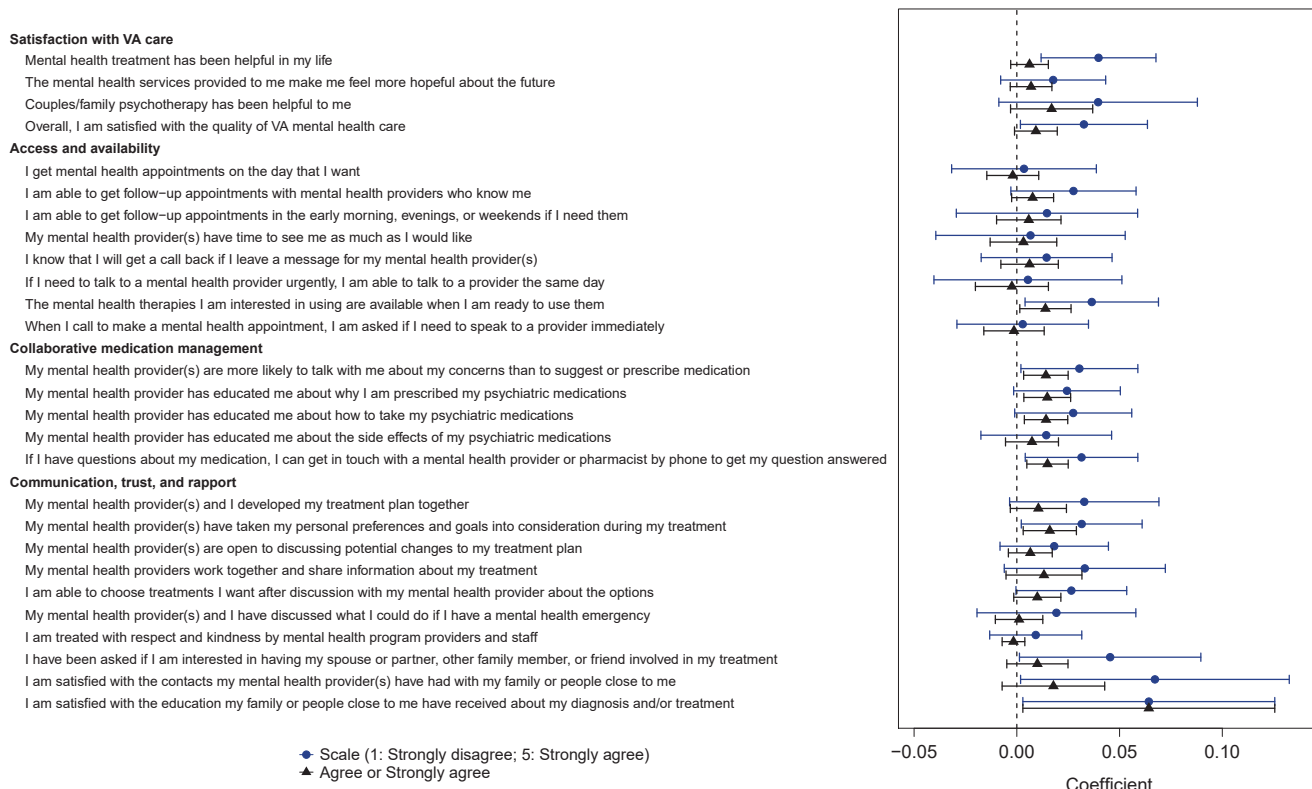


(c) Major Depressive Disorder Screen



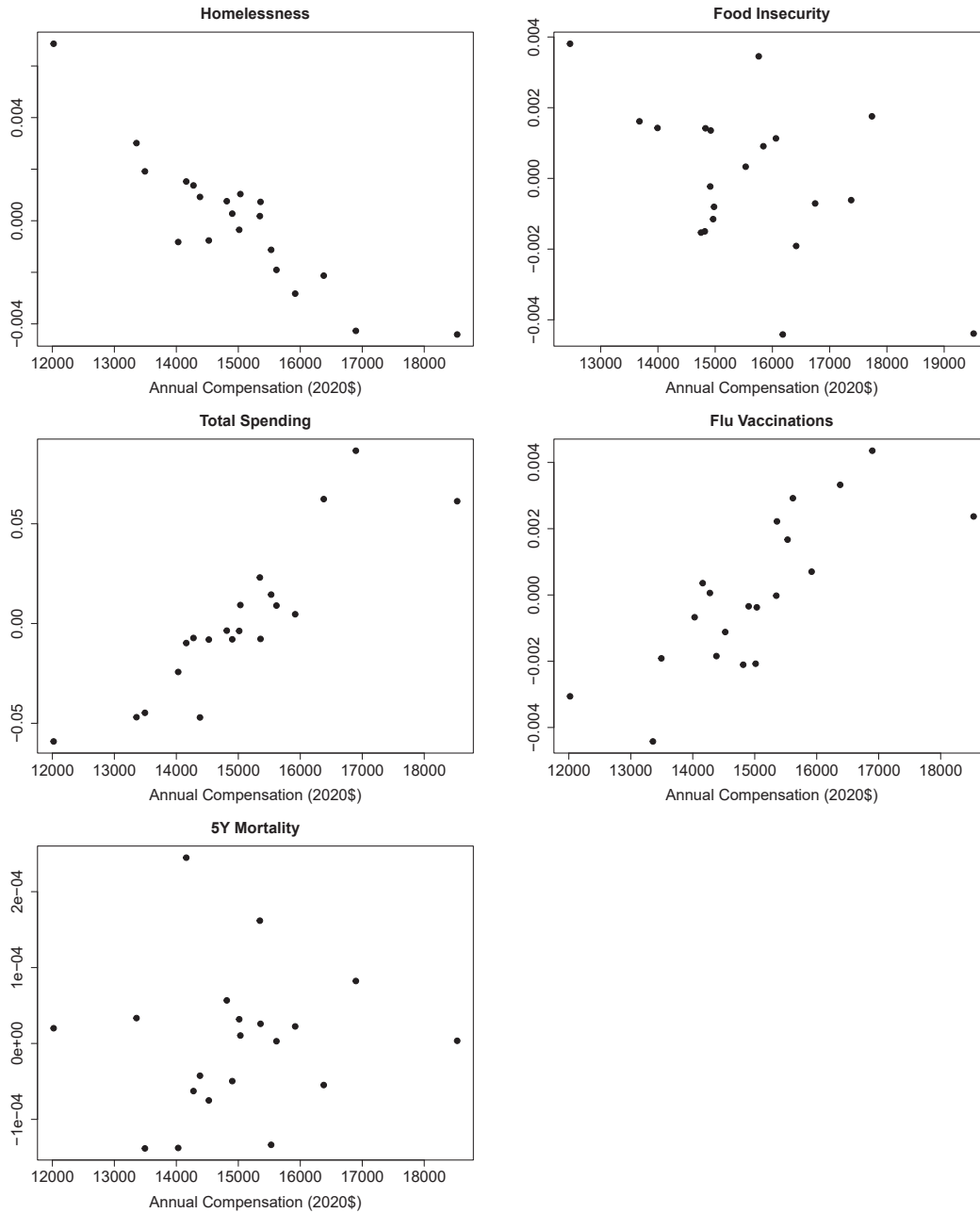
Notes: This figure displays estimated 2SLS coefficients from Equation 1 for alcohol use disorder (AUDIT-C questionnaire; panel a), a proxy for weekly binge drinking (AUDIT-C question 3; panel b), and major depressive disorder screens (PHQ-2 questionnaire; panel c), estimated separately for each 365 day period relative to the initial disability claim (one year prior and five years post). Benefit compensation amounts are scaled to units of an additional \$1,000 per year for interpretability. The black circles (left y-axis) correspond to the average raw questionnaire response as the outcome variable and the red triangles (right y-axis) correspond to screening “positive” as the outcome variable. All regressions are estimated on samples of veterans that are alive for the entire five years following the claim. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran’s Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. Mean AUDIT-C score and positive AUD screen rate (panel a) in the prior year are 2.04 and 14%; mean binge drinking at a weekly or more frequent (panel b) in the prior year is 7.6%, and mean PHQ-2 score and positive MDD screen rate (panel c) in the prior year are 1.54 and 23%. Analysis samples are not balanced; the number of observations range from 235,024 to 501,028 for panels a and b, and 171,028 to 323,036 for panel c.

