Provider Supply and Access to Primary Care

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Abstract
Resource-constrained delivery systems often have access issues, causing patients to wait a long time to see a provider. We develop theoretical and empirical models of wait times and apply them to primary care delivery by the U.S. Veterans Health Administration (VHA). Using instrumental variables to handle simultaneity issues, we estimate the effects of clinician supply on new patient wait times. We find that it has a sizeable impact on waiting times. A 10% increase in capacity reduces wait times by 7%. Clinician productivity also reduces wait times. Wait times are affected by patient access to alternative sources of care. The VHA has adopted our models to achieve certain goals of the MISSION Act of 2018, specifically in identifying underserved areas.

Keywords: wait time; access to care; resource allocation; public health care; provider supply capacity; demand elasticity

JEL classification: H21; H44; I11; I13; I18

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I. Introduction

In many countries, patients must wait a long time to receive health care (Merritt Hawkins 2017; Viberg et al. 2013). Nicolova et al. (2016), Sutherland et al. (2016), and Pizer and Prentice (2011) document the potential adverse effects of waiting on patient outcomes. Access issues are exacerbated in supply-constrained systems, such as public health care delivery systems, and managing such issues is not trivial. Reducing demand through cost sharing is unpopular (Siciliani and Hurst, 2005). Reducing wait times by increasing capacity or improving productivity requires additional resources. For many systems, a better approach may be to reevaluate the allocation of resources and target investments to achieve maximum impact.

In this study, we develop an aggregate supply and demand model that illustrates how market-level equilibrium wait times are determined. Empirically, we estimate a reduced-form model using data from the U.S. Veterans Health Administration (VHA), the largest public delivery system in the U.S. with an annual budget of approximately $80 billion. Using a fixed-effects specification and instrumental variables approach, we examine factors that affect wait times, such as: changes in clinician supply, patient access to alternative (non-VHA) health care options, and local area economic and demographic factors. We focus our study on access to care for new patients seeking primary care appointments at the VHA.

Our conceptual model builds off a substantial literature starting with Lindsay (1980) and Lindsay and Feigenbaum (1984). Authors in this tradition assume that the value of care decays as time passes between diagnosis and treatment (e.g., Goddard et al., 1995; Besley et al., 1999; Martin and Smith, 1999; Goddard and Smith, 2001). Consequently, the waiting time acts like a price – imposing a cost on the patient that reduces demand. On the supply side, much of the literature assumes that supply is either inelastic to wait times (Swami et al. 2018) or positively related to wait times because managers are altruistic or incentivized to care about wait times (e.g., Siciliani, 2006; Riganti and Siciliani, 2017; Gravelle, Smith, and Xavier, 2003; Martin and Smith, 1999, 2003). Cullis et al. (2000) and Siciliani and Iversen (2012) provide excellent reviews of the literature.

We revisit the mechanics of supply and show that it can be positively related to wait times, even without these assumptions, if we make a slight adjustment to the paradigm in which we typically think about supply and demand. While this does not translate to different qualitative implications, it clarifies the supply side of the model and supports applications.

We contribute to the literature by estimating the effect of supply changes from a clinic operations manager's perspective. Previous studies have investigated the effect of other types of supply changes: Siciliani and Martin (2007) and Propper et al. (2008) examined changes in hospital competition; Propper et al. (2002) and Dusheiko et al. (2004) examined a national (U.K.) policy change in provider incentive structures; Propper et al. (2010) examined another national (U.K.) policy that forced hospitals to have wait times below a certain threshold; Swami et al. (2018) studied the effect of a change in hours worked by clinicians (caused by personal family changes) on wait times. We examine changes in capacity or clinical full-time equivalents and changes in productivity or the rate at which clinicians can produce visits. A set of empirical studies have estimated structural supply equations, identifying supply elasticities and the relationship between wait times and utilization (e.g., number of appointments or admissions). While these estimates are useful in forecasting access to care issues, we focus our study on the reduced-form effect of *supply capacity* on wait times. This estimate can be useful in designing policies regarding the clinician workforce and operationally useful for managers of health care systems.

We also add to the literature by studying a new population and service group – primary care in the U.S. The literature has largely focused on elective surgery in national delivery systems in European countries, i.e. the U.K., Italy, Australia, and Norway (e.g., Martin and Smith, 1999, 2003; Gravelle et al., 2002, 2003; Martin et al., 2007; Fabbri and Monfardini, 2009; Riganti et al., 2017; Stavrunova & Yerokhin, 2011; Monstad et al., 2006; Sivey, 2012), with the exception of Swami et al. (2018) who studied primary care in Australia. To our knowledge, the responsiveness of wait times with respect to supply shocks has not been estimated for the U.S., where the delivery and financing of health care is different in many ways from the pattern seen in other countries (Mossailos et al., 2016).

This study is timely for U.S. policy. In 2014, several veterans died while waiting to see a VHA provider, highlighting the access issue. In response, the Veterans' Access to Care through Choice, Accountability, and Transparency Act (Choice Act) of 2014 and the Maintaining Systems and Strengthening Integrated Outside Networks Act (MISSION Act) of 2018 dedicate public VHA funds to pay for privately provided care. These Acts revisit the tradeoffs between purchasing community care (like the Medicare system in the U.S.) or providing care in-house. While the Acts may increase the number of available clinicians, it is unclear whether paying for private care will improve timeliness of care at an affordable price (Yee et al. 2016). With limited funds, the VHA should make efficient use of spending, identifying the most underserved areas and using workforce policy levers that yield the highest return (greatest access improvement) for the next dollar spent. One of the applications of our model is that it can be used to identify such areas. In fact, it has been adopted by the VHA to achieve one of MISSION Act's goal – identifying underserved areas. We discuss this policy application in the Discussion Section.

II. Institutional Background of the VHA

The Veterans Health Administration (VHA) is a federally owned, federally financed health care system for veterans. It comprises 168 hospitals, 1,053 community-based outpatient clinics, and 135 nursing homes (Department of Veteran Affairs "About VA", 2016). The 2020 budget for the VHA is $79.1 billion. There are 21.6 million U.S. veterans (National Center of Veteran Analysis and Statistics, 2015), with approximately 9.1 million enrolled in VHA health benefits (Bagalman, 2014). They often have more health issues and a higher incidence of chronic illnesses (e.g. diabetes, hypertension, cancer) than the civilian population (Kramarow and Pastor, 2012).

To be eligible for VHA health benefits, a veteran needs to have served for 24 continuous months and discharged under other than dishonorable conditions or be discharged due to a military service-connected disability. Unlike Medicare and other types of health care coverage, the VHA does not require veterans to pay a premium to receive benefits. Furthermore, copayments are relatively small for veterans, depending on their disability status and need for financial assistance.

The VHA, like many public health care systems, provides care under a finite budget and at minimal cost to patients. This leads to rationing health care through wait times. The VHA scandal of 2014 recently drew attention to the long wait times (VA Office of Inspector General, 2014). The VHA was under even more scrutiny as medical centers manipulated their scheduling data to obscure the access problem.

In the past, policymakers have addressed the access problem by setting maximums for wait times. In 1995, the VHA set a maximum of 30 days. A 2001 government report showed that VHA medical centers were having problems meeting the 30-day goal (U.S. Government Accountability Office, 2001). In 2007, the VHA was sued for "failing to provide adequate and timely benefits and medical care," according to Veterans for Common Sense, an advocacy group for veterans (2014). In 2011, the wait-time requirement was reduced to 14 days for many types of appointments, despite the already evident difficulties in meeting the 30-day requirement and the future increase in the number of veterans who would be returning from Afghanistan and Iraq (Brunker, 2014).

Congress passed the Choice Act of 2014 and MISSION Act of 2018 to extend VHA coverage to services provided outside the VHA. The Choice Act appropriated $10 billion to be used between 2014 and 2017 to pay for such "community care" (Congressional Budget Office, 2014; Department of Veteran Affairs "Budget in Brief", 2017). Since 2014, the budget for the VHA has also increased approximately $5 billion per year, in effort to bolster VHA staffing and infrastructure and improve access to VHA care. The MISSION Act of 2018 extends funding to the Choice program of $5.2 billion per year as the community care program is set up (Department of Veterans Affairs "Budget in Brief", 2018). Under the program, veterans can more fluidly seek care outside the VHA (i.e., there are no eligibility criteria). Unlike the Choice Act, funding for the community care program comes from main VHA budget. Title IV Section 401 of the MISSION Act also requires the VHA to identify underserved areas, with the intention of redistributing funds to target those areas with more resources.

Federal funds are annually allocated across medical centers. Each medical center comprises of at least one VHA hospital and potentially a number of outpatient clinics and other facilities. The funds pay for the salaries of clinicians and staff, the maintenance of clinics, and sometimes the building of new clinics. Funding allocation decisions are based on the patients treated in previous years (Wasserman et al. 2005). It is not directly related to enrollment or potential demand. For example, a center experiencing high demand relative to supply, which is observed through long wait times, is not allocated more funds if the staff is only able to see the same number of patients as they did in previous years.

However, medical center directors do have discretion within their jurisdiction. They have the ability to shift resources across departments and service lines, as well as shift between hiring staff and spending funds on infrastructure.

Access to care is dependent on the size of and motivation of the clinician workforce to be productive. Unlike in a fee-for-service payment system, most VHA clinicians are salaried and thus are not incentivized to provide more services. The salaries are constrained by the federal personnel system, but clinicians can negotiate how much of their time is clinical versus research. More time allocated to research can lead to grants and additional compensation. Clinicians also can work part time at the VHA and part time at their own private clinic, in which they likely do get paid fee-for-service.

Although not financially at risk for access problems, clinicians may be sensitive to them if their medical director or health system managers draw attention to the long wait times. In areas that are short-staffed, managers may hire consultants or virtual doctors who are paid per day of service or may pay community (non-VHA) providers to assist with the load. The latter has become more common with the passage of the MISSION Act of 2018, especially for specialty care. This unintentionally may create a competitive environment for VHA providers, encouraging them to be more productive.

III. Methodology

A. CONCEPTUAL MODEL

In a cash market in which patients pay the full price of health care, excess demand drives up prices until equilibrium is reached. However, in many health care systems, prices are established by regulation or contracts and held fixed for a duration longer than demand fluctuations. In such settings, prices cannot rise in the short term. Instead, variation in waiting time through queues takes the place of changes in out-of-pocket prices (Goddard et al., 1995). Ultimately, the equilibrium health care quantity delivered is determined by a sticky out-of-pocket price and a highly responsive wait time.

At a given price, the supply and demand curves in the *wait-appointment* space are analogous in many ways to the curves in a *price-appointment* space that hold constant the wait times. As wait times increase (and price is fixed), fewer patients will demand appointments. A patient's decision to schedule an appointment is based on his or her willingness to wait, compared to the number of days until the next available appointment (i.e., the *wait time*). Willingness to wait for an appointment at a given VHA center may be dependent on whether the patient has *alternative health coverage* options or access to other providers. Willingness to wait may also depend on the patient's *affluence*; having more income gives one more flexibility in choosing providers. In addition, it may be related to one's value of time, and thus willingness to wait. Finally, the *need* for medical services may influence a patient's willingness to wait for an appointment. We can express the demand as $Appt^D = G(w;\theta)$, where w is the wait time, or number of days until the next available appointment; and θ represents other factors that might affect demand, such as alternative health coverage, affluence, and need for medical services.

In the case of the VHA, many veterans have additional health care coverage, such as Medicaid, Medicare, or employer-sponsored insurance. On one hand, veterans may rather see VHA providers because copayments for VHA care are very low and the care may be more coordinated or of higher quality (Trivedi et al. 2011). However, when wait times are longer at the VHA than they are at alternative providers, veterans may opt to see a non-VHA provider.

On the supply side, the relationships are different from that in a market in which price equilibrates the quantity. In these markets, when price increases, suppliers increase labor and/or capital inputs to produce more since it is more profitable. In a market in which wait times ration the quantity, it is not obvious whether the supply curve (in the wait-appointment space) is upward sloping or not. Swami et al. (2018) assumed that the number of appointments supplied is inelastic to wait times (Figure 1a). Others have assumed that managers are altruistic or incentivized to supply more when wait times are high (e.g., Siciliani, 2006; Riganti et al., 2017; Gravelle, Smith, and Xavier, 2003; Martin and Smith, 1999, 2003). This leads to an upward supply curve but with a feedback loop that does not exist in a price-rationing market: when wait times (exogenously via demand) increase and managers increase capacity (labor input), which affects not only the number of appointments supplied but also the wait time (unless specific conditions are met about the rate at which patients get on and off the wait list). See Figure 1b.

