Complementing Public Care with Private: Evidence from Veterans Choice Act

Hiroki Saruya Todd Wagner Diana Zhu*

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Abstract

We study the effect of complementing public health care with private care. Leveraging a policy at the Veterans Health Administration that generates discontinuity in private care access, we find that expanding coverage to private care increases private outpatient care by \$53 (SE: 5) and decreases VA outpatient care by \$20 (SE: 7), with no impact on inpatient care. The policy led to a marginally significant 0.1 p.p. (2.8%, SE: 0.04) decrease in one-year mortality, possibly because of decreased wait times and increased access to certain specialty care. Given our estimates, the benefit of access expansion significantly outweighs the increased costs.

Keywords: veterans, healthcare access, public health care, public policy, regression discontinuity

JEL Code: H1, I1

*Hiroki Saruya (corresponding author) and Diana Zhu: Department of Economics, Yale University (email: `hiroki.saruya@yale.edu` and `diana.zhu@yale.edu`). Todd Wagner: Department of Veterans Affairs and Stanford University (email: `twagner@stanford.edu`). We are grateful to Jason Abaluck, Joseph Altonji, Susan Athey, Costas Meghir and Christopher Ruser for immense support and guidance. We also thank Anna Aizer, Orazio Attanasio, Steven Berry, Zack Cooper, Paul Goldsmith-Pinkham, Philip Haile, Nathaniel Hendren, John Eric Humphries, Simon Jäger, Cormac O'Dea, Katja Seim and participants at Yale IO and Labor seminars for helpful comments. Any errors are our own. Declarations of interest: none.

1 Introduction

Many countries deliver health care in a mixed public and private care model. Public health insurance systems, such as those under the Veterans Health Administration in the US and National Health Services in many countries, often feature restricted coverage of private care. Granting publicly insured patients coverage of private care might benefit those patients by reducing wait times and increasing access to care not adequately provided by public providers. Alternatively, it might result in more fragmented care and make it harder for the public insurance system to control costs. These effects are hard to identify due to patient selection: patients that have health coverage for both public and private care are often systematically different from those that stay within the narrow-network public insurance. A simple comparison between the outcomes of these two types of patients would yield biased results.

We study the impact of granting access to private care in the Veterans Health Administration (VHA), the largest integrated healthcare system in the US. The VHA provides health care at its own medical facilities and purchases care at private medical facilities for eligible veterans. We investigate whether allowing patients access to private care in lieu of the public care improves care access and health outcomes, leveraging the Choice, Accountability, and Transparency Act of 2014 (the Choice Act). Under the Choice Act, the "40-mile rule" grants patients living over 40 miles from the closest VA facility access to private care. This creates a discontinuity, where patients living just above this threshold gain access to private care while otherwise similar patients just below this threshold do not under this rule.[1] Notably, discontinuity arises from an arbitrary threshold based on distance rather than municipality boundaries, at which various factors affecting healthcare utilization and outcomes may change. We study patients whose drive distance from the closest VA

[1]Patients can gain private care coverage via the VHA under several eligibility criteria including expected wait times, geographical isolation, unavailable service at VA and so on. The focus of this paper is on the 40-mile rule since distance eligibility is directly observable to the researchers, unlike eligibility by other criteria. Specifically, we are able to observe a patient's distance to the closest VA, which determines her eligibility. By contrast, patients' eligibility under the wait time criteria is determined by the expected wait time at the point of time when the service is requested, which is not available to the researchers. Therefore, in this article, "eligibility" refers to eligibility for private care under the 40-mile rule, rather than general access to private care.

medical facility is between 30 and 50 miles in the years from 2015 to 2018. We show evidence that patient characteristics are continuously distributed around the eligibility threshold.

We find some evidence that gaining access to private care under the 40-mile rule increases outpatient care utilization, improves timely access to care, and reduces one-year mortality. Measuring outpatient utilization using Relative-Value-Unit (RVU) weighted spending, we find that gaining eligibility increases private outpatient consumption by $53 (SE: 5) and decreases VA outpatient care by $20 (SE: 7), leading to an overall net increase of outpatient care of $34 (SE: 10). On the other hand, gaining eligibility does not have a significant impact on inpatient care (a 1.8% increase in private inpatient spending with a SE of 1.7 and a 4.3% decrease in VA inpatient spending with a SE of 4.3). Our estimates also suggest that 40-mile rule potentially reduced one-year mortality by 0.10 p.p. (SE: 0.04), a 2.8% reduction from a baseline mortality rate of 3.6%. It also reduces the average wait times per visit by 5.8 hours (SE: 1.3), a 1.8% reduction from a baseline of 13 days.

Our results show that gaining access to private care especially benefits patients that typically experience challenges in care access and those with higher clinical needs. Racial minorities, patients with above-median predicted one-year mortality risk, patients with COPD, and those over age 65 experience a 0.19 p.p. (SE: 0.1), 0.15 p.p. (SE: 0.08), 0.20 p.p. (SE: 0.11) and 0.13 p.p. (SE: 0.07) decrease in one-year mortality, respectively. Diabetic patients with complications, COPD patients, rural and patients with above-median predicted one-year mortality risk experience a decrease of 2.8%, 2.3%, 2.2% and 2.0% in wait times, respectively.

Patterns of care utilization around the discontinuity are suggestive about the underlying mechanisms. In addition to reducing wait times, private care eligibility increases access to some types of services. Private facilities appear to specialize in procedure-heavy care such as surgery and radiology related services, which some worry may be less efficiently provided at VA due to staffing capacity and infrastructure constraints, while VA's Health IT and integrated care allows it to provide high-quality essential services (e.g., Chan et al. (2022), Jha et al. (2003)). The majority of private care received by high utilizers is surgical procedures, while the majority of their VA care is medicine, evaluation, and management related services.

Gaining eligibility at the discontinuity further increases consumption of surgery and radiology-related services, as well as essential services under the internal medicine category which may be inaccessible for patients far away from the VA.

Based on our estimates of cost and mortality effects, the 40-mile rule was a highly cost-effective expansion of healthcare access. With a value of a statistical life of $100,000 per year, the estimated 0.1 p.p. reduction in mortality from gaining eligibility to private care corresponds to a $100 value per patient-year, while the total annual cost to the VA only increases by $16.[2] Our counterfactual simulations also suggest that further expanding the eligibility criteria can save more lives cost-effectively. For example, our estimates suggest that compared to the 40-mile rule, allowing patients that live above 20 miles from the closest VA to access private care can further prevent 1,533 deaths and the finding of the large number of lives saved is robust to allowing the treatment effects to vary with patient observable characteristics such as risk profile and the differential distance between the closest VA and private facility.

This article relates to the literature on the public and private provision of health care and other services. The interactions and relative performances of public and private healthcare providers have been studied in the context of the VHA (O'Hanlon et al., 2017; Chan et al., 2022), the US Military Health System (Frakes et al., 2020), Swedish ambulances (Knutsson and Tyrefors, 2022), and the English National Health Service (Cooper et al., 2018; Moscelli et al., 2021). The small number of studies which adopt credible identification strategies yield mixed results on whether private firms perform better than public firms, depending on the contexts and outcomes they consider. Moreover, whereas most such studies compare the quality of public care with private care, few studies address the question of whether *complementing* public care with private care leads to better outcomes. Our results suggest that granting less restricted access to providers can lead to better health outcomes by reducing wait times and providing types of care which may be undersupplied in the VHA system. This finding is important not just for healthcare policies for the U.S. veterans, but general public healthcare systems across the world,

[2]Total cost takes into account VA's internal operating cost for each encounter and the actual amount paid to private facilities.

which typically feature narrow-network public health insurance.[3] Our article is most closely related to the article by Rose et al. (2021) that studies the impact of Choice Act on care utilization and mortality using a regression discontinuity design. Our articles differ in the following aspects. (1) The two articles study different outcome measures. In terms of care utilization, Rose et al. (2021) investigates the impact of the 40-mile rule on the number of visits whereas we measure costs, intensity-weighted procedure volume and wait times. The cost measure allows us to conduct cost-benefit analysis, and wait times are considered a key dimension in which the Choice program, and broader networks more generally, improves healthcare access and outcomes. (2) Rose et al. (2021) compare patients living between 40-60 miles from the closest VA facility to those living between 20-40 miles, and find no evidence for a mortality effect of relaxing private-care access. However, this is not inconsistent with our estimate of a statistically significant mortality reduction effect. This is because our sample is confined to patients living within a narrower bandwidth of 30-50 miles from the closest VA facility, who are considered relatively homogeneous in unobserved health risks. As Figures 2b and 4 below show, patient observable characteristics differ as distance from the closest VA increases. If we adopt too wide of a bandwidth, we may be comparing patients of systematically different health profiles, which could bias the estimate of the mortality reduction towards zero. In Appendix C, we test sensitivity of our results with respect to the choice of bandwidth and find that the point estimate is stable below a bandwidth of 14 miles and shrinks gradually as bandwidth goes above 14 miles. Although the estimates of mortality effect are imprecise at much smaller or larger bandwidths relative to ours, we speculate that the former could be due to insufficient power and the latter could be due to the attenuation bias discussed above.

Researchers have also investigated performances and behaviors of private insur-

[3] One caveat about the generalizability of our results is that VHA is a highly unique healthcare system in terms of organization and financing. However, we note that VA facilities are present in every major market in the US. On the demand side, although our study focuses on a small fraction of veterans who live close to the Choice Act's eligibility threshold, veterans comprise a large fraction of the US population and most of them suffer from the same ailments as non-veterans, including hypertension, diabetes, and heart disease.

ance plans in the context of Medicare Advantage,[4] Medicare Part D,[5], and Medicaid[6]. These studies often find that private plans contain healthcare consumption by narrow provider networks or formularies. Outside of health care, private entities are playing an increasingly important role in providing education (Epple et al., 2016, 2017) and many other services (see Andersson et al. (2019) for a review of the literature on the outsourcing of public services.).

The remainder of this article proceeds as follows. Section 2 documents the institutional background. Section 3 describes our empirical design and data. Section 4 presents our main findings. Section 5 investigates the mechanisms through which access to private care improves outcomes. Section 6 presents our counterfactual exercise to expand the eligibility criteria of the existing 40-mile rule and conduct cost-benefit analyses. Section 7 concludes.

2 Institutional Background

The Veterans Health Administration (VHA) is one of the largest, vertically integrated healthcare systems in the United States and serves 9 million veterans nationally each year with its 171 medical centers and 1,283 outpatient sites. The VHA serves its patients through care at their own facilities (VA facilities) as well as purchased private care.

The VHA has historically purchased private care. The VA Fee Basis medical program, which dates back to 1957, allows veterans to access private care on an individual authorization basis for geographic inaccessibility reasons or services unavailable at the VA (Rosen et al., 2018).[7] The VHA purchases care from a relatively

[4] See Duggan et al. (2018) and Curto et al. (2019) on healthcare utilization of public and private plan enrollees, Brown et al. (2014) on risk selection, and Geruso and Layton (2020) on upcoding by private firms.

[5] See Duggan and Scott Morton (2010) on cost containment by private insurers, Carey (2017) and Lavetti and Simon (2018) on risk selection, and Decarolis (2015) on private insurers' gaming of the subsidy design.

[6] See Cutler and Gruber (1996), Card and Shore-Sheppard (2004) and Gruber and Simon (2008) on crowd-out of private insurance, Duggan (2004) on earlier work on Medicaid managed care plans and Layton et al. (2019) and Duggan et al. (2021) on more recent investigation on private Medicaid.

[7] The veterans can also have supplemental insurance coverage (e.g., Medicare, Medicaid and private insurance) for private care.

small network of providers who are willing to accept VHA payments through a fee-for-service arrangement.