Figure C.4: Veteran Satisfaction Survey Responses: Discrete Responses and Agree/Strongly Agree



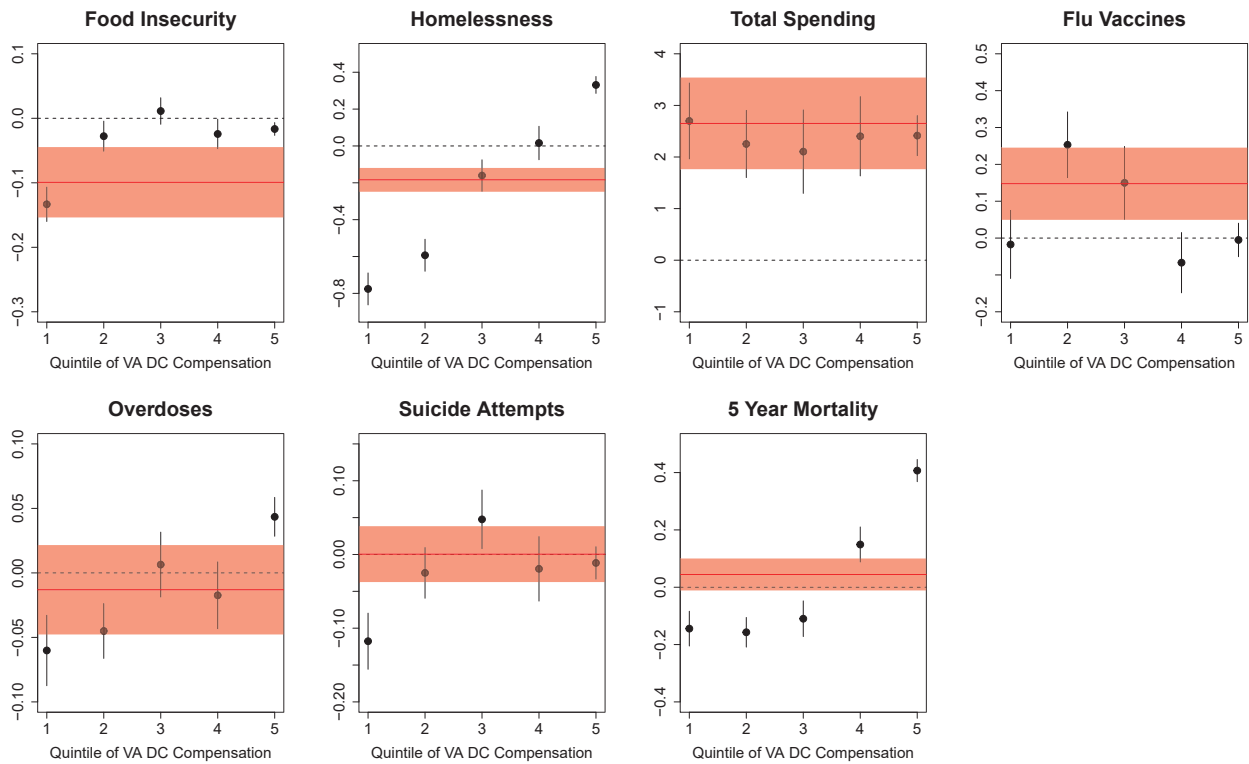
Notes: This figure displays the estimated coefficients of separate 2SLS regressions of individual survey question response (1 to 5 scale of strongly disagree to strongly agree; blue circle) OR survey response of at least agree (black triangle) on disability benefit compensation. The impact of \$1,000 on completing the survey (response bias) is 0.00017 (SE=0.00011) and statistically insignificant at the 10% level. The sample size is 1,401 veterans, which reflects the randomly selected veterans from 2017-2020 who completed the survey within five years of first claiming mental disorder disability. Regression coefficients and 95% confidence intervals (robust standard errors are clustered at the facility-level) are graphed. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Veterans who are not selected for the survey, do not complete the survey, or skip the question are dropped.

Figure C.5: Exploring Nonlinearities in the Impacts of Disability Compensation



Notes: This figure explores non-linear impacts of VA DC by plotting binscatters of select outcomes on VA DC compensation. The average residualized outcome is plotted against average residualized compensation benefit amount based on each veterans' examiner tendency (within a facility-year). The mean annual compensation amount is added back to the residualized compensation amounts, but the outcome variables remain demeaned. The residualization process includes facility-by-year fixed effects along with controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period.

Figure C.6: Heterogeneous Impacts of Disability Compensation: Masten and Torgovitsky (2016)



Notes: This figure investigates heterogeneous impacts of disability compensation on our main outcomes, using a correlated random coefficients approach following Masten and Torgovitsky (2016); Benson et al. (2022). We use 50 conditional ranks, and 50 bootstrap samples to compute standard errors.

Table C.1: Top 10 Rated Disabilities

	# Veterans	Age (2)	1 Year Mortality (3)	Average (4)	Disability Rating:						Change in Rating (5 Year) (10)
					SD	$\geq 30\%$	$\geq 50\%$	$\geq 70\%$	$=100\%$		
Tinnitus	2,434,637	52.50	0.009	10.00	0.16	0	0	0	0	0	0
Limitation of flexion, knee	1,236,109	41.57	0.003	10.30	3.79	0.01	0	0	0	0	0.18
Paralysis of the sciatic nerve	1,166,288	54.48	0.017	14.34	7.99	0.05	0.01	0	0	0	0.95
PTSD	1,149,921	48.91	0.010	50.11	20.68	0.95	0.66	0.32	0.05	0.05	5.88
Lumbosacral or cervical strain	980,696	38.92	0.003	14.22	7.60	0.06	0	0	0	0	0.94
Limitation of motion of the ankle	604,127	41.38	0.003	10.78	4.72	0	0	0	0	0	-0.09
Limitation of motion of the arm	569,208	41.52	0.003	19.83	5.28	0.03	0	0	0	0	0.02
Degenerative arthritis of the spine	480,835	47.82	0.005	15.18	8.78	0.08	0	0	0	0	1.09
Hearing loss	467,397	73.14	0.028	28.19	23.42	0.41	0.18	0.09	0.04	0.04	1.58
Diabetes mellitus	437,942	65.92	0.035	19.02	6.09	0.02	0.01	0	0	0	0.62

Notes: This table reports statistics of the top 10 disabilities that were newly rated by the VA between 2005-2020 ranked by the number of veterans with each disability (column 1). Columns 2 and 3 display the average age of veterans at the time of the claim and the fraction that die within one year of the time of the claim. Columns 4 to 9 displays statistics of the initial disability claim. Column 10 reports the average growth of the disability rating over five years (in percentage point levels); e.g., a growth of 1 means that claim's rating percentage increased up by one point over five years.

Table C.2: Bounding Effect Sizes for Outcomes with Incomplete Observations

	Sample Complier % (1)	Baseline Mean (2)	$\hat{\beta}$ (3)	LB (4)	UB (5)
Food Insecurity Screen	0.26	2.40%	-0.099	-0.354	-0.093
Medication Outcomes	0.47	75.4%	0.047	-0.068	0.400
MDD Screen or diagnosis	0.22	75.0%	-0.048	-0.103	0.117
AUD/SUD Screen or diagnosis	0.20	54.8%	-0.068	-0.156	0.041
Body Mass Index	0.49	30.5	-0.003	-0.083	0.053
Pain Scores	0.23	2.98	-0.015	-0.028	-0.008
HbA1c	0.46	6.04	0.0003	-0.0220	0.0070
Systolic Blood Pressure	0.22	128.5	0.007	-0.079	0.069
Diastolic Blood Pressure	0.22	77.7	-0.025	-0.075	0.020

Notes: This table presents a bounding exercise on our outcomes with incomplete observations. Column 1 displays the fraction of the sample with observed responses that are induced into the sample by having a higher-tendency provider that results in an additional \$1,000 per year. Columns 2 and 3 displays the baseline mean and estimated 2SLS impact of an additional \$1,000 per year on each outcome. Columns 4 and 5 displays the implied lower and upper bounds of the effect size after making assumptions on the outcomes of those induced into the sample. For binary outcomes, we assume either all or none of the induced sample have the indicator for the outcome and for continuous outcomes we assume the induced sample have 1 and 99 percentile values (in the year prior to VA DC claim) of the outcome.