Figure 1. Demand and Supply for Appointments

Alternatively, we can think about appointments from a planned scheduling perspective and show that the number of appointments scheduled is determined by the number of clinicians, how productive each one is, and the wait time. It is easiest to illustrate this relationship with an example.

Suppose a newly hired clinician can perform five appointments in a day. The first five patients who desire an appointment (patients 1-5) would have a zero-day wait time, patients 6-10 would have a 1-day wait time, and this continues until the wait time is too high for the next patient to desire scheduling an appointment. If the wait time is 9 days, the clinician must be scheduled to provide 50 appointments (10 days x 1 clinician x 5 appointments per day). If a clinic has two clinicians and a 9-day wait time, the number of appointments scheduled would be 10 days x 2 clinicians x the average productivity of the two clinicians. This logic holds if we assume that patients always take the first available appointment. In this simple case, the number of appointments planned to be supplied is the product of the wait time at a given point in time (w), the number of full-time equivalent (FTE) clinicians, and the potential productivity or the number of appointments per clinician per day (P).

Specifically, this can be written as $Appt^S = w \times FTE(w, z) \times P(x)$.[6] Holding constant the number of FTE clinicians on staff and productivity, there is a positive relationship between the number of appointments and the wait time (Figure 1c). The number of clinicians hired is a decision made by health care managers and may depend on wait times if managers are altruistic or incentivized in some way to mitigate high wait times. This notion is in line with the previous literature. The number of FTEs may be dependent on supply shifters (z), such as lower costs to retaining clinicians and events that affect the number of hours clinicians can work.

Typically, economists think of supply as this kind of "flow" concept, e.g., appointments supplied per day. The model here is slightly different in that the supply and demand are for *planned* appointments, i.e., slots in the appointment schedule at any given point in time. In terms of supplied or delivered care, $Appt^S$ is more of a "stock" concept. Between any given day and the next available appointment, a stock of appointments is booked in the schedule. The stock and flow are connected by the wait time. The product of the wait time and the conventional supply per unit time S_t = $FTE(w, z) \times P(w, x)$ (i.e., production rate of appointments per day) is equal to the stock of appointments, i.e., $Appt^S = w \times S_t$. This relationship is similar to the physics concept of energy which equals power (e.g., kilowatts per hour) multiplied by time (e.g., hours).

This framework for supply nests the traditional way of thinking about supply. Moreover, supply is not inelastic to wait times in the stock (or planned supply) framework, but it still could be in the flow

[6] More generally, the number of appointments supplied can be written as $Appt^S = \sum_{t=0}^{t=w} FTE_t(E(w), z) \times P_t(x)$, where FTE and P can be different each day leading up to the next available appointment and so each has a subscript t.

framework. Even if capacity do not change with respect to wait times, the planned number of appointments to be supplied is higher when the wait time is higher. The stock concept is helpful (academically) in that it allows us to consider the direct (mechanical) and indirect (incentives-based) avenues through which wait times are related to appointments supplied. Another advantage is that this framework differentiates actual supply from planned supply. In a market with excess demand (due to no patient cost-sharing), actual supply is in a way censored at the maximum production rate, or number of visits achievable given a certain capacity and productivity. Understanding planned supply allows us to receive information that is beyond the maximum number of visits achievable within a month.

In equilibrium, the wait time is determined by the demand for a slot in the schedule and the supply of slots in the schedule.[7] The equilibrium wait time would be $\boldsymbol{w}^*$ such that $Appt^D = Appt^S$ (Figure 1c). While previous studies have focused on estimating a more structural supply equation (the relationship between a shift in supply on utilization), our goal is to estimate the effect of a shift in supply on wait times, i.e., the reduced-form model.

B. EMPIRICAL MODEL

Stemming from the conceptual framework, the reduced-form model of wait times is a function of demand factors, clinician capacity, and clinician productivity. We estimate a linear model of primary care wait times for new patients using monthly panel data on VHA medical centers:

$$Wait_{c,t} = \beta_1 \cdot capacity_{c,t} + \beta_2 \cdot productivity_{c,t} + \boldsymbol{\gamma} \cdot \boldsymbol{\theta_{c,t}} + \boldsymbol{\delta} \cdot \boldsymbol{RR_{c,t}} + \alpha_c + y_t + q_t + u_{c,t}$$

[7] To be analogous with supply, demand could be written as $Appt^D = \sum_{t=0}^{t=w} D_t(\theta)$, where D_t is the number of appointments patients decide to schedule on each day leading up to the next available appointment.

in which the dependent variable is the average wait time for a new patient primary care appointment at a given VHA medical center (*c*) in a given year-month (*t*) The wait time is the number of days between when a veteran made an appointment and the scheduled clinic visit date. A new patient is defined as a veteran who has not seen a VHA primary care clinician in two or more years.

The model includes (as independent variables) clinician capacity, productivity, demand factors ($\boldsymbol{\theta_{c,t}}$), certain control variables ($\boldsymbol{C_{c,t}}$), medical center fixed effects (α_c), year indicators (y_t), and quarter indicators (q_t). Clinician capacity, productivity, demand factors, and other control variables vary by medical center (*c*) and time (*t*). Clinician capacity is similar the number of clinical FTEs. It is the total number of days that primary care clinicians are in the clinic treating patients, divided by the number of weekdays in the month, and scaled by the number of thousands of enrollees associated with the medical center. Productivity is the number of primary care appointments that occurred per clinic day. To handle potential endogeneity issues, we instrument capacity by several instruments, discussed later.

Factors potentially influencing the demand for VHA care (and thus the wait time) include alternative health coverage options, affluence measures, health status measures, economic factors, and drive time to the closest primary care clinic. The measures of affluence and economic factors in the surrounding area include median household income levels, average housing prices, population density, and local unemployment rates. Measures of access to alternative health coverage options include the proportion of VHA-enrolled veterans who have non-VHA comprehensive coverage (i.e., through Medicare, TRICARE, or private/commercial insurance), medical-only and no prescription drug coverage, Medicaid, and the Medicare Advantage penetration rate. For health status, we include the HCC average score among Medicare beneficiaries in the local area as a proxy for health status of veterans. The model also includes the proportion of veteran enrollees who are female, measures of the race composition of enrollees, and the number of enrollees. Medical center fixed effects, year indicators to control for national trends in new patient primary care wait times, and quarter indicators to control for seasonality.

Finally, the model includes as a control a policy variable that has been shown to affect the wait time for new patients during our sample period. Between September 2010 and May 2016, the VHA instituted a nationwide policy called the Recall Reminder policy, which limited access to the schedule for established patients and improved access for new patients. Yee et al. (2020) showed that the wait time for new patients seeking primary care appointments was strongly affected by whether established patients had special access to scheduling their follow-up appointments. In many medical centers, established patients tend to crowd out new patients by scheduling their appointments months in advance. Moreover, due to advanced scheduling, the schedule in general was filled with appointments that would later be cancelled. We created the same Recall Reminder policy variable as that used in Yee et al. (2020). It measures the scheduling advantage of established patients (i.e., non-compliance to the Recall Reminder policy) by the proportion of established patient primary care appointments that were booked more than 3 months in advance. See Yee et al. (2020) for more information and Figure 2 for an illustration of the change in the measure once the policy was rescinded in May 2016.

Figure 2. Recall Reminder Scheduling Policy Change in May 2016

C. DATA SOURCES, SAMPLE, VARIABLE CONSTRUCTION

We use multiple administrative data sets for this study. The VA Corporate Data Warehouse (CDW) is a national repository of several VA clinical and administrative systems. The data contain the service group (what the VHA calls the stop code), the date on which a veteran made an appointment, and the date of the corresponding clinic visit. Primary care is identified by three VHA stop codes: 323, 350, and 322. We use the two date variables to derive wait times[8]. A patient-level wait time is generated, which is the number of days between when a veteran made a primary care appointment and the date of the appointment. The dependent variable in our model is the mean wait time at a given medical center in a given month.

Figure 3. Geographic Variation in Wait Times (2014) - placeholder

The VHA Support Service Center provides enrollment status of veterans. The VHA Planning Systems Support Group (PSSG) provides veteran enrollment counts, county of residence, the VHA primary care clinic that is closest to the veteran, and the VHA medical center closest to the veteran. We compute an enrollee-level drive time to the nearest VHA primary care clinic among enrollees associated with a given medical center. We then aggregate this enrollee-level drive time to medical center level by constructing the proportion of enrollees who do not have to drive more than 20 minutes (base group), the proportion that have to drive between 20 and 40 minutes, and the proportion that has to drive more than 40 minutes.

We use the VHA Time Attendance Records and Employee Payroll Record Tracking Data to create measures regarding the clinician workforce. We identify when clinicians in a given month were in clinic or taking personal leave or sick leave. We use these data to create our instrumental variables, discussed below.

[8] To avoid issues of misreporting (as documented by investigations following the VA Scandal of 2014), we did not use the time between the desired date of appointment and the appointment date as the wait time measure (Office of Inspector General 2014).

The VHA Survey of Enrollees provides information on enrollees based on a survey that was administered starting in 2014. In our models, we include the proportion of enrollees who have alternative health coverage besides the VHA, income levels, age, race, gender, marital status, and employment status. For health coverage, we used the Survey responses to generate the proportion of enrollees who have comprehensive coverage, i.e., those who likely have both medical and prescription drug coverage by either Medicare (traditional or Medicare Advantage) or commercial insurance (e.g., through an employer). We also identified the proportion of enrollees who are covered by Medicaid and VHA but no other comprehensive plan, and we identified the proportion that has medical coverage only and no prescription drug coverage. Each group is mutually exclusive. Since the other variables are self-explanatory, we do not provide detailed descriptions of their construction here. See Table 1 for descriptive statistics.

We additionally use non-VHA data, which describe local economic and health care market conditions. The Area Health and Resource File (AHRF) provides county-year level data on the number of non-federal, active physicians; non-federal, active primary care physicians; and population count. Zillow provides a monthly housing price index at the county level (called the Home Value Index). The Centers for Medicare and Medicaid Services provides a monthly Medicare Advantage penetration rate by county and the average Hierarchical Condition Category (HCC) score of Medicare beneficiaries in the county.

We aggregate and merge these non-VHA-sourced variables to the monthly VHA medical center level. All non-VHA data were provided at the county level. We linked these county-level variables to each medical center by taking a weighted average of the values associated with the counties in which enrolled veterans resided (referred to as the center's *catchment area*). The weights are defined as the proportion of a medical center's veteran enrollees (in 2010) who resided in a given county. For VHA and non-VHA data that were only available at the annual level, we interpolated the variables to the month level[9]. Table 1 provides summary statistics on each of the variables and the data source of each variable (whether it was VHA or another source).

A medical center's capacity was computed as the total number of hours that unique clinicians in the medical center worked in clinic in a given month, divided by 8 (to get the number of working clinic days), divided by the number of weekdays in the month (e.g., 20), and divided by the number of thousands of enrollees associated with the clinic. We normalize the number of clinicians by the number of enrollees because one new clinician hire would not have the same impact in a large center with many clinicians and enrollees as in a small center[10]. Clinicians included are those who provided primary care visits. The number of hours that a primary care clinician on a given day worked was computed as the time between the start of the clinician's first appointment and the end of the last appointment of the day.

Ignoring the enrollee scale, this measure of capacity is similar to a full-time equivalent (FTE) count. An FTE count would use the total number of clinic days in a month and divide by the number of potential workdays in the month. The slight difference is that we divide by weekdays in a month instead of potential workdays so that the denominator would not be sensitive to holidays (one of our instrumental variables), leaving only the numerator to be sensitive to holidays. In a month with no holidays, one FTE would equal 1 unit of capacity (ignoring the scaling by enrollees). In months with

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[9] The month that was assigned to the values provided by AHRF for a given year depends on the month that the data was collected, as reported in the AHRF documentation. For example, if the survey of the number of primary care physicians was conducted in December of each year, we interpolated monthly values from December of year Y to December of year Y+1. The interpolated values were then aggregated to the medical center catchment area-year-month level.

[10] We recognize that by dividing by the number of enrollees rather than the actual caseload of the primary care division, we may be using a less accurate depiction normalized capacity. However, we did not use the division's actual caseload because it is likely to be correlated with wait times and thus suffer from endogeneity issues. In contrast, local enrollment is stable – once enrolled, veterans remain enrolled for life, regardless of whether they use VHA services.

holidays, one FTE would equal a less than 1 unit of capacity. Our measure of capacity may underreport the potential clinical capacity if all appointments were cancelled by patients on a given clinician-day, even though the clinician was in the clinic that day. We excluded clinicians who had 5 or fewer clinic days for the seven-year span of the data. Ultimately, we identified approximately 20,000 VHA primary care clinicians per year during this period.