In August 2014, the Veterans Access, Choice and Accountability Act (“Choice Act") was passed in direct response to an “access crisis" involving long wait times and delays in outpatient care (Shulkin, 2017). The Veterans Choice Program (“Choice") expanded the eligibility criteria for private care coverage. Eligibility criteria are as follows (Panangala et al., 2015): (1) VA expected wait times exceeding 30 days for an outpatient appointment;[8] (2) patient living more than 40 miles from the nearest VA medical facility with a full-time primary care physician (henceforth, “the 40-mile rule"); (3) patient living in a state without a full-service VA medical facility, or (4) patient experiencing hardship in receiving care at the VA. On June 6, 2018, the Maintaining Internal Systems and Strengthening Integrated Outside Networks (MISSION) Act was enacted to replace and expand the Choice Act, allowing more VHA patients to access private care by relaxing the wait times and drive time criteria.

Under the Choice Act, eligible veterans may choose to receive care from VA providers or a participating community care provider (henceforth private provider), including hospitals and physicians that participate in the Medicare or Medicaid program. Eligible veterans can switch between a VA provider and a private provider at any time, though care delivery via a private provider under the Choice program requires a prior authorization by the VA. Consults and referrals can be initiated by either a veteran's request (via his/her local VA provider or staff) or a VA physician's request based on the veteran's clinical need. Veterans can generally receive private care at the same out-of-pocket costs as the VHA out-of-pocket costs, which are typically lower than the out-of-pocket costs under Medicare.

To participate in the Choice program, an interested provider must contact a third-party administrator and become a qualified community care provider. To qual-

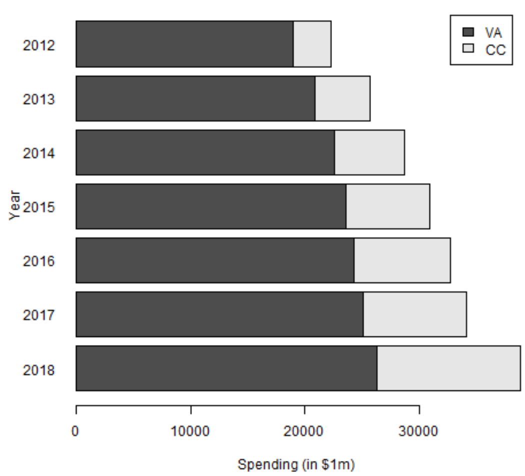
[8]More specifically, veterans become eligible under the wait-time criterion if they are informed by a local VA medical center that an appoint cannot be scheduled “within 30 days of the clinically determined date of when the veteranâs provider determines that he or she needs to be seen" or “within 30 days of the date of when the veteran wishes to be seen" (Panangala, 2018). We do not use this eligibility criterion for our analysis, because the wait times used to determine eligibility are expected wait times rather than realized ones (only the latter of which we observe).

ify, providers must accept Medicare or Medicaid rates, as well as they must have required licenses.

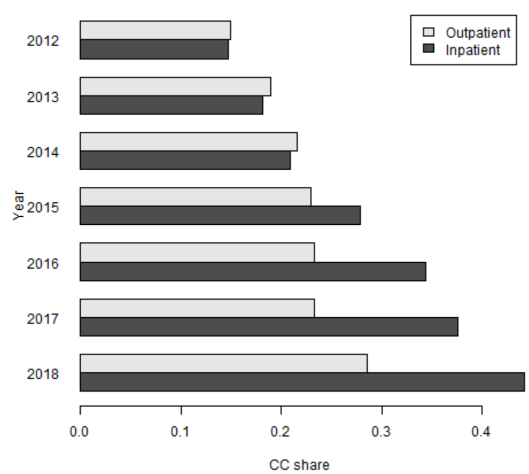
Both VA's total expenditure and the share of its private expenditure have continuously grown over time, as shown in Figure 1. This has provoked debates about whether the expanded private options are cost effective. With the increased budget that goes toward private care, understanding whether and how to complement VA with private care is crucial for the VHA.

Figure 1: Aggregate Spending

(a) Total Spending



(b) Private Spending Share



Note: Figure 1a plots total utilization by year. Figure 1b shows the fraction of private care utilization among total expenditure in each year. The outpatient spending is computed by weighting the CPT procedures by Relative Value Units and multiplying by a conversion factor ($35.9) per Medicare rule. The inpatient spending is computed by multiplying the diagnosis-related group (DRG) code associated with an inpatient visit with a hypothetical hospital rate of $6,000.

3 Empirical Design and Data

3.1 Empirical Design

Estimating the effect of expanding coverage for private care is inherently challenging because patients who are given private care coverage can be systematically different from those who are without it. If unobservably sicker patients are more likely to have coverage for private care, comparing the outcomes of patients who have such coverage and those who do not would lead to biased conclusions.

The 40-mile rule generates a natural regression discontinuity (RD) design to study the causal effect of private care coverage. By comparing otherwise similar patients right around the eligibility threshold who do or do not gain access to private care by the 40-mile rule, we can isolate the effect of gaining access to private care. Our RD design based on distance has an advantage over RD based on municipality boundaries, because various factors affecting healthcare utilization and outcomes may change at municipality boundaries.

One potential concern with our design is that patients may strategically move above the cutoff to gain eligibility for private care.[9] We show below that baseline patient characteristics are continuously distributed around the threshold.

Our main “local linear" regression model is the following:[10]

$$Y_{it} = \alpha + \beta_1 Z_{it} + \beta_2 D_{it} + \beta_3 Z_{it} \cdot D_{it} + \beta_4 X_{it} + \delta_c + \delta_t + \varepsilon_{it} \tag{1}$$

where Y_{it} represents patient i's outcome at time t such as care utilization, realized wait times or one-year mortality, Z_{it} is the eligibility indicator such that $Z_{it} = 1$ if patient i lives at least 40 miles away from the closest VA facility at time t and $Z_{it} = 0$

[9]Note, however, that if sicker patients are more likely to move into eligibility, then the effect on care utilization will be overestimated and the effect on survival is underestimated, which implies that the Choice program was even more effective than our estimates suggest.

[10]We prefer the local linear regression to global polynomial regression, because the latter is more heavily influenced by observations far away from the threshold and more likely to yield biased estimates (see also Appendix C). To ensure enough statistical power with our local approach, we pool post-policy observations from different years. Similarly, for placebo tests discussed in Section 4.2.2, we pool pre-policy observations from different years to ensure that failure to find significant effects is not due to insufficient power.

otherwise, and D_{it} denotes the distance between patient i's residence and her closest VA facility at time t. We normalize the distance so that the eligibility threshold is zero, i.e., transform the raw distance $\tilde{D}_{it}$ by $D_{it} = \tilde{D}_{it} - 40$. X_{it} is a vector of rich baseline patient characteristics prior to the start date of each episode. These characteristics include age, female indicator, racial minority indicator, history of MI, history of heart failure, history of Atrial fibrillation, history of valvular diseases, history of peripheral vascular disease, history of COPD, history of depression, history of PTSD, 31 Elixhauser comorbidities, and the rurality level of the patient's residence. δ_c and δ_t denote the county and year fixed effects, respectively. To relate this regression to the Average Treatment Effect (ATE) of eligibility, let $Y(1)$ and $Y(0)$ denote the outcome with and without treatment (satisfying the eligibility), respectively, and similarly denote treated and untreated covariates by $X(1)$ and $X(0)$, respectively. Let d denote the running variable. Key assumptions for consistently estimating the ATE include the following:

Assumption 1. *$E[Y(1) \mid D_{it} = d]$ and $E[Y(0) \mid D_{it} = d]$ are continuous at $d = 0$.*

Assumption 2. *$E[X(1) \mid D_{it} = d]$ and $E[X(0) \mid D_{it} = d]$ are continuous at $d = 0$.*

Assumption 1 says that patients' expected outcome conditional on each treatment is continuous at the threshold, whereas Assumption 2 states that the expected covariates conditional on each treatment are continuous at the threshold. With additional regularity assumptions, the estimate of β_1 converges in probability to the ATE of gaining access to private care under the 40-mile rule (Calonico et al., 2019).

In Section 4.2, we test for the continuity of covariates X_{it} by estimating Eq. (1) with each covariate as an outcome while excluding X_{it} from the right-hand side to test for Assumption 2 and build support for Assumption 1. Moreover, in Appendix A.2, we conduct placebo tests using pre-policy data to further build support that our results are not driven by discontinuity in unobservable patient characteristics.

As robustness checks, we also perform the regression analyses with different kernels and bandwidths, and conduct robust inference that accounts for the discrete nature of our running variable.

3.2 Data and Sample

We combine five different data sources to construct the final analysis sample:

VA electronic health record data VA health record data offer detailed information for all outpatient and inpatient care provided at VA facilities across the nation, including dates of the service and the Current Procedural Terminology (CPT), International Classification of Diseases (ICD), and Diagnosis-related Group (DRG) codes associated with each visit.

Private care claims data that are submitted to the VA system For private care, we use the claims data that are approved by the VHA for reimbursement from FEE Basis Data (FEE) and Program Integration Tool system (PIT). Prior to FY2015, FEE Basis Data was the primary source of VHA Community Care data. In 2013, the VHA introduced the Non-VA Care Program Integrity Tools (PIT) system that are comprised of multiple community care claims data sources. In our study period of interest (2015-2018), both data sources are in use for documenting VHA patients' community care utilization.

Patient residential information data A patient's location information is taken from the Planning Systems Support Group (PSSG), which is updated quarterly with information from the US Postal Service National Change of Address file. This file uses geo-coding to estimate travel distances and travel times to the nearest VA facility that provides primary care. A patient's discrete drive distance to the closest primary care facility from this file is used to determine eligibility under the 40-mile rule in this article and serve as our running variable.

Patient demographics Patient demographics including race, birth date, and death date are taken from the Observational Medical Outcomes Partnership (OMOP) files.

Consultation Scheduling Data The VHA Corporate Data Warehouse (CDW) contains a record for every referral to primary or specialty care, regardless of whether patients are seen at a VA facility or a private medical center. We measure the number of days between the date when a visit is requested and the date when a visit is completed as a patient's wait times for that visit. See Feyman et al. (2021) for a more detailed description of the data.

Sample Construction To construct our main study sample, we first take all patients that visited a VA or private care facility during 2015/1/1 - 2018/12/31. The choice of the study period is motivated by the rollout details of the Choice and MISSION Acts. Although the Choice Act was passed on August 7 of 2014, the first round of implementation was supposed to be done by the 90th day of the enactment, which is November 5 of 2014. On June 6 of 2019, the U.S. Department of Veterans Affairs (VA) launched its new and improved Veterans Community Care Program, the MISSION Act, that replaces the Choice Act. Therefore, we restrict our study period to the years between 2015 and 2018, which covers most of the period in which the Choice Program was in effect and in which patients are unlikely to change their care-seeking behavior in response to the MISSION Act.

Our final sample is at the patient-year level.[11] Each patient-year is a 365-day period that starts from patient-specific initial start date. The initial start date is identified by the first date in which the patient visited a VA or private facility using VA's coverage during the sample period. The sample includes all patient-years that begin after January 2015 and end before the end of 2018.

Given the potential differences in patient population as we increase the distance bandwidth, we focus on patient-years that live between 30 to 50 miles away from the closest VA facility in the year.[12] Although this restriction makes our RD estimates more credible, it comes at a cost that only a small subset of observations are used for our regressions.

We extract a rich set of patient disease histories from VA electronic health records and private care claims data including various forms of cardiovascular diseases, mental illnesses, and Elixhauser comorbidities. We link a patient's residential

[11] We will refer to patient-years simply as patients unless it causes a major confusion.

[12] In robustness checks, we also explore how the effect estimates change as we vary the bandwidth of the distance from the closest VA.

zip code to Rural-Urban Communiting Area Codes available from the Department of Agriculture in order to obtain the rurality level.

In terms of care utilization, we construct the outpatient expenditures at both VA and private facilities by weighting CPT codes according to Medicare Relative Value Units (RVUs) and then multiplying it by the 2017 Medicare conversion factor of $35.89/unit. Inpatient costs are computed by multiplying the DRG weights of each inpatient visit by the hospital rate, which we assume to be $6,000.