Table C.3: Select Outcomes Without Non-Attrition Restrictions

Panel A. 1-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	Log Total Util \$	Homeless- ness	Food Insecurity	# Debt Collection	Overdose Poisoning	Suicide Event	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
\$1,000 per year	2.46*** (0.38)	-0.07*** (0.02)	-0.06* (0.03)	-0.04** (0.02)	-0.001 (0.004)	-0.01 (0.01)	0.002 (0.01)
Mean Dep Var ($\times 100$)	718.51	7.76	2.17	1.55	0.31	0.94	1.42
N=	867,016	867,016	64,405	279,564	867,016	663,692	867,016

Panel B. 5-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	Log Total Util \$	Homeless- ness	Food Insecurity	# Debt Collection	Overdose Poisoning	Suicide Event	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
\$1,000 per year	2.60*** (0.47)	-0.16*** (0.03)	-0.10*** (0.03)	-0.10*** (0.02)	-0.01 (0.02)	-0.001 (0.02)	0.04 (0.03)
Mean Dep Var ($\times 100$)	950.95	14.22	2.41	1.58	1.32	2.90	8.07
N=	626,523	626,523	126,244	282,793	626,523	565,225	626,523

Notes: This table reports estimated 2SLS coefficients of select main outcomes without restrictions on non-attrition. That is, unlike the main tables which are estimated only on the sample of veterans who are alive for the entire outcome period, these regressions are estimated on the sample of all veterans, including those who die before the end of the outcome period. The coefficients are scaled by 100 for interpretability and readability. All regressions include facility-by-year fixed effects and five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period; robust standard errors are clustered at the facility-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.4: OLS of Select Outcomes on Disability Compensation Benefit Amount

Panel A. 1-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	Log Total Util \$	Homeless- ness	Food Insecurity	# Debt Collection	Overdose Poisoning	Suicide Event	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
\$1,000 per year	3.80*** (0.06)	-0.01*** (0.004)	-0.03*** (0.005)	-0.02*** (0.003)	0.01*** (0.001)	0.02*** (0.002)	0.01*** (0.002)
Mean Dep Var ($\times 100$)	724.01	7.75	2.17	1.56	0.30	0.91	1.42
N=	854,873	854,873	64,035	276,121	854,873	654,967	867,016

Panel B. 5-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	Log Total Util \$	Homeless- ness	Food Insecurity	# Debt Collection	Overdose Poisoning	Suicide Event	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
\$1,000 per year	4.02*** (0.07)	0.01*** (0.01)	-0.04*** (0.01)	-0.05*** (0.004)	0.03*** (0.002)	0.08*** (0.004)	0.06*** (0.004)
Mean Dep Var ($\times 100$)	961.92	14.33	2.41	1.68	1.23	2.89	8.07
N=	576,677	576,677	124,180	261,448	576,677	522,847	626,523

Notes: This table reports estimated coefficients from Equation 1 from an OLS estimation for select main outcomes. One-year and five-year outcomes are displayed in panels A and B, respectively. Benefit compensation amounts (in 2020 dollars) are scaled to units of an additional \$1,000 per year and the coefficients are scaled by 100 for interpretability and readability. All regressions are estimated on samples of veterans that are alive for the entire outcome period. All regressions include facility-by-year fixed effects and five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period; robust standard errors are clustered at the facility-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.5: Impact of Examiner Tendency on Subsequent Appeals, Increases, and New Claims

	<i>Dependent variable: ($\times 100$)</i>							
	Appeal		Increase		New MH Claims		New Non-MH Claims	
	1Y	5Y	1Y	5Y	1Y	5Y	1Y	5Y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1 SD of Examiner IV	-0.03*** (0.01)	-0.09*** (0.01)	0.16*** (0.06)	-0.45*** (0.10)	0.12* (0.07)	0.04 (0.05)	0.12* (0.07)	0.04 (0.05)
Mean Dep Var ($\times 100$)	0.16	0.61	6.98	20.88	0.47	0.69	0.47	0.90
N=	854,873	576,677	854,873	576,677	854,873	576,677	854,873	576,677

Notes: This table reports estimated coefficients of a reduced form regression of the impact of examiner tendency on various subsequent disability claim related outcomes: whether the veteran appeals the initial (index) mental health disability claim (columns 1 and 2), whether the veteran files for an increased rating on the mental health disability (columns 3 and 4), the number of new MH disability claims filed (columns 5 and 6), and the number of new non-MH disability claims filed (columns 7 and 8). Odd (even) numbered columns report one-year (five-year) outcomes. The explanatory variable is the standardized examiner tendency instrument. The coefficients are scaled by 100 for interpretability and readability. All regressions include facility-by-year fixed effects and five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period; robust standard errors are clustered at the facility-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.6: Reduced Form Regressions of Select Outcomes on Examiner Tendency

Panel A. 1-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	Log Total Util \$	Homeless- ness	Food Insecurity	# Debt Collection	Overdose Poisoning	Suicide Event	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 SD of Examiner IV	3.59*** (0.56)	-0.10*** (0.02)	-0.09* (0.05)	-0.06** (0.03)	-0.002 (0.01)	-0.01 (0.001)	0.003 (0.01)
Mean Dep Var ($\times 100$)	724.01	7.75	2.17	1.56	0.30	0.91	1.42
N=	854,873	854,873	64,035	276,121	854,873	654,967	867,016

Panel B. 5-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	Log Total Util \$	Homeless- ness	Food Insecurity	# Debt Collection	Overdose Poisoning	Suicide Event	All-Cause Mortality
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1 SD of Examiner IV	3.15*** (0.57)	-0.23*** (0.04)	-0.13*** (0.04)	-0.14*** (0.03)	-0.02 (0.02)	0.001 (0.02)	0.06 (0.04)
Mean Dep Var ($\times 100$)	961.92	14.33	2.41	1.68	1.23	2.89	8.07
N=	576,677	576,677	124,180	261,448	576,677	522,847	626,523

Notes: This table reports estimated coefficients from a reduced form regression of select main outcomes on standardized examiner tendency instrumental variable. The impact of a standard deviation increase in examiner tendency on benefit compensation amounts are presented in [Figure 2](#). The coefficients are scaled by 100 for interpretability and readability. All regressions are estimated on samples of veterans that are alive for the entire outcome period. All regressions include facility-by-year fixed effects and five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period; robust standard errors are clustered at the facility-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.7: Frandsen et al. (2023) Test of Null of Exclusion and Monotonicity

	Disability Rating Threshold for Binary Treatment:		
	$\geq 30\%$	$\geq 50\%$	$\geq 70\%$
	(1)	(2)	(3)
Fit-based test	> 0.999	> 0.999	> 0.999
Slope-based test	0.980	0.974	> 0.999

Notes: This table presents results from the test proposed in Frandsen et al. (2023) for the null hypothesis that the monotonicity and exclusion restrictions hold. The p-values are reported for both the fit-based and slope-based tests with five year mortality rate as the outcome variable. The treatment is discretized into binary treatments based on three thresholds: 30%, 50%, and 70% disability rating.

Table C.8: Subsample First Stages

<i>Subsample:</i>	Cumulative Benefit (2020\$)		Mean Yr1 Benefit	N=
	1 Year	5 Year		
	(1)	(2)	(3)	(4)
Full Sample	1,444.9*** (19.7)	6,150.9*** (128.6)	15,090	867,016
Sex: Female	1,472.1*** (39.7)	6,125.7*** (259.8)	16,055	93,706
Sex: Male	1,439.1*** (20.7)	6,149.7*** (139.6)	14,965	761,167
Race: White (Non-Hispanic)	1,411.7*** (22.2)	6,006.9*** (145.4)	15,014	517,099
Race: Black	1,535.2*** (41.4)	6,466.2*** (271.6)	15,429	192,099
Race: API, Hispanic, Native	1,459.0*** (33.0)	6,373.9*** (215.8)	14,888	93,452
Age: < 45	1,399.0*** (29.1)	5,905.5*** (169.0)	14,841	317,213
Age: ≥ 45	1,468.4*** (27.5)	6,284.2*** (170.0)	15,228	537,660
Type: Anxiety Disorders	1,556.8*** (28.2)	6,594.7*** (161.3)	14,740	528,399
Type: Mood Disorders	1,423.7*** (48.4)	6,566.7*** (309.4)	16,092	176,207
Type: Other Disorders	1,374.3*** (61.1)	6,137.2*** (366.9)	16,590	80,780
Predicted Benefit: Top Tercile	1,525.10*** (24.9)	6,699.4*** (145.9)	17,736	285,315
Predicted Benefit: Middle Tercile	1,408.3*** (24.5)	6,016.9*** (154.6)	14,869	285,018
Predicted Benefit: Bottom Tercile	1,325.9*** (43.9)	5,722.2*** (236.5)	12,641	284,540

Notes: This table reports estimated coefficients from first stage regressions of one year and cumulative five year disability compensation benefit (in 2020 dollars) on standardized examiner tendency instrument for various subsamples, displayed in rows. Columns 1 and 2 report the estimated first stage coefficients. Column 3 and 4 display the average first year benefit amount and sample size for each subsample. Predicted benefit amount (in the first year) is fit using pre-examination covariates from [Figure 3a](#). The regressions are estimated on veterans who are alive over the entire outcome period. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the facility-level. *p<0.1; **p<0.05; ***p<0.01.