A medical center's productivity is the number of visits per clinic day per clinician. It was computed by dividing the total number of primary care office visits (appointments that were not cancelled) by the number of clinic days in a given month. By including capacity and productivity in the model, we decompose the number of visits that a medical center produces into two components: the capacity size and the productivity rate.

Our study sample includes 139 VHA medical centers in the U.S. We excluded several medical centers that either were not in the U.S. (e.g. Philippines, Caribbean) or had limited data (e.g., new medical centers). The unit of observation in the analysis is a medical center-year-month. The main data span October 2013 to September 2018, although we provide robustness checks with a longer panel (but without the Survey of Enrollees measures) starting October 2011.

Instrumental Variables

The focus of this study is to identify the effect of capacity on wait times. Since we are interested in the reduced-form parameters rather than structural parameters (i.e., the relationship between wait times and supply), instrumental variables are not needed to handle this type of simultaneity bias. However, capacity decisions may also be simultaneously determined with supply and demand. Potential reverse causation could lead to bias. As noted in the conceptual model, VHA managers (due to altruism or other incentives) may increase capacity as a response to poor access.

We constructed three instrumental variables that exploit supply shocks to VHA clinician capacity: 1) the proportion of days in a month that are federal holidays, 2) the proportion of paid time that clinicians took as personal leave in a given month, and 3) the proportion of paid time that clinicians took as sick leave in a given month.

The instrumental variables are related in that they directly affect the number of hours that clinicians work. The proportion of weekdays in a given month that are federal holidays affects the number of days that VHA clinicians can work because VHA medical centers are closed on those days. The proportion of time taken as personal leave or sick leave affect amount of time that VHA clinicians see patients. These measures could be considered an input price shock to a clinician hour: clinicians are salaried, and when a clinician takes time off, the price per visit produced increases.

For the exclusion restriction assumptions to hold, the instruments need to be related to VHA wait times for new patient, primary care appointments only through their correlation with VHA primary care clinician capacity. It is difficult to think of an appropriate falsification test for this context. We have not been able to find an alternative outcome or subpopulation that is not affected by the treatment (primary care capacity) but is correlated with confounders (e.g., demand for primary care) that provide an alternative connection between the instrumental variables (primary care clinician leave or holidays) and the primary care wait time. Fortunately, most of the potential confounders we have thought of (demand shifting with the supply shifts) would bias our IV estimates toward zero.

Furthermore, demand shifts are less likely to be as sudden as supply shifts. When suffering from a health issue, patients would like to see a provider as soon as possible. Although veterans may travel around holidays, temporarily reducing demand, they will shift their requested appointments, not eliminate them. In other words, demand gets redistributed across a certain time frame whereas supply is simply cut off. A similar argument could be made for the personal leave instrument. Sick leave is even more of a shock to supply in that it is more of a last minute decision and visits are likely cancelled unexpectedly.

The proportion of time that was taken as personal or sick leave was constructed using VHA payment data. The numerator is the total number of hours that were taken as personal leave (or sick leave) in a given month among clinicians in the sample (i.e., who had clinic days in that month and who had more than 5 clinic days in the timeframe of the data). The denominator is the total number of work hours (including clinical time, research time, sick leave, and personal leave).

To illustrate the variation in the holiday, personal leave, and sick leave instrumental variables, Figure 2 shows that the three variables are not as highly correlated as one might expect. Personal leave is higher during summer months and in March and April. This suggests that it may be more related to school vacation times than to holidays. Federal holidays are spread throughout the year but more frequent in November and January. Although not shown, the federal holidays instrument does vary over time because it is dependent on how many weekdays vs weekends are in a particular month. Figure 3 and Figure 4 illustrate the cross-sectional variation in personal leave and sick leave, using 2017 as an example year. As we will show, these instruments pass the weak instrument test.

Figure 4. Comparison of Personal Leave and Holiday Instrumental Variables (2017) - placeholder

Figure 5. Cross-Sectional Variation by Month in Personal Leave Instrumental Variable (2017) - placeholder

Figure 6. Cross-Sectional Variation by Month in Sick Leave Instrumental Variable (2017) - placeholder

D. DESCRIPTIVE STATISTICS

Table 1 provides definitions, means, and standard deviations of the variables in the analysis. The average wait time across facilities in the sample is 23.7 days for a new patient primary care appointment. However, average wait times vary substantially across VHA facilities, with a max of 74 days and a minimum of 7 days. The average VHA medical center capacity is 26.1 full-time approximate clinicians, which is 4 primary care clinicians per 10,000 enrollees. The average number of visits provided across VHA medical centers is 5,289 per month, and clinicians are providing on average 9 visits per day.

Table 1. Summary Statistics - placeholder

IV. RESULTS

A. NAÏVE MODEL RESULTS

Table 2 shows the OLS estimates of the naïve model, exhibiting a negative relationship between wait times and capacity. This suggests even without correcting for endogeneity, the higher the capacity of a clinic, the lower the wait time. The results are robust to the inclusion of other factors that might affect wait times, such as factors that might influence the demand for VHA health care. The variation between medical centers explains more than half of the total variation in wait times, as exhibited by the increase in R-squared once controlling for medical center fixed effects.

Table 2. OLS estimates

B. FIRST STAGE RESULTS

Table 3 shows the first-stage regression estimates. The first model [1] does not include any covariates. Models [2] and [3] include medical center, then year and quarter fixed effects. Much of the variation in capacity is due to differences across medical centers. The R-squared increases from 0.034 to 0.929 after including medical center fixed effects. Model [4] is the first stage of the preferred specification. The coefficients on the instrumental variables have the signs we would expect. The proportion of days that are holidays and the proportion of time that is taken as paid personal or sick leave are all negatively associated with primary care capacity, although sick leave is not statistically significant. This means that an increase in any of them is associated with fewer days in which clinicians are in the clinic, thereby shrinking the supply.

Table 3. First Stage Results - placeholder

The Cragg-Donald Wald F-statistic for the first stage with all the covariates is 426.01. The results indicate that we can reject the null of weak instruments. Stock and Yogo (2005) provide two tables of critical values for TSLS weak instrument tests, which are based on: 1) the maximal TSLS bias (from weak instruments) relative to the potential OLS bias (from endogeneity) and 2) the “maximal size” (or the worst-case rejection rate *r*) of the Wald test statistic when using weak instruments, given the critical value of the Chi-squared distribution at the 5% level and *n* degrees of freedom. Weak instruments distort (inflate) the Wald test statistic such that the likelihood of being larger than the 5%-level critical value (under the null of no endogeneity or weak instruments) is actually more than 5%. With three instruments and one endogenous variable, the critical value for a 5% maximal TSLS bias relative to the potential OLS bias is 13.91 (Table 1 in Stock and Yogo); and the critical value for a 5% maximal IV size distortion relative to the 5% level Wald test (i.e., maximal size of *r*=10% for a 5%-level Wald test) is 22.30 (Table 2 in Stock and Yogo).

As a sensitivity analysis, we tested specifications using two instruments.[11] A specification using the holiday and personal leave instruments has an Cragg-Donald Wald F-statistic of 608.89, well above 19.93 – the Stock and Yogo critical value for a 5% maximal IV size distortion (maximal size of *r*=10% for a 5%-level Wald test) in a model with one endogenous variable and two instrumental variables. We also tested a model in which productivity is treated as endogenous as well. Using the three instruments, the Cragg-Donal Wald F-statistic is 6.37; and with two instruments (holiday and personal leave) is XXX. If we extend the panel to begin in Oct 2011 instead of Oct 2014, the F-statistics increase to 6.37 using three instruments and 7.19 using two instruments, the latter of which barely passes the Stock and Yogo critical value of 7.03. The drawback is that the R-squared decreases substantially. This may be due to including less relevant demand covariates that describe the local area rather than the veteran enrollee population (variables from the Survey of Enrollees).

C. SECOND STAGE RESULTS

[11] With two instruments and one endogenous variables, we must perform the maximal size distortion test (critical values from Table 2 in Stock and Yogo) rather than the bias test. See Stock and Yogo (2005).

Comparing the naïve model with the instrumental variable (IV) model, we find that the potential endogeneity is not sizeable (Table 4). The magnitude of the clinician capacity coefficient in the IV model is 1.01 times the magnitude of that in the naïve model.

The results show that increases in primary care clinician capacity lead to lower wait times for primary care appointments. This is consistent with a downward sloping demand curve: when capacity increases (supply shifts), wait times decrease. A one standard deviation increase in primary care clinician capacity (a value of 1.19 or approximately 1.19 more full-time clinician working 20 weekdays in the clinic in a month per 10,000 enrollees) would reduce wait times by 5.1 days. This reduction is approximately 58% of the sample standard deviation of the wait time. A 10% increase in capacity is 0.40 more full-time clinicians per 10,000 enrollees and yields a 1.7-day reduction in wait times, which is 7% of the sample average wait time.

We also found that clinician productivity is associated with lower wait times. A one standard deviation increase in clinician productivity (or 0.92 more visits per clinic day per clinician per month) is associated with a1.5-day reduction in wait times, which is 18% of the standard deviation of the wait time. A 10% increase in productivity is 0.93 more visits per clinic day per clinician per month, and so is associated with approximately the same decrease in wait times, which is 6.6% of the sample average wait time.

Table 4. Wait Time Model Estimates - placeholder

Some of the demand factors and other covariates are important in explaining the within-medical center variation in wait times. The results suggest that having alternative health care options (e.g., Medicaid, Medicare Advantage penetration) is associated with less demand for VHA-provided health care. The number of non-federal specialists also is negatively associated with VHA wait times, suggesting less demand for VHA-provided health care. Employment is associated with lower wait times, suggesting it is tied to less demand for VHA care. Housing prices and income are statistically significant. Lower incomes are associated with higher wait times (more demand). Higher housing prices (which may mean higher rents) are associated with higher wait times.

For demographics, relative to the 75+ age group, the 65-74 age group is associated with lower wait times, suggesting that there may be less reliance on the VHA just as veterans become age-eligible for Medicare. Increasing proportions of enrollees who are female or who are married or living with another person are associated with higher wait times (more demand). Increasing proportions of Black or Hispanic enrollees (relative to the White proportion) is associated with increasing wait times (more demand).

Counter to expectations, longer driving distances for veterans are associated with higher wait times, suggesting more demand. This could be identifying other mechanisms. First, veterans are moving toward urban areas. If urban areas have lower wait times, urbanization and decreasing the number of those who live more than 40 minutes away from a VHA clinic may be associated with lower wait times. Another potential explanation is that when clinics close, reliance on the VHA for health care may be more important, increasing the demand and thereby the wait time for the remaining VHA clinics.

Finally, we find that the Recall Reminder policy change is an important factor affecting new patient wait times. This supports the findings of Yee et al. (2020). Giving established patients priority access (allowing them to book their appointments more than 3 months in advance) worsens access for new patients by increasing the wait time. A one standard deviation increase in priority access for established patients increases the wait time for new patients by 43% of a standard deviation. The Recall Reminder (non-compliance) measure increases the R-squared by three percentage points, comparing Models [IV-1] to [IV-2], or 46% of the totally change in the R-squared from including all the covariates (i.e., 0.064).

D. ROBUSTNESS CHECKS

We estimated several alternative models to better understand the relationships between capacity and wait times (Table 5). First, we excluded the facility fixed effects and year fixed effects. Without medical center fixed effects, the magnitude of the capacity effect on wait times is reduced. This suggests that the between-medical center variation in capacity may be positively associated with wait times, or areas with higher capacity also have higher wait times. There are other changes in significance among the covariates. For example, when including between- and within-medical center variation, productivity is not negatively or significantly related to wait times. Drive time is negatively related to wait times, although not statistically significant. Medicare Advantage no longer relates in a significant way with wait times, but the Survey of Enrollee measures of alternative health care options become more important. Full-time employment of enrollees is also more negatively (and significantly) related to wait times. There are some differences in age and the other race category as well.

The second set of analyses tests a longer panel, extending back to October 2011. Since the Survey of Enrollees began in 2014, we had to supplement these variables with local area variables, such as the AHRF’s proportion of those aged 18 to 64 years old who have private insurance coverage and the

Small Area Health Insurance Estimates (SAHIE) programs' unemployment rate and household median income. We also created age variables from the VHA's PSSG database and race variables from VHA's CDW database. We estimated a model with these variables in both the longer panel and short panel to isolate the differences due to sample period from that due to variable specification. The estimates of the effect of capacity on wait times is very similar to our main model estimates; the productivity effect is smaller than our main model estimates.