Care utilization expenditures hold constant the "price" of an outpatient procedure or inpatient stay at VA and private facilities (hence a comparative measure of care quantity). We additionally measure costs to the VA that is composed of VA's internal cost measure and the amounts paid for private care under the fee-for-service arrangements. The former is constructed based on RVU-weighted CPT codes for outpatient care and DRG weights for inpatient visits and then scaled to match the funding allocated to each VA facility (Chan et al., 2022; Wagner et al., 2003; Phibbs et al., 2014).

4 Main Results

4.1 Descriptive Statistics

We begin by showing how patient characteristics vary as distance from the closest VA facility increases in Figures 2a and 2b. VA facilities are generally located in urbanized areas[13]. Patients farther away from the VA facilities are older and live in more rural areas. An average patient at the 40-mile cutoff is a 65.8 year-old residing in an area with a rurality score of 5 out of 10.[14] As shown in Figure 2c, 80.4% of patients reside within 30 miles from the closest VA, 12.1% between 30 and 50 miles and 3.6% above 50 miles.

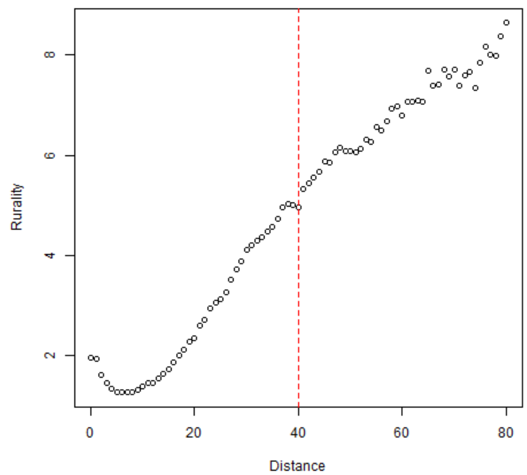
Column (1) of Table 1 presents the summary statistics of our sample for patients that live between 30 and 50 miles. The one-year mortality in our sample is 3.6%.

[13]Urbanized areas here are defined by the Rural Urban Commuting Area codes below 2 on a scale of 10, where 1 is the most urbanized.

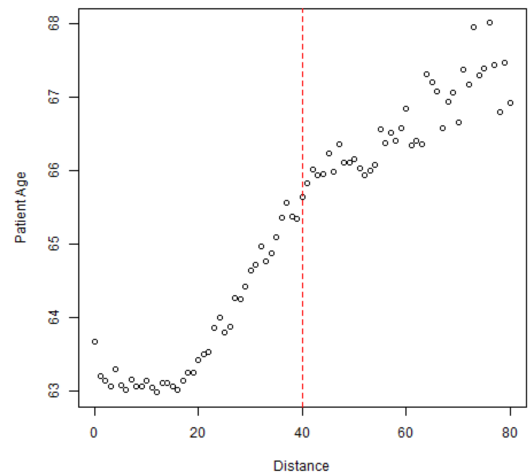
[14]A rurality score of 5 corresponds to cities or towns of from 2,500 through 49,999 populations. Example locations are Barnstead, New Hampshire and Cayuga County, New York.

Figure 2: Patient Characteristics by Distance

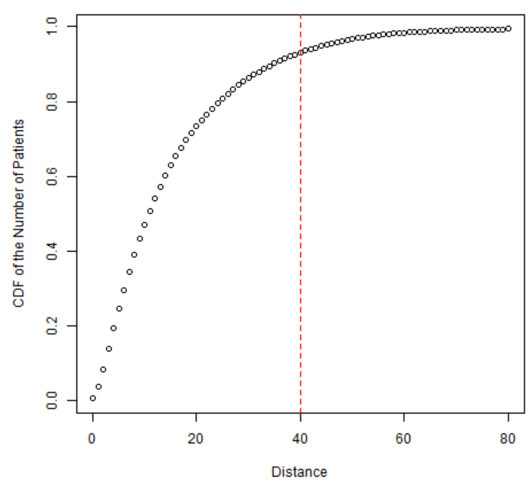
(a) Average Rurality



(b) Average Age



(c) CDF of the Number of Patients

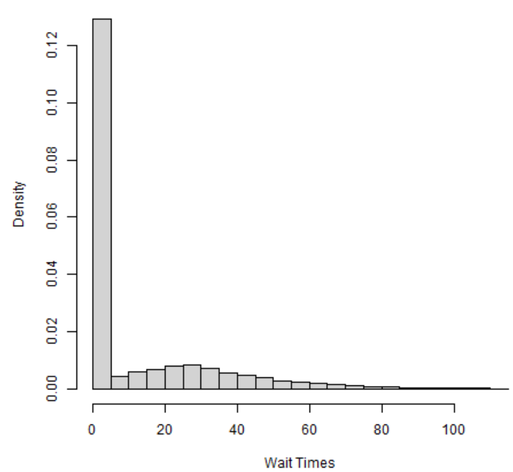


Note: Figure 2 plots patient characteristics by distance to the closest VA in 2015. Figure 2a plots the average rurality level for patients living at each mile to the closest VA, where rurality level is computed by associating each patient's residential zipcode with the rurality level from Rural-Urban Commuting Area codes from a scale of 1 to 10. Figure 2b plots patients' average age at each mile. Figure 2c plots the cumulative distribution function of the number of patients at each mile. The red line indicates the 40-mile eligibility threshold.

The average age in our sample is 63.8 years old, 19% are racial minorities, 32% have a history of cardiovascular diseases and 38% have mental illnesses. Columns (2) and (3) of Table 1 show the average characteristics among patients who visit a private facility and those who always utilize VA care in a given year, respectively. On average, patients that use private care are sicker. Their likelihood of having a history of cardiovascular diseases and mental illnesses are 1.3 and 1.4 times higher than those who always use VA care, respectively. To compare overall health risks of patients, we compute predicted one-year mortality based on patient's baseline characteristics (see below for details). Patients that ever visit a private facility has 1.3 times higher likelihood of one-year mortality than those who stay in the VA.

Figure 3 shows the histogram of average wait times per visit for each patient in a given year. Although more than 60% of patients face almost no wait times in a given year, others wait substantially longer: over 20% of patients wait more than 30 days on average.

Figure 3: Distribution of Wait Times (days)



Note : Figure 3 plots the distribution of average realized wait times per visit in a given year for patients in our main sample (patients living between 30 and 50 miles from the closest VA) in days.

Table 2 documents the distribution of outpatient and inpatient care utilization at

Table 1: Summary Statistics

	All	Ever Visited Private Facility	Always Visited VA Facility
	(1)	(2)	(3)
Age	63.8	63.3	65.1
	(16)	(14.7)	(15.4)
Non-White	19.3	18.1	17.9
	(39.5)	(38.5)	(38.4)
Female	6	8.9	4.5
	(23.7)	(28.5)	(20.8)
Rurality	4.9	5.1	4.9
	(3.1)	(3.1)	(3.1)
Cardiovascular Disease	32.2	40.7	32.3
	(46.7)	(49.1)	(46.8)
Mental Health Disease	38.2	51	35.7
	(48.6)	(50)	(47.9)
Eligibility	35.2	39.1	33.7
	(47.7)	(48.8)	(47.3)
Pred. 1-Year Mortality	3.6	3.8	3
	(4.9)	(5.4)	(4.3)
1-Year Mortality	3.6	4	2.6
	(18.7)	(19.6)	(15.9)
N. obs.	2930764	787929	1705175

Note: This table reports the means and standard deviations of the characteristics of the patient-year observations in our sample. Column 1 shows the characteristics among all patients. Column 2 shows the characteristics of patients who ever visit a private facility in a given year. Column 3 presents the mean among all patients who only visit VA facility in a given year. The row “Pred. 1-Year Mortality" row shows the average predicted one-year mortality obtained from a linear regression of one-year mortality on patient age, female indicator, nonwhite indicator, age above 65 indicator, history of various cardiovascular diseases and mental illnesses, the 31 Elixhauser Comorbidities, and county and year fixed effects.

VA and private facilities, respectively, after winsorizing the top 1% of spending in each category. The average total VA outpatient utilization is $2,496, private outpatient utilization is $551 and VA outpatient utilization is $1,945. The average total inpatient utilization is $351, private inpatient utilization is $54 and VA inpatient utilization is $297. Similarly, Table B.1 documents the distribution of outpatient and inpatient costs to the VA. The average total outpatient cost is $4,255, private outpatient cost is $610 and VA outpatient cost is $3,644. The average total inpatient cost is $819, private inpatient cost is $166 and VA inpatient cost is $653.

Table 2: Spending Distribution

	Mean	S.D.	Q(0)	Q(0.25)	Q(0.5)	Q(0.75)	Q(0.95)	Q(1)	N. obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VA Inpatient Spending	296.5	1577.8	0	0	0	0	0	15792.6	2801482
Private Inpatient Spending	54.1	608.7	0	0	0	0	0	10510.2	2801482
Total Inpatient Spending	350.6	1735.6	0	0	0	0	0	25828.2	2801482
VA Outpatient Spending	1944.8	2677.2	0	238.3	828	2627.5	7758	16364.8	2801482
Private Outpatient Spending	551	1681.4	0	0	0	0	3753.4	14610.1	2801482
Total Outpatient Spending	2495.8	3487.7	0	238.3	1003.5	3395.6	10097.7	30806.2	2801482

Note: This table presents the distribution of inpatient and outpatient utilization (in $) at VA and private facilities. It includes all care paid by the VHA, including both Choice-related and other claims. We separate inpatient and outpatient data using Healthcare Cost and Utilization Project's Clinical Classification Software. $Q(\tau)$ represents the τ-th quantile of each expenditure. We winsorize each category of spending at 99 percentile. The sample in this table include all patients with no missing expenditure in any of the above categories.

Table 3: VA and Private Care Utilization Patterns

(a) Ever Visited VA and/or Private Care

	Never visited Private	Ever visited Private
Never visited VA	15.0	0.8
Ever visited VA	58.2	26.1

(b) Fraction of Private Care Visits

	Mean	S.D.	Q(0)	Q(0.25)	Q(0.5)	Q(0.75)	Q(0.95)	Q(1)	N. obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fraction of Private Visits	35.8	28.9	0.3	11.1	26.1	55	94.7	100	788528

Note: This table presents the patterns of private and VA facility visits. It includes all visits for care paid by the VHA, including both Choice-related and other claims. Panel (a) shows the fraction of patient-years that ever visit a VA and/or private facility in a given year. Panel (b) shows the distribution of the fraction of visits to private facilities among the total number of visits in a given year, among patients that ever visit a private facility.

Tables 3a and 3b document the VA and private care utilization patterns. Conditioning on having any medical visit in a given year, almost all patients utilize VA care and 26% of them additionally use private care. Among those that visit a private facility at least once in a given year, their private care visits constitute 26% of their total visits for the median patient.