Table C.9: VA Debt: Number of Collections and Balances by Type

	Number of Collections	Collection Balance (\$)			
		Q1	Median	Mean	Q3
Education benefits	18,750	125	555	1,452	1,633
Disability compensation & pension	3,597	1,902	5,782	13,283	15,038
Vocational training and employment	378	338	804	1,372	1,680
Home loan guaranty	159	10,310	19,727	21,713	30,423

Notes: This table summarizes the number of debt collections and collection balances by type of debt. Education loans include Chapter 33 Post-9/11 GI Bill education benefits (tuition, housing, books and fees, relocation fees) and debt is usually triggered when the veteran drops out of school or stops attending school full-time. Disability compensation and pension debt is usually triggered when a veteran's dependent situation changes. Vocational training and employment programs pay veterans for employment training and debt can accrue if the veteran disenrolls early. Home loan guaranty programs provide assistance with purchasing homes (e.g., no downpayment, favorable interest rates, loan guaranty, etc.) and debt can accrue if for instance, the veteran falls behind mortgage payments. Incorrect overpayment can also result in debt for all four types.

Table C.10: Elasticities of Demand for Healthcare

	<i>Dependent variable: Log (1+Total Utilization)</i>	
	Benefits Elasticity	Income Elasticity [†]
	(1)	(2)
Log(1+Benefits)	0.14*** (0.02)	
Log(1+Benefits+Avg Income)		1.08*** (0.16)

†: Without accounting for labor market effects of disability income

Notes: This table reports benefits (column 1) and income (column 2) elasticities of demand for healthcare. Column 1 reports the coefficient of a log utilization-log benefits specification and column 2 reports the coefficient of a log-utilization-log benefits plus average veteran income specification. Note that the income elasticity does not account for labor market effects of disability income which are well-established (Autor and Duggan, 2003). See text for our preferred estimate where we conduct back-of-envelope calculations using causal estimates of the effect of VA disability income on veteran employment from Autor et al. (2016). In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the facility-level. *p<0.1; **p<0.05; ***p<0.01.

Table C.11: 5-Year Medication Possession Ratios by Drug Class

	<i>Dependent variable: ($\times 100$)</i>				
	Anti-depressants (1)	Anti-psychotics (2)	Sedatives/ Hypnotics (3)	Statins (4)	Hypertensive Drugs (5)
\$1,000 per year	0.027 (0.032)	0.039 (0.057)	0.049 (0.066)	0.074** (0.033)	0.114*** (0.038)
Mean Dep Var ($\times 100$)	80.12	82.01	72.95	86.15	87.80
N=	308,218	86,656	152,210	184,692	192,361

Notes: This table reports 2SLS estimates of the effect of disability compensation on 5-year medication possession ratios by drug class. MPRs are drug episode duration-weighted averages, which are only defined for individuals who fill at least the same drug (irrespective of dose) twice; see [Appendix A](#) for more details on outcome variable definitions. The coefficients are scaled by 100 for interpretability and readability. All regressions are estimated on samples of veterans that are alive for the entire outcome period. All regressions include facility-by-year fixed effects and five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period; robust standard errors are clustered at the facility-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.12: Utilization Effects for Sample With Actual and Expected Zero Medical Copayments

	<i>Dependent variable: ($\times 100$)</i>					
	Total Util		Outpat Util		Inpat Util	
	Actual	Expected	Actual	Expected	Actual	Expected
	(1)	(2)	(3)	(4)	(5)	(6)
\$1,000 per year	1.90*** (0.54)	2.83*** (0.49)	1.92*** (0.47)	2.90*** (0.44)	1.74 (1.46)	1.10 (1.21)
Mean Dep Var ($\times 100$)	\$39,368	\$35,957	\$28,407	\$26,727	\$10,961	\$9,230
N=	511,216	516,329	511,216	516,329	511,216	516,329

Notes: This table reports 2SLS estimates of the effect of disability compensation on healthcare utilization (inverse hyperbolic sine transformed) for veterans whom examiner tendency should only impact disability income and not VHA medical copayments. Veterans with a combined disability rating of at least 10% have no copayments for medical care and thus the instrument does not affect the cost of healthcare. The 2SLS regressions are estimated on the sample with realized disability ratings of at least 10% and sample with predicted disability rating of at least 10% using veteran observables (demographics, income, period of service, prior medical comorbidities; see Figure 3a) in the odd and even columns, respectively. Predicted disability rating is estimated via a logistic regression and the response threshold value is selected to match the number of veterans who actually receive at least 10% disability. The coefficients are scaled by 100 for interpretability and readability. All regressions are estimated on samples of veterans that are alive for the entire outcome period. All regressions include facility-by-year fixed effects and five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period; robust standard errors are clustered at the facility-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.13: Healthcare Utilization and Distance to Nearest VA Primary Care Facility

	<i>Dependent variable: IHS Utilization ($\times 100$)</i>	
	1-Year (1)	5-Year (2)
Distance to VA: [5,10) mi	-9.50*** (1.38)	-7.97*** (1.18)
Distance to VA: [10,25) mi	-20.35*** (1.57)	-15.65*** (1.47)
Distance to VA: 25+ mi	-23.53*** (1.99)	-17.38*** (1.56)
\$1,000 per year	1.76*** (0.61)	1.78** (0.74)
\$1,000 per year \times Distance to VA: [5,10) mi	0.20 (0.66)	0.35 (0.76)
\$1,000 per year \times Distance to VA: [10,25) mi	1.27** 0(0.64)	1.57** (0.76)
\$1,000 per year \times Distance to VA: 25+ mi	1.51* (0.88)	0.88 (0.90)
Mean Dep Var ($\times 100$)	780.16	1021.47
N=	663,133	401,753

Notes: This table reports 2SLS estimates of the effect of disability compensation benefits on healthcare utilization (measured in inverse hyperbolic sine of total average cost) by driving distance to the nearest VA primary care facility. Distance to the nearest VA primary care facility (in miles) is calculated by the VA Planning Systems Support Group (PSSG) which maintains location files for veterans enrolled in VHA care using information from the US Postal Service National Change of Address File; this data is available starting in 2009. We use the distance observed in the year *prior* to the veteran's disability claim in the interaction to avoid endogenous moves driven by benefit compensation. All regressions are estimated on samples of veterans that are alive for the entire outcome period. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veterans Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. *p<0.1; **p<0.05; ***p<0.01.