Finally, we tested a measure of capacity that is not adjusted by the number of enrollees but rather the number of enrollees is controlled for directly in the model. The number of enrollees is positively correlated with wait times, as one would expect (increased demand). The capacity effect is somewhat larger. A one standard deviation in this measure of capacity (13.4 FTE-approximations) is associated with a 9-day reduction in wait times or 1.0 of a standard deviation of the wait time (instead of 0.58). The last model in Table 5 is for convenience, normalizing all the variables (except the wait time dependent variable) by taking each value, subtracting the sample mean, and dividing by the sample standard deviation. This allows for easy comparison of the magnitudes of the variables in the model.

Table 5. Testing Longer Panel and Alternative Specifications

We also tested different sets of instruments and with and without inclusion of productivity in the model. Productivity could potentially be endogenous if providers (and more importantly, their schedulers) try to squeeze in more visits when the wait times are higher. Ultimately, instrumenting for productivity did not pass the weak instrument test using the FY2014-FY2018 sample. Whether we include it or not, instrument for it or not, the coefficient on capacity is robust. Without productivity in the model, the coefficient is smaller by 5.7%. Dropping sick leave as an instrument (which based on other tests seems to be the weakest instrument) and using only holiday and annual leave as instruments, the coefficient is larger by 5.6%.

V. APPLICATION TO VHA POLICY

An earlier version of the model is currently being used to identify underserved areas for veterans per the requirement of the MISSION Act of 2018. Underserved is defined as high demand relative to supply. When predicted wait times at a given VHA medical center are high given the clinician supply and other control factors for demand, the catchment area of the medical center is considered to be an underserved area. We used the predicted (z-scored) wait times to identify these areas, in which access could be improved if provided more resources. The difference between the earlier version and this version of the model is that we now include clinician productivity (in addition to clinician capacity) and other factors, such as patient demographics. The MISSION Act requires VHA to continue to update the model and use it to target resources and mitigation strategies. Please see Appendix A for more information.

VI. DISCUSSION

Our findings suggest that the VHA potentially has three levers for improving access to primary care. Medical centers can increase clinician capacity to reduce wait times for primary care appointments. Although the concept is not new, the magnitude of the effect is sizable. A 10% increase in average clinician capacity leads to a 7.2% reduction in wait times. The VHA could potentially also alter or incentivize productivity among its staff. The results show that a 10% increase in average productivity is associated with a 6.6% reduction in wait times. Finally, carving out access for new patients by simply not scheduling returning patient visits more than 3 months in advance is also associated with a significant reduction in wait times. Yee et al. (2020) found that rescinding the Recall Reminder scheduling policy (and allowing returning patients to schedule in advance) effectively increased wait times by 14%, which seems to be a lower bound given the timeframe of their data.

Health system managers can increase clinician capacity by either hiring more clinicians (increasing supply on the extensive margin) or by making the clinicians work more days in the clinic (increasing supply on the intensive margin). However, in a system with limited resources, like public systems under a fixed budget, this may not be easy. Funds allocated to research, maintenance, or other designations would need to be re-directed to hiring. The benefit per dollar spent on increasing clinician capacity would need to be higher than it is for other designations.

Alternatively, managers could improve access by increasing clinician productivity, another way to increase supply on the intensive margin. Studies have shown the effectiveness of interventions that improved both productivity and wait times (see Ansell et al. 2017 for a review of the interventions). Our findings suggest that clinician productivity is important and potentially should be maximized before considering a reallocation of resources (similar to the argument made by Baicker and Chandra (2011) that productive efficiency needs to be achieved before allocative efficiency can be considered).

Currently, the average number of visits that a clinician has per day is approximately 9. Part of the reason that a clinician might only do 9 per day is that last-minute cancellations leave slots open in the schedule. Thus, having more optimal scheduling systems that fill in cancellations or reduce the likelihood of cancellations may prove to be useful. Yee et al. (2020) showed that the Recall Reminder policy can reduce the number of cancellations.

Scheduling inefficiencies are a kind of production inefficiency. As Baicker and Chandra (2011) state, “allocative efficiency cannot be evaluated when productive inefficiency persists.” The decision to allocate resources within the VHA toward treating patients versus the alternatives is hard to make when the system is not fully using its current set of resources. In other words, the decision to purchase more clinician time (i.e., increasing clinician capacity whether inside the VHA or outside) cannot truly be evaluated until the VHA optimizes productivity.

Other potential ways to improve production is by having medical scribes or by using telemedicine. Scribes can reduce the administrative burden for physicians (Pearson and Frakt 2019). Telemedicine could re-allocate clinician time across VHA clinics. For example, clinicians in one area who have openings in their schedules could treat patients in other clinics that have access issues and relatively high demand. A more agile workforce, adjusting to the ebbs and flows of demand that vary geographically may be a more efficient structure.

Our results are in line with the only other study that has estimated the effect of clinician supply on primary care wait times. Swami et al. (2018) used survey data from general practitioners’ offices in Australia to estimate the effect of (self-reported) hours worked by clinicians on (self-reported) wait times. They find that a 10% increase in the number of hours would decrease the wait time by 11.7%. Although the number of hours per clinician is not directly comparable to the way we measure supply, a 10% increase in hours is similar to a 10% increase in the total number of clinic days (numerator of our clinician capacity measure). We find a slightly smaller number: a 10% increase in clinician capacity reduces wait times by 4%.

On the demand side, our results are consistent with previous findings that show the interdependency between VHA health care and other public health care coverage options. If veterans have access to coverage from Medicaid, Traditional Medicare, or Medicare Advantage, they use VHA health care less (Hebert et al. 2018, Liu et al. 2018, Frakt et al. 2015, Pizer and Prentice 2011). We find that having access to these alternative sources of care is associated with lower wait times for primary care.

VII. LIMITATIONS

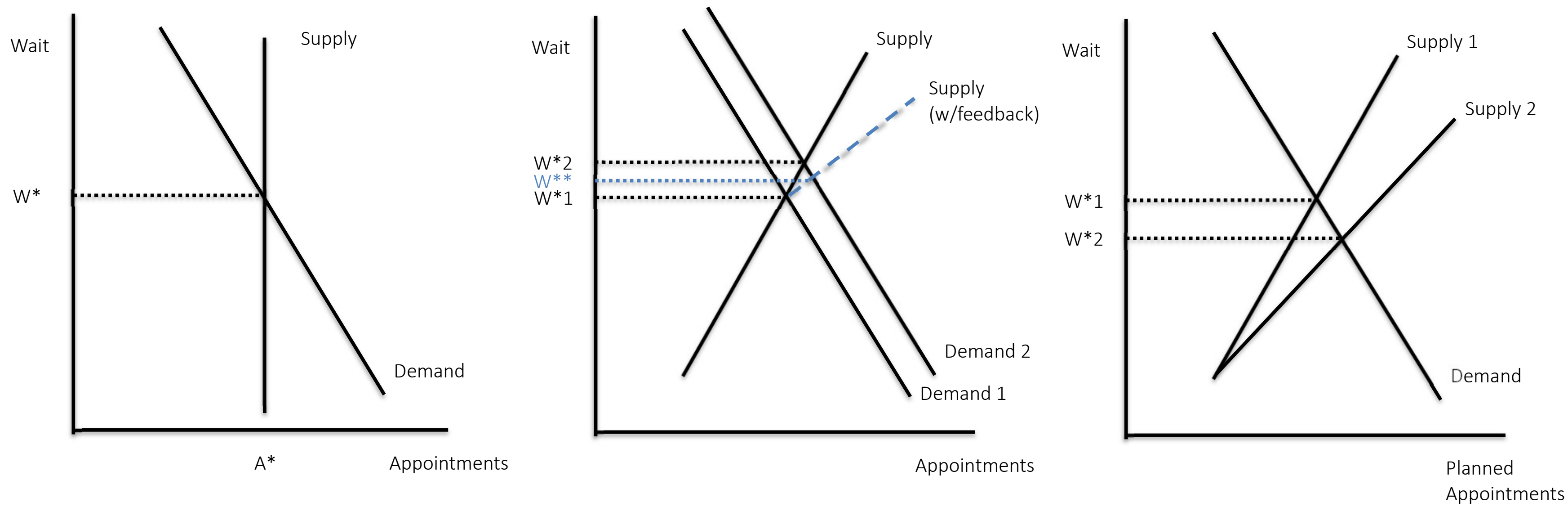
Our study is limited in two ways. First, we do not control for quality in the empirical model. Quality is potentially endogenous. While it may be a demand shifter, it is also an outcome of production. Medical centers have to decide between committing resources to quality of services versus quantity of services, e.g., the number of appointments (Minegishi 2019; Grieco and McDevitt 2016). The quality/quantity decisions are likely simultaneously determined. Furthermore, studies have found that quality (at least those measured by report cards) may not be a salient factor in determining demand (Mukamel et al. 2014). Thus, we do not include a quality measure.

Second, in theory, demand affects the equilibrium appointments supplied through the wait time. In practice, it is possible that patients schedule appointments even if they plan to find alternative (non-VHA) health care and so are not actually willing to wait the wait time quoted at the time of scheduling. This ultimately would affect cancellations, which affects observed productivity – the number of visits per clinic day. We have tested an alternative way to measure productivity: number of appointments, including cancellations, per clinic day. We found the results to be very similar to the main results.

VIII. CONCLUSION

This study estimates the effect of supply capacity and productivity on access to care, based on an aggregate supply and demand framework. The results indicate that a shift in capacity can alter the wait time for primary care. They also demonstrate that a resource-constrained health care system, such as the VHA, may be able to improve wait times, potentially without increasing the budget, by reallocating clinical resources or instituting policies that improve the efficiency of each clinic day. The degree of the access problem in a given area is also dependent on alternative health care options. The VHA operates in markets with a variety of other public and private alternatives and serves an economically heterogeneous population. Our findings have direct implications for current VHA policy that determines where needs are greatest and how the VHA should respond to those needs.

Figure 1. Supply and Demand Framework for VHA Primary Care Appointments



(a) Supply that is inelastic with respect to wait times (providers choose optimal A*, which determins W*)

(b) Incentives-based supply that is responsive to wait times and can affect wait times

(c) Planned supply with slope that is determined by capacity * productivity (illustrated is an increase in capacity or productivity)

