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DOING MORE WITH LESS:
PREDICTING PRIMARY CARE PROVIDER EFFECTIVENESS

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ABSTRACT

This paper uses data from 802,777 veterans assigned to 7,548 primary care providers (PCPs) within the Veterans Health Administration (VHA) to examine variations in the efficacy of primary care providers (PCPs), their consequences for health outcomes, and their determinants. Leveraging quasi-random assignment of veterans to PCPs, we measure PCP effectiveness along three dimensions: the probability their patients have subsequent hospitalizations or emergency department (ED) visits for mental health conditions, circulatory conditions, or a hospitalization for ambulatory care sensitive conditions (ACSC). We find a significant range in these effectiveness measures across PCPs. For example, a one standard deviation improvement in our measure of mental health effectiveness predicts a 0.21 percentage point (3.8%) lower risk of patient death over the next three years and 4.4% lower total costs. We also find moderate correlations between the three metrics, indicating that doctors who are effective at treating one type of condition also tend to be more effective in treating others. Our strongest conclusion is that more effective PCPs do more with less: Their patients have fewer primary care visits, referrals to specialists, lab panels or imaging tests. Effective PCPs are slightly more likely to comply with guidelines for mental health screenings, and slightly less likely to comply with guidelines for physical health screenings, but these differences in screening propensities are negligible in magnitude.

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Critics of the U.S. health care system argue that the system provides too much high cost-low value care, and not enough low cost-high value care, especially of the type that is often offered in primary care settings (Chandra and Skinner, 2012). It has been suggested that providers should be compensated on the basis of the value, rather than the quantity, of care they provide, where high-value care is care that yields better health outcomes on average (Cutler, 2014; Lopez et al. 2020). These arguments beg several questions: Are some providers more effective than others in promoting patient health and how can we measure that? Is provider effectiveness correlated across different aspects of patient health or are some providers much better at some types of care than others? And if some providers are generally more effective than others, what characteristics of providers predict effectiveness?

This paper investigates these questions using the unique setting of primary care providers (PCPs) in the Veterans Health Administration (VHA). The most important aspect of this setting is that veterans who enter the system seeking primary care are assigned to PCPs in a quasi-random, first-come, first-served basis which depends only on the patient's desired appointment time and the PCP's availability. A second advantage is that the VHA was a pioneer in the use of electronic medical records, so that we have detailed records of inpatient, outpatient, and pharmaceutical claims including rich information about referrals, screenings, tests and labs which will allow us to investigate possible reasons for variations in provider effectiveness. A third advantage is that providers in the VHA system are salaried, so they have no financial incentive to provide low-value care, such as excessive screening.

Using data from 802,777 veterans assigned to 7,548 PCPs at 725 clinics we first ask whether PCP assignment is predictive of future patient health outcomes including hospitalizations and emergency department (ED) visits for mental health and circulatory problems, two of the most common types of health problems in the VHA. We also look at hospitalizations for ambulatory care sensitive conditions (ACSC), which are tracked by the VHA itself.

Past research provides considerable evidence of variations in provider effectiveness, beginning with the literature on geographical variations in care (e.g. Cutler et al., 2019; Finkelstein, Gentzkow, and Williams, 2016; Fisher et al. 2003a,b); continuing with studies of quasi-random assignment in ambulance referrals and emergency departments (e.g. Doyle et al, 2011, 2015, forthcoming; Gowrisankaran, Joiner, and Leger, 2017; Van Parys, 2016); and including attempts to quantify physician practice style and link it with patient outcomes (e.g. Abaluck et al., 2020; Currie and MacLeod 2016, 2020; Currie, MacLeod, and Van Parys, 2016; Epstein and Nicholson, 2009; Fadlon and Van Parys, 2020; Fletcher, Horwitz, and Bradley, 2014; Grytten and Sorensen, 2003, Simeonova, Skipper, and Thingholm 2021).

Consistent with these studies we find a significant range in our effectiveness measures across PCPs, and we find that patient outcomes differ significantly depending on the physician they are assigned to. For example, a one standard deviation improvement in our measure of mental health effectiveness predicts a 0.21 percentage point (3.8%) lower risk of patient death over the next three years and 4.4% lower costs.

Turning to the two more novel questions that we ask, we find that the three different metrics we examine are strongly, though not perfectly, positively correlated with each other. Correlations between any two of these measures vary from 0.35 to 0.40. Moreover, doctors who are effective at preventing hospitalizations due to ambulatory care sensitive conditions are also effective in preventing deaths from cancer, heart conditions, and possible suicides (external causes of death measured by suicides plus overdoses, poisonings, and accidents). The one exception to this generalization is that only mental health effectiveness predicts fewer patient visits for mental health. These results suggest that it is unnecessary to measure effectiveness in every possible dimension.

Our strongest and most novel conclusion is that the most effective PCPs do more with less: Their patients have fewer primary care visits, referrals to specialists, lab panels or imaging tests. Effective PCPs are slightly more likely to comply with guidelines for mental health screenings, and slightly less likely to comply with guidelines for physical health screenings, but these differences in screening propensities are negligible in magnitude.

We also find that older PCPs, those who see more patients per day, those who see more new patients over the period we observe them, and especially those who take advantage of options to coordinate care with mental health professionals tend to be more effective. Regarding care coordination, PCPs in some facilities at the VHA have the option to call in mental health professionals for immediate same-day patient consultations joint with the PCP rather than referring them for later appointments. Conditional on these measures, part-time physicians also tend to be more effective, which leads us to interpret part-time status as a marker for physicians who devote some of their time to research. We also find some evidence that nurse practitioners/physician assistants are more effective primary care providers than physicians in the VHA.

A few previous studies have shown results with a similar flavor: Currie and MacLeod (2016) find that obstetricians with better diagnostic skills perform fewer C-sections on low-risk women and have better patient outcomes and Chan, Gentzkow, and Yu (2019) find that radiologists who are less skilled at diagnosing pneumonia compensate by treating marginal patients more aggressively. In contrast to these two studies focusing on specialist's use of particular procedures for specific conditions, we construct broader measures of effectiveness and consider a wide range of health inputs and outputs.

Our work may be more similar to Doyle, Ewer, and Wagner (2010) who compare physicians from two different medical schools who were employed at the same Veterans Affairs hospital. They find that physicians from the lower ranked school achieved similar patient outcomes but at a higher cost because they ordered more tests and took longer to perform each test. In contrast to their work, we do not use an external proxy for effectiveness (e.g., medical school ranking) but propose ways to construct and validate effectiveness measures from within the data.

The rest of this paper proceeds as follows. Section 2 provides an overview of the VHA setting and the data. Section 3 discusses our empirical strategy. Results appear in Section 4 and conclusions are in Section 5.

2. Setting, Data, and Sample

2.1 Assignment of Veterans to PCPs

Veterans entering primary care in the VHA system are assigned to patient aligned care teams[1] that coordinate care. Teams are led by a PCP, who can be a physician, nurse practitioner, or physician's assistant (all of whom have full diagnosing and prescribing authority in the VHA). The PCPs are supported by an advanced nurse (e.g. a registered nurse care manager), a clinical associate (e.g. a licensed practical nurse, licensed vocational nurse, or certified nursing assistant, medical assistant, or health technician), and an administrative associate. Because the PCP is responsible for the most advanced tasks such as diagnosing and prescribing, we use the term

[1] Referred to internally as PACT teams.

"PCP" to refer to the primary care team; however, it is important to note that these teams may be differentially resourced and organized even within a given facility. We investigate team resource and mental health embeddedness in section 4.3.

Assignment to a PCP is based on geographic location, scheduling availability, and team capacity.[2] Generally, the assignment is done after a veteran completes Form 1010-EZ to enroll in VHA health benefits. See the appendix for the most recent Form 1010-EZ. The veteran lists basic demographic information, military history, their preferred outpatient clinic, and whether they would like to be contacted by the VA to set up their first appointment. If this last box is checked—as it is on roughly three quarters of all 1010-EZ forms, then a scheduling administrator contacts the veteran. At this point, the veteran explains the reason for their request and gives a desired appointment date[3] and the administrator schedules an appointment. The scheduling typically occurs within seven days after a request is made. Primary care appointments for new patients are made based on which PCP is available on the desired date or on the earliest available date thereafter. When the initial primary care visit takes place, the PCP is assigned to the veteran and the relationship is entered into the system.[4] Veterans can choose to switch PCPs, but this is not actively encouraged in the VHA and empirically we do not observe many switches in our sample. Hence, we focus on the first PCP assigned in an "intent-to-treat" framework though we also look at the length of a patient's relationship with the initial PCP as an outcome. In sum,

[2] Per an email exchange with the National VA Office of Primary Care: "New enrollee appointment requests are reviewed for preferred clinic, panel capacity, and [scheduling] availability. If there is capacity and appointment availability at the patient's preferred clinic, an appointment is scheduled and [the patient is assigned to a primary care] team."

[3] The General Accountability Office (GAO) mandates that the VHA collects desired time to monitor wait times.

[4] Veterans who do not request an appointment on Form 1010-EZ when enrolling for health benefits get assigned to a PCP at a later point in time, whenever they request their first primary care appointment. We exclude these veterans from our analysis because we do not observe the appointment process where a patient gives their desired date.

new benefit enrollees seeking primary care services are quasi-randomly assigned to PCPs, conditional on clinic and year by month.