Table C.14: Utilization Among Medicare and VA Dual-Eligible Population

Panel A. 1-Year Outcomes

	<i>Dependent variable: Encounters ($\times 100$)</i>	
	VA (1)	Medicare (2)
\$1,000 per year	7.69*** (2.59)	0.97 (0.84)
Mean Dep Var ($\times 100$)	1,569.00	145.23
N=	157,648	157,648

Panel B. 5-Year Outcomes

	<i>Dependent variable: Encounters ($\times 100$)</i>	
	VA (1)	Medicare (2)
\$1,000 per year	60.18*** (18.42)	-2.27 (3.83)
Mean Dep Var ($\times 100$)	7,925.41	621.43
N=	76,752	76,752

Notes: This table reports estimated 2SLS coefficients from [Equation 1](#) for number of VHA (column 1) and Medicare (column 2) outpatient encounter days for veterans over the age of 65. Medicare claims data is available between 2011-2019. All regressions are estimated on samples of veterans that are alive for the entire outcome period. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.15: Starting and Completing Prolonged Exposure (PE) Therapy

Panel A. 1-Year Outcomes

	<i>Dependent variable: Encounters ($\times 100$)</i>			
	1-Year		5-Year	
	Start PE	Complete PE Start	Start PE	Complete PE Start
	(1)	(2)	(3)	(4)
\$1,000 per year	-0.003 (0.01)	3.31* (1.96)	-0.01 (0.01)	0.98 (0.68)
Mean Dep Var ($\times 100$)	0.52	83.77	0.79	86.55
N=	207,077	1,374	193,657	2,037

Notes: This table reports estimated 2SLS coefficients from [Equation 1](#) for starting and completing prolonged exposure therapy for PTSD. One-year and five-year outcomes are displayed. Benefit compensation amounts are scaled to units of an additional \$1,000 per year and the coefficients are scaled by 100 for interpretability and readability. Prolonged exposure therapy is a form of behavioral psychotherapy for PTSD strongly encouraged by the VHA in recent years. It includes repeated retelling of the underlying trauma and gradual exposure to objects and situations that remind the patient of the trauma or feel dangerous. All regressions are estimated on samples of veterans that are alive for the entire outcome period. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table C.16: Mortality and Cause of Death

Panel A. 1-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	All-Cause	Cancer	Heart Disease	Chronic Low. Respiratory	External Causes	Suicide	Overdose
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
\$1,000 per year	0.0022 (0.0091)	-0.0096** (0.0043)	0.0091* (0.0053)	-0.0030 (0.0020)	-0.0066** (0.0033)	-0.0034* (0.0018)	-0.0017 (0.0023)
Mean Dep Var ($\times 100$)	1.421	0.367	0.314	0.072	0.164	0.048	0.054
N=	867,416	767,658	767,658	767,658	767,658	767,658	767,658

Panel B. 5-Year Outcomes

	<i>Dependent variable: ($\times 100$)</i>						
	All-Cause	Cancer	Heart Disease	Chronic Low. Respiratory	External Causes	Suicide	Overdose
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
\$1,000 per year	0.0445 (0.0284)	0.0065 (0.0190)	0.0495** (0.0193)	0.0078 (0.0125)	0.0126 (0.0104)	-0.0007 (0.0062)	-0.0018 (0.0066)
Mean Dep Var ($\times 100$)	8.070	2.106	1.939	0.502	0.807	0.219	0.268
N=	626,523	463,910	463,910	463,910	463,910	463,910	463,910

Notes: This table reports estimated 2SLS coefficients from [Equation 1](#) for mortality outcomes. One-year and five-year outcomes are displayed in panels A and B, respectively. Benefit compensation amounts are scaled to units of an additional \$1,000 per year and the coefficients are scaled by 100 for interpretability and readability. Cause of death is constructed from CDC's National Death Index Plus data until the end of 2018. Cancer, heart disease, external causes, and chronic lower respiratory disease are the four leading causes of death in the United States. Suicide and overdoses deaths are a (non-exhaustive) subset of external causes of death. The All regressions include station-by-year fixed effects and baseline controls in the text; standard errors are clustered at the station-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table C.17: Heterogeneity of 5-Year Main Outcomes

	<i>Dependent variable: ($\times 100$)</i>											
	Util	Flu	HCV	MPR	Food	Homeless	Debt	Suicide	Pain	SBP	DBP	Mortality
\$1,000 per year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Male	2.58*** (0.45)	0.14*** (0.05)	0.30*** (0.07)	0.05** (0.02)	-0.09*** (0.03)	-0.20*** (0.03)	-0.10*** (0.02)	-0.02 (0.02)	-1.61*** (0.41)	1.16 (2.17)	-2.15 (2.30)	0.04 (0.03)
Female	2.52*** (0.85)	0.19 (0.12)	0.42** (0.20)	-0.03 (0.07)	-0.19 (0.12)	-0.09 (0.14)	-0.20** (0.09)	0.12* (0.07)	-0.07 (0.96)	-3.09 (3.94)	-6.30* (3.52)	0.07 (0.05)
White (Non-Hispanic)	2.42*** (0.58)	0.13* (0.07)	0.24*** (0.07)	0.03 (0.02)	-0.09*** (0.03)	-0.20*** (0.04)	-0.08*** (0.02)	0.02 (0.02)	-1.45*** (0.41)	0.78 (2.58)	-2.93 (3.06)	0.04 (0.04)
Black	2.79*** (0.51)	0.25*** (0.09)	0.37*** (0.11)	0.01 (0.04)	-0.16* (0.09)	-0.26*** (0.10)	-0.21*** (0.05)	-0.02 (0.04)	-1.66* (0.90)	1.40 (3.39)	-2.76 (1.86)	0.06 (0.05)
Other Race	2.81*** (0.46)	0.18*** (0.06)	0.42*** (0.11)	0.06* (0.04)	-0.11* (0.06)	-0.16*** (0.06)	-0.15*** (0.04)	-0.02 (0.03)	-1.29* (0.67)	0.76 (2.65)	-1.70 (1.62)	0.06 (0.04)
Age < 45	3.13*** (0.62)	0.17*** (0.05)	0.45*** (0.12)	0.06 (0.05)	-0.14*** (0.05)	-0.28*** (0.07)	-0.23*** (0.05)	0.01 (0.04)	-1.41** (0.59)	0.76 (2.65)	-4.71* (2.71)	0.01 (0.02)
Age \geq 45	2.18*** (0.44)	0.15** (0.06)	0.25** (0.10)	0.04* (0.02)	-0.08** (0.04)	-0.12*** (0.04)	-0.02** (0.01)	-0.01 (0.02)	-1.51*** (0.45)	0.73 (2.48)	-1.54 (2.23)	0.06 (0.04)
Income < \$30,000	2.28*** (0.43)	0.14*** (0.05)	0.26*** (0.08)	0.05** (0.02)	-0.12*** (0.04)	-0.21*** (0.04)	-0.13*** (0.02)	-0.01 (0.02)	-1.48*** (0.46)	0.29 (2.31)	-2.90 (2.17)	0.07** (0.03)
Income \geq \$30,000	3.47*** (0.69)	0.19** (0.09)	0.44*** (0.10)	0.03 (0.05)	0.01 (0.03)	-0.12* (0.07)	-0.05 (0.04)	-0.005 (0.03)	-1.61*** (0.55)	0.64 (3.34)	-1.82 (3.40)	-0.02 (0.05)
PTSD Claims	2.36*** (0.43)	0.19*** (0.05)	0.28*** (0.08)	0.05** (0.02)	-0.07** (0.03)	-0.20*** (0.04)	-0.09*** (0.02)	-0.02 (0.02)	-1.68*** (0.38)	-0.48 (2.43)	-1.87 (2.26)	0.02 (0.03)
Non-PTSD Claims	2.78*** (0.74)	0.08 (0.08)	0.40*** (0.10)	0.08** (0.04)	-0.16*** (0.06)	-0.12 (0.08)	-0.15*** (0.04)	0.04 (0.04)	-1.21* (0.67)	2.19 (3.31)	-4.15 (2.96)	0.13** (0.06)

Notes: This table reports estimated 2SLS coefficients from Equation 1 for our main 5-year outcomes (columns) for separate subsamples (rows). Moving from left (column 1) to right (column 12) the outcomes are: log of 1+ total utilization, annual flu vaccinations, any hepatitis C screen, average medication possession ratio, homelessness, number of VA Debt collections (referrals to Treasury), suicide, self-reported pain score, systolic blood pressure, diastolic blood pressure, and all-cause mortality. All regressions are estimated on samples of veterans that are alive for the entire outcome period. In addition to facility-by-year fixed effects, all regressions include controls for five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period. Robust standard errors are clustered at the station-level. *p<0.1; **p<0.05; ***p<0.01.