Figure 2. Geographic Variation in Wait Times, FY 2014

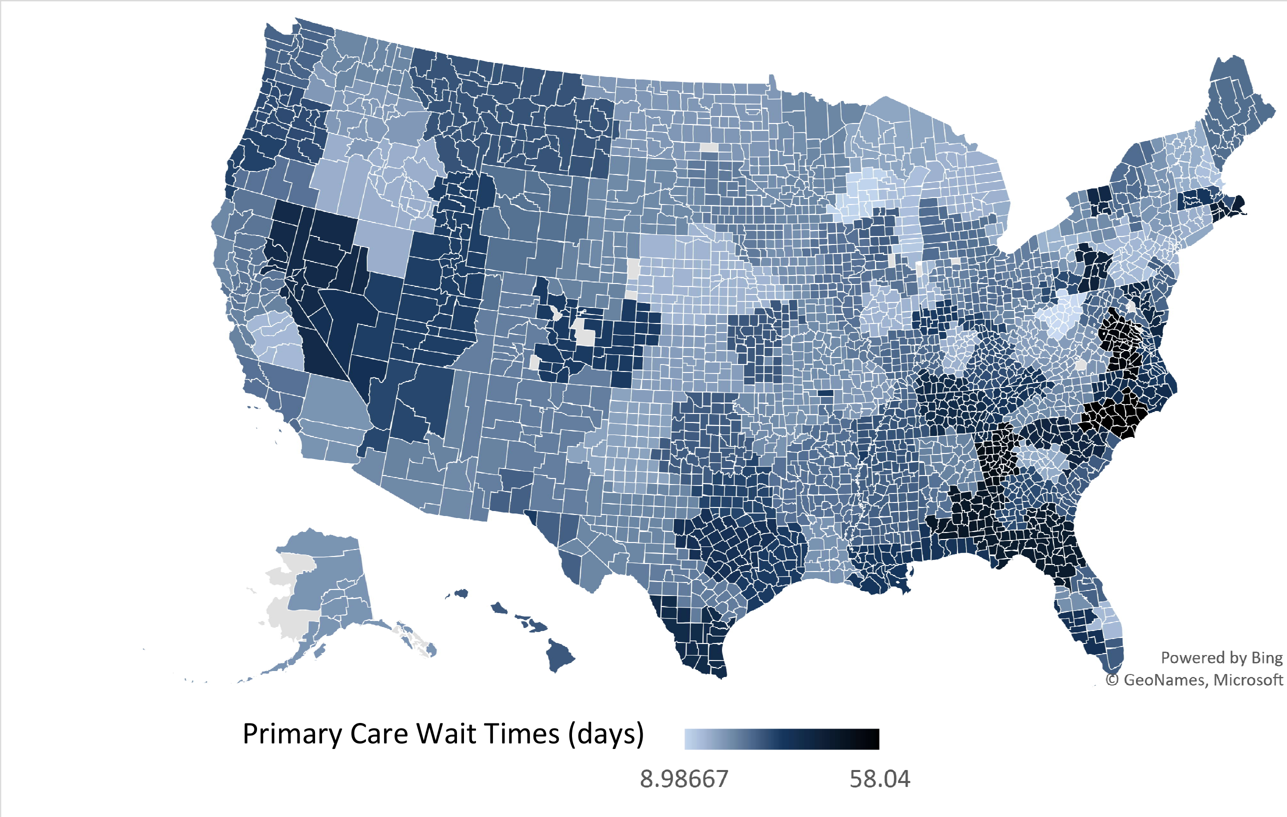
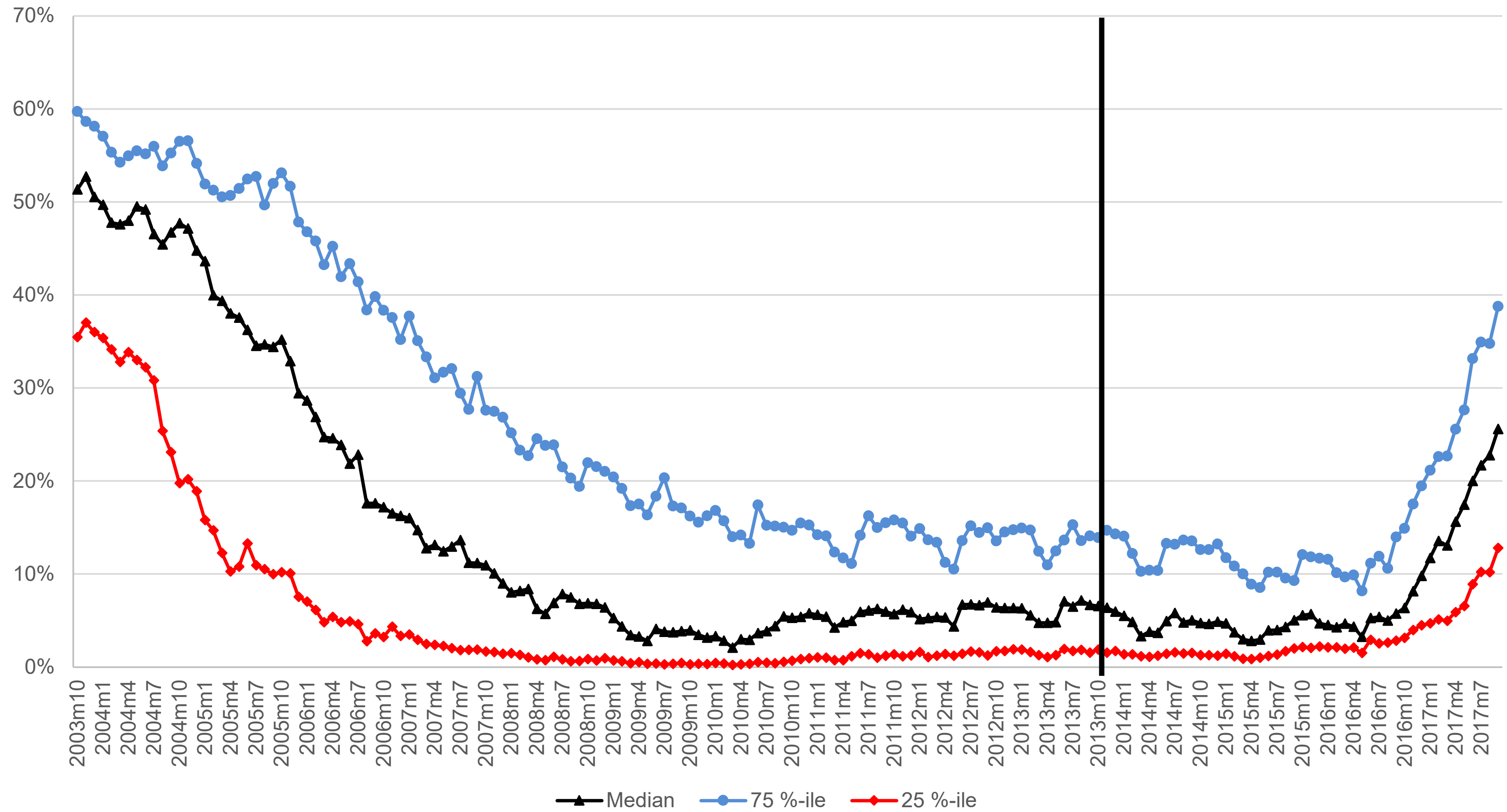


Figure 3. Measuring the Recall Reminder Scheduling Policy Change in May 2016



This is a copy of Figure 2 in Yee et al. (2020). The measure on the y-axis is the % of established patient appointments with greater than 90 day booking lead times. The Figure shows the median, 25th percentile and 75th percentile of this measure across medical centers over time. Overlayed on the graph is a black vertical bar, which represents the month in which our main sample begins. May 2016 is when Recall Reminder was rescinded.

Figure 4. Comparison of Instrumental Variables (Mean Values for 2017)

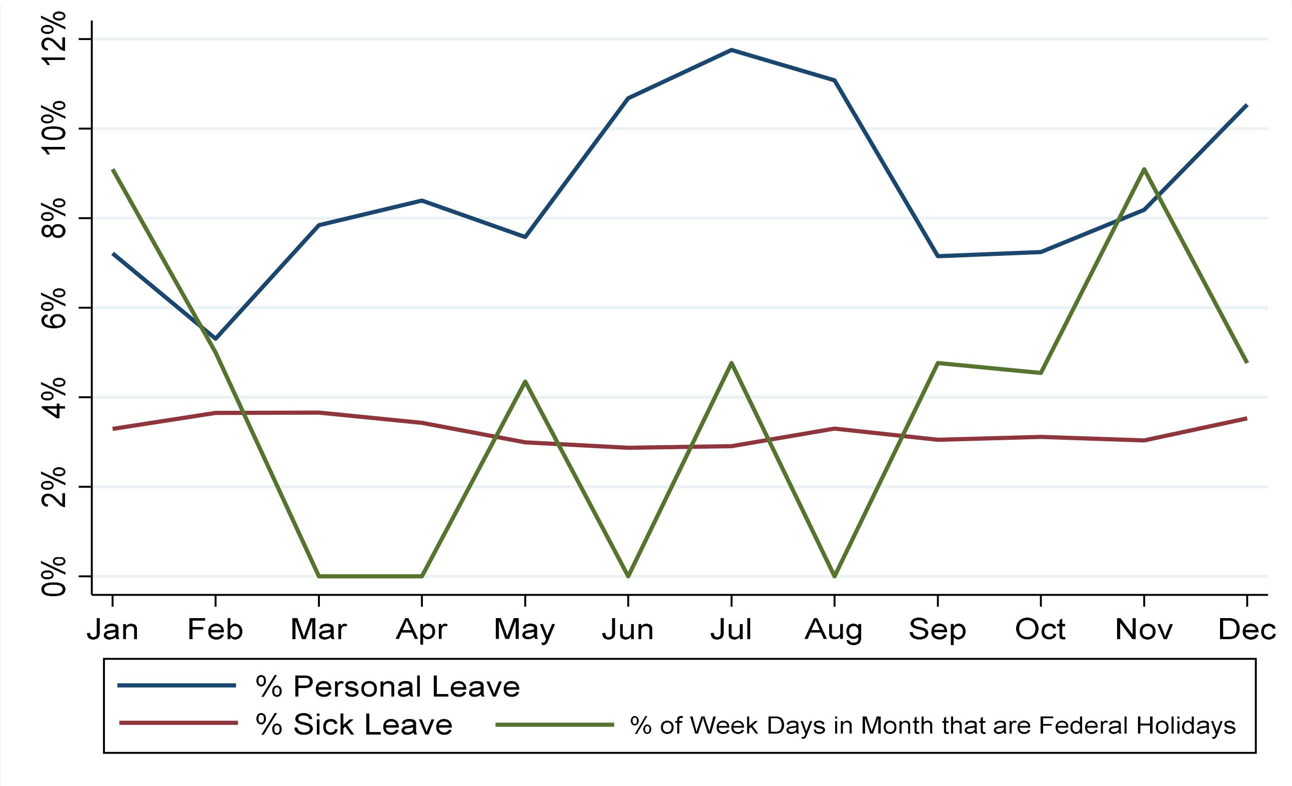


Figure 5. Cross-Sectional Variation in Personal Leave Instrumental Variable (2017)

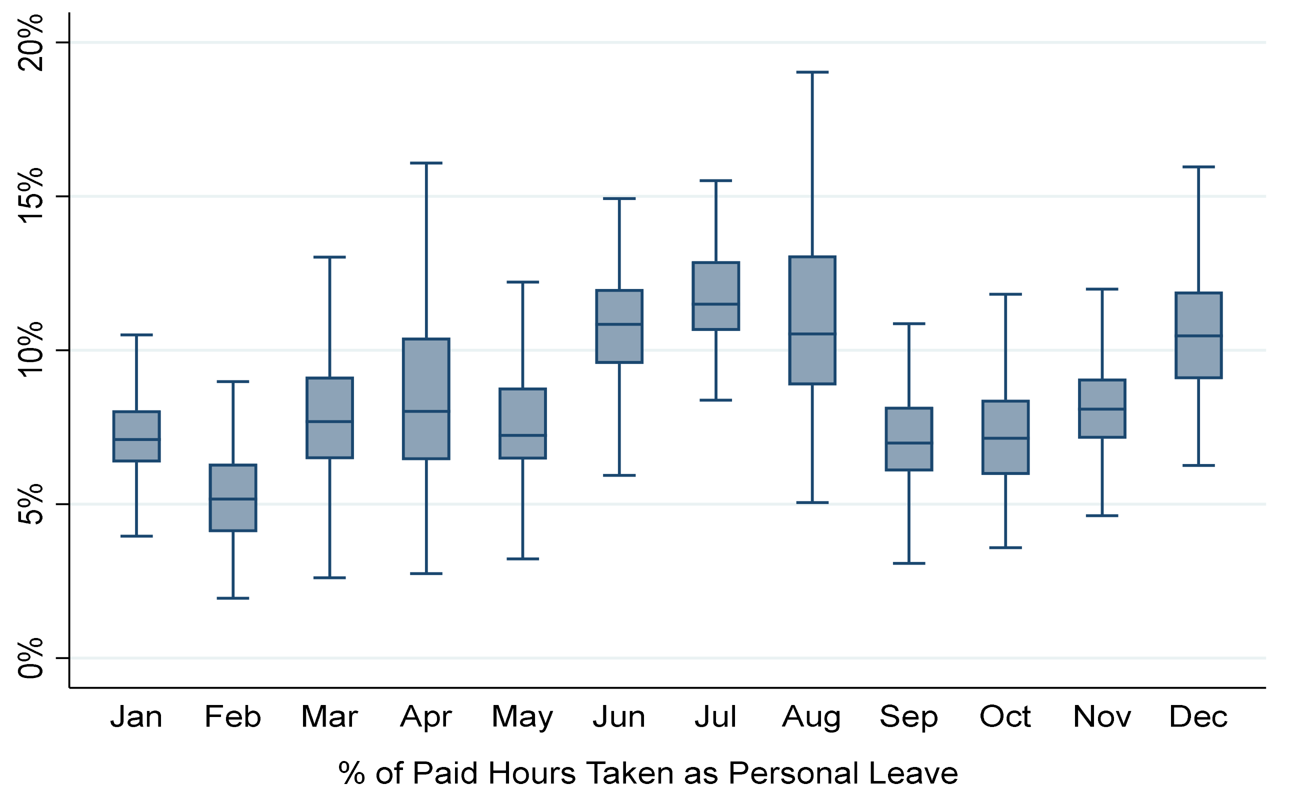


Figure 6. Cross-Sectional Variation in Sick Leave Instrumental Variable (2017)