2.2 Description of Data Sources

We analyze electronic health records data from the Veterans Health Administration's Corporate Data Warehouse (CDW) between 2004 and the end of February 2020. The standard outpatient, inpatient, and pharmacy data include fields such as hospital, patient, and physician identifiers, diagnoses, procedures performed, origin of prescriptions, prescriber, visit times and dates, etc. Form 1010-EZ and appointment data are available to identify when the patient first enrolled, their preferred clinic, and desired appointment time, which can be linked to the visit with their new PCP. Access to electronic health records gives us a deeper and more complete view of a patient's health and medical care. For example, we observe referrals to specialists, physician orders (e.g., orders for lab and imaging tests, vaccinations, prosthetics, etc.), patient surveys and questionnaires (e.g., wellness and depression screens); lab and imaging results (e.g., hemoglobin A1c levels which are used for diabetes screening, cancer staging results); vital signs (e.g., blood pressure, body mass index); and receipt of patient education (e.g., interventions to promote smoking cessation).[5]

[5] Our main analysis focuses on care provided by the VA (i.e., VA medical clinics and community-based outpatient clinics that are VA-staffed or contracted). For some years we also have VA data linked to Medicare claims (2011-2016) and Medicaid (2011-2014). In addition, we observe some community non-VA care that is paid for by the VA when the VA does not have capacity, or if the veteran lives sufficient far away from a VA clinic. Such care may include emergency care, nursing homes, childbirth at private hospitals, and various types of specialty care. In Appendix Table A1 we show that including the available Medicare, Medicaid and non-VA data on hospitalizations and ED visits has little impact on our main findings.

Finally, we have data on veteran deaths from the VHA Vital Status files through early 2020, and from the Center for Disease Control National Death Index (NDI) Plus files which gives us both date and cause of death through the end of 2017.[6]

2.3 Sample and Variable Construction

We analyze male veterans between the ages of 20 and 90 who enrolled in VA benefits and first requested a primary care appointment between January 2005 and February 2017. Starting with 2005 gives us a one year "look back" window to see the patient's previous health history, while ending in 2017 allows us to follow all patients for three years after enrolling in the VHA. We focus on male veterans because female veterans are often assigned to Women's Health PACT teams (Leung et al. 2020). Often there is only one such team in a given clinic so there is no possibility of random assignment within a clinic and we have little power to conduct a within-clinic analysis for female veterans.

We begin with 1.02 million Form 1010-EZs representing new VHA enrollees who a) requested a primary care appointment; b) submitted the form between January 2005 and the end of February 2017; and c) had at least one completed appointment with a PCP.[7] We restrict our attention to veterans seen at clinics with at least two PCPs in each year (which results in a loss of 40,000 patients) and to PCPs with at least 20 new patients over our study period. The

[6] These data come from a variety of different sources, including the SSA Death master File, Medicare Vital Status File, and internal VA records (e.g., inpatient deaths, deaths informed by family members, and National Cemetery Administration records).

[7] We excluded patients whose first visits were connected to an application for disability compensation or a referral to social work or occupational health. We also excluded patients whose first visit was not to a PCP but to a specialist. The most common specialists for first visits were (in order of frequency): Audiologists, mental health, dentists, optometrists, orthopedics, and ophthalmology. It is possible that some of these veterans have private health insurance but rely on the VA to provide services that are not covered by their private plans such as optometry. The fact that patients who need an immediate referral for mental health to see a specialist are not in our sample strengthens the case that the remaining patients are quasi-randomly assigned.

purpose of this latter restriction is to focus on PCPs with enough patients that we can identify variations in practice style. As discussed further below, we use Bayesian shrinkage methods to compensate for the additional error involved in measuring practice style in doctors with few patients. We lose 3,819 PCPs at this stage. The final baseline sample covers 802,777 veterans who are assigned to 7,548 PCPs at 725 clinics.

We measure PCP effectiveness in the three years following the veteran's initial assignment using hospitalizations and emergency department (ED) visits for mental health/substance abuse and circulatory conditions, and hospitalizations for ambulatory care sensitive conditions. We chose these conditions not only because they are extremely common, but because they arguably require different types of expertise.

Mental health conditions are among the most common conditions affecting veterans with over a quarter of primary care veterans have at least one diagnosis of depression, post-traumatic stress disorder (PTSD), substance use disorder, anxiety disorder, or other serious mental illness (Trivedi et al. 2015). Improving the quality of these services has been a VA focus in recent years.[8] VHA guidelines for primary care now recommend annual mental health screenings for depression, post-traumatic stress disorder (PTSD), and alcohol/substance abuse for all new enrollees.

Diseases of the circulatory system are also among the most common health issues among veterans; veterans are twice as likely as non-veterans to have heart disease (Assari 2014).[9] Earlier and correct management of heart disease in a primary care setting is thought to lead to

[8] Mental health conditions include a wide range of diagnoses including, but not limited to, psychotic conditions, psychoses and episodic mood episodes, depression, substance use disorders, and suicide attempts/ideation.
[9] This category includes International Classification of Disease (ICD-10) codes beginning with "I", including rheumatic fever and heart diseases, hypertension, ischemic heart disease, pulmonary heart disease, cerebrovascular diseases, and other diseases affecting the arteries, veins, and lymphatic vessels etc.

fewer hospitalizations and better patient health outcomes (Bottle et al., 2018; Anderson et al., 2020).

ACSC hospitalizations are hospitalizations due to conditions such as diabetes, asthma, hypertension and pneumonia that can largely be avoided with timely, effective, and continued primary care (Barker et al. 2017; Hodgson et al. 2019). Hospitalizations for ACSC are currently tracked at the clinic and geographic region level by the VHA as an indicator of the quality of care and as a cost driver.[10] They are not currently tracked at the level of the individual PCP.

For all three metrics, we construct an indicator for whether the patient experiences the adverse outcome within three years of requesting an initial PCP appointment. Because veterans are quasi-randomly assigned to PCPs and PCPs are broadly responsible for managing a patient's care, we interpret any significant differences in patient's propensity for subsequent adverse events as an indicator of PCP effectiveness. The VHA also computes the average cost for each patient in each fiscal year.[11] We study average costs both one year and three years after the initial appointment request.

As an early adopter of electronic health records, the VHA has rich data across multiple sources which allows us to go beyond studying differences in outcomes to examine processes of care. We study PCP adherence to VHA clinical guidelines on mental and physical health

[10] We construct ACSC hospitalizations using a VHA-modified version of the measure used by the Agency for Health Care Research and Quality (AHRQ 2018). For instance, angina without procedure was dropped by AHRQ in July 2016, but remains in the VHA version.

[11] This average cost is constructed using non-VHA relative value weights (a CMS resource-based relative value scale) to distribute aggregate, national-level costs to each individual inpatient and outpatient encounter (Wagner et al. 2003) and allow dollar-for-dollar comparisons of costs across geographic areas and clinics.

screenings. The VHA has clinical guidelines on mental health screenings,[12] colorectal cancer (CRC), hepatitis C (HCV), HIV, influenza immunization, and tobacco use. Depending on the specific screen, we use outpatient procedure codes, chemical labs, radiology tests, referrals, and orderable request items to identify the performance of these screenings (e.g., the PCP can place an order/request for a technician to conduct a blood test). All screening metrics are restricted to suitable populations when necessary; for example, guidelines for CRC recommend annual fecal occult blood testing for adults between ages of 50 and 75 but not for younger or older veterans. We construct indicators for whether the veteran got each recommended screening in the first year after the initial primary care appointment.

Finally, we examine diabetes management and cancer staging. Appropriate diabetes management can greatly improve health and reduce health care costs. Similarly, catching cancer at an early stage improves the patient's prognosis and may offer less invasive treatment options. For diabetes screening, hemoglobin A1c (HbA1c) and low-density lipoprotein cholesterol (LDL-c) levels are obtained from the results of chemistry labs. In diabetics, HbA1c is considered 'controlled' if the average across all their tests in the first year following their first diabetes diagnosis is below 8% and LDL-c levels are below 100mg/dL (The Guideline Advantage, 2013).

For all our metrics, we do not require the screen or outcome to be linked to the PCP. The VHA's primary care philosophy is one where the PCP team is responsible for coordinating a patient's care which could well be rendered by other practitioners. Because of this, we adopt an intent-to-treat research design as discussed further below.

[12] Specifically, for mental health VHA guidelines recommend all new patients receive a Patient Health Questionnaire (PHQ; two item or nine item), Primary Care PTSD Screen for DSM-5 (PC-PTSD-5), and Alcohol Use Disorders Identification Test-Concise (AUDIT-C).

3. Empirical Strategy

3.1 Constructing measures of PCP effectiveness

Measures of PCP effectiveness are constructed using an empirical Bayes jackknifed value-added measure (Kane and Staiger 2008, Chetty, Friedman, and Rockoff 2014, Jackson et al. 2020).[13] This approach improves on using the raw probability that a doctor's patients experience an adverse outcome calculated by leaving out the index patient. Instead, probabilities are reweighted using the number of new patients assigned to each PCP each year. The effectiveness measure is thus constructed as a weighted average of the residualized probabilities that a PCP's patients suffer adverse outcomes where the weights depend on the number of observations in each period.

In order to calculate the yearly, residualized, leave-out jackknife effectiveness measure for each PCP we first estimate the following equation for patient i, PCP j, and year t:

$$Y_{ijt} = \theta X_{it} + \gamma_{ym} + \gamma_{clinic} + \gamma_{day} + \gamma_{desired} + \varepsilon_{ijt} \quad (1)$$

where Y_{ijt} is an indicator variable for an ED or hospital encounter for mental health, circulatory condition, or an ACSC within three years of assignment to a new PCP. This outcome variable is regressed on indicators for year by month, γ_{ym}; primary care clinic, γ_{clinic}; day of week of the initial visit, γ_{day}; and bins for the number of days between the veteran's desired date for a first appointment and the date of the actual appointment, $\gamma_{desired}$ (0, 1-7 days, 8-14 days, 15-21 days, 22-30 days, 30-60, and 60+ days).