Table C.18: Outcomes by Mental Health Combined Disability Rating and Residualized Benefits

<i>5-Year Outcomes:</i>							
	Food (1)	Homeless (2)	Spending (3)	Flu (4)	Overdose (5)	Suicide (6)	Mortality (7)
Mental Health Combined Disability Rating:							
0	0.033	0.167	47,722	0.362	0.013	0.026	0.099
10	0.012	0.079	33,734	0.332	0.006	0.014	0.065
30	0.016	0.093	38,859	0.359	0.008	0.020	0.065
50	0.021	0.130	46,409	0.376	0.011	0.028	0.068
70	0.025	0.175	54,742	0.375	0.016	0.043	0.068
100	0.030	0.280	87,798	0.398	0.033	0.077	0.128
Residualized Benefits Quintile:							
1	0.039	0.218	53,374	0.362	0.016	0.032	0.089
2	0.021	0.115	40,576	0.354	0.009	0.020	0.082
3	0.018	0.100	39,351	0.360	0.008	0.020	0.075
4	0.020	0.114	43,712	0.371	0.010	0.026	0.068
5	0.024	0.172	59,795	0.380	0.018	0.047	0.089

Notes: This table reports sample means for main 5-year outcomes by mental health combined disability rating (CDR) and residualized benefits quintile from the first stage of the control function approach (i.e., quintile bins from [Figure 5](#)).

D. Disability Benefit Questionnaires

In this appendix we present details of the mental health disability benefit questionnaire (DBQ), explore the underlying source of examiner variation (e.g., what drives differences in our tendency IV?), and probe exclusion restriction concerns. The DBQ is a form which closely mimics the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) and is used by the examiner to perform the examination starting in 2010. The form includes guidance for the examination along with spaces for structured and free-text responses. The completed form is then passed on to an administrative rater who assigns a final rating based on a rubric mandated by the Code of Federal Regulations. The first page of a mental health DBQ can be found in [Figure D.1](#). We observe 384,965 (44.4% of our baseline sample) completed and digitized DBQs.

D.1 Occupational and Social Impairment

A particularly salient section of the DBQ appears near the end: Occupational and Social Impairment (OSI; see [Figure D.2a](#)). This section asks the examiner to “best summarize the veteran’s level of occupational and social impairment with regards to all mental diagnoses” on a seven-item scale. One can see how clinical judgment and interpretation along these blurred lines may lead to certain examiners making different choices when faced with similarly “occupationally and socially impaired” veterans. We return to this point later.

In addition to serving as a succinct summary, the individual response options (i.e., boxes) almost maps verbatim to the rater rubric in [Figure D.2b](#). For example, the third box of the OSI reads “occupational and social impairment due to mild or transient symptoms which decrease work efficiency and ability to perform occupational tasks only during periods of significant stress, or symptoms controlled by medication” which is exactly the rating description for a 10% disability rating in the rater rubric. Therefore, we should expect the OSI response to have predictive power in the veteran’s disability rating and their realized benefit compensation amount.

D.2 Free-Text Response

In addition to structured responses like the OSI, there is a final free-text “Remarks, if any” section where the examiner can leave residual comments that do not fit into the structured sections, similar to a clinical note. We extract the text from this section from all 384,965 DBQs.

D.3 OSI Has Predictive Power

We empirically check that the OSI responses have predictive power in the veteran’s realized benefit compensation amount. [Table D.2](#) display the output of a regression of realized benefit amount on veteran characteristics (column 1) and veteran characteristics with OSI responses (column 2). We see that the R-squared jumps from 0.107 to 0.193 just by including the OSI responses. This implies that much of the variation in examiner tendency measured by realized disability compensation benefits (our instrumental variable) is driven by underlying differences in how examiners’ OSI responses.

D.4 Testing Exclusion Restriction Using Free-Text

As mentioned in the main text, one way to probe the exclusion restriction is to make use of the examiners’ free-text remarks. For example, more careful examiners may leave longer text responses or examiners with inappropriate behavior (e.g., not believing the veteran’s experiences, stigmatizing their disability, etc.) may leave more negative sentiment. We measure the sentiment and word count of the “remarks” section response. We use a lexicon-based sentiment analysis to obtain (positive/negative) polarity.⁹ A histogram of the word count and sentiment polarity can be found in [Figure D.3](#).

Columns 3 and 4 of [Table D.2](#) show that the two dimensions of the free-text have very little predictive power beyond veteran characteristics and beyond veteran characteristics and OSI response (the R-squared do not change). We conclude from this exercise that


⁹Specifically, we use the Syuzhet lexicon: <https://cran.r-project.org/web/packages/syuzhet/index.html>.

examiner behavior and actions during the examination—to the extent they are captured by the free-text sentiment and word count—are unlikely to have any meaningful influence on veteran outcomes.

D.5 Testing Monotonicity Assumption Using OSI Thresholds

The multi-valued responses of the OSI section prescribe a simple monotonicity test. Examiners who we measure as having greater tendency (via veterans realized disability benefit compensation) should also have higher tendencies along the entire OSI spectrum. In other words, examiners who are more likely to check off boxes 4 or above, should also be more likely to check off boxes 1 or above. We build six OSI threshold instrumental variables using replacing $Benefits_i$ in [Equation 2](#) with indicator variables for checking off at least a certain box, and correlate it with our baseline (continuous) instrument. The result of this exercise can be found in [Figure D.4](#); each of the six OSI threshold instruments are strongly correlated with our baseline measure of examiner tendency.

Figure D.1: First Page of a Mental Health Disability Benefit Questionnaire (DBQ) Form

 Department of Veterans Affairs	INTERNAL VETERANS AFFAIRS USE MENTAL DISORDERS (OTHER THAN PTSD AND EATING DISORDERS) DISABILITY BENEFITS QUESTIONNAIRE
IMPORTANT - THE DEPARTMENT OF VETERANS AFFAIRS (VA) WILL NOT PAY OR REIMBURSE ANY EXPENSES OR COST INCURRED IN THE PROCESS OF COMPLETING AND/OR SUBMITTING THIS FORM. PLEASE READ THE PRIVACY ACT AND RESPONDENT BURDEN INFORMATION BEFORE COMPLETING FORM.	
NAME OF PATIENT/VETERAN	PATIENT/VETERAN'S SOCIAL SECURITY NUMBER
Your patient is applying to the U. S. Department of Veterans Affairs (VA) for disability benefits. VA will consider the information you provide on this questionnaire as part of their evaluation in processing the Veteran's claim. Please note that this questionnaire is for disability evaluation, not for treatment purposes. <u>This evaluation should be based on DSM-5 diagnostic criteria.</u>	
NOTE: If the Veteran experiences a mental health emergency during the interview, please terminate the interview and obtain help, using local resources as appropriate. You may also contact the Veterans Crisis Line at 1-800-273-TALK (8255). Stay on the Crisis Line until help can link the Veteran to emergency care.	
NOTE: In order to conduct an initial examination for mental disorders, the examiner must meet one of the following criteria: a board-certified or board-eligible psychiatrist; a licensed doctorate-level psychologist; a doctorate-level mental health provider under the close supervision of a board-certified or board-eligible psychiatrist or licensed doctorate-level psychologist; a psychiatry resident under close supervision of a board-certified or board-eligible psychiatrist or licensed doctorate-level psychologist; or a clinical or counseling psychologist completing a one-year internship or residency (for purposes of a doctorate-level degree) under close supervision of a board-certified or board-eligible psychiatrist or licensed doctorate-level psychologist.	
In order to conduct a review examination for mental disorders, the examiner must meet one of the criteria from above, OR be a licensed clinical social worker (LCSW), a nurse practitioner, a clinical nurse specialist, or a physician assistant, under close supervision of a board-certified or board-eligible psychiatrist or licensed doctorate-level psychologist.	
This Questionnaire is to be completed for both initial and review mental disorder(s) claims.	
IS THIS DBQ BEING COMPLETED IN CONJUNCTION WITH A VA21-2507, C&P EXAMINATION REQUEST?	
<input type="checkbox"/> YES <input type="checkbox"/> NO	
If no, how was the examination completed (check all that apply)?	
<input type="checkbox"/> In-person examination	
<input type="checkbox"/> Records reviewed	
<input type="checkbox"/> Other, please specify:	
Comments:	
SECTION I: DIAGNOSIS	
1. DIAGNOSIS	
1A. DOES THE VETERAN NOW HAVE OR HAS HE OR SHE EVER BEEN DIAGNOSED WITH A MENTAL DISORDER(S)?	
<input type="checkbox"/> YES <input type="checkbox"/> NO	
ICD CODE:	
NOTE: If the Veteran has a diagnosis of an eating disorder, complete the Eating Disorders Questionnaire, in lieu of this questionnaire. NOTE: If the Veteran has a diagnosis of PTSD, the Initial PTSD Questionnaire must be completed by a VHA staff or contract examiner in lieu of this questionnaire.	
If the Veteran currently has one or more mental disorders that conform to DSM-5 criteria, provide all diagnoses:	
MENTAL DISORDER DIAGNOSIS #1	ICD CODE:
COMMENTS, IF ANY:	
MENTAL DISORDER DIAGNOSIS #2	ICD CODE:
COMMENTS, IF ANY:	
MENTAL DISORDER DIAGNOSIS #3	ICD CODE:
COMMENTS, IF ANY:	
IF ADDITIONAL DIAGNOSES, LIST USING ABOVE FORMAT:	
1B. MEDICAL DIAGNOSES RELEVANT TO THE UNDERSTANDING OR MANAGEMENT OF THE MENTAL HEALTH DISORDER (to include TBI):	
ICD CODE:	
COMMENTS, IF ANY:	