4.2 Continuity

4.2.1 Continuity in Patient Baseline Characteristics

We begin our analyses by empirically assessing the plausibility of Assumptions 1 and 2 by testing whether patient baseline characteristics that are correlated with mortality are continuous at the cutoff. Specifically, we conduct the following regression, similar to Eq. (1):

$$f(X_{it}) = \gamma_0 + \gamma_1 Z_{it} + \gamma_2 D_{it} + \gamma_3 Z_{it} \cdot D_{it} + \delta_c + \delta_t + \varepsilon_{it} \tag{2}$$

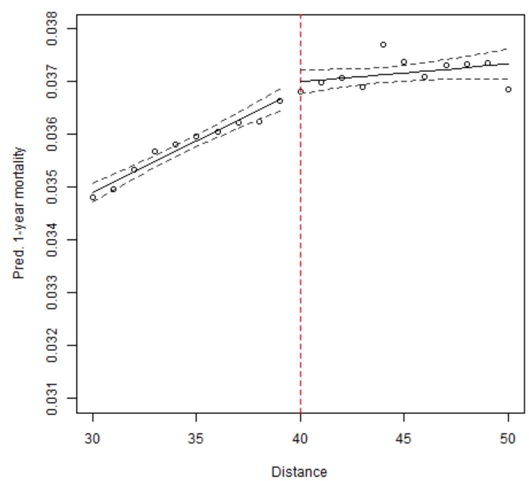
where $f(X_{it})$ is a function of the covariate vector X_{it}. Specifically, we compute a patient's predicted mortality $\hat{Y}_{it}$ by running a linear regression of one-year mortality on patient characteristics mentioned above (with R-squared of 0.06) and then conduct the regression (2) with $\hat{Y}_{it}$ as a dependent variable. $\hat{\gamma}_1$ captures the jump of predicted mortality at the 40-mile cutoff. We find an insignificant estimate of 0.02 p.p (SE: 0.02). Figure 4 plots the mean of predicted mortality at each distance value. Mirroring the regression result, it shows that there is no evidence of discontinuity at the 40-mile cutoff. Additionally, we repeat the exercise for 38 patient characteristics and report the estimates of γ_1 in Appendix A.1. Among the 38 covariates, only 5 have statistically significant estimates and are small in magnitude.[15]

4.2.2 Placebo Check with Pre-Choice Period Data

We additionally conduct a placebo test to assess Assumption 1 with data from the pre-Choice era. Specifically, we implement regression (1) for the outcomes of interest using a sample composed of patients that live between 30 and 50 miles from

[15] The discontinuity of some covariates does not affect identification, as we control for them.

Figure 4: Predicted 1-Year Mortality



Note: Figure 4 plots the average one-year predicted mortality by distance conditioning on county and year fixed effects. The predicted mortality is computed by regressing one-year mortality on age, female indicator, nonwhite indicator, histories of cardiovascular diseases, mental illnesses, COPD, and 31 Exlihauser Comorbidities.

the closest VA between 2009 to 2012. Table A.1 reports the estimates of β_1 for private, VA and total outpatient and inpatient utilization, as well as wait times and one-year mortality. All the estimates other than that of private outpatient utilization are small and statistically insignificant. Private outpatient care exhibits a jump of \$4.8 (SE: 1.9) at the threshold. As we will show below, this is 10 times smaller than the jump in private outpatient care in the post-Choice period. This discontinuity is likely caused by the increasing trend in private care as a patient's distance to the closest VA increases, which makes VA care increasingly inaccessible.

4.3 Effects on Care Utilization and Cost

We now study the impact of the 40-mile rule on inpatient and outpatient care utilization at VA and private medical facilities. Table 4 presents $\hat{\beta}_1$ from the local linear regressions as specified in Eq. (1). We also present graphical evidence of the RD analyses in Figure 5.

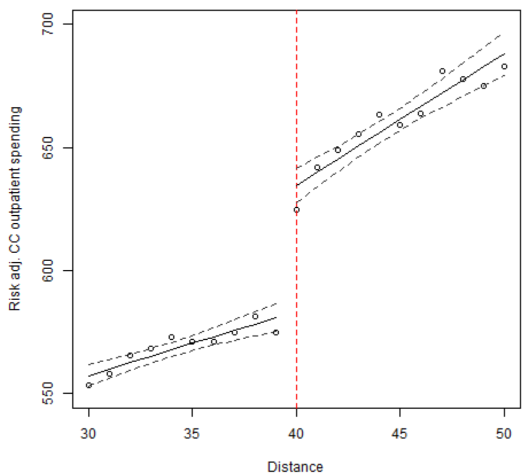
Private Outpatient Utilization Figure 5a shows that spending on private outpatient care mildly increases as distance from the closest VA increases, as patients are more likely to live in geographically isolated areas and thus qualify for private care under other eligibility criteria. At the 40-mile cutoff, there is a discrete upward jump. Above the 40-mile threshold, outpatient spending at private facilities increases much more aggressively with distance compared to below the cutoff. As documented in Column (1) of Table 4a, the estimated effect of eligibility is \$53.1 (SE: 4.9), which is 8.9% of the average private outpatient care.

VA Outpatient Utilization Patients receive less VA care as distance from VA increases, as shown in Figure 5b. At the 40-mile cutoff, there is a jump downwards. Above the cutoff, the decreasing trend of VA outpatient utilization becomes more aggressive. The estimated effect is \$20.0 (SE: 7.3) (a 1.0% reduction from the baseline utilization of \$2,592), as Column (2) of Table 4a shows.

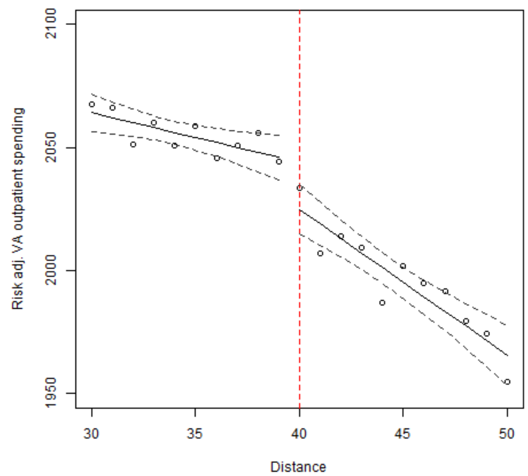
Total Outpatient Utilization Figure 5c shows that total outpatient utilization does not significantly change as distance increases. At the 40-mile cutoff, how-

Figure 5: RD Plots

(a) Private Outpatient Spending



(b) VA Outpatient Spending



(c) Total Outpatient Spending

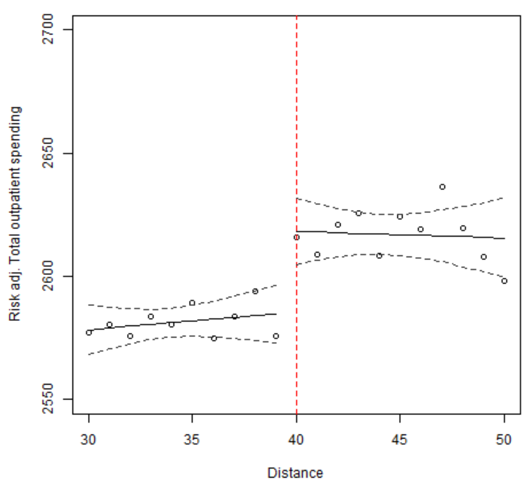
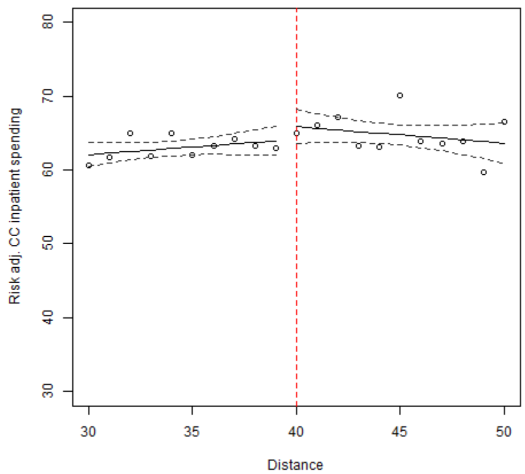
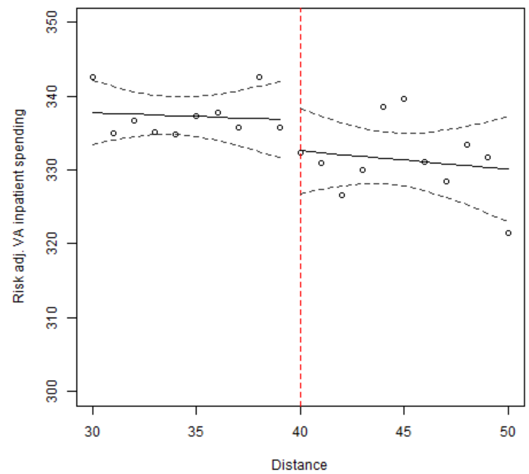


Figure 5: RD Plots (Continued)

(d) Private Inpatient Spending



(e) VA Inpatient Spending



(f) Total Inpatient Spending

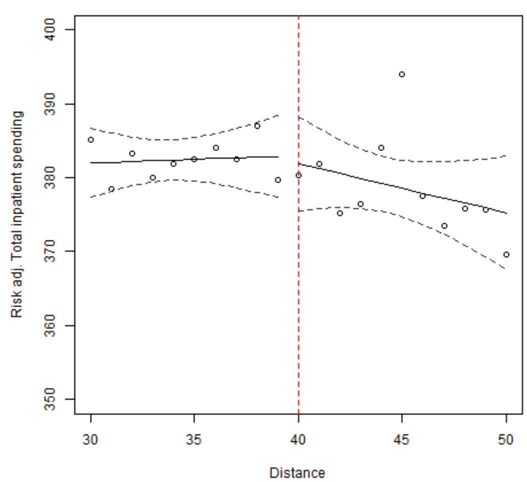
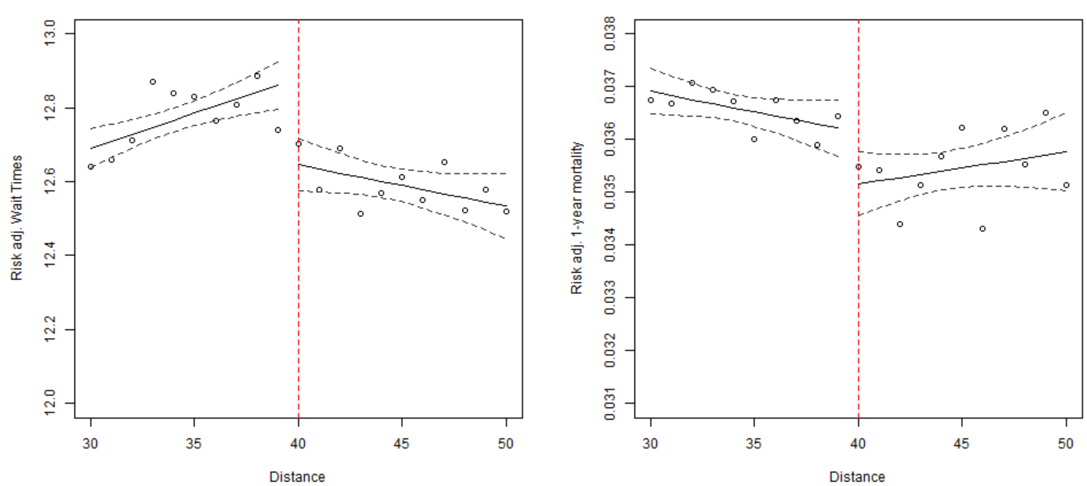


Figure 5: RD Plots (Continued)

(g) Wait Times

(h) 1-Year Mortality



Note: Figure 5 plots the average risk-adjusted outcomes by each mile. The patient characteristics used in the risk adjustment are the same as the controls in Eq. (1). The red line indicates the 40-mile eligibility threshold. Standard errors are clustered at the patient level.

Table 4: Local Linear Regressions

(a) Outpatient Spending

	Private Outpatient Spending (1)	VA Outpatient Spending (2)	Total Outpatient Spending (3)
Eligibility	53.1	-20	33.8
	(4.9)	(7.3)	(9.5)
Mean	599	2035	2592
N. obs.	2869826	2869825	2843031

(b) Inpatient Spending

	Private Inpatient Spending (1)	VA Inpatient Spending (2)	Total Inpatient Spending (3)
Eligibility	1.8	-4.3	-1.2
	(1.7)	(4.3)	(4.6)
Mean	64	335	381
N. obs.	2869422	2869828	2843116

(c) Wait Times and 1-Year Mortality

	Wait Times (1)	1-Year Mortality (2)
Eligibility	-5.8	-0.1
	(1.3)	(0.04)
Mean	304.6	3.6
N. obs.	2869393	2930729

Note: This table reports the estimates of the coefficient on eligibility (β_1) in Eq. (1) for inpatient and outpatient utilization, wait times and one-year mortality. Utilization is reported in dollars, wait times are reported in hours and one-year mortality is reported in percentage points. Standard errors are clustered at the patient level.

ever, it jumps up significantly. The regression estimate shows the effect is \$33.8 (SE: 9.5) (a 1.3% increase) as reported in Column 3 of Table 4a.