We also include variables that are pre-determined as of baseline assignment to a PCP to improve precision; these controls are not required for unbiased effectiveness measures. These

[13] The approach is also similar to studies using a "judge instrument" such as Doyle et al. 2015, Dobbie et al. 2018, and Eichmeyer and Zhang 2021.

baseline controls, X_{it} include race (Asian/Pacific Islander, Black, Hispanic, White); five-year age bins, marital status, enrollment priority groups;[14] indicators for being a beneficiary of Medicare or Medicaid; whether the patient used the VHA in the previous year; whether they had any prior year mental health, circulatory conditions, or ACSC hospitalizations; whether the veteran has any service-connected disability or is considered unemployable; indicators for era of service (e.g. Korean war, Vietnam war), and exposure to Agent Orange or radiation. Yearly jackknife PCP propensities are calculated by averaging the residuals leaving out the own residual term corresponding to patient i, PCP j: $\widehat{W}_{jt} = \sum_{i \in K_{jt}} \hat{\varepsilon}_{ijt}$, where K_{jt} denotes the set of patients assigned to PCP j in year t.

The final step computes the empirical Bayes PCP effectiveness measure as a function of the vector of yearly effectiveness measures for that PCP, $\overrightarrow{W_j}$, and a vector of the number of newly assigned veterans for each PCP, $\overrightarrow{N_j}$: $\hat{Z}_j = Z(\overrightarrow{W_j}, \overrightarrow{N_j})$. Multiple years are used to improve statistical power and the weights are determined semi-parametrically and estimated from the data. Specifically, we estimate the following equation:

$$Y_{ijt} = \sum_{t=2005}^{2017} \sum_k \beta_{kt} 1\{N_{jt} = k\} \times \widehat{W}_{jt} + \epsilon_{ijt}, \tag{2}$$

where N_{jt} denotes the number of new veterans assigned to PCP j in year t. We create four bins for the number of new patients seen: 0-9, 10-24, 25-50, and over 50 new veterans. Finally, we take our fitted predicted values from equation (2), $\hat{Y}_{ijt}$, standardize the variable, and take its negative to be able to interpret it as effectiveness (as opposed to being the propensity to have patients experience *adverse* outcomes). We denote this effectiveness measure as:

[14] Priority for enrollment in VHA benefits depends on the veteran's income, disability status, and combat history. We include an indicator for each group.

$$E_{ijt} = -(\hat{Y}_{ijt} - E(\hat{Y}_{ijt}))/\sqrt{Var(\hat{Y}_{ijt})}.$$

Empirically equation (2) places more weight on yearly jackknife probabilities that are estimated with more precision and less weight on probabilities estimated with more noise. The latter shrink towards zero, the expected value of $\widehat{W}_{jt}$. Chetty et al. (2014) note that calculating the probabilities over multiple years could allow for "drift," that is the idea that professionals learn and change their behavior over time. However, here we calculate a single effectiveness measure for each PCP; in the results reported below, we use measures for multiple years purely to increase statistical power.

We also constructed effectiveness measures over two mutually exclusive time periods for each provider to account for provider learning and to check for the within-provider reliability of our effectiveness measures. We constructed empirical Bayes shrinkage effectiveness measures from Equations (1) – (4) for two time periods, 2005-2011 and 2012-2017, for PCPs who had at least 20 new patients in each time period. This left us with 2,566 PCPs for whom we could measure effectiveness in both periods. The correlation in 2005-2011 and 2012-2017 mental health effectiveness across providers was 0.81; the correlation for circulatory conditions was 0.79; and the correlation for ACSC was lower at 0.49. This lower correlation across time periods might reflect the effort the VHA has put into tracking and reducing ACSC.

Figure 1 plots histograms for each of our raw PCP effectiveness measures before standardization. The value of each measure represents the percent increase in the probability that a PCP's patient visits an ED or hospital within three years, relative to all other providers, conditional on the controls included in Equation (1). All three raw PCP effectiveness metrics are symmetric around mean zero by construction. Circulatory conditions exhibit the largest variation while ACSC exhibit the lowest. It is important to keep in mind that these measures capture *within-clinic*, and within-year and month variation in PCP effectiveness. Hence, regional differences in health or trends over time should not affect them.

After standardization, PCPs with a one standard deviation (SD) higher mental health effectiveness are 1.56 percentage points (pp) less likely to have their patients visit an ED or be hospitalized for mental health, over a base of 4.97% (a 31% reduction). Similarly, a one SD higher circulatory condition effectiveness PCP is 1.96pp less likely to have an adverse circulatory outcome (over a base of 7.37%; a 27% reduction); a one SD higher ACSC effectiveness PCP is 1.12pp less likely to have their patient be hospitalized for ACSC (over a base of 2.52%; a 44% reduction). Regressions underlying these calculations are shown in Table A3 and are based on Equation (3) below.

PCP effectiveness is also positively correlated across the three conditions (Figure 2) with Pearson correlation coefficients between any two measures varying from 0.35 to 0.40. This degree of correlation suggests that while doctors who are more effective in one dimension tend to be more effective in other dimensions, there are also significant differences in the degree of effectiveness for the three types of conditions within doctors.

Table 1 shows how the mean characteristics of veterans in our sample vary across PCPs in different effectiveness bands. The first column shows means for the entire sample while columns two through four show means for patients divided into terciles of provider effectiveness for circulatory issues. Since the three PCP metrics are highly correlated, dividing the sample by mental health or ACSC metrics yield similar patterns.

The average veteran is a late-middle aged (55) white male; the sample is 74.3% non-Hispanic White, 5.8% Hispanic, 13.2% Black, and 1.7% Asian/Pacific Islander. About 58% are currently married. About 30% are on Medicare and 5.4% are on Medicaid at the time of enrollment. Half have some form of service-connected disability. The average veteran's income is $44,413 in 2019 dollars. For some veterans (13.2%), we observe their prior medical history if they were previously treated at a VA hospital or emergency department without enrolling in VA health benefits. Prior circulatory hospitalization or ED use was most common, followed by mental health, and then an ACSC, but less than one percent of new enrollees had one of these events. As alluded to earlier, patients do not often switch providers; the average PCP-patient relationship over the three-year window in which we follow patients is 23 months (693 days). Table 1 also includes some information about diagnosis at the veteran's first visit, which was not included in Equation (1) as it may not be pre-determined.

Looking across terciles of PCP circulatory care effectiveness measures (columns 2 through 4) supports the idea that patients are quasi-randomly assigned. There is little difference in any of the measures across columns suggesting that veterans are distributed evenly across terciles in terms of their demographics, service history, and medical conditions.

Figure 3 provides another look at the assumption that veterans are randomly assigned to PCPs of differing levels of effectiveness by showing a "balance" test. The figure is constructed by first regressing the PCP effectiveness measures on clinic, year-month, day of week, and the number of days between the veteran's desired date and the date their appointment was made and then regressing the residuals from this first regression on all of the observable patient characteristics. Note that the controls in equation (1) are *not* included in the minimal PCP effectiveness measure plotted in this figure.

The figure allows us to see whether, within a clinic, veterans who are assigned to PCPs with higher levels of effectiveness differ in terms of observable variables such as demographics, military service history, eligibility category, and prior year's medical history. An important thing to determine is whether patients assigned to the more effective PCPs within a clinic appear to be systematically healthier or less healthy than other patients. Although a few coefficients are statistically significant (which is not surprising given our large sample size) there is little indication that PCP effectiveness is systematically related to factors that would signal better or worse patient health on average.[15] Furthermore, we control for prior patient health (MH, circulatory condition, and ACSC) in all our specifications.

In Appendix Table A1 we construct effectiveness measures and replicate our analyses on a subsample of veterans who had no prior VHA utilization. Recall that there is no information about health conditions on the intake form veterans complete. For the subset of patients in this table, schedulers also have no possible access to any prior information about health problems that might have been gleaned from VHA records. They could not have directed patients to practitioners on the basis of information they did not have, so this exercise addresses remaining concerns about the randomness of matching patients to PCPs. Our findings are robust.

3.2 Correlating PCP effectiveness with other measures of PCP practice variation and PCP characteristics

Equipped with these measures of PCP effectiveness, we first seek to validate them by asking whether each individual effectiveness (i.e., mental health, circulatory, or ACSC) are individually predictive of other patient outcomes of interest, notably mortality and health care costs. Importantly, mortality and health care costs were not used to construct the metrics. We

[15] To the extent that certain prior characteristics are statistically significant, some are in the "opposite" direction implying that sicker patients are assigned less effective doctors. Moreover, our final effectiveness measures control for some of the variables.

estimate the effects of PCP effectiveness, E_{ijt}, on mortality and total costs for the 802,777 new patients assigned to PCPs over the sample period:

$$Y_{ijt} = \beta E_{ijt} + \theta X_{it} + \gamma_{ym} + \gamma_{clinic} + \gamma_{day} + \gamma_{desired} + \varepsilon_{ijt}. \tag{3}$$

The parameter of interest, β, represents the impact of a standard deviation increase in one of our measures of PCP effectiveness on a patient outcome (for example, death in the next three years). Equation (3) includes the same controls as in equation (1).

We next explore how these measures of PCP effectiveness are related to measure of practice style. Do more effective physicians achieve better results by ordering more tests, by making more referrals, or by encouraging more visits? Are they more likely to conduct screenings as recommended by the VHA? These questions are explored using models similar to Equation (3) but using alternative outcome measures.