Notes: The first page of a sample mental health disability benefit questionnaire (DBQ) form. Note that the instructions of the form explicitly clarify that the form is for evaluation purposes only and not for treatment purposes. It also states that the evaluation should be based on DSM-5 diagnostic criteria and must be performed by a board-certified psychiatrist, licensed doctorate-level psychologist, or a trainee that is closely supervised by a board-certified psychiatrist/licensed doctorate-level psychologist.

Figure D.2: Mental Health Disabilities: DBQ scale and rater rubric

(a) DBQ OSI scale

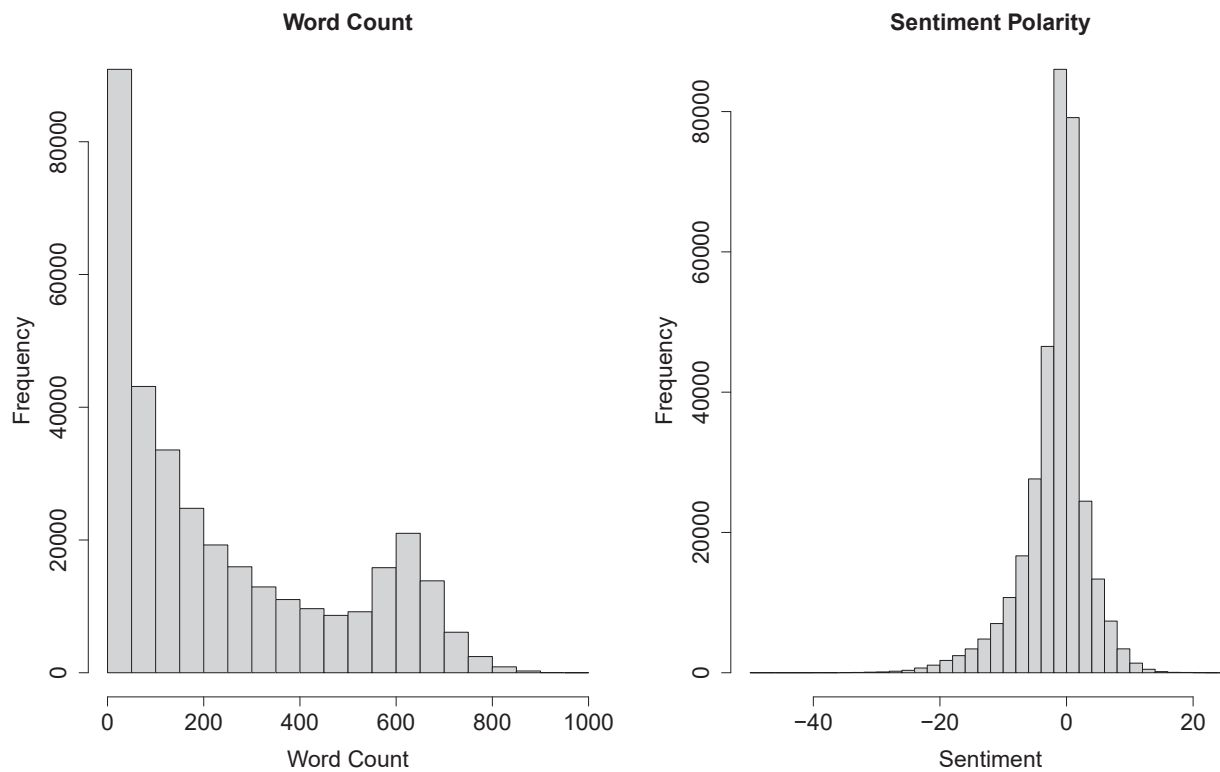
SECTION IV - OCCUPATIONAL AND SOCIAL IMPAIRMENT	
4A. WHICH OF THE FOLLOWING BEST SUMMARIZES THE VETERAN'S LEVEL OF OCCUPATIONAL AND SOCIAL IMPAIRMENT WITH REGARDS TO ALL MENTAL DIAGNOSES? (Check only one)	
<input type="checkbox"/>	NO MENTAL DISORDER DIAGNOSIS
<input type="checkbox"/>	A MENTAL CONDITION HAS BEEN FORMALLY DIAGNOSED, BUT SYMPTOMS ARE NOT SEVERE ENOUGH EITHER TO INTERFERE WITH OCCUPATIONAL AND SOCIAL FUNCTIONING OR TO REQUIRE CONTINUOUS MEDICATION
<input type="checkbox"/>	OCCUPATIONAL AND SOCIAL IMPAIRMENT DUE TO MILD OR TRANSIENT SYMPTOMS WHICH DECREASE WORK EFFICIENCY AND ABILITY TO PERFORM OCCUPATIONAL TASKS ONLY DURING PERIODS OF SIGNIFICANT STRESS, OR SYMPTOMS CONTROLLED BY MEDICATION
<input type="checkbox"/>	OCCUPATIONAL AND SOCIAL IMPAIRMENT WITH OCCASIONAL DECREASE IN WORK EFFICIENCY AND INTERMITTENT PERIODS OF INABILITY TO PERFORM OCCUPATIONAL TASKS, ALTHOUGH GENERALLY FUNCTIONING SATISFACTORILY, WITH NORMAL ROUTINE BEHAVIOR, SELF-CARE AND CONVERSATION
<input type="checkbox"/>	OCCUPATIONAL AND SOCIAL IMPAIRMENT WITH REDUCED RELIABILITY AND PRODUCTIVITY
<input type="checkbox"/>	OCCUPATIONAL AND SOCIAL IMPAIRMENT WITH DEFICIENCIES IN MOST AREAS, SUCH AS WORK, SCHOOL, FAMILY RELATIONS, JUDGMENT, THINKING AND/OR MOOD
<input type="checkbox"/>	TOTAL OCCUPATIONAL AND SOCIAL IMPAIRMENT

(b) Rater rubric

	Rating
Total occupational and social impairment, due to such symptoms as: gross impairment in thought processes or communication; persistent delusions or hallucinations; grossly inappropriate behavior; persistent danger of hurting self or others; intermittent inability to perform activities of daily living (including maintenance of minimal personal hygiene); disorientation to time or place; memory loss for names of close relatives, own occupation, or own name.	100
Occupational and social impairment, with deficiencies in most areas, such as work, school, family relations, judgment, thinking, or mood, due to such symptoms as: suicidal ideation; obsessional rituals which interfere with routine activities; speech intermittently illogical, obscure, or irrelevant; near-continuous panic or depression affecting the ability to function independently, appropriately and effectively; impaired impulse control (such as unprovoked irritability with periods of violence); spatial disorientation; neglect of personal appearance and hygiene; difficulty in adapting to stressful circumstances (including work or a worklike setting); inability to establish and maintain effective relationships.	70
Occupational and social impairment with reduced reliability and productivity due to such symptoms as: flattened affect; circumstantial, circumlocutory, or stereotyped speech; panic attacks more than once a week; difficulty in understanding complex commands; impairment of short- and long-term memory (e.g., retention of only highly learned material, forgetting to complete tasks); impaired judgment; impaired abstract thinking; disturbances of motivation and mood; difficulty in establishing and maintaining effective work and social relationships.	50
Occupational and social impairment with occasional decrease in work efficiency and intermittent periods of inability to perform occupational tasks (although generally functioning satisfactorily, with routine behavior, self-care, and conversation normal), due to such symptoms as: depressed mood, anxiety, suspiciousness, panic attacks (weekly or less often), chronic sleep impairment, mild memory loss (such as forgetting names, directions, recent events).	30
Occupational and social impairment due to mild or transient symptoms which decrease work efficiency and ability to perform occupational tasks only during periods of significant stress, or symptoms controlled by continuous medication.	10
A mental condition has been formally diagnosed, but symptoms are not severe enough either to interfere with occupational and social functioning or to require continuous medication.	0