Inpatient Utilization Figures 5d through 5f plot the average inpatient spending by distance to VA. The 40-mile rule does not have significant impact on inpatient utilization. This is confirmed by regression results in Table 4b.

Costs to the VA The utilization measures above hold constant the price difference between VA and private facilities and purely compare the intensity-weighted utilization difference. We also analyze the impact of the 40-mile rule on the "costs" to VA that take into account VA's operating costs for care received at VA and the actual costs paid to private providers. The results for the regression discontinuity analyses are documented in Table B.2. In line with our findings for utilization, actual costs paid to private facilities increase by \$48.7 (SE: 6.0) at the 40-mile cutoff, costs to VA decrease by \$38.6 (SE: 14.4), and total outpatient costs increase by \$11.6, though the effect on total outpatient costs is not precisely estimated (SE: 16.5). Costs paid for private inpatient care also increase by \$20.5 (SE: 4.3). Costs paid for VA inpatient care decrease by 4.1 (SE: 11.2) and total inpatient costs increase by 12.6 (SE: 12), neither of which is statistically significant.

4.4 Effects on Wait Times and Mortality

Wait Times The discussion on expanding private care for VA patients was partially motivated by the long wait times at certain VA facilities (recall Figure 3). Figure 5g shows that wait times on average increase with distance below the 40-mile cutoff, and there is a decrease at the 40-mile. The estimated effect from regression (1) is 0.24 days (5.8 hours) as reported in Column (1) of Table 4c, a 1.9% reduction relative to the baseline wait times of 12.7 days.

One-Year Mortality Finally, we measure the impact of the 40-mile rule on one-year mortality. Figure 5h shows a reduction of mortality at the 40-mile cutoff. The mortality reduction is estimated to be 0.1 p.p. (SE: 0.04) as reported in Column (2) of Table 4c. This amounts to a 2.8% decrease from the baseline mortality rate of

3.6%. In our sample of on average 725,000 patients receiving care every year, this translates to saving 725 lives.

4.5 Robustness

We consider estimation with different kernels (uniform and triangular) and bandwidths (from 5 to 20, compared to the benchmark bandwidth of 10). In addition, we also conduct robust inference that accounts for the discrete nature of our running variable. Specifically, we use the bias-aware approach proposed by Armstrong and Kolesár (2018, 2020) and Kolesár and Rothe (2018) to address the potential bias in our estimates and construct confidence intervals that are valid under such bias. In Appendix C, we show that our point estimate of the mortality effect is robust to the choice of kernels and a reduction in bandwidths, though the estimates are less precise at smaller bandwidths, due likely to the lack of statistical power. The estimates are similar to our main estimate at bandwidths of 5 to 14. However, we find that estimates approach zero as the distance band further widens, which is possibly because the eligible and ineligible patients are no longer comparable under larger bandwidths: eligible patients are much older and live in much more rural places compared to ineligible people (recall Figure 2), which biases the mortality effects toward zero. The implementation details and results are reported in Appendix C.

4.6 Heterogeneous Treatment Effects

Patients with higher healthcare needs or those that typically experience access challenges may especially benefit from access to private care. We repeat the analysis in Section 4 separately for various subsets of patients that fall into these two categories and document the results in Table 5.[16]

[16]Given that we do not find overall impacts of eligibility on inpatient spending, we only report the estimates for outpatient spending, wait times and mortality for the rest of this section.

Table 5: Heterogeneous Treatment Effects

(a) Outpatient Spending

	Private Outpatient Spending (1)	VA Outpatient Spending (2)	Total Outpatient Spending (3)
Age above 65	53.3	-20.9	33
	(6.1)	(9.4)	(12.1)
Mean	555	2050	2560
N. obs.	1693747	1693889	1676986
Nonwhite	40.2	-15.8	22.1
	(10.4)	(15.9)	(20.5)
Mean	519	1864	2347
N. obs.	554347	553976	549651
Rural	57.9	-34.1	20.7
	(8.1)	(11.8)	(15.6)
Mean	656	2033	2646
N. obs.	1089502	1091336	1079873
High Mortality Risk	55.9	-19.1	36.1
	(7.2)	(10.9)	(14.2)
Mean	660	2333	2935
N. obs.	1433011	1431989	1413150
Low Mortality Risk	49.7	-23.3	28.9
	(6.3)	(9.1)	(12)
Mean	539	1739	2255
N. obs.	1436734	1437755	1429800
COPD	71.3	-16.7	54.7
	(11.2)	(16.7)	(21.8)
Mean	883	2974	3789
N. obs.	778736	777150	764301
Complicated Diabetes	66.4	-45.4	27.3
	(15.2)	(22.4)	(29.3)
Mean	935	3249	4115
N. obs.	445525	443892	436147

Table 5: Heterogeneous Treatment Effects (Continued)

(b) Wait Times and 1-Year Mortality

	Wait Times (1)	1-Year Mortality (2)
Age above 65	-6.43	-0.13
	(1.59)	(0.07)
Mean	290.98	5.5
N. obs.	1696101	1727067
Nonwhite	-2.64	-0.19
	(2.9)	(0.1)
Mean	299.4	3.7
N. obs.	552486	566275
Rural	-6.81	-0.03
	(2.02)	(0.07)
Mean	304.58	3.9
N. obs.	1090619	1112500
High Mortality Risk	-6.24	-0.15
	(1.76)	(0.08)
Mean	316.46	6.5
N. obs.	1439276	1465414
Low Mortality Risk	-5.67	-0.01
	(1.77)	(0.03)
Mean	293.16	0.7
N. obs.	1430036	1465234
COPD	-9.1	-0.2
	(2.55)	(0.11)
Mean	388.61	6
N. obs.	783845	794688
Complicated Diabetes	-11.74	0.02
	(3.42)	(0.14)
Mean	424.99	6
N. obs.	448385	454763

Note: This table presents the estimates of the coefficients on eligibility (β_1) in Eq. (1) for private, VA and total outpatient utilization expenditure, wait times and one-year mortality. The regression is separately run for each patient category. “Rural" represents patients who live in an area with a rurality index of 5 or above. “High Risk" represents patients with an above-median predicted mortality, where predicted mortality is obtained by regressing one year mortality on demographics, disease histories, county and year fixed effects. For comparison, we also present results for “Low Risk" patients, whose predicted mortality is below median. Standard errors are in parentheses. Expenditures are reported in dollars, wait times are reported in hours and one-year mortality is reported in percentage points.

Patients with Access Challenges Racial minorities and patients in rural areas have often been documented to experience challenges in care access. In our sample, racial minorities spend 9% less than a typical patient in outpatient care. Gaining eligibility to private care leads to a 7% increase in their private outpatient care utilization and a 0.19 p.p. (SE: 0.10) decrease in one-year mortality, which is a 5.1% decrease from the baseline of 3.7%. For rural patients,[17] eligibility increases private outpatient care by $57.9 (SE: 8.1) and decreases VA outpatient care by 34.1 (SE: 11.8). Their wait times decrease by 6.8 hours (SE: 2.0), a 2.2% reduction.

Patients with Complex Healthcare Needs Upon gaining eligibility, patients aged 65 or above increase their private outpatient spending by $53.3 (SE: 6.1) and decrease VA outpatient care by $20.9 (SE: 9.4), with a net increase in outpatient spending of $33 (SE: 12.1).[18] Their wait times decrease by 6.4 hours (a 2.2% decrease from the baseline) and mortality is reduced by 0.13p.p. (SE: 0.07), a 2.4% decrease from their baseline mortality rate of 5.5%. Next, patients with above-median predicted mortality[19] (labeled "High Mortality Risk" in Table 5) increases their private outpatient care by $55.9 (SE: 7.2) and decreases their VA outpatient care by 19.1 (SE: 10.9), and a net increase of outpatient care by $36.1 (SE: 14.2). Their wait times are reduced by 6.2 hours (a 2.0% decrease from their baseline). Their one-year mortality is decreased by 0.15 p.p. (SE: 0.08), a 2.3% decrease from their baseline mortality rate of 6.5%. For comparison, patients with below-median predicted mortality (labeled "Low Mortality Risk") also increases their private outpatient care by $49.7 (SE: 6.3) and decreases their VA outpatient care by $23.3 (SE: 9.1), leading to a net increase of outpatient care of 28.9 (SE: 12). Their wait times are decreased by 5.7 hours (SE: 1.8) (a 1.9% decrease) with no significant changes in their one year mortality.

Diabetic patients with complications utilize 59% more total outpatient care than an average patient in our sample. Upon gaining eligibility, their private outpatient

[17]Rual patients are defined as those reside in areas whose rurality score according to RUCA is above 5 on a scale of 10.

[18]The elderly people have Medicare coverage, so there utilization effects likely reflect VHA's lower copayments.

[19]Predicted mortality is defined in Section 4.2.1.

care increases by \$66.4 (SE: 15.2). Their VA outpatient care decreases by 45.4 (SE: 22.4). Their total outpatient care increases by 27.3 (SE: 29.3). Their wait times decrease by 11.7 hours (SE: 3.4), a 2.8% decrease from a baseline of 18 days, with no significant changes in one-year mortality. Patients with COPD also utilize 46% more outpatient care than an average patient in our sample. Upon gaining eligibility, their private outpatient care increases by \$71.3 (SE: 11.2). Their VA outpatient care decreases by 16.7 (SE: 16.7). Their total outpatient care increases by 54.7 (SE: 21.8). Their wait times decrease by 9.1 hours (SE: 2.6), a 2.3% decrease from a baseline of 16 days. Their one-year mortality decreases by 0.2 p.p. (SE: 0.1), a 3.3% reduction.

In sum, gaining access to private care increases care access, improves timely access to care and reduces mortality especially for patients with challenges in care access and those with higher healthcare needs, contributing to health equity.

5 Mechanisms

This section probes into two potential mechanisms behind the mortality reduction effect of gaining access to private care on top of VA care: (1) decreased wait times and (2) increased access to care that is hard to obtain otherwise.

5.1 Decreased Wait Times

Long wait times have been recognized as a driver for worse outcomes (e.g. Peterson et al. (2014), Pizer and Prentice (2011)). The Choice Act was enacted in part to counteract the long wait times at VA medical centers (Shulkin, 2017). Our results show that gaining access to private care under the 40-mile rule reduces wait times by 5.8 hours (SE: 1.3) per visit on average from a baseline of 13 days. This effect is especially large for patients with chronic diseases: for example, patients with renal failure wait 10.6 hours less (SE: 4.1) on average per visit upon gaining eligibility (a 2.9% reduction), and patients with COPD wait 8.9 hours less (SE: 2.6) (a 2.4% reduction). Patients who are predicted to wait longer than median based on their baseline characteristics on average wait for 16 days for their appointments. Gaining eligibility reduces their wait times by 7.4 hours (SE: 1.7) (a 1.9% reduction). More timely access to care is likely one of the contributors to the mortality reduction, though it alone is unlikely to explain a large portion of the effect.[20]

5.2 Increased Care Access

In addition to reduced wait times, complementing VA coverage with private care coverage also gives patients access to care that may be difficult to obtain otherwise either because private facilities could be better equipped to provide certain types of care or VA care is inaccessible for patients living far away.

A closer look at the impact of eligibility on care utilization suggests that some procedures are not merely substituted from VA to private care. Upon gaining eligibility to private care under the 40-mile rule, private outpatient consumption under all care categories rises, as Table 6 shows: evaluation services (a 14% increase), radiology (a 11% increase), medicine (a 9.2% increase), pathology (10% increase) and surgery (8.3% increase). Among them, surgery, radiology, and medicine services experience a net increase by 1.5%, 1.3% and 1.5% respectively. On the other hand, patients mostly replaced their VA evaluation and pathology services with private care and overall utilization under these categories did not change.