We also correlate PCP effectiveness with time-invariant provider characteristics such as the demographics of the provider. Instead of patient-level regressions, these models focus on a provider-level measure of effectiveness obtained by averaging the fitted values in equation (2) across each PCPs' patients: $E_j = \sum_{it} \hat{Y}_{ijt}$. We then estimate a regression of this provider-level PCP effectiveness measure on a provider's own characteristics Q_j, for 7,548 PCPs:

$$E_j = \mu + \theta Q_j + \eta_j + \varepsilon_j. \tag{4}$$

A fixed effect for the PCPs home clinic, η_j is included to ensure that we are identifying within-clinic provider differences.

4. Results

Table 2 explores the relationship between being assigned to a PCP with a one standard deviation increment in PCP effectiveness, 3-year mortality, 1-year costs, and 3-year costs. Each element of the table corresponds to a separate regression and only the coefficient of interest, β, is shown. The regressions are in the form of Equation (3) and the standard errors are clustered at the PCP level.

Table 2 shows that assignment to a PCP with a one standard deviation higher effectiveness measure is associated with a reduction of 0.20 to 0.23 percentage points in the risk of mortality in the next three years. Given the baseline 3-year mortality risk of 5.5%, this estimate translates into a 3.6 to 4.2% reduction in mortality. Both 1 year and 3 year total costs also fall by between 2.5 and 5.4% depending on the measure, with the largest reductions in total costs being for PCPs who are relatively more effective than others within their clinics at preventing ER visits and hospitalizations for circulatory conditions. The impact of high spending PCPs on patient spending has been shown in prior research (Kwok 2019), but we demonstrate that these effectiveness measures are also predictive of important patient outcomes that were not used in their construction.

Table 3 drills down on the mortality results by examining 3-year mortality by for the largest cause of death categories. It is reasonable to assume, for example, that PCPs who are effective in reducing ER visits and hospitalizations for circulatory conditions might be good at helping patients avoid deaths due to heart conditions. It is unclear though whether they would also be good at helping patients avoid deaths due to other common causes such as cancer. The extent to which there are spillovers onto other causes of death depends on how correlated effectiveness is across domains of care. Table 3 suggests that there are some spillovers, but that these different measures also capture particular domains of expertise.

For example, being assigned to a PCP with a one standard deviation higher measure of mental health effectiveness is associated with reductions of 13.3% reduction in the probability of death from suicide, and an 8.7% fall in the probability of death from external causes. This latter category includes confirmed suicides as well as deaths from overdoses, poisonings, and accidents, some of which may have been suicides. A one standard deviation improvement in mental health effectiveness is also associated with a -0.050 percentage point reduction in the probability of a cancer death, on a baseline of 1.48%, a 3.4% reduction. The estimates also imply a 4.0% reduction in the probability of death from heart disease.

Patients assigned to PCPs with a one standard deviation higher measure of circulatory care effectiveness see similar reductions in the probability of death from cancer or heart disease, but no reduction in the probability of death from suicide, and only a 4.0% reduction in the probability of death from external causes. These results suggest that some PCPs who are effective at caring for patients with circulatory conditions may lack expertise in caring for patients with mental health risks.

Patients whose PCPs are one standard deviation higher in terms of effectiveness in preventing ambulatory care sensitive conditions achieve the largest reductions in deaths from cancer (4.3%), and heart disease (4.5%), as well as a 6.3% reduction in external causes of death over the next three years, though there is no statistically significant effect for confirmed suicides.

None of the three measures predict reductions in deaths from lower respiratory conditions or cerebrovascular events suggesting either that these deaths may be harder to prevent, or that they represent another dimension of care effectiveness that may not be highly correlated with the measures we examine.

4.1 Effects on use of care

So far we have seen that patients of PCPs with higher effectiveness scores face a lower risk of death and incur lower total costs over a one year or a three year horizon. How are these positive results achieved? Is it the case, for example, that the patients consume more preventive care and thus are spared expensive illnesses? These questions are explored in Tables 4 through Table 6 which estimate models in the form of Equation (3), separately for each effectiveness measure.

Table 4 examines the relationship between PCP effectiveness and the number of medical encounters in the first year after assignment to a PCP. The first column shows that a one standard deviation in PCP effectiveness is associated with a reduction of 2 to 3% in the overall number of medical encounters (e.g. a one standard deviation improvement in mental health effectiveness reduces the total number of visits by 0.395 percentage points on a baseline of 13.4%). Some of this improvement is due to large reductions in the probability of any ED visits or inpatient hospitalizations as shown in columns 4 and 5. However, since the effectiveness measures were constructed with reference to ED visits and hospitalizations these significant relationships are not surprising.

What is more surprising is that there are reductions in the number of primary care visits of 1.3 to 2.2%, as well as in reductions in the number of mental health visits. It is striking that patients assigned to a PCP who is one standard more effective at treating mental health have 8.2% fewer mental health visits in the first year (a reduction of 0.106 on a baseline of 1.3 visits). Hence, it does not seem to be the case that more effective doctors are providing more general primary care or more mental health care. Column 6 shows that in the subset of patients over 65 who also qualify for Medicare (and for whom we have Medicare records) there are no differences in the number of visits outside of the VA. Hence, the reduction in visits at the VHA is not offset by increases in visits elsewhere.

Table 5 examines referrals, laboratory tests, and imaging. Another way that a PCP might achieve greater effectiveness is by referring patients to specialists when needed, or by conducting more lab and imaging tests. Table 5 suggests however that more effective PCPs are less likely to do any of these things.

While some of the differences in referrals are quite small, a one standard deviation increase in mental health effectiveness is estimated to reduce referrals for mental health by 3.0% (0.63 on a baseline of 20.9%) and to reduce referrals to cardiology by 4.1% (0.29 on a baseline of 7.0%). A one standard deviation increase in circulatory condition effectiveness reduces referrals for mental health by 1.5% but reduces referrals to cardiology by 9.6% (0.67 on a baseline of 7.0%). The measure of effectiveness at preventing hospitalizations for ambulatory care sensitive conditions has little effect on referrals.

However, all three measures of PCP effectiveness are negatively associated with ordering laboratory panels, with reductions ranging from 1.5% for a one standard deviation increase in mental health effectiveness to 3.2% for a one standard deviation increase in circulatory condition effectiveness. Similarly, for imaging there are reductions of 2.0% (for mental health effectiveness) to 4.0% (for circulatory condition effectiveness).

Table 6 looks at whether PCPs who are more effective according to our measures are more likely to follow VHA guidelines for screening veterans. For some types of screens, compliance is already very high in the VHA, leaving little room for within-clinic variation across PCPs. Panel A of Table 6 focuses on screenings for depression, PTSD, and substance use. Compliance with all these screens varies from 94.2% to 96.9% for new enrollees, in keeping with the strong emphasis the VHA places on mental health. Nevertheless, we do see some statistically significant, albeit small positive relationships between PCP effectiveness for circulatory conditions and ACSC and the probability of conducting these mental health screenings. The magnitudes vary from increases of 0.11% to 0.29%.

Panel B of Table 6 looks at whether patients received recommended screenings for colorectal cancer, hepatitis C, HIV, and tobacco use, and whether they received immunizations for influenza. Aside from screening for tobacco use, these physical health screenings have much lower average compliance rates. While most of the estimated coefficients are not statistically significant, those that are significant suggest a small negative relationship between PCP effectiveness and these screenings. For example, a one standard deviation increase in effectiveness for circulatory conditions is estimated to reduce the probability of screening for hepatitis C by 1.9% (0.9 on a baseline of 47.3%) while a one standard deviation increase in effectiveness for ACSC reduces it by 1.6%. A one standard deviation improvement in mental health effectiveness reduces the probability of screening for HIV by 1.4%. The only positive and significant coefficient in the table is for the effect of ACSC effectiveness on tobacco screening, but the magnitude is very small: 0.11%.

This section demonstrates that assignment to some PCPs generates better outcomes while reducing the amount of care consumed along most dimensions.

4.3 Characteristics of effective PCPs and the patient-PCP match

We have argued that some PCPs appear to be more effective than others working within the same clinics in terms of avoiding negative health outcomes for their patients. How are our measures of PCP effectiveness related to observable PCP characteristics? This question is explored in Table 7 which shows estimates of Equation (4). Because we are looking at within-clinic variations in PCP effectiveness, the PCPs home clinic, η_j, is included in the model to ensure that we are identifying within-clinic variation.

Unfortunately, we do not see information about the PCP's training, but we do know whether they are a physician or not, their gender, and their age. Because age changes over time and this is a PCP-level regression, we take the weighted average of the PCP's age at the time each new patient is assigned. We can also generate information about the means of certain practice characteristics from the data. Here we look at the number of patients they see per day, the number of new patients they see per year, and whether they are a full time equivalent (defined as seeing at least one patient on 250 days a year). While PCPs who work full-time may amass more relevant experience, in the VHA many research faculty hold part-time appointments so this flag may also be capturing that distinction.