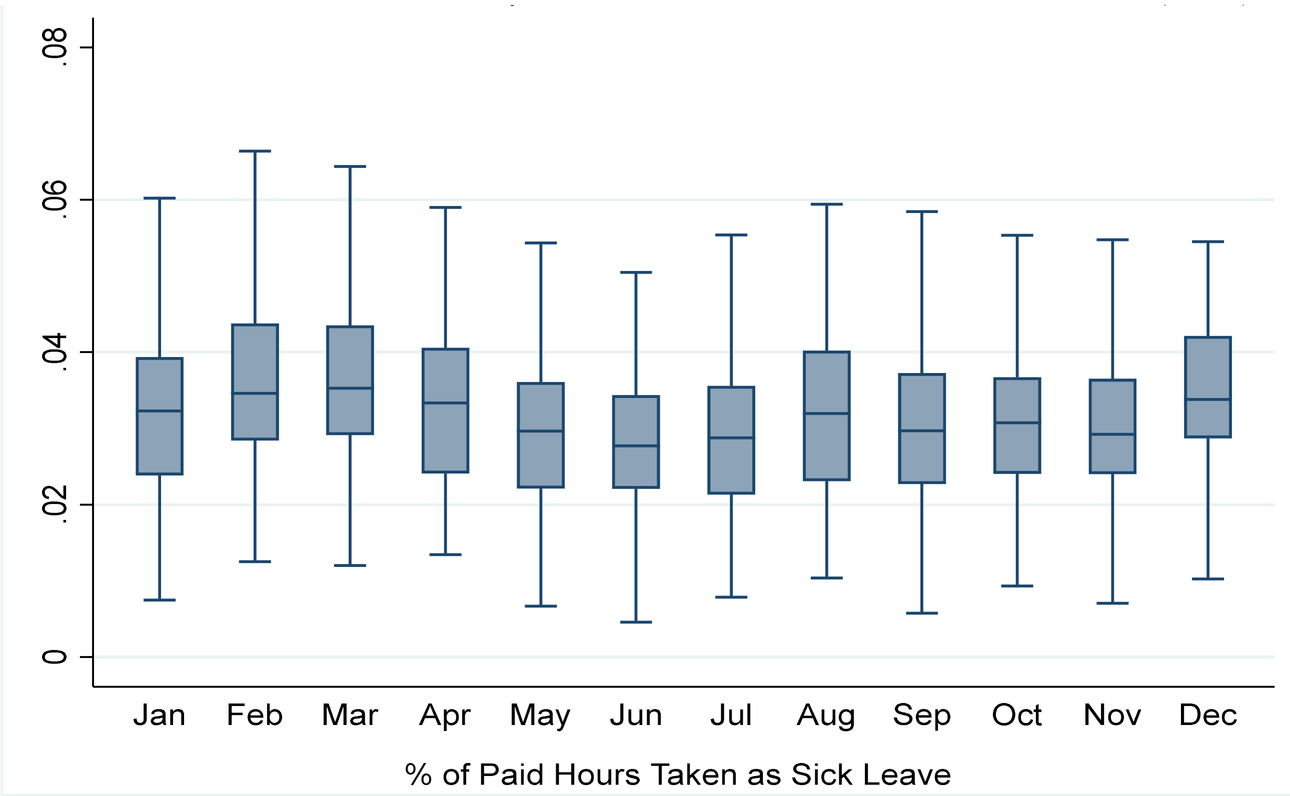


Table 1. Summary Statistics

Dependendent Variable	Source	mean	sd	min	max
Primary Care Wait Time for New Patients	VHA CDW	23.74	8.77	7.51	73.96
Number of New Patient Appointments[a]	VHA CDW	519.79	362.62	69.00	3216.00
Endogenous Variables of Interest					
Clinic Days (physician/APPs)[b]	VHA CDW	567.64	293.17	111.11	1990.82
Clinic FTE-A (physician/APPs)[b]	VHA CDW	26.10	13.44	5.29	91.80
# Enrollees	VHA PSSG	70,822	40,615	10,220	227,686
Clinic FTE-A per 10,000 Enrollees (Capacity)	VHA CDW	3.97	1.19	1.27	10.66
Total Scheduled Visits[b]	VHA CDW	5,289	2,806	1,097	17,255
Scheduled Visits per Clinic Day (Productivity)	VHA CDW	9.31	0.92	5.17	13.22
Instrumental Variables					
Holiday % of Weekdays (0-1)	VHA TAEP	3.85%	3.19%	0.00%	10.00%
Annual Leave % of Weekday Hours (0-1)	VHA TAEP	8.45%	2.69%	1.80%	20.53%
Sick Leave % of Weekday Hours (0-1)	VHA TAEP	3.17%	1.17%	0.27%	11.43%
Primary Covariates I					
% Enrollees 20-40 Mins Drive Time (0-100)	VHA PSSG	20.65%	11.42%	0.00%	50.76%
% Enrollees >= 40 Mins Drive Time (0-100)	VHA PSSG	8.42%	8.35%	0.00%	46.30%
Recall Reminder non-compliance measure: % VHA Est Patient Appts >= 90 Days (0-100)	VHA CDW	12.87%	12.84%	0.00%	54.16%
Primary Covariates II: Health / Health Coverage					
Medicare Advantage Penetration (0-100)	CMS	29.50%	11.66%	0.39%	60.23%
Non-federal Specialists per 1,000 population	AHRF	2.41	0.87	0.92	5.13
Medicare HCC Severity Index	CMS	0.99	0.08	0.77	1.24
Population Density (in 1,000s)	AHRF	0.91	2.53	0.01	25.60
% Enrollees Comprehensive Insurance (0-100)	VHA SoE	57.23%	6.35%	37.26%	81.89%
% Enrollees Medicaid Coverage (0-100)	VHA SoE	7.21%	1.97%	1.82%	17.11%
% Enrollees w/ Medical Only (no Part D) (0-100)	VHA SoE	26.51%	6.06%	9.34%	45.72%
% MISSING Insurance from Survey (0-100)	VHA SoE	0.25%	0.28%	0.00%	2.32%
% of Survey Respondants Who Identify as Enrollee (0-100)	VHA SoE	88.82%	3.32%	73.13%	96.95%
% MISSING Enrollee Info from Survey (0-100)	VHA SoE	6.12%	1.65%	0.69%	12.31%
Primary Covariates III: Socioeconomic					
% Enrollees Full-Time Employed (0-100)	VHA SoE	16.87%	4.42%	7.29%	42.28%
% Enrollees Part-Time Employed (0-100)	VHA SoE	8.13%	1.86%	2.63%	16.11%
% MISSING Employment from Survey (0-100)	VHA SoE	1.96%	0.72%	0.00%	5.00%
% Enrollees Income < 20k (0-100)	VHA SoE	21.38%	7.38%	0.35%	46.81%
% Enrollees Income 50 - 75k (0-100)	VHA SoE	10.73%	4.88%	0.00%	25.78%
% Enrollees Income > 75k (0-100)	VHA SoE	13.10%	6.32%	0.00%	53.13%
% MISSING Income from Survey (0-100)	VHA SoE	17.92%	24.41%	0.39%	97.58%
Zillow Index (in 100,000s)	Zillow	2.07	1.24	0.76	9.01
Primary Covariates IV: Demographics					
% Enrolles Age Below 40 (0-100)	VHA SoE	3.38%	2.29%	0.00%	20.54%
% Enrollees Age 40-65 (0-100)	VHA SoE	28.85%	6.90%	12.94%	54.48%
% Enrollees Age 65-75 (0-100)	VHA SoE	37.70%	5.10%	16.95%	57.61%
% MISSING Age from Survey (0-100)	VHA SoE	0.00%	0.03%	0.00%	0.56%
% Enrollees Female (0-100)	VHA SoE	6.43%	3.23%	1.10%	31.83%
% MISSING Gender from Survey (0-100)	VHA SoE	0.00%	0.02%	0.00%	0.56%
% Enrollees African American (0-100)	VHA SoE	10.47%	10.58%	0.00%	45.59%
% Enrollees Hispanic (0-100)	VHA SoE	5.48%	7.93%	0.00%	62.63%
% Enrollees Other Race (0-100)	VHA SoE	3.93%	5.36%	0.00%	65.58%
% MISSING Race from Survey (0-100)	VHA SoE	3.12%	2.04%	0.00%	27.53%
% of Enrollees Married (0-100)	VHA SoE	65.01%	4.40%	46.84%	79.20%
% MISSING Married from Survey (0-100)	VHA SoE	1.59%	0.62%	0.00%	4.86%

The number of observations is 6,486 medical center-months.

a The number of new patient appointments is used as weight in the model due to the dependent variable being an average value.

b These variables are not in the model directly but are used to create Capacity and Productivity measures.

Abbreviations. FTE-A: Full-time Equivalent Approximation - this is the number of total clinician hours divided by eight and divided by the number of weekdays in a month.

Table 2. Naïve Model of Primary Care Wait Times

Dependent variable: Average Wait Time	[1]		[2]		[3]		[4]		[5]		[6]		[7]	
	β		β		β		β		β		β		β	
	(s.e.)		(s.e.)		(s.e.)		(s.e.)		(s.e.)		(s.e.)		(s.e.)	
Capacity					-4.324	***	-4.641	***	-4.440	***	-4.376	***	-4.240	***
					(0.307)		(0.298)		(0.295)		(0.293)		(0.284)	
Efficiency					-1.682	***	-1.748	***	-1.688	***	-1.668	***	-1.668	***
					(0.253)		(0.244)		(0.243)		(0.243)		(0.244)	
% Est Patient Appts >= 90 Days							0.264	***	0.289	***	0.294	***	0.297	***
							(0.016)		(0.017)		(0.017)		(0.017)	
Population Density (in 1,000s)							-3.139	***	-3.740	***	-4.123	***	-4.410	***
							(0.806)		(0.899)		(0.875)		(0.861)	
% of Survey Respondants Enrollees							0.352	***	0.349	***	0.426	***	0.446	***
							(0.079)		(0.080)		(0.085)		(0.086)	
% MISSING Enrollee Info from Survey							0.119		0.057		0.107		0.127	
							(0.127)		(0.126)		(0.130)		(0.128)	
% Enrollees 20-40 Mins Drive Time							0.044		0.007		0.006		0.029	
							(0.056)		(0.056)		(0.058)		(0.058)	
% Enrollees >= 40 Mins Drive Time							0.226	**	0.246	***	0.234	**	0.298	***
							(0.095)		(0.094)		(0.095)		(0.095)	
% Enrollees Comprehensive Insurance							-0.189	***	-0.158	***	-0.085		-0.133	**
							(0.050)		(0.057)		(0.063)		(0.064)	
% Enrollees Medicaid Coverage							-0.067		-0.183	**	-0.145	*	-0.133	*
							(0.066)		(0.077)		(0.076)		(0.076)	
% Enrollees w/ Medical Only (no Part D)							-0.366	***	-0.415	***	-0.291	***	-0.234	***
							(0.061)		(0.063)		(0.070)		(0.069)	
% MISSING Insurance from Survey							1.690	***	2.116	***	2.090	***	2.012	***
							(0.571)		(0.568)		(0.575)		(0.586)	
Medicare Advantage Penetration							-0.359	***	-0.369	***	-0.350	***	-0.273	***
							(0.076)		(0.078)		(0.080)		(0.077)	
Non-VA Specialists per 1,000 Population							-6.019	***	-6.075	***	-6.050	***	-5.594	***
							(1.866)		(1.895)		(1.902)		(1.835)	
% Enrollees Full-Time Employed									0.069		-0.033		-0.049	
									(0.051)		(0.058)		(0.057)	
% Enrollees Part-Time Employed									-0.018		-0.032		-0.047	
									(0.076)		(0.077)		(0.077)	
% MISSING Employment from Survey									0.339	*	0.255		0.117	
									(0.180)		(0.181)		(0.200)	
% Enrollees Income < 20k									0.196	***	0.204	***	0.237	***
									(0.046)		(0.047)		(0.046)	
% Enrollees Income 50 - 75k									0.046		0.089		0.123	*
									(0.064)		(0.065)		(0.065)	
% Enrollees Income > 75k									-0.041		-0.018		0.042	
									(0.042)		(0.045)		(0.044)	
% MISSING Income from Survey									-0.013		-0.023		-0.024	
									(0.025)		(0.025)		(0.025)	
Zillow Index (in 100,000s)									2.525	***	2.683	***	2.836	***
									(0.696)		(0.739)		(0.738)	
% Enrolles Age Below 40											0.278	***	0.039	
											(0.102)		(0.104)	
% Enrollees Age 40-65											0.080		-0.046	
											(0.063)		(0.062)	
% Enrollees Age 65-75											-0.102	***	-0.124	***
											(0.038)		(0.039)	
% MISSING Age from Survey											-7.695	**	2.086	
											(3.282)		(5.234)	
Medicare HCC Severity Index											15.873		9.374	
											(12.120)		(11.692)	
% Enrollees Female													0.501	***
													(0.081)	
% MISSING Gender from Survey													-9.568	
													(6.564)	
% Enrollees African American													0.507	***
													(0.066)	
% Enrollees Hispanic													0.404	***
													(0.070)	
% Enrollees Other Race													-0.252	***
													(0.087)	
% MISSING Race from Survey													-0.302	***
													(0.099)	
% of Enrollees Married													0.219	***
													(0.043)	
% MISSING Married from Survey													0.924	***
													(0.213)	
Constant	26.308	***	17.323	***	51.457	***	58.861	***	55.012	***	26.085		12.005	
	(0.113)		(0.748)		(3.124)		(11.338)		(11.662)		(16.279)		(16.213)	
Facility Fixed Effects			X		X		X		X		X		X	
Year and Quarter Fixed Effects			X		X		X		X		X		X	
Observations	12,627		6,438		6,438		6,438		6,438		6,438		6,438	
R-squared	0.000		0.606		0.625		0.668		0.675		0.677		0.688	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. First Stage Models of Capacity