VA and private facilities have distinct advantages in providing essential services and specialized procedures. VA's health IT and integrated care have long been documented to facilitate better care coordination across providers, leading to better provision of essential services such as more appropriate diagnoses and treatment plans (e.g. Chan et al. (2022), Jha et al. (2003)).

On the other hand, compared to VA, private facilities may be more efficient in providing procedures that require special equipment. In fact, not all VA facilities have the capacity to perform surgeries and radiology services.[21] Even within these VA facilities, capacity and resource constraints often mean that these are performed less efficiently at the VA. For example, operating room staffing constraints make

[20] Since emergency care is out of the scope of the Choice program, the mortality reduction is likely driven by planned care, to which wait times are relevant.

[21] For example, the Community-Based Outpatient Clinics (CBOCs) are only able to provide primary care and mental health services. Any services that require specialized equipment is either referred to a larger VA medical center or a private facility (Liu et al., 2010).

Table 6: Spending by Procedure Types

(a) CC Spending

	Private Evaluation (1)	Private Medicine (2)	Private Pathology (3)	Private Radiology (4)	Private Surgery (5)
Eligibility	8.4	10.5	0.2	7.9	4.9
	(0.7)	(1.4)	(0.1)	(1)	(0.9)
Mean	62	114	2	67	59
N. obs.	2869821	2869832	2868672	2869827	2869816

(b) Total Spending

	Total Evaluation (1)	Total Medicine (2)	Total Pathology (3)	Total Radiology (4)	Total Surgery (5)
Eligibility	3.4	8.9	0.3	4.4	2.6
	(2.2)	(3)	(0.4)	(2.2)	(1.4)
Mean	650	603	36	348	176
N. obs.	2842923	2842188	2840724	2843191	2841719

Note: This table reports the estimates of coefficients on eligibility (β_1) in Eq. (1) for private outpatient utilization and total outpatient utilization under each care category as the outcome. Panel (a) shows the results using spending in private outpatient care and panel (b) shows those using total outpatient spending as outcomes. Spending is represented by the dollar. Standard errors are clustered at the patient level.

performing surgeries less efficient at VA compared to private medical facilities.[22] Similarly, for radiology services, even though larger VA facilities have the equipment to perform these procedures in-house, the operating cost is usually quite high due to capacity constraints and the wait times are long. As a result, VA providers tend to refer more of these procedures to private facilities.[23]

[22] We interviewed surgeons at VA. Here is an example quote: "I could perform twice as many surgeries a day if I were were at a private practice or an academic center with the support from more nurses and staff to do the preparation."

[23] We interviewed primary care providers at the VA and here is an example quote: "Even though VA offers diagnostic radiology services, we have limited staffing resources to perform these services

Table 7: Spending Shares of Each Procedure Type

	Evaluation (1)	Medicine (2)	Pathology (3)	Radiology (4)	Surgery (5)	Other (6)
VA	30.2	32.7	4.0	21.4	11.6	0.2
Private	5.4	13.7	6.2	8.3	65.5	1.0

Note: This table presents the utilization expenditure in each major CPT category as a fraction of total spending for patients whose total outpatient utilization expenditure falls under the top quartile, separately for VA and private care.

These intuitions are confirmed in our sample. For the high utilizers,[24] 67% of their outpatient expenditure at VA is composed of medicine, pathology, evaluation and management related services, while 65% of their spending at private facilities is surgical procedures, as shown in Table 7. Upon gaining eligibility to private care, surgical and radiology related services further increase by 1.5% and 1.3%.

Even though VA may have a comparative advantage for essential services such as internal medicine care, access to these services is challenging for patients far away from the VA (e.g. Adams et al. (2019)). Gaining access to essential services closer to home may be very beneficial, especially since those living farther away from the VA are more likely to be chronically ill.[25] Upon gaining access to private care under the 40-mile rule, private internal medicine care increases by $10 (9%, SE: 1), among which private mental health care utilization increases by $6 (19%, SE: 0.4). Overall internal medicine care increases by $9 (1.5%, SE: 3).

5.3 Other Issues on Interpretations

Although our findings in Section 5.2 suggest that different types of services provided at public and private providers may contribute to better health outcomes, they do not suggest whether public or private ownership itself affects care quality. De-

so we prefer to refer these procedures out into the community and focus more on other types of care."

[24] High utilizers are defined as patients that fall under the top quartile in terms of their outpatient care utilization.

[25] 38% of those that live 30 to 50 miles from the VA are mentally ill and 32% of them have prior history of cardiovascular diseases according to Table 1.

termining the effect of ownership on care quality is beyond the scope of this paper.

An alternative interpretation of our findings is that the effect of eligibility is driven by shorter distance to the local provider rather than expanded care options. Because emergency treatment is out of scope of the Choice program, the mortality reduction is not driven by eligible patients receiving more timely emergency treatment.[26] Although travel distance to receive planned care may partially explain the mortality reduction, the above evidence for specialization suggests that public and private providers' specializing in different services, rather than pure distance reduction, likely plays an important role in reducing mortality.

There are two reasons that our estimates of the mortality reduction effect can be conservative. First, we focus on distance eligibility rather than eligibility to private care coverage for any reasons (e.g., wait times), because the latter is harder to determine from data. Some veterans who are considered "ineligible" in this study (i.e., those living below the 40-mile threshold) will be eligible under alternative eligibility criteria. Our estimate will then be conservative relative to the effect of eligibility to private care coverage under any reasons. Second, if patient sorting based on unobserved health occurs, then it will bias our mortality effect estimate toward zero. This is consistent with Figure C.1e in Appendix C, which shows that the estimate becomes closer to zero as we expand the bandwidth.

6 Policy Evaluation and Simulation

Two relevant policy questions are (i) whether the 40-mile rule is cost effective and (ii) whether the eligibility criteria should be expanded to patients below 40 miles. To answer these questions, we first conduct a cost-benefit analysis of the 40-mile rule using the policy's estimated impact on one-year mortality and total costs to the VHA. Next, we conduct a counterfactual exercise that examines patients' counterfactual health outcomes and costs under the c-mile rule, for $c = 0, 10, 20$ and 30.

Following Chan et al. (2022), costs to the VHA are measured as the medical and hospital operating costs at VA facilities for each encounter and the amounts

[26] Avdic (2016) documents that, in Sweden, the probability of surviving an acute myocardial infarction decreases as residential distance from a hospital increases due to a hospital closure.

paid to private facilities. Benefits are measured by converting the policy-induced reduction in one-year mortality to a monetary metric with a value of statistical life of \$100,000 per year.[27]

6.1 Cost-Benefit Analysis of the 40-Mile Rule

With the above cost and benefit measures, the 40-mile rule of the Choice Program is highly cost effective. The 0.1 p.p. reduction in mortality reported in Table 4 translates to \$100 per patient-year in value. This is much larger than the increase in the total cost of \$16.4 per patient-year, which is obtained from the regression of total (VA and private, inpatient and outpatient) costs reported in Table D.1a.

6.2 Counterfactual Policy Simulation

In this section, we investigate the impact of expanding the eligibility criteria from 40 miles to c miles ($c = 0, 10, 20$ and 30) on total costs and one-year mortality. In the baseline counterfactual exercise, we apply the constant ATE of gaining access to private care as captured by $\hat{\beta}_1$ from Eq. (1) to eligible patients under different counterfactual policy rules. We use our main sample (patients who live 30-50 miles away from the closest VA in 2015-2018) to estimate treatment effects as in Section 4 and simulate counterfactual policies using a prediction sample (patients who live 0-39 miles away from the closest VA facility in 2018).[28]

One concern with applying the constant ATE in counterfactual policy analysis is that treatment effects may differ for patients in the estimation and prediction sample due to differences such as in health profiles or access to care. Although it is beyond the scope of this article to fully incorporate patient heterogeneity across distance to the closest VA in our counterfactual, we partially account for it by allowing the treatment effect to vary with patient characteristics as robustness checks. Specifically, we consider the following extension of our baseline regression (1):

[27] See Cutler et al. (2006) for discussions on the appropriate value of statistical life per year.

[28] Our focus on the 2018 sample is to mitigate computational burden.

$$Y_{it} = \alpha + Z_{it} \cdot \left(\bar{\beta} + \beta^W W_{it}\right) + \beta_2 D_{it} + \beta_3 Z_{it} \cdot D_{it} + \beta_4 X_{it} + \delta_c + \delta_t + \varepsilon_{it} \tag{3}$$

where W_{it} is a vector of patient characteristics which affect the treatment effects. By allowing the treatment effect $\tau\left(W_{it};\beta\right) = \bar{\beta} + \beta^W W_{it}$ to depend on W_{it}, our counterfactual simulations account for some of the differences between the estimation and prediction samples that are captured by W_{it}.

Given the treatment effects from Eq. (3) with $\beta^W = 0$ corresponding to the baseline model, we evaluate the costs and benefits of expanding eligibility as follows. For each patient, the effect of introducing the counterfactual eligibility rule $\tilde{Z}^c_{it} = I\left\{\tilde{D}_{it} \geq c\right\}$ in place of the actual eligibility rule $Z_{it} = \tilde{Z}^{40}_{it}$ is given by

$$\left(\tilde{Z}_{it} - Z_{it}\right) \tau\left(W_{it};\beta\right). \tag{4}$$

We define the total changes in the outcome when the eligibility threshold moves from 40 miles to c miles as

$$\Delta\left(c\right) = \sum_i \left(\tilde{Z}^c_{it} - Z_{it}\right) \tau\left(W_{it};\beta\right). \tag{5}$$

and the *Average Treatment Effect on the Marginally Treated* (ATMT) as the average effect of treatment among patients whose eligibility status changes (from being ineligible under the 40-mile rule to being eligible under the c-mile rule):

$$ATMT\left(c\right) = \Delta(c) \bigg/ \sum_i \left(\tilde{Z}^c_{it} - Z_{it}\right). \tag{6}$$

We compare the $ATMT\left(c\right)$ of total costs with that of one-year mortality as the policy's costs and benefits to evaluate the cost effectiveness of expanding the eligibility threshold from 40 miles to c miles.

Table 8 shows the counterfactual results based on our baseline treatment effect estimates from Table D.1a. Because we assume constant treatment effects, the

ATMT is the same as our main regression estimates. Extending the 40-mile rule to 30, 20, 10 and 0 miles would mean 509, 1533, 2776 and 4552 lives saved in the prediction sample. Costs increase as we extend the eligibility criteria. However, note that even though care utilization has a statistically significant increase as patients gain access to private care as documented in Table 4a, its impact on total cost to VHA is not precisely estimated as shown in Table D.1a. Next, to incorporate the differences in patient populations as we extend the policy, we consider treatment effect heterogeneity in the following dimensions.

Differential distance to the closest VA and private facility Private care take-up upon gaining access may depend on a patient's differential distance to the closest private versus VA facility. If private and VA care are close substitutes, gaining access to private care would impact those relatively close to private facilities more since these patients wouldn't have to travel as far for similar services. If, on the other hand, private facilities offer services difficult to obtain at the VA, then the impact of gaining access to private care should not significantly depend on the differential distance. Because relative distance to private and VA facilities may systematically differ between our estimation and prediction samples, we allow the treatment effect to depend on relative distance (distance to the closest VA minus distance to the closest private facility, normalized by its mean) and then conduct simulation based on the heterogeneous treatment effects. As Table D.1b shows, the coefficient estimate $\hat{\beta}^W$ is an insignificant 0.0025 p.p. (SE: 0.0061) for one-year mortality, suggesting that the treatment effect of gaining eligibility does not significantly depend on differential distance. Nevertheless, Table 9 shows the simulation results based on the distance-dependent treatment effects. For the 20-mile and especially 30-mile rules, the simulated results are similar to the baseline results qualitatively. As we extrapolate the ATE estimates further, however, the simulated results become less precise, because they put more weight on the imprecisely estimated interaction coefficient $\hat{\beta}^W$. We therefore do not give the results for $c = 0, 10$ and 20 as much credibility as those for $c = 30$.