Table 7 suggests that physicians are slightly less effective (about 0.1 standard deviations) than nurse practitioners and physician assistants in terms of avoiding ED visits and hospitalizations.[16] Effectiveness increases with age, number of patients per day and the number of new patients per year. A one standard deviation increase in patients per day (4.25 patients) is estimated to improve circulatory condition effectiveness and ACSC effectiveness by 0.068 and 0.11 of a standard deviation, respectively. A one standard deviation in new patients per year (12.29 patients) would increase mental health, circulatory condition, and ACSC effectiveness by 0.17, 0.25, and 0.11 standard deviations, respectively. PCPs whose patients receive a larger proportion of mental health visits within the embedded mental health team—settings where the PCP is present with a licensed mental health specialist in the same clinic without needing a

[16] In Appendix Table A4 we find that our main results are robust to focusing only on physicians.

separate consultation[17]—achieve higher effectiveness along all three dimensions. This measure of greater care coordination may reconcile the mental health referral results from earlier. Providers who spend more of their time at the VHA as part-time workers also have higher effectiveness ratings. This may be because these PCPs are more likely to be researchers, training residents, or in administrative leadership roles.

Table 8 seeks to address the question of whether patients are aware of provider effectiveness. As discussed above, patients are not encouraged to switch providers in the VHA, and switching is relatively rare, however we do see variation in the length of time that a patient stays with a particular PCP after their initial assignment. Column 1 shows that there is a small positive relationship (a little over a week on a baseline of 693 days) between our measures of PCP effectiveness and the length of a patient's relationship with that PCP. Some of this could be mechanical since more effective PCPs were shown to reduce the patient's probability of death. Column (2) shows that if we exclude patients who die within three years, we see a very similar relationship between effectiveness and the length of the patient-PCP relationship.

5. Discussion

In this paper we address the following questions in the unique context of the VHA: Are some providers more effective than others in promoting patient health and how can we measure that? Is provider effectiveness correlated across different aspects of patient health or are some

[17] Internally referred to in the VA as Primary Care-Mental Health Integration, PCMHI integrates mental health care with the veterans' primary care team in the same primary care clinic, usually in the same day, to achieve patient-centered mental health care coordination. This is in contrast to traditional referrals to separate mental health specialist clinics for a future date. The independent variable is defined as the fraction of all outpatient mental health visits that are integrated with primary care.

providers much better at some types of care than others? And if some providers are generally more effective than others, what characteristics of providers predict effectiveness?

These questions are hard to answer for the same reasons that make teacher "value-added" measures controversial. Teacher value-added models seek to assess teacher effectiveness by looking at student outcomes. Similarly, in health settings we may try to assess provider effectiveness using patient outcomes. In most settings, patients sort non-randomly across providers. If patients choose their providers, if sicker patients are referred to more experienced providers, or if some patients do not have access to more skilled providers, then inferences based on patient outcomes may be biased. Researchers typically try to solve this problem through risk adjustment, that is by correcting for observable differences in patient mix. But there may be important characteristics of patients that are observed by providers and not by the risk adjusters. The VHA's system of quasi-randomly assigning patients to PCPs within a clinic provides a solution to these problems.

An alternative approach to measuring effectiveness in a health care setting focuses on what the provider does rather than on patient outcomes. Effectiveness may be assessed using checklists. But this can generate problems if some patients are more likely to demand certain procedures (or shun them). A second problem with checklists is akin to the idea of "teaching to the test." Providers may focus on "checking the boxes" and neglect other important aspects of patient care.[18] Moreover, dealing with checklist can take time away from direct patient care and communication between providers and patients.

This paper focuses on measuring effectiveness using patient outcomes, leveraging the unique quasi-random assignment of patients to PCPs in the VHA. Our results suggest the

[18] For example, Medicare's Physician Quality Reporting System included 194 separate quality metrics (Centers for Medicare & Medicaid Services 2012).

following answers to the questions we posed: First, some PCPs are indeed more effective than others. While we constructed our measures with reference to future ER visits and hospitalizations, we were able to validate them by showing that our measures of PCP effectiveness predicted future risk of death and future health care costs.

Second, provider effectiveness is highly correlated across the three domains of effectiveness we examine (mental health, circulatory conditions, and hospitalizations for ambulatory care sensitive conditions), with correlations between any two of these measures ranging from 0.35 to 0.40. These results suggest that it is not necessary to measure effectiveness in every possible dimension. Perhaps the VHA's current practice of tracking the effectiveness of *clinics* in terms of avoiding hospitalizations due to ambulatory care sensitive conditions could potentially be extended to identify PCPs within clinics who are effective in helping patients to avoid hospitalizations, ED visits, and ultimately mortality.

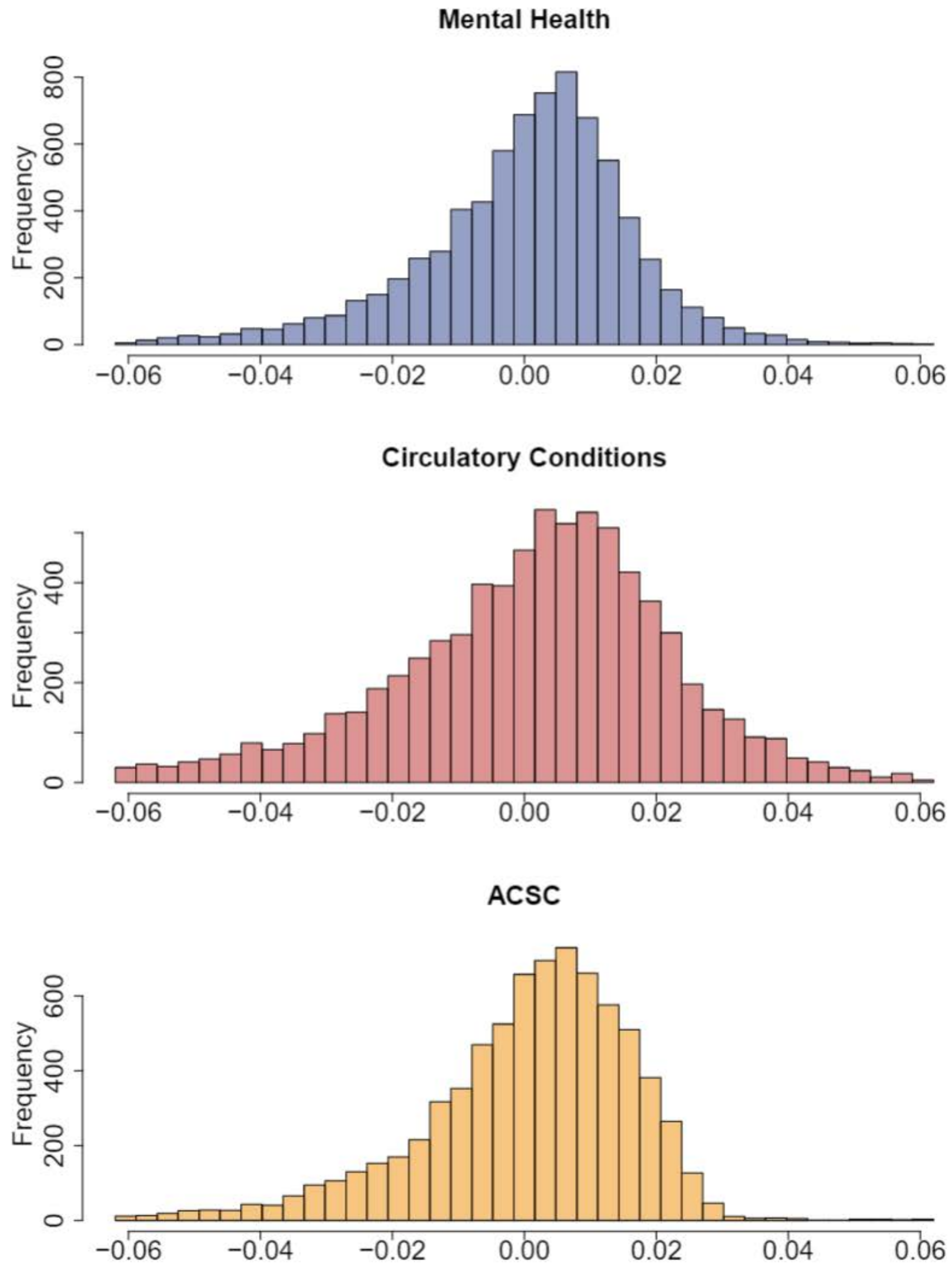
Our third and most striking finding is that more effective PCPs do more with less. Patients of these providers have fewer primary care visits, fewer referrals, fewer lab and imaging tests, and even fewer preventive health screenings. Better communication between some PCPs and their patients is one possible mechanism that might help to explain these results. For example, Alsan, Garrick, and Graziani (2019) found that Black patients were more likely to accept preventive services when they were matched with a Black doctor. Since in their setting doctors of all races attempted to persuade patients to take up these services, the authors attributed the higher take up when providers and patients were of the same race to better communication. Koulayev, Simeonova, and Skipper (2016) and Simeonova, Skipper, and Thingholm (2021) find that providers can improve medication adherence and these providers achieve better patient outcomes. They attribute this to better communication quality.It is possible that some PCPs at the

VHA are able to allow patients to forego some visits, tests and referrals because better communication with patients allows them to obtain the information they need and avoid ordering unnecessary tests. Our finding that providers with better outcomes rely more on integrated mental health providers than mental health specialist referrals also support the communication and rapport hypothesis.

Determining the reasons why some PCPs are able to do more with less is an important avenue for future work. In the meantime, our results suggest that health administrators should be cautious in seeking to eliminate “unnecessary” referrals and tests: Given variations in provider effectiveness, some providers may need to use more resources to achieve the same patient health outcomes.