Dependent variable: Average Wait Time	[1] β (s.e.)		[2] β (s.e.)		[3] β (s.e.)		[4] β (s.e.)	
Holiday %	-4.872	***	-4.526	***	-3.929	***	-3.910	***
	(0.470)		(0.129)		(0.148)		(0.139)	
Annual Leave Pct (phys/APP)	-5.645	***	-4.680	***	-4.250	***	-4.087	***
	(0.560)		(0.157)		(0.163)		(0.153)	
Sick Leave Pct (phys/APP)	-11.073	***	-1.952	***	-2.715	***	-2.581	***
	(1.265)		(0.394)		(0.385)		(0.363)	
Scheduled Visits per Clinic Day							-0.212	***
							(0.010)	
% Est Patient Appts >= 90 Days							0.001	**
							(0.001)	
Population Density (in 1,000s)							-0.074	
							(0.051)	
% of Survey Respondants Enrollees							-0.004	
							(0.004)	
% MISSING Enrollee Info from Survey							-0.008	
							(0.006)	
% Enrollees 20-40 Mins Drive Time							0.011	***
							(0.003)	
% Enrollees >= 40 Mins Drive Time							0.006	
							(0.004)	
% Enrollees Comprehensive Insurance							0.015	***
							(0.003)	
% Enrollees Medicaid Coverage							0.007	**
							(0.003)	
% Enrollees w/ Medical Only (no Part D)							0.016	***
							(0.003)	
% MISSING Insurance from Survey							0.007	
							(0.018)	
Medicare Advantage Penetration							-0.004	
							(0.003)	
Non-VA Specialists per 1,000 Population							-0.459	***
							(0.094)	
% Enrollees Full-Time Employed							-0.003	
							(0.003)	
% Enrollees Part-Time Employed							-0.001	
							(0.004)	
% MISSING Employment from Survey							-0.015	*
							(0.008)	
% Enrollees Income < 20k							0.000	
							(0.002)	
% Enrollees Income 50 - 75k							0.003	
							(0.003)	
% Enrollees Income > 75k							0.005	**
							(0.002)	
% MISSING Income from Survey							0.004	***
							(0.001)	
Zillow Index (in 100,000s)							-0.354	***
							(0.037)	
% Enrolles Age Below 40							-0.009	**
							(0.004)	
% Enrollees Age 40-65							-0.003	
							(0.002)	
% Enrollees Age 65-75							0.006	***
							(0.002)	
% MISSING Age from Survey							0.220	
							(0.349)	
Medicare HCC Severity Index							0.036	
							(0.487)	
% Enrollees Female							-0.021	***
							(0.003)	
% MISSING Gender from Survey							0.243	
							(0.401)	
% Enrollees African American							-0.011	***
							(0.003)	
% Enrollees Hispanic							0.003	
							(0.003)	
% Enrollees Other Race							-0.003	
							(0.004)	
% MISSING Race from Survey							-0.002	
							(0.004)	
% of Enrollees Married							-0.004	*
							(0.002)	
% MISSING Married from Survey							-0.005	
							(0.009)	
Constant	4.989	***	4.935	***	4.703	***	7.405	***
	(0.073)		(0.051)		(0.053)		(0.741)	
Facility Fixed Effects			x		x		x	
Year and Quarter Fixed Effects					x		x	
Observations	6,438		6,438		6,438		6,438	
R-squared	0.034		0.929		0.934		0.942	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Naïve and Second Stage Models of Primary Care Wait Times

Dependent variable: Average Wait Time	[IV-1]		[IV-2]		[IV-3]		[IV-4]		[IV-5]		Naïve OLS Model	
	β		β		β		β		β		β	
	(s.e.)		(s.e.)		(s.e.)		(s.e.)		(s.e.)		(s.e.)	
{Predicted) Capacity	-4.506	***	-4.369	***	-4.334	***	-4.314	***	-4.286	***	-4.240	***
	(0.807)		(0.769)		(0.739)		(0.737)		(0.717)		(0.284)	
Efficiency	-1.748	***	-1.744	***	-1.668	***	-1.653	***	-1.675	***	-1.668	***
	(0.312)		(0.304)		(0.299)		(0.301)		(0.297)		(0.244)	
% Est Patient Appts >= 90 Days			0.245	***	0.285	***	0.289	***	0.293	***	0.297	***
			(0.017)		(0.017)		(0.018)		(0.017)		(0.017)	
Population Density (in 1,000s)					-3.946	***	-4.309	***	-4.555	***	-4.410	***
					(0.894)		(0.881)		(0.881)		(0.861)	
% of Survey Respondants Enrollees					0.372	***	0.446	***	0.465	***	0.446	***
					(0.081)		(0.087)		(0.087)		(0.086)	
% MISSING Enrollee Info from Survey					0.110		0.157		0.170		0.127	
					(0.128)		(0.132)		(0.130)		(0.128)	
% Enrollees 20-40 Mins Drive Time					0.006		0.014		0.035		0.029	
					(0.058)		(0.060)		(0.060)		(0.058)	
% Enrollees >= 40 Mins Drive Time					0.218	**	0.205	**	0.279	***	0.298	***
					(0.099)		(0.100)		(0.099)		(0.095)	
% Enrollees Comprehensive Insurance					-0.148	**	-0.081		-0.126	*	-0.133	**
					(0.059)		(0.065)		(0.066)		(0.064)	
% Enrollees Medicaid Coverage					-0.176	**	-0.137	*	-0.119		-0.133	*
					(0.078)		(0.077)		(0.077)		(0.076)	
% Enrollees w/ Medical Only (no Part D)					-0.402	***	-0.286	***	-0.225	***	-0.234	***
					(0.064)		(0.071)		(0.070)		(0.069)	
% MISSING Insurance from Survey					2.197	***	2.163	***	2.059	***	2.012	***
					(0.569)		(0.574)		(0.584)		(0.586)	
Medicare Advantage Penetration					-0.345	***	-0.327	***	-0.252	***	-0.273	***
					(0.077)		(0.079)		(0.077)		(0.077)	
Non-VA Specialists per 1,000 Population					-5.503	***	-5.502	***	-5.076	***	-5.594	***
					(1.968)		(1.988)		(1.965)		(1.835)	
% Enrollees Full-Time Employed					0.049		-0.045		-0.055		-0.049	
					(0.053)		(0.059)		(0.058)		(0.057)	
% Enrollees Part-Time Employed					-0.004		-0.016		-0.024		-0.047	
					(0.078)		(0.078)		(0.079)		(0.077)	
% MISSING Employment from Survey					0.388	**	0.296		0.181		0.117	
					(0.185)		(0.186)		(0.204)		(0.200)	
% Enrollees Income < 20k					0.202		0.211	***	0.238	***	0.237	***
					(0.047)		(0.047)		(0.046)		(0.046)	
% Enrollees Income 50 - 75k					0.039		0.080		0.115	*	0.123	*
					(0.068)		(0.069)		(0.068)		(0.065)	
% Enrollees Income > 75k					-0.024		-0.001		0.057		0.042	
					(0.045)		(0.047)		(0.047)		(0.044)	
% MISSING Income from Survey					-0.006		-0.015		-0.015		-0.024	
					(0.026)		(0.026)		(0.026)		(0.025)	
Zillow Index (in 100,000s)					2.654	***	2.732	***	2.814	***	2.836	***
					(0.738)		(0.771)		(0.767)		(0.738)	
% Enrolles Age Below 40							0.236	**	0.002		0.039	
							(0.105)		(0.107)		(0.104)	
% Enrollees Age 40-65							0.072		-0.056		-0.046	
							(0.064)		(0.062)		(0.062)	
% Enrollees Age 65-75							-0.115	***	-0.138	***	-0.124	***
							(0.040)		(0.041)		(0.039)	
% MISSING Age from Survey							-6.751	**	1.993		2.086	
							(3.251)		(5.080)		(5.234)	
Medicare HCC Severity Index							11.959		7.098		9.374	
							(12.376)		(11.904)		(11.692)	
% Enrollees Female									0.463	***	0.501	***
									(0.086)		(0.081)	
% MISSING Gender from Survey									-7.944		-9.568	
									(6.426)		(6.564)	
% Enrollees African American									0.503	***	0.507	***
									(0.068)		(0.066)	
% Enrollees Hispanic									0.400	***	0.404	***
									(0.072)		(0.070)	
% Enrollees Other Race									-0.269	***	-0.252	***
									(0.087)		(0.087)	
% MISSING Race from Survey									-0.285	***	-0.302	***
									(0.097)		(0.099)	
% of Enrollees Married									0.207	***	0.219	***
									(0.044)		(0.043)	
% MISSING Married from Survey									0.822	***	0.924	***
									(0.214)		(0.213)	
Constant	52.823	***	51.349	***	48.996	***	25.327		11.550		12.005	
	(5.655)		(5.440)		(12.332)		(16.727)		(16.705)		(16.213)	
Facility Fixed Effects	X		X		X		X		X		X	
Year and Quarter Fixed Effects	X		X		X		X		X		X	
Observations	6,438		6,438		6,438		6,438		6,438		6,438	
R-squared	0.610		0.640		0.659		0.662		0.674		0.688	