Risk profile Figures 2b and 4 show that patients closer to the VA tend to be younger with a lower predicted mortality. And as shown in Table 5, patients at higher risk of one-year mortality benefit more from gaining access to private care. To capture risk differences in the estimation and prediction sample, we conduct another exercise where we allow treatment effects for high-risk patients (those whose predicted mortality is above median) to differ from those for low-risk patients (with below-median predicted mortality).

Table 10 displays the simulation results where we allow treatment effects to differ between by high-risk and low-risk patients. The regression results underlying the simulation are reported in Table D.1c. The effects on mortality are very similar to those in the baseline case. The simulation suggests that expanding eligibility will be highly cost effective according to our ATE estimates.

7 Discussion and Conclusion

Integrated health systems like the VHA have a distinct advantage in providing high quality essential care given its health IT infrastructure but often lack enough capacity to offer specialized procedures that meet patient demand. Outsourcing some of these procedures to the private sector can improve access and decrease wait times. One concern with such policies is that they could increase healthcare costs by fragmenting care and paying for care in settings where the VA has no direct ability to control costs. Our findings suggest that granting less restricted access to private care via broader insurance coverage improves outcomes in a cost-effective way. Specifically, we find that gaining private care coverage potentially reduces one-year mortality by 0.1 p.p. (a 2.8% reduction from the baseline), reduces average wait times per visit by 5.8 hours (a 1.3% reduction), while only increasing total outpatient utilization by $33.8 (1.3% increase). With a value of a statistical life of $1 million per patient year, the 0.1 p.p. reduction in mortality from gaining eligibility corresponds to a $1,000 value per patient, while costs only rises by $16 per patient year.

This article advances the prior research such as Rose et al. (2021) by suggesting potential mechanisms behind the mortality effect. The mortality reduction effect from adding coverage for private care is potentially the result of decreased wait times and increased access to care that is difficult to obtain otherwise. Upon gaining eligibility, patients increase their utilization of care that requires specialized equipment such as surgery and radiology, which private facilities may have an advantage for. There is also an increase in medicine service utilization – even though VA may have an advantage for this type of care given its integrated IT infrastructure, access may be challenging for patients that live far away.

In a counterfactual exercise where we expand the eligibility criteria from 40 miles to 20 miles assuming a constant treatment effect of gaining eligibility, our results show that an additional 1,533 lives could be saved. We further allow treatment effects to vary with patient observable characteristics such as risk profile and the differential distance to the closest VA and private facility and find that our result is robust to these specifications.

However, there are several limitations in our counterfactual analysis: (1) We do not take into account the general equilibrium effects. As more patients seek care at the private sector, VA facilities become less crowded and the care for existing VA patients may improve. On the other hand, the funding at each VA facility depends on patient flow, which may decrease with more patients going out to seek private care, leading to a decline in quality at VA. (2) we do not take into account the unobserved differences in patients as we expand the eligibility criteria, although we condition on a rich set of patient characteristics.

Our findings are especially notable in light of Chan et al. (2022), who found a striking mortality reduction effect of VA care compared to private care for emergency conditions. Our findings by no means contradict their conclusion. Even if VA care is considerably better than private care for emergency conditions, complementing private care with VA care may still improve patient outcome if it increases overall care access or allows patients to receive more care that is not sufficiently provided at VA. Whether additional private care complements VA care is a very different question from whether private care can adequately replace VA care.

Our findings provide clarity on one piece of a much more general question: many healthcare systems restrict the providers that patients can see. Private insurers often have limited networks with financial incentives to remain in-network, HMOs typically reimburse only in network, and public insurers like the VHA provide access to a limited set of providers. Our results suggest that the adequacy of the *bundle* of services that a patient can access within a given health system can directly impact their health. More generally, access provided to one patient of a rival resource such as a good surgeon may reduce access for other patients. Understanding how different healthcare systems impact the general equilibrium adequacy and efficiency of the providers to which patients have access is a first-order question in health economics which demands further research.

Table 8: Counterfactual Simulations: Constant Treatment Effect

(a) Mortality

	Mean	Mean (Marginally Treated)	Total Change $\Delta(c)$	Change Per Marginally Treated $ATMT(c)$	N. obs.
	(1)	(2)	(3)	(4)	(5)
Est. Sample	3.62				2930764
Pred. Sample	3.59				4487838
30-mile		3.52	-509	-0.1	4487838
			(221)	(0.04)	
20-mile		3.33	-1533	-0.1	4487838
			(666)	(0.04)	
10-mile		3.41	-2776	-0.1	4487838
			(1206)	(0.04)	
0-mile		3.59	-4552	-0.1	4487838
			(1977)	(0.04)	

(b) Total Costs

	Mean	Mean (Marginally Treated)	Total Change $\Delta(c)$	Change Per Marginally Treated $ATMT(c)$	N. obs.
	(1)	(2)	(3)	(4)	(5)
Est. Sample	4991				2789695
Pred. Sample	8371.7				4296660
30-mile		5144.9	7539319	16.4	4296660
			(9825066)	(21.4)	
20-mile		5053.2	23422566	16.4	4296660
			(30592482)	(21.4)	
10-mile		7006.4	42891902	16.4	4296660
			(55964772)	(21.4)	
0-mile		8371.7	70499134	16.4	4296660
			(91945966)	(21.4)	

Note: This table reports the results of the counterfactual simulations based on the average treatment effects from regression (1). Column (1) shows the average outcome among our estimation sample (patients who live 30-50 miles away from the closest VA in 2015-2018) and prediction sample (patients who live 0-39 miles away from the closest VA in 2018). Column (2) shows the average outcome among marginally treated patients, i.e., those whose eligibility status changes under each counterfactual policy. Column (3) shows the total change in the outcome (sum of the treatment effects on marginally treated patients) defined in Eq. (5). Column (4) shows the average treatment effects on the marginally treated (ATMT) defined in Eq. (6). Column (5) shows the sizes of our estimation and prediction samples. Standard errors in the parentheses are clustered at the individual level.

Table 9: Counterfactual Simulations: Heterogeneous Treatment Effect (Relative Distance)

(a) Mortality

	Mean	Mean (Marginally Treated)	Total Change $\Delta(c)$	Change Per Marginally Treated $ATMT(c)$	N. obs.
	(1)	(2)	(3)	(4)	(5)
Est. Sample	3.62				2930726
Pred. Sample	3.59				4487825
30-mile		3.52	-585	-0.12	4487825
			(281)	(0.06)	
20-mile		3.33	-2005	-0.13	4487825
			(1295)	(0.09)	
10-mile		3.41	-4029	-0.15	4487825
			(3205)	(0.12)	
0-mile		3.59	-7304	-0.16	4487825
			(6844)	(0.15)	

(b) Total Costs

	Mean	Mean (Marginally Treated)	Total Change $\Delta(c)$	Change Per Marginally Treated $ATMT(c)$	N. obs.
	(1)	(2)	(3)	(4)	(5)
Est. Sample	4991.1				2789657
Pred. Sample	8371.7				4296647
30-mile		5145	4724597	10.3	4296647
			(12746433)	(27.8)	
20-mile		5053.2	4075012	2.9	4296647
			(61960239)	(43.3)	
10-mile		7006.5	-9978796	-3.8	4296647
			(155776745)	(59.6)	
0-mile		8371.7	-46636581	-10.9	4296647
			(333016395)	(77.5)	

Note: This table presents the results of counterfactual simulations based on the treatment effects from regression (3) where we allow the treatment effects to vary with patients' differential distance between the closest VA and private facility.

Table 10: Counterfactual Simulations: Heterogeneous Treatment Effect (High Mortality Risk)

(a) Mortality

	Mean	Mean (Marginally Treated)	Total Change $\Delta(c)$	Change Per Marginally Treated $ATMT(c)$	N. obs.
	(1)	(2)	(3)	(4)	(5)
Est. Sample	3.62				2930764
Pred. Sample	3.59				4484418
30-mile		3.52	-505	-0.1	4484418
			(219)	(0.04)	
20-mile		3.33	-1506	-0.1	4484418
			(652)	(0.04)	
10-mile		3.41	-2747	-0.1	4484418
			(1189)	(0.04)	
0-mile		3.59	-4541	-0.1	4484418
			(1964)	(0.04)	

(b) Total Costs

	Mean	Mean (Marginally Treated)	Total Change $\Delta(c)$	Change Per Marginally Treated $ATMT(c)$	N. obs.
	(1)	(2)	(3)	(4)	(5)
Est. Sample	4991				2789695
Pred. Sample	8378.2				4293243
30-mile		5144.9	8706907	19	4293243
			(9807753)	(21.4)	
20-mile		5064.4	34056308	23.9	4293243
			(30401396)	(21.3)	
10-mile		7015	55563405	21.3	4293243
			(55729174)	(21.3)	
0-mile		8378.2	79949273	18.6	4293243
			(91729769)	(21.4)	

Note: This table presents the results of counterfactual simulations based on the treatment effects as specified in regression (3) where we allow the treatment effects to vary with a patient's risk bucket (whether above or below median in terms of predicted one-year mortality).

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For Online Publication

A More on the Validity of RD Analyses

In this section, we present the results of exercises to validate our regression discontinuity approach. In Section A.1, we present the results of the continuity test described in Section 4.2.1. In Section A.2, we show the results of the placebo test described in Section 4.2.2.

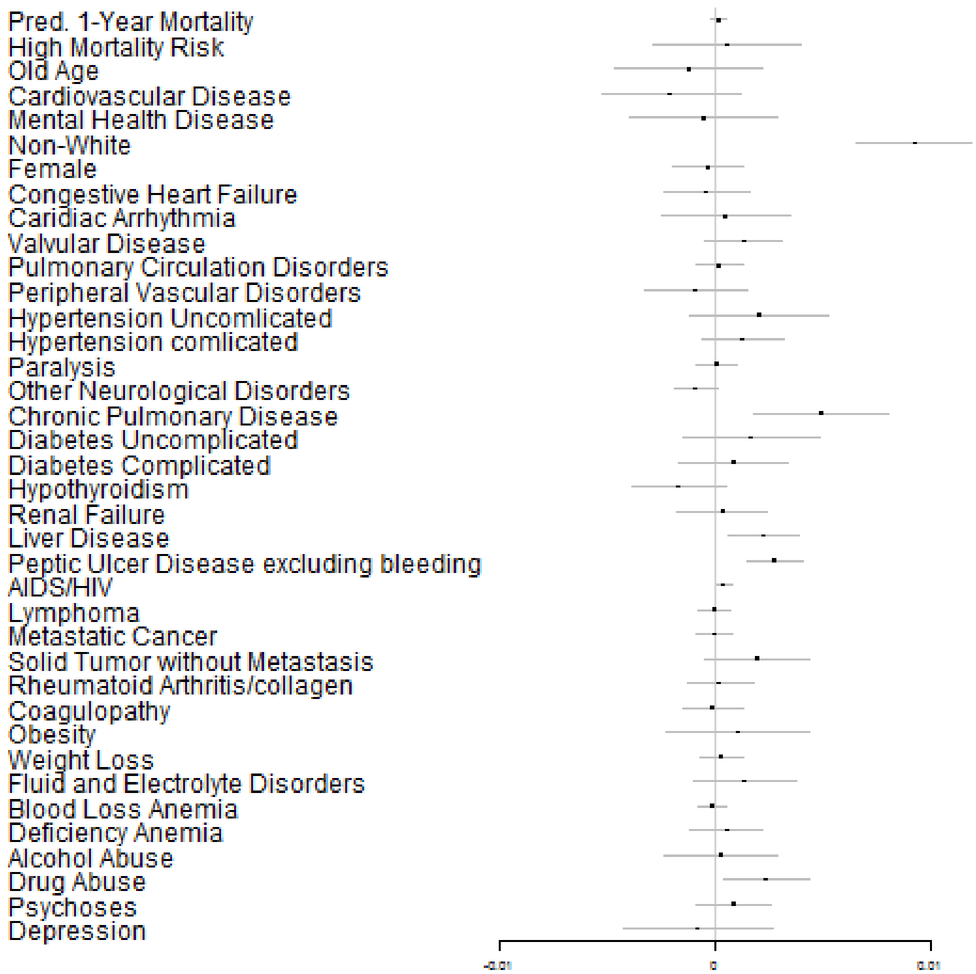
A.1 Continuity Tests with Patient Baseline Characteristics

Figure A.1 plots the estimates of γ_1 and its 95-percent confidence interval, for each of our covariates as well as predicted mortality and high-risk indicator. Predicted mortality has a small and statistically insignificant γ_1 estimate of 0.02 (SE: 0.02). Among the 38 covariates being tested, only 5 have a statistically significant estimate of γ_1, although small in magnitude.