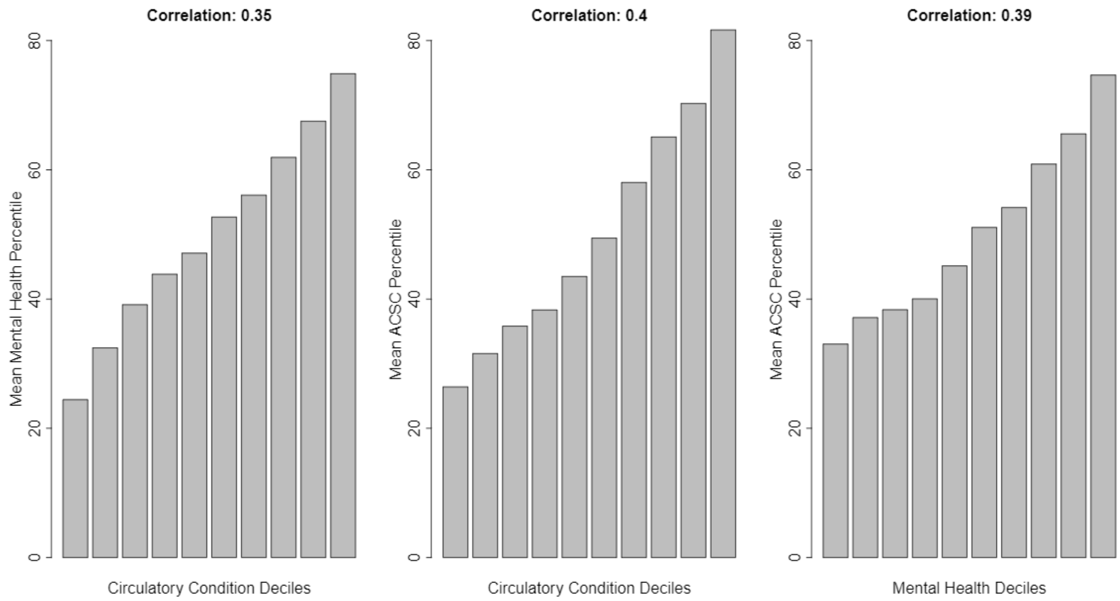
Figures and Tables

Figure 1: Histogram of PCP Effectiveness Metrics



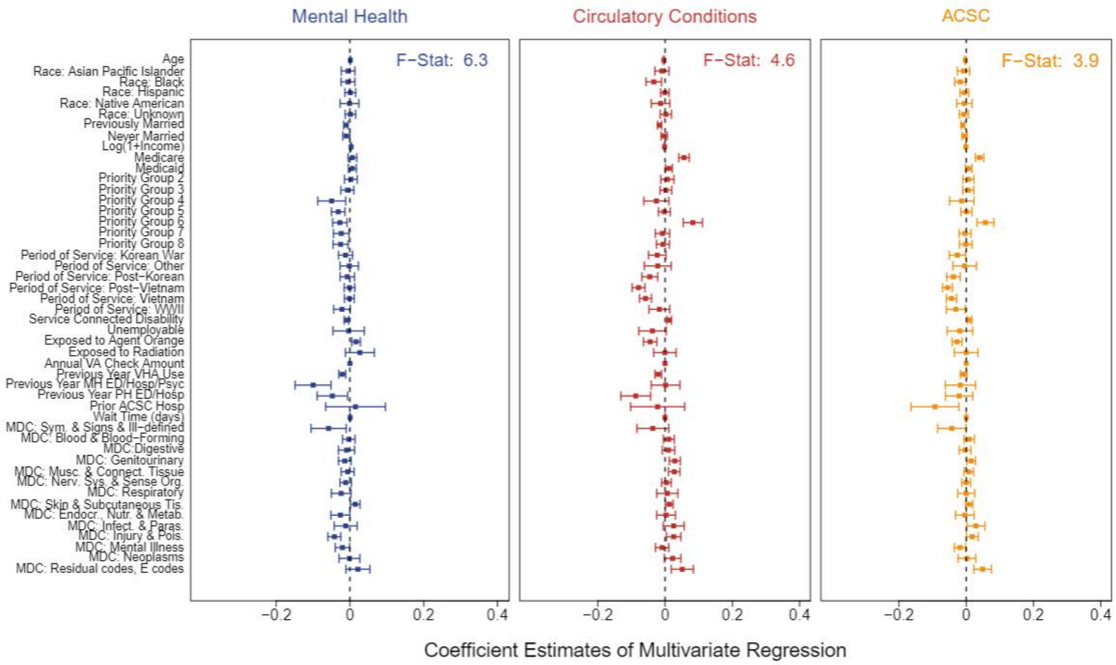
Notes: This figure plots the distribution of our 7,548 PCPs measured by the three dimensions of patient outcomes. The measures are not standardized; see text for details on construction.

Figure 2: Relationship Between Within-Clinic Provider Effectiveness Metrics



Notes: This figure plots the relationship between our three effectiveness metrics for 7,548 PCPs which are split into decile bins based on a particular metric. Correlations are weighted by each PCP's number of new patients. See text for details on construction.

Figure 3: Balance Table for Quasi-Random Assignment



Notes: This figure tests for quasi-random assignment of new patients to PCPs. Moving from left to right, the first panel regresses the mental health effectiveness measure on a set of observables including (jointly) patient demographics, military history, prior year utilization and adverse health outcomes and major diagnostic categories observed on their initial visit. The second and third panels repeat the exercise with the circulatory condition and ambulatory care sensitive condition measures. Estimated regression coefficients and associated 95% confidence intervals (constructed from robust standard errors clustered at the clinic-level) are shown. All three metrics are standardized and constructed from residuals taken after controlling for clinic, year-month, day of week, and desired days to appointment fixed effects. These fixed effects are also included in the balance test regressions, along with age categories. The joint F-statistics are reported. The number of observations is 802,777 for all regressions.

Table 1: Summary Statistics for Patients

	Sample Mean	Assigned PCP: Circulatory Terciles		
		Bottom	Middle	Top
Age	55.3	55.6	55.4	54.8
Asian Pacific Islander	1.7	1.6	2.0	1.5
Black	13.2	13.4	12.8	13.2
Hispanic	5.8	5.6	6.1	5.8
Native American	0.7	0.7	0.8	0.7
White (non-Hispanic)	74.3	74.4	74.0	74.4
Currently Married	57.7	57.4	58.3	57.5
Previously Married	29.1	29.6	28.7	28.9
Never Married	13.2	13.1	13.0	13.6
Income	44,413	44,440	44,403	44,396
Medicare	29.7	29.7	30.5	28.8
Medicaid	5.4	5.5	5.3	5.4
Period of Service: Korean War (1950-55)	5.5	5.5	5.4	5.4
Period of Service: Vietnam War (1961-75	41.4	42.2	41.2	40.8
Period of Service: Gulf War Era (1990+)	30.9	29.6	31.3	31.9
Period of Service: Other	22.3	22.7	22.1	22.0
Any Service Connected Disability	50.7	49.9	51.4	50.8
Deemed Unemployable	0.3	0.3	0.3	0.3
Agent Orange Exposure	16.8	17.1	16.4	16.8
Other Radiation Exposure	0.3	0.3	0.3	0.4
Annual VA Check Amount	1,694	1,669	1,780	1,633
Any Prior Year VHA Care	13.2	13.5	13.1	13.0
Prior Year MH ED/Hosp	0.3	0.4	0.3	0.3
Prior Year Circulatory ED/Hosp	0.4	0.5	0.4	0.4
Prior Year ACSC Hosp	0.1	0.1	0.1	0.1
Wait Time (days)	5.6	5.6	5.6	5.6
Initial Diagnosis: Circulatory	25.5	26.4	25.1	25.0
Initial Diagnosis: Endocrine, Nutritional, & Metabolic	14.8	14.9	14.9	14.7
Initial Diagnosis: Musculoskeletal & Connective Tissue	13.6	13.3	13.5	14.0
Initial Diagnosis: Mental	7.5	7.6	7.4	7.5
Initial Diagnosis: Respiratory	3.8	3.8	3.8	3.8
Initial Diagnosis: Other	34.8	34.0	35.3	35.0
Relationship Length with PCP (days)	693	679	702	697
N=	802,777			

Notes: This table presents the raw baseline summary statistics for our baseline sample of new veteran health benefit enrollees, and those who are assigned to various PCPs, classified by their circulatory condition effectiveness.

Table 2: Impacts of PCP Effectiveness Metrics on Mortality and Cost

	Dependent variable: (×100)		
	3-Year Mortality	Log 1Y Avg Cost	Log 3Y Avg Cost
One SD of..	(1)	(2)	(3)
Mental Health	−0.21***	−4.50***	−4.43***
	(0.03)	(0.33)	(0.19)
Circulatory Conditions	−0.20***	−5.40***	−5.23***
	(0.03)	(0.33)	(0.30)
ACSC	−0.23***	−2.85***	−2.48***
	(0.03)	(0.36)	(0.32)
FE + Controls?	Yes	Yes	Yes
Mean Dep. Var.	5.50%	$4,275	$12,120
Observations	802,777	788,743	758,655

Notes: This table reports the regression output of regressions of 3-year all-cause mortality, log of one plus one-year average cost, and log of one plus three-year average cost on a leave-out PCP effectiveness metric. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Coefficient estimates are scaled by 100, and robust-standard errors are clustered at the PCP-level. The sample in columns 2 and 3 are constrained such that the veteran is alive for the outcome period. *p<0.1; **p<0.05; ***p<0.01.