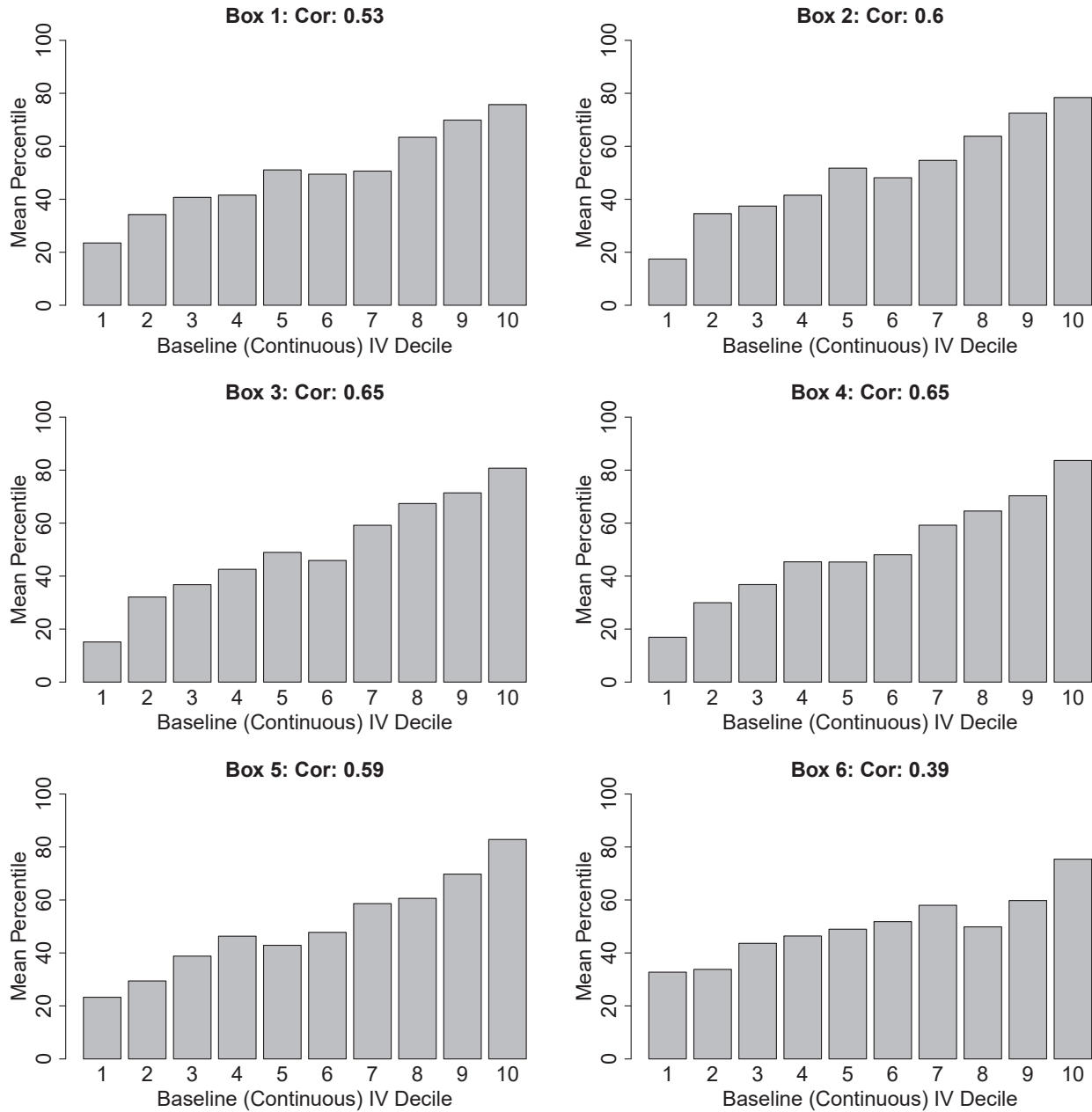
Notes: Figure (a) displays the Section IV–Occupational and Social Impairment Section of the Disability Benefit Questionnaire. Figure (b) displays the administrative rater’s rubric for mental health claims from Code of Federal Regulations §4.130: Scheduling of ratings-mental disorders (<https://ecfr.io/Title-38/Section-4.130>). The OSI section and the rater rubric map very closely.

Figure D.3: Histogram of Sentiment and Word Count of Free-Text Remarks DBQ Section



Notes: This figure plots the histogram of word count (left panel) and sentiment (right panel) of the final free-text “Remarks, if any” section of the DBQs. The Syuzhet lexicon is used.

Figure D.4: Binary Threshold IV Measures versus Baseline IV



Notes: This figure probes the monotonicity assumption by reducing the examiner’s decision to their occupational and social impairment (OSI) response—we demonstrate OSI response has strong predictive power in explaining realized compensation benefits in [Table D.2](#)—and testing whether more higher tendency examiners have higher tendency across the entire OSI range. We examine the correlation between examiner threshold-tendencies constructed using different binary response dependent variables versus our baseline (continuous) tendency measure for each examiner. Six examiner IVs are constructed as in [Equation 2](#) and [Equation 3](#) without the leave-out using an indicator corresponding to ticking strictly above each box (e.g., an indicator variable for coding strictly above box 1 in the DBQ would correspond to the first figure). Examiner tendency deciles are calculated for each of the six threshold instruments and the baseline instrument and correlations are displayed.

Table D.1: Combined Disability Rating Schedule: Monthly VA DC Payments

CDR	Monthly Payments
10%	142.29
20%	281.27
30%	435.69
40%	627.61
50%	893.43
60%	1,131.68
70%	1,426.17
80%	1,657.80
90%	1,862.96
100%	3,106.04

Notes: This table displays the tax-free monthly VA DC payments for each combined disability rating for a single veteran with no dependents in 2020. See <https://www.va.gov/disability/compensation-rates/veteran-rates/past-rates-2020/> for more details.

Table D.2: Disability Benefit Compensation Amount and Information in DBQs

	<i>Dependent variable: Benefit Amount</i>			
	Veteran Characteristics (1)	+ OSI Boxes (2)	+ Free-Text (3)	+ OSI Boxes + Free-Text (4)
OSI Box: 2		1,394.32*** (158.71)		1,396.61*** (158.45)
OSI Box: 3		3,421.50*** (168.11)		3,420.75*** (166.52)
OSI Box: 4		5,904.04*** (192.98)		5,898.72*** (190.79)
OSI Box: 5		8,596.90*** (198.44)		8,592.40*** (195.28)
OSI Box: 6		12,035.13*** (247.53)		12,032.46*** (243.19)
OSI Box: 7		16,924.42*** (596.36)		16,929.85*** (591.53)
Sentiment			-268.84*** (71.05)	-38.04 (44.71)
Word Count			-196.74** (100.05)	-190.71*** (60.58)
Baseline controls and FEs	Yes	Yes	Yes	Yes
R-squared	0.107	0.193	0.108	0.193
N=	331,248	331,248	331,248	331,248

Notes: This table reports the estimated coefficients of first-year benefit compensation amount (in 2020 dollars) on information scraped from examination Disability Benefit Questionnaires (DBQ). Column 1 corresponds to a regression of benefit amount on facility-by-year fixed effects and baseline controls (five-year age bins, gender, race, marital status, period of service, theater of combat operations, Agent orange and radiation exposure indicators, year of military discharge, indicators of prior-year depression, suicide, substance use disorder, and homelessness, and the veteran's Elixhauser comorbidity score based on a one-year look-back period). Column 2 adds the occupational and social impairment (OSI) response to the set of fixed effects and baseline controls. Column 3 adds the standardized sentiment and standardized word count from the free-text section to the set of fixed effects and baseline controls. Column 4 includes all covariates. Robust standard errors are clustered at the facility-level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.