A.2 Placebo Test with Pre-Choice Data

Table A.1 reports the estimates of γ_1 for private, VA and total outpatient utilization, as well as wait times and one-year mortality. All the estimates other than that of private outpatient utilization are small and statistically insignificant. Private outpatient care exhibits a jump of $4.8 (SE: 1.9) at the threshold. This is 10 times smaller than the jump in private outpatient care in the post-Choice period. This discontinuity is likely caused by the increasing trend in private care as a patient's distance to the closest VA increases, which makes VA care increasingly inaccessible.

Figure A.1: Continuity of Baseline Characteristics



Note: This figure plots the estimate and confidence interval of γ_1 in the regression (2) of patient baseline characteristics. Standard errors are clustered at the patient level.

Table A.1: Placebo Tests

	Private Outpatient Spending (1)	VA Outpatient Spending (2)	Total Outpatient Spending (3)	Wait Times (4)	1-Year Mortality (5)
Eligibility	4.8	-8.3	-3.4	-0.44	-0.03
	(1.9)	(6.6)	(7.1)	(1.09)	(0.05)
Mean	162	1697	1827	138.29	3.5
N. obs.	2158202	2158203	2138552	2158010	2180012

Note: This table presents the estimates of the coefficient on eligibility (β_1) in Eq. (1) for private, VA and total outpatient utilization, wait times and one-year mortality for patients that live between 30 and 50 miles from the closest VA facility between the years 2009 and 2012. Utilization is reported in dollars, wait times are reported in hours and mortality is reported in percentage points. Standard errors are clustered at the patient level.

B Results on Cost Measures

Table B.1: Cost Distribution

	Mean	S.D.	Q(0)	Q(0.25)	Q(0.5)	Q(0.75)	Q(0.95)	Q(1)	N. obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VA Inpatient Cost	653.2	4071.2	0	0	0	0	0	49730	2799831
Private Inpatient Cost	166	1562	0	0	0	0	0	26083.5	2799831
Total Inpatient Cost	819.1	4467.4	0	0	0	0	0	74901.3	2799831
VA Outpatient Cost	3644	5291.2	0	461.9	1604.1	4539.1	14761.1	36425.1	2799831
Private Outpatient Cost	610.6	2036	0	0	0	0	3733.5	20186.9	2799831
Total Outpatient Cost	4254.6	6116.3	0	502.2	1825.9	5389.7	17318.5	56247.4	2799831

Note: This table reports the distribution of inpatient and outpatient costs at VA and private facilities. $Q(\tau)$ represents the τ-th quantile of a given cost measure. We winsorize each cost measure at the 99 percentile. The sample in this table include all patients with no missing costs in any categories above. Costs are reported in dollars.

Table B.2: Local Linear Regressions of Cost Measures

	Private Outpatient Cost (1)	VA Outpatient Cost (2)	Total Outpatient Cost (3)	Private Inpatient Cost (4)	VA Inpatient Cost (5)	Total Inpatient Cost (6)
Eligibility	48.7	-38.6	11.6	20.5	-4.1	12.6
	(6)	(14.4)	(16.5)	(4.3)	(11.2)	(12)
Mean	668.5	3835.4	4421.3	193.7	751	899.1
N. obs.	2869823	2869832	2842934	2869831	2869828	2843551

Note: This table presents the estimates of the coefficient on eligibility (β_1) in Eq. (1) for private, VA and total outpatient and inpatient costs. Standard errors are reported in parentheses. Costs are reported in dollars.

C Robustness of Regression Discontinuity Results

We investigate robustness of our results in Section 4 by using different kernels and bandwidths. We also conduct inference which accounts for discreteness of the running variables, which we now elaborate.

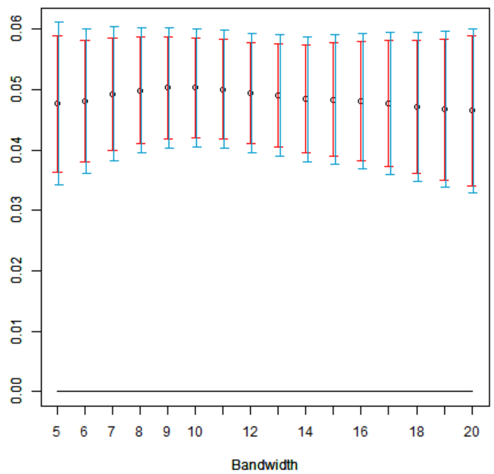
Because our distance variable is measured only by integer, predicting an outcome of ineligible patients at 40 miles based on local linear regressions requires linear extrapolation. If the true conditional expectation function (CEF) of the outcome is nonlinear, this extrapolation introduces bias to the inference about the average treatment effect. Following Armstrong and Kolesár (2018, 2020), Kolesár and Rothe (2018) and Goldsmith-Pinkham et al. (2021), we allow the underlying CEFs to belong to a class of potentially nonlinear functions and construct confidence intervals (CIs) that attain correct asymptotic coverage uniformly over the class of CEFs. This method needs to place a bound M to the second derivative of the CEFs in the class. We do this by first fitting the outcome of ineligible patients to a quadratic function of distance and then letting $M = 2\hat{a}_2$, where $\hat{a}_2$ is the coefficient on the quadratic term. Also, instead of incorporating observed covariates, we risk-adjust the outcome variables and run the local linear regression Eq. (1) without covariates.

Figure C.1 presents bias-aware CIs for various outcomes with the triangular kernel[29] under different bandwidths. Overall, the results are qualitatively similar to our main findings in Section 4, confirming that the statistically significant increase in private and total outpatient spending, decrease in wait times, and decrease in one-year mortality remain under robust inference, though the statistical significance becomes weaker under robust inference. In particular, the mortality effect with the bandwidth of 10 (corresponding to observations within 30-50 miles of the closest VA facility) is both quantitatively similar to our main estimates of -0.1 p.p. and is similar to estimates from smaller bandwidths, suggesting internal validity. The estimates of the mortality effect becomes closer to zero as the bandwidth expands, potentially because the eligible population is less healthy relative to the ineligible population as the distance band widens.

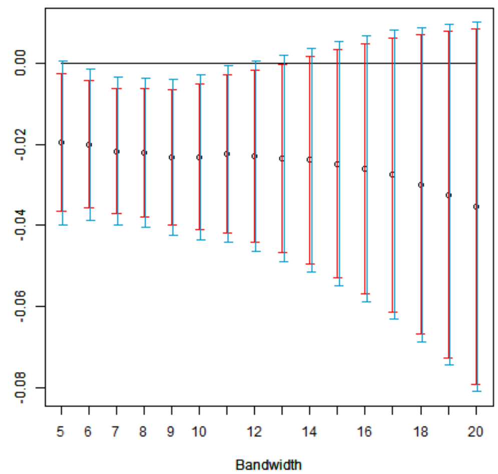
[29] Results with the uniform kernel (not reported) are similar.

Figure C.1: Robustness of RD Results

(a) Private Outpatient Spending



(b) VA Outpatient Spending



(c) Total Outpatient Spending

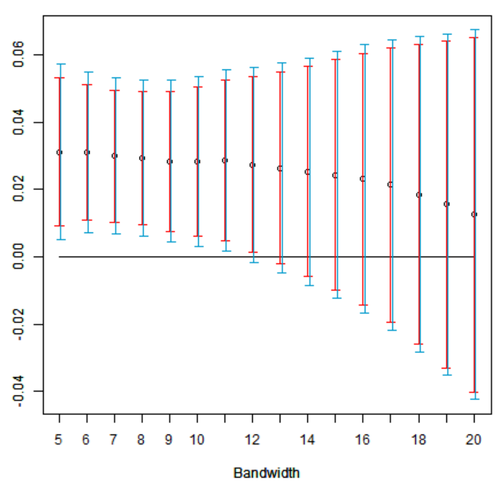
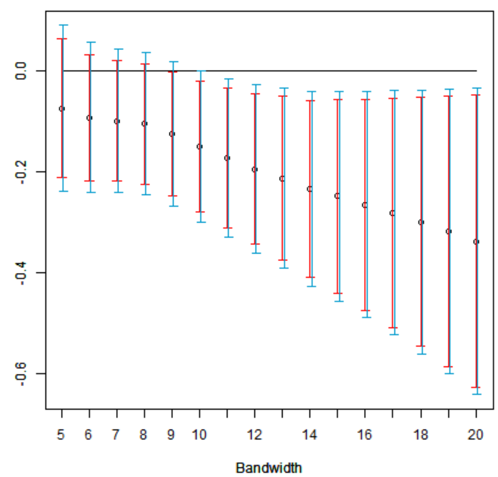
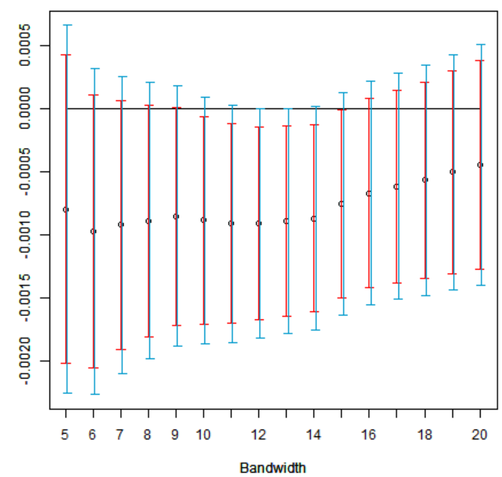


Figure C.1: Robustness of RD Results (Continued)

(d) Wait Times



(e) 1-Year Mortality



Note: Figure C.1 shows the bias-aware confidence intervals of the coefficient estimates on eligibility with bandwidths for from 5 miles to 20 miles centering at the 40-mile cutoff using the triangular kernel. The outcomes include private, VA and total outpatient utilization, wait times and one-year mortality. The confidence intervals are computed following the method of Kolesár and Rothe (2018). The red bars represent the 90 percent CIs and the light-blue bars represent the 95 percent CIs. Utilization is reported in dollars, wait times are reported in days and one-year mortality is reported in a hundredth of percentage points.

D Regression Results for Counterfactual Analysis

Table D.1: Regressions with Heterogeneous Treatment Effects

(a) Baseline: Constant ATE

	Cost	1-Year Mortality
	(1)	(2)
Eligibility	16.42	-0.1
	(21.40)	(0.04)
Observations	2,789,695	2,930,764

Table D.1: Regressions with Heterogeneous Treatment Effects (Continued)

(b) Relative Distance

	Cost	1-Year Mortality
	(1)	(2)
Eligibility	14.24	-0.11
	(22.54)	(0.05)
Elig. × Relative Distance	1.156	0.0025
	(3.106)	(0.0061)
Observations	2,789,657	2,930,726

(c) High Mortality Risk

	Cost	1-Year Mortality
	(1)	(2)
Eligibility	87.03	-0.08
	(23.11)	(0.04)
Elig. × High Risk	-141.2	-0.04
	(22.21)	(0.04)
Observations	2,789,695	2,930,764

Note: This table reports the estimates of $\bar{\beta}$ and β^W as specified in regression (3). Panel (a) shows the results from our baseline regression (1). Panel (b) shows the coefficient estimates where the treatment effects are allowed to depend on differential distance to the closest VA and private facility. Panel (c) shows the coefficient estimates where the treatment effects are allowed to depend on whether a patient is above or below median predicted mortality risk. Standard errors are clustered at the patient level.