Table 3: Causes of Death

	Dependent variable: 3Y Mortality (×100)					
	Cancer	Heart	Suicide	External Causes	Lower Respiratory	Cerebro -vascular
One SD of..	(1)	(2)	(3)	(4)	(5)	(6)
Mental Health	−0.050**	−0.043***	−0.012***	−0.026***	−0.006	0.006
	(0.014)	(0.012)	(0.004)	(0.007)	(0.007)	(0.005)
Circulatory Conditions	−0.046***	−0.042***	−0.005	−0.012*	−0.008	−0.006
	(0.015)	(0.012)	(0.004)	(0.007)	(0.007)	(0.005)
ACSC	−0.063***	−0.049***	−0.006	−0.019***	−0.008	−0.009
	(0.015)	(0.013)	(0.004)	(0.007)	(0.007)	(0.006)
FE + Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var. (%)	1.48	1.08	0.09	0.30	0.31	0.20
Observations	802,777	802,777	802,777	802,777	802,777	802,777

Notes: This table reports the regression output of 3-year mortality by cause of death on each of our PCP effectiveness metrics, separately. Cause is determined from multiple cause of death records, so a veteran may appear in more than one cause of death category. Cancer, heart disease, lower respiratory, and cerebrovascular diseases are selected as the five most common causes of death among veterans (and the American population more generally). External causes of death include suicides, overdoses and poisonings, and accidents. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Coefficient estimates are scaled by 100, and robust-standard errors are clustered at the PCP-level. *p<0.1; **p<0.05; ***p<0.01.

Table 4: Number of Encounters by Type

	Dependent variable: Number of Encounter Days					
	All VA	Primary Care	Mental Health	Emergency	Inpatient	Medicare
One SD of..	(1)	(2)	(3)	(4)	(5)	(6)
Mental Health	-0.395^{***}	-0.108^{***}	-0.106^{***}	-0.029^{***}	-0.016^{***}	0.011
	(0.025)	(0.010)	(0.009)	(0.001)	(0.001)	(0.008)
Circulatory Conditions	-0.407^{***}	-0.112^{***}	-0.016^{***}	-0.030^{***}	-0.017^{***}	0.008
	(0.024)	(0.010)	(0.007)	(0.001)	(0.001)	(0.009)
ACSC	-0.255^{***}	-0.066^{***}	-0.004	-0.022^{***}	-0.015^{***}	0.002
	(0.026)	(0.010)	(0.007)	(0.002)	(0.001)	(0.008
FE + Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	13.4	5.0	1.3	0.26	0.095	1.47
Observations	802,777	802,777	802,777	802,777	802,777	238,386

Notes: This table reports the regression output of the number of encounter (days) a veteran has in the first year on our PCP effectiveness metrics. Columns 1 to 5 report the number of encounter days for its respective type of care. Column 6 reports the number of Medicare encounter days (across all settings and modalities) for veterans over the age of 65 at assignment. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Robust-standard errors clustered at the PCP-level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 5: Referrals and Testing

	Dependent variable: ($\times 100$)				
	Referrals (indicator)			Testing (Counts)	
	Any	MH	Cardiology	Lab Panels	Imaging
One SD of..	(1)	(2)	(3)	(4)	(5)
Mental Health	-0.54^{***}	-0.63^{***}	-0.29^{***}	-0.13^{***}	-0.03^{***}
	(0.09)	(0.08)	(0.06)	(0.02)	(0.01)
Circulatory Conditions	-0.67^{***}	-0.31^{***}	-0.67^{***}	-0.27^{***}	-0.06^{***}
	(0.09)	(0.08)	(0.08)	(0.02)	(0.01)
ACSC	-0.38^{***}	-0.16^{***}	-0.42^{***}	-0.18^{***}	-0.04^{***}
	(0.10)	(0.09)	(0.08)	(0.03)	(0.01)
FE + Controls?	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	74.8%	20.9%	7.0%	8.5	1.5
Observations	802,777	802,777	802,777	802,777	802,777

Notes: This table reports the regression output of referrals (any, MH referrals, and cardiology referrals) and testing (number of outpatient lab panels, and imaging) orders on our PCP effectiveness metrics. Referrals are indicators for whether the patient is ever referred in the first year and testing orders are the number of distinct orders in the first year. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Robust-standard errors clustered at the PCP-level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 6: Annual Mental and Physical Health Guidelines

Panel A. Mental Health Guidelines

	Dependent variable: (×100)		
	Depression	PTSD	SUD
One SD of..	(1)	(2)	(3)
Mental Health	0.04	−0.07	0.03
	(0.05)	(0.08)	(0.04)
Circulatory Conditions	0.14**	0.27***	0.11***
	(0.06)	(0.08)	(0.05)
ACSC	0.13**	0.26***	0.12**
	(0.06)	(0.09)	(0.06)
FE + Controls?	Yes	Yes	Yes
Mean Dep. Var. (%)	96.9	94.2	96.5
Observations	670,060	670,060	670,060

Panel B. Physical Health Guidelines

	Dependent variable:(×100)				
	CRC	HCV	HIV	Flu	Tobacco
One SD of..	(1)	(2)	(3)	(4)	(5)
Mental Health	0.005	−0.37	−0.31**	−0.12	−0.04
	(0.19)	(0.23)	(0.15)	(0.09)	(0.04)
Circulatory Conditions	−0.33*	−0.90***	−0.21	−0.33***	0.06
	(0.19)	(0.24)	(0.17)	(0.08)	(0.05)
ACSC	0.03	−0.74***	−0.06	−0.07	0.11**
	(0.20)	(0.25)	(0.17)	(0.09)	(0.05)
FE + Controls?	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var. (%)	49.3	47.3	22.3	45.3	97.1
Observations	437,203	738,225	532,853	802,777	802,777

Notes: This table reports the relationship between adherence to annual physical and mental health guidelines set forth by the VHA and our PCP effectiveness metrics. Mental health screens are for depression, PTSD, alcohol and substance use disorder via mental health questionnaires and begin after 2008. The sample is restricted to new enrollees after 2008. Physical health adherence for colorectal cancer screens (for patients between the ages of 50 and 75), hepatitis C screens (patients under the age of 80), HIV screens (patients under the age of 65), flu immunizations, and tobacco screens are our physical health margins. All dependent variables are indicators for screenings in the first year and samples are restricted to age groups relevant to each guideline. See text for details on the construction of each. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Robust-standard errors clustered at the PCP-level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 7: Provider Demographics and Characteristics

		Dependent variable: One SD of		
	Weighted Mean	Mental Health	Circulatory Conditions	ACSC
	(1)	(2)	(3)	(4)
Physician	0.76	0.004	-0.095^{**}	-0.077
		(0.047)	(0.047)	(0.049)
Female	0.46	0.022	-0.049	-0.048
		(0.036)	(0.038)	(0.030)
Age: 35-44	0.24	-0.063	0.060	0.122^{**}
		(0.073)	(0.070)	(0.058)
Age: 45-54	0.35	-0.003	0.125^{*}	0.174^{**}
		(0.063)	(0.081)	(0.074)
Age: 55+	0.36	0.039	0.155^{*}	0.158^{**}
		(0.073)	(0.081)	(0.074)
Part-Time	0.32	0.128	0.240^{***}	0.505^{***}
		(0.079)	(0.083)	(0.079)
Primary Care-MH Integration	0.095	1.211^{***}	0.884^{***}	1.055^{***}
		(0.178)	(0.157)	(0.079)
Patients Per Day	12.1	0.009	0.016^{***}	0.027^{***}
		(0.007)	(0.005)	(0.006)
New Patients Per Year	23.6	0.014^{***}	0.020^{***}	0.009^{***}
		(0.002)	(0.002)	(0.002)
Observations	-	7,544	7,544	7,544

Notes: This table reports the output of regressing each of our PCP effectiveness metrics on provider observables, controlling for clinic fixed effects. Regressions are weighted by each PCP's number of new patients and robust-standard errors are clustered at the clinic-level. Age is a weighted average of age at each new patient assignment, part time indicator is the fraction of the years where the provider works fewer than 240 days during the calendar year, and primary care-MH integration is the fraction of each PCP's mental health outpatient visits that are joint with their primary care team in the same clinic. *p<0.1; **p<0.05; ***p<0.01.

Table 8: Provider Effectiveness and Length of Provider-Patient Relationship

	Dependent variable:	
	Length of Relationship (days)	
	(1)	
Mental Health	8.2***	8.0***
	(2.2)	(2.2)
Circulatory Conditions	6.9***	6.5***
	(2.1)	(2.2)
ACSC	10.1***	9.7***
	(2.6)	(2.6)
FE + Controls?	Yes	Yes
Mean Dep. Var.	693	703
Observations	802,777	758,655

Notes: This table reports the regression output of relationship length (in days) on our PCP effectiveness metrics. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Robust-standard errors clustered at the PCP-level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Appendix Figures and Tables

OMB Control No. 2900-0091
Estimated Burden Avg. 30 min.
Expiration Date 12/31/2020

Department of Veterans Affairs | **APPLICATION FOR HEALTH BENEFITS**

SECTION I - GENERAL INFORMATION

Federal law provides criminal penalties, including a fine and/or imprisonment for up to 5 years, for concealing a material fact or making a materially false statement. (See 18 U.S.C. 1001)

1A. VETERAN'S NAME *(Last, First, Middle Name)*
1B. PREFERRED NAME
2. MOTHER'S MAIDEN NAME

3A. BIRTH SEX: ☐ MALE ☐ FEMALE
3B. SELF-IDENTIFIED GENDER IDENTITY: ☐ MALE ☐ FEMALE
4. ARE YOU SPANISH, HISPANIC,OR LATINO? ☐ YES ☐ NO
5. WHAT IS YOUR RACE? *(You may check more than one. Information is required for statistical purposes only.)* ☐ ASIAN ☐ AMERICAN INDIAN OR ALASKA NATIVE ☐ BLACK OR AFRICAN AMERICAN ☐ WHITE ☐ NATIVE HAWAIIAN OR OTHER PACIFIC ISLANDER
6. SOCIAL SECURITY NO.

7. VA CLAIM NUMBER
8A. DATE OF BIRTH *(mm/dd/yyyy)*
8B. PLACE OF BIRTH *(City and State)*
9. RELIGION

10A. PERMANENT ADDRESS *(Street)*
10B. CITY
10C. STATE
10D. ZIP CODE
10E.COUNTY

10F. HOME TELEPHONE NO. *(optional)* *(Include Area Code)*
10G. MOBILE TELEPHONE NO. *(optional)* *(Include Area Code)*
10H. E-MAIL ADDRESS *(optional)*

11A. RESIDENTIAL ADDRESS *(Street)*
11B. CITY
11C. STATE
11D. ZIP CODE
11E.COUNTY

12. TYPE OF BENEFIT(S) APPLYING FOR *(You may check more than one)* ☐ ENROLLMENT/HEALTH SERVICES ☐ DENTAL
13. CURRENT MARTIAL STATUS ☐ MARRIED ☐ NEVER MARRIED ☐ SEPARATED ☐ WIDOWED ☐ DIVORCED

14A. NEXT OF KIN NAME
14B. NEXT OF KIN ADDRESS
14C. NEXT OF KIN RELATIONSHIP

14D. NEXT OF KIN TELEPHONE NO. *(Include Area Code)*
14E. NEXT OF KIN WORK TELEPHONE NO. *(Include Area Code)*
15. DESIGNEE - INDIVIDUAL TO RECEIVE POSSESSION OF YOUR PERSONAL PROPERTY LEFT ON PREMISES UNDER VA CONTROL AFTER YOUR DEPARTURE OR AT THE TIME OF DEATH (*Note: This does not constitute a will or transfer of title*)

16. I AM ENROLLING TO OBTAIN MINIMUM ESSENTIAL COVERAGE UNDER THE AFFORDABLE CARE ACT ☐ YES ☐ NO
17. WHICH VA MEDICAL CENTER OR OUTPATIENT CLINIC DO YOU PREFER? *(for listing of facilities visit www.va.gov/directory)*
18. WOULD YOU LIKE FOR VA TO CONTACT YOU TO SCHEDULE YOUR FIRST APPOINTMENT? ☐ YES ☐ NO

SECTION II - MILITARY SERVICE INFORMATION

1A. LAST BRANCH OF SERVICE
1B. LAST ENTRY DATE
1C. FUTURE DISCHARGE DATE
1D. LAST DISCHARGE DATE

1E. DISCHARGE TYPE
1F. MILITARY SERVICE NUMBER

2. MILITARY HISTORY *(Check yes or no)*	YES	NO		YES	NO
A. ARE YOU A PURPLE HEART AWARD RECIPIENT?	☐	☐	G. DO YOU HAVE A VA SERVICE-CONNECTED RATING?	☐	☐
B. ARE YOU A FORMER PRISONER OF WAR?	☐	☐	IF "YES", WHAT IS YOUR RATED PERCENTAGE ______ %		
C. DID YOU SERVE IN A COMBAT THEATER OF OPERATIONS AFTER 11/11/1998?	☐	☐	H. DID YOU SERVE IN VIETNAM BETWEEN JANUARY 9, 1962 AND MAY 7, 1975?	☐	☐
D. WERE YOU DISCHARGED OR RETIRED FROM MILITARY FOR A DISABILITY INCURRED IN THE LINE OF DUTY?	☐	☐	I. WERE YOU EXPOSED TO RADIATION WHILE IN THE MILITARY?	☐	☐
E. ARE YOU RECEIVING DISABILITY RETIREMENT PAY INSTEAD OF VA COMPENSATION?	☐	☐	J. DID YOU RECEIVE NOSE AND THROAT RADIUM TREATMENTS WHILE IN THE MILITARY?	☐	☐
F. DID YOU SERVE IN SW ASIA DURING THE GULF WAR BETWEEN AUGUST 2, 1990 AND NOVEMBER 11, 1998?	☐	☐	K. DID YOU SERVE ON ACTIVE DUTY AT LEAST 30 DAYS AT CAMP LEJEUNE FROM AUGUST 1, 1953 THROUGH DECEMBER 31, 1987?	☐	☐

Notes: Page 1 of Form 1010-EZ for enrollment in VA health benefits. This is the page with basic demographics, military service information, and preferred clinic and whether the veteran would like to be contacted for their first appointment (in red box).

Appendix Table A1

Main Outcomes Dropping Veterans with Prior VHA Utilization

	Dependent variable:			
	3-Year Mortality (×100)	Log 3Y Avg Cost (×100)	# Visits	Any Referral (×100)
One SD of..	(1)	(2)	(3)	(4)
Mental Health	−0.21***	−4.91***	−0.358***	−0.49***
	(0.03)	(0.33)	(0.015)	(0.05)
Circulatory Conditions	−0.21***	−5.38***	−0.394***	−0.66***
	(0.03)	(0.33)	(0.016)	(0.06)
ACSC	−0.23***	−2.63***	−0.263***	−0.38***
	(0.03)	(0.36)	(0.017)	(0.06)
FE + Controls?	Yes	Yes	Yes	Yes
Mean Dep. Var.	5.50%	$12,120	13.4	74.8%
Observations	679,541	642,298	642,298	642,298

Notes: This table reports select main outcomes on an effectiveness measure on a sample of veterans without prior VHA utilization. The effectiveness measure is also constructed on the same sample. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Coefficient estimates are scaled by 100, and robust-standard errors are clustered at the PCP-level. *p<0.1; **p<0.05; ***p<0.01.

Appendix Table A2

Main Outcomes Including non-VA ED and Hospitalizations

	Dependent variable:			
	3-Year Mortality ($\times$100)	Log 3Y Avg Cost ($\times$100)	# Visits	Any Referral ($\times$100)
One SD of..	(1)	(2)	(3)	(4)
Mental Health	-0.20^{***}	-4.36^{***}	-0.403^{***}	-0.54^{***}
	(0.03)	(0.29)	(0.015)	(0.05)
Circulatory Conditions	-0.18^{***}	-4.79^{***}	-0.388^{***}	-0.68^{***}
	(0.03)	(0.30)	(0.015)	(0.05)
ACSC	-0.26^{***}	-2.96^{***}	-0.285^{***}	-0.41^{***}
	(0.03)	(0.30)	(0.015)	(0.05)
FE + Controls?	Yes	Yes	Yes	Yes
Mean Dep. Var.	5.50%	$12,120	13.4	74.8%
Observations	802,777	758,655	802,777	802,777

Notes: This table reports select main outcomes on an effectiveness measure constructed using VA and non-VA encounters. Non-VA encounters include community care reimbursed by the VA, and Medicare and Medicaid care. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Coefficient estimates are scaled by 100, and robust-standard errors are clustered at the PCP-level. *p<0.1; **p<0.05; ***p<0.01.

Appendix Table A3: Effects of a One Standard Deviation Change in an Index on Mental Health, Circulatory Condition and ACSC Measures

	Dependent variable: (×100)		
	Mental Health	Circulatory Conditions	ACSC
One SD of..	(1)	(2)	(3)
Mental Health	-1.56^{***}		
	(0.03)		
Circulatory Conditions		-1.96^{***}	
		(0.03)	
ACSC			-1.12^{***}
			(0.02)
FE + Controls?	Yes	Yes	Yes
Mean Dep. Var. (%)	4.97	7.37	2.52
Observations	802,777	802,777	802,777

Notes: This table reports the regression output of first stage regressions of each effectiveness measure on its respective outcome: mental health ED and hospitalizations, circulatory condition ED and hospitalizations, and ACSC hospitalizations. All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Coefficient estimates are scaled by 100, and robust-standard errors are clustered at the PCP-level. *p<0.1; **p<0.05; ***p<0.01.

Appendix Table A4

Main Outcomes Excluding Nurse Practitioners and Physician Assistants

	Dependent variable:			
	3-Year Mortality ($\times$100)	Log 3Y Avg Cost ($\times$100)	# Visits	Any Referral ($\times$100)
One SD of..	(1)	(2)	(3)	(4)
Mental Health	-0.22^{***}	-4.41^{***}	-0.383^{***}	-0.59^{***}
	(0.03)	(0.35)	(0.017)	(0.06)
Circulatory Conditions	-0.18^{***}	-5.00^{***}	-0.403^{***}	-0.73^{***}
	(0.03)	(0.35)	(0.018)	(0.06)
ACSC	-0.23^{***}	-2.24^{***}	-0.259^{***}	-0.41^{***}
	(0.03)	(0.39)	(0.019)	(0.07)
FE + Controls?	Yes	Yes	Yes	Yes
Mean Dep. Var.	5.60%	$12,214	13.4	74.9%
Observations	579,878	547,316	579,878	579,878

Notes: This table reports select main outcomes on our effectiveness measures on a sample of veterans treated only by physician PCPs (excluding nurse practitioners and physician assistants). All regressions include clinic, year-by-month, day of week, bins for days between desired and actual appointment date, race, five-year age bins, marital status, priority groups, Medicare/Medicaid beneficiary status, prior year mental health, circulatory, and ACSC hospitalizations, disability/unemployable status, era of service, and exposure to Agent Orange or radiation. Coefficient estimates are scaled by 100, and robust-standard errors are clustered at the PCP-level. *p<0.1; **p<0.05; ***p<0.01.

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