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

Table 5. Testing Longer Panel and Alternative Specifications

Dependent Variable: Average Wait Time	IV: Main		No Year FE		No VAMC FE		Long Panel, no SoE		Short Panel, no SoE		Unadjusted Capacity (FTE-A)		Z-scored	
Panel length if not FY2014-FY2018							FY2011-FY2018							
Survey of Enrollee Variables	X		X		X						X		X	
Predicted Capacity	-4.286	***	-3.979	***	-3.278	***	-4.142	***	-4.297	***	-0.676	***	-4.975	***
	(0.717)		(0.745)		(0.756)		(0.675)		(0.766)		(0.113)		(0.832)	
Scheduled Visits per Clinic Day	-1.675	***	-1.581	***	0.051		-1.208	***	-1.781	***	-1.528	***	-1.741	***
	(0.297)		(0.309)		(0.218)		(0.223)		(0.306)		(0.279)		(0.308)	
% Est Patient Appts >= 90 Days	0.293	***	0.222	***	0.321	***	0.277	***	0.285	***	0.311	***	3.559	
	(0.017)		(0.014)		(0.017)		(0.013)		(0.018)		(0.018)		(0.209)	
Population Density (in 1,000s)	-4.555	***	-3.479	***	-0.155	***	-3.286	***	-3.162	***	-4.658	***	-11.433	***
	(0.881)		(0.892)		(0.057)		(0.813)		(1.021)		(0.878)		(2.212)	
% of Survey Respondants Enrollees	0.465	***	0.526	***	0.302	**					0.475	***	1.544	***
	(0.087)		(0.085)		(0.137)						(0.087)		(0.289)	
% MISSING Enrollee Info from Survey	0.170		0.228	*	0.085						0.161		0.281	
	(0.130)		(0.133)		(0.155)						(0.130)		(0.214)	
% Enrollees 20-40 Mins Drive Time	0.035		0.088		0.024		0.032		-0.046		-0.002		0.405	
	(0.060)		(0.061)		(0.017)		(0.050)		(0.061)		(0.061)		(0.683)	
% Enrollees >= 40 Mins Drive Time	0.279	***	0.171	*	-0.031		-0.067		0.227	**	0.277	***	2.338	***
	(0.099)		(0.101)		(0.021)		(0.057)		(0.105)		(0.099)		(0.829)	
% Enrollees Comprehensive Insurance	-0.126	*	-0.180	***	-0.148	**					-0.162	**	-0.799	*
	(0.066)		(0.068)		(0.061)						(0.065)		(0.419)	
% Enrollees Medicaid Coverage	-0.119		-0.107		-0.129	**					-0.135	*	-0.233	
	(0.077)		(0.079)		(0.065)						(0.077)		(0.151)	
% Enrollees w/ Medical Only (no Part D)	-0.225	***	-0.282	***	-0.138	**					-0.242	***	-1.366	***
	(0.070)		(0.072)		(0.060)						(0.070)		(0.424)	
% MISSING Insurance from Survey	2.059	***	1.494	**	0.694						2.067	***	0.580	***
	(0.584)		(0.596)		(0.741)						(0.578)		(0.165)	
Medicare Advantage Penetration	-0.252	***	-0.501	***	-0.007		-0.207	***	-0.208	***	-0.216	***	-3.021	***
	(0.077)		(0.079)		(0.018)		(0.056)		(0.076)		(0.076)		(0.918)	
Non-VA Specialists per 1,000 Population	-5.076	***	-6.970	***	-0.154		-2.487	**	-7.733	***	-5.458	***	-4.928	***
	(1.965)		(2.007)		(0.188)		(1.182)		(1.824)		(1.969)		(1.908)	
% Enrollees Full-Time Employed	-0.055		-0.159	***	-0.175	***					-0.027		-0.243	
	(0.058)		(0.056)		(0.061)						(0.058)		(0.257)	
% Enrollees Part-Time Employed	-0.024		0.081		0.100						-0.017		-0.044	
	(0.079)		(0.083)		(0.088)						(0.079)		(0.146)	
% MISSING Employment from Survey	0.181		0.297		-0.103						0.205		0.131	
	(0.204)		(0.211)		(0.212)						(0.204)		(0.148)	
% Enrollees Income < 20k	0.238	***	0.230	***	0.161	***					0.219	***	1.756	***
	(0.046)		(0.048)		(0.055)						(0.046)		(0.341)	
% Enrollees Income 50 - 75k	0.115	*	0.029		0.382	***					0.100		0.561	*
	(0.068)		(0.071)		(0.084)						(0.067)		(0.330)	
% Enrollees Income > 75k	0.057		0.044		-0.098	**					0.024		0.358	
	(0.047)		(0.039)		(0.047)						(0.047)		(0.298)	
% MISSING Income from Survey	-0.015		-0.006		-0.031						-0.029		-0.362	
	(0.026)		(0.024)		(0.029)						(0.026)		(0.639)	
Zillow Index (in 100,000s)	2.814	***	-1.279	*	0.609	***	-1.736	**	-2.917	**	3.863	***	3.126	***
	(0.767)		(0.707)		(0.171)		(0.712)		(1.480)		(0.727)		(0.853)	
% Enrolles Age Below 40	0.002		0.072		-0.003						0.024		0.004	
	(0.107)		(0.108)		(0.113)						(0.107)		(0.245)	
% Enrollees Age 40-65	-0.056		0.110	*	0.229	***					-0.041		-0.388	
	(0.062)		(0.059)		(0.053)						(0.062)		(0.430)	
% Enrollees Age 65-75	-0.138	***	-0.141	***	0.294	***					-0.137	***	-0.703	***
	(0.041)		(0.043)		(0.037)						(0.040)		(0.209)	
% MISSING Age from Survey	1.993		5.613		-12.508	***					0.090		0.054	
	(5.080)		(5.286)		(3.899)						(5.127)		(0.136)	
Medicare HCC Severity Index	7.098		2.391		-33.936	***	10.411		15.225		6.644		0.560	
	(11.904)		(12.227)		(3.614)		(7.742)		(14.324)		(11.861)		(0.939)	
% Enrollees Female	0.463	***	0.432	***	0.503	***					0.446	***	1.493	***
	(0.086)		(0.087)		(0.098)						(0.087)		(0.277)	
% MISSING Gender from Survey	-7.944		-10.950		-5.604						-7.107		-0.188	
	(6.426)		(6.705)		(5.480)						(6.519)		(0.152)	
% Enrollees African American	0.503	***	0.414	***	0.226	***					0.484	***	5.326	***
	(0.068)		(0.068)		(0.021)						(0.068)		(0.718)	
% Enrollees Hispanic	0.400	***	0.248	***	0.197	***					0.299	***	3.170	***
	(0.072)		(0.072)		(0.032)						(0.073)		(0.568)	
% Enrollees Other Race	-0.269	***	-0.274	***	0.108	***					-0.232	***	-1.442	***
	(0.087)		(0.090)		(0.035)						(0.086)		(0.465)	
% MISSING Race from Survey	-0.285	***	-0.286	***	-0.132						-0.243	**	-0.582	***
	(0.097)		(0.100)		(0.100)						(0.097)		(0.199)	
% of Enrollees Married	0.207	***	0.295	***	0.201	***					0.217	***	0.909	***
	(0.044)		(0.046)		(0.042)						(0.043)		(0.192)	
% MISSING Married from Survey	0.822	***	0.680	***	1.383	***					0.829	***	0.510	***
	(0.214)		(0.211)		(0.256)						(0.214)		(0.133)	

Table 5. Testing Longer Panel and Alternative Specifications (continued)

% Private Insurance Coverage (Males 16-64)							0.384	***	0.730	***				
							(0.070)		(0.125)					
Unemployment Rate (SAHIE)							-0.001		-0.116					
							(0.126)		(0.190)					
Household Median Income (SAHIE)							0.000	***	0.001	***				
							(0.000)		(0.000)					
PSSG % Age < 40							0.369		1.247	**				
							(0.347)		(0.571)					
PSSG % Age >= 40, <65							-0.482	***	0.799	**				
							(0.182)		(0.338)					
PSSG % Age >= 65, <75							-0.190		0.968	**				
							(0.209)		(0.437)					
PSSG % Female							-4.948	***	-8.242	***				
							(0.575)		(0.932)					
CDW % Enrollees African American							0.337		0.826					
							(0.218)		(0.522)					
CDW % Enrollees Asian							-1.715		-3.279					
							(1.183)		(2.172)					
CDW % Enrollees Other Race							1.828	***	0.456					
							(0.590)		(0.907)					
Number of Enrollees (10,000s)											0.944	**		
											(0.411)			
Constant	11.550		16.209		18.113		48.122	**	-46.085		4.011		25.755	***
	(16.705)		(16.511)		(11.126)		(19.626)		(32.380)		(16.531)		(2.455)	
Facility Fixed Effects	X		X				X		X		X		X	
Year and Quarter Fixed Effects	X		only quarter		X		X		X		X		X	
Observations	6,438		6,438		6,438		11,531		6,438		6,438		6,438	
R-squared	0.674		0.660		0.365		0.560		0.660		0.675		0.674	

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses

Table 6. Testing Instrument Combinations

Dependent Variable: Average Wait Time	**1 EV**	**1 EV, no Prod**	**1 EV**	**2 EV**	**2 EV**	**2 EV**
	% Holiday, Annual Leave, Sick Leave	% Holiday, Annual Leave, Sick Leave	% Holiday, Annual Leave	% Holiday, Annual Leave, Sick Leave	% Holiday, Annual Leave, Sick Leave	% Holiday, Annual Leave
Panel Length	FY2014-2018	FY2014-2018	FY2014-2018	FY2014-2018	FY2011-FY2018	FY2011-FY2018
Cragg-Donald Wald F-statistic relative to critical value for weak instrument test based on maximal *size distortion* of 5% (Stock and Yogo, 2005)	426.01>22.30 (reject H_0: weak instruments)	416.89>22.30 (reject H_0: weak instruments)	608.89>19.93 (reject H_0: weak instruments)	2.00>13.43 (cannot rejct H_0)	5.72<13.43 (cannot rejct H_0)	6.25>7.03 (reject H_0: weak instruments)
	β (s.e.)	β (s.e.)	β (s.e.)	β (s.e.)	β (s.e.)	β (s.e.)
Predicted Capacity	-4.286 ***	-4.041 ***	-4.527 ***	-6.826 ***	-5.206 ***	-5.114 ***
	(0.717)	(0.699)	(0.733)	(1.162)	(0.894)	(0.910)
Scheduled Visits per Clinic Day	-1.675 ***		-1.723 ***	-23.609 ***	-9.730 **	-8.352
	(0.297)		(0.299)	(7.673)	(4.476)	(5.127)
% Est Patient Appts >= 90 Days	0.293 ***	0.291 ***	0.293 ***	0.296 ***	0.265 ***	0.267 ***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)	(0.015)
Population Density (in 1,000s)	-4.555 ***	-5.096 ***	-4.570 ***	3.170	-3.777	-3.700 ***
	(0.881)	(0.896)	(0.876)	(2.851)	(0.847)	(0.858)
% of Survey Respondants Enrollees	0.465 ***	0.497 ***	0.465 ***	0.081		
	(0.087)	(0.086)	(0.087)	(0.161)		
% MISSING Enrollee Info from Survey	0.17	0.238 *	0.169	-0.697 **		
	(0.130)	(0.129)	(0.130)	(0.330)		
% Enrollees 20-40 Mins Drive Time	0.035	0.050	0.037	-0.101	-0.063	-0.047
	(0.060)	(0.059)	(0.060)	(0.078)	(0.071)	(0.077)
% Enrollees >= 40 Mins Drive Time	0.279 ***	0.291 ***	0.279 ***	0.238 **	0.092	0.065
	(0.099)	(0.100)	(0.099)	(0.101)	(0.098)	(0.110)
% Enrollees Comprehensive Insurance	-0.126 *	-0.142 **	-0.122 *	-0.040		
	(0.066)	(0.066)	(0.066)	(0.074)		
% Enrollees Medicaid Coverage	-0.119	-0.117	-0.115	-0.136 *		
	(0.077)	(0.077)	(0.077)	(0.077)		
% Enrollees w/ Medical Only (no Part D)	-0.225 ***	-0.256 ***	-0.221 ***	0.073		
	(0.070)	(0.069)	(0.070)	(0.130)		
% MISSING Insurance from Survey	2.059 ***	1.934 ***	2.073 ***	3.537 ***		
	(0.584)	(0.583)	(0.585)	(0.780)		
Medicare Advantage Penetration	-0.252 ***	-0.218 ***	-0.254 ***	-0.626 ***	-0.229 ***	-0.227 ***
	(0.077)	(0.076)	(0.077)	(0.148)	(0.057)	(0.057)
Non-VA Specialists per 1,000 Population	-5.076 ***	-4.848 **	-5.223 ***	-8.093 ***	-2.529 **	-2.530 **
	(1.965)	(1.968)	(1.966)	(2.183)	(1.191)	(1.194)
% Enrollees Full-Time Employed	-0.055	-0.057	-0.056	-0.108 *		
	(0.058)	(0.058)	(0.058)	(0.060)		
% Enrollees Part-Time Employed	-0.024	0.025	-0.024	-0.568 ***		
	(0.079)	(0.079)	(0.079)	(0.208)		
% MISSING Employment from Survey	0.181	0.147	0.181	0.607 **		
	(0.204)	(0.203)	(0.204)	(0.245)		
% Enrollees Income < 20k	0.238 ***	0.247 ***	0.238 ***	0.101		
	(0.046)	(0.046)	(0.046)	(0.068)		
% Enrollees Income 50 - 75k	0.115 *	0.142 **	0.117 *	-0.185		
	(0.068)	(0.069)	(0.068)	(0.128)		
% Enrollees Income > 75k	0.057	0.067	0.057	-0.047		
	(0.047)	(0.047)	(0.047)	(0.061)		
% MISSING Income from Survey	-0.015	-0.005	-0.014	-0.133 ***		
	(0.026)	(0.027)	(0.026)	(0.051)		
Zillow Index (in 100,000s)	2.814 ***	3.065 ***	2.726 ***	-1.331	-4.375 ***	-3.945 **
	(0.767)	(0.757)	(0.767)	(1.601)	(1.606)	(1.785)
% Enrolles Age Below 40	0.002	-0.004	-0.001	0.287 **		
	(0.107)	(0.107)	(0.107)	(0.145)		
% Enrollees Age 40-65	-0.056	-0.060	-0.057	-0.016		
	(0.062)	(0.062)	(0.062)	(0.064)		
% Enrollees Age 65-75	-0.138 ***	-0.139 ***	-0.138 ***	-0.133 ***		
	(0.041)	(0.041)	(0.041)	(0.041)		
% MISSING Age from Survey	1.993	2.571	2.024	-7.106		
	(5.080)	(4.957)	(5.019)	(5.859)		

Table 6. Testing Instrument Combinations (continued)

Medicare HCC Severity Index	7.098		5.749		7.255		15.119		24.180	**	21.981	**
	(11.904)		(11.950)		(11.895)		(12.210)		(10.170)		(11.094)	
% Enrollees Female	0.463	***	0.480	***	0.459	***	0.208	*				
	(0.086)		(0.085)		(0.086)		(0.123)					
% MISSING Gender from Survey	-7.944		-9.926		-7.833		11.920					
	(6.426)		(6.359)		(6.378)		(9.454)					
% Enrollees African American	0.503	***	0.493	***	0.501	***	0.788	***				
	(0.068)		(0.068)		(0.068)		(0.119)					
% Enrollees Hispanic	0.4	***	0.357	***	0.402	***	0.773	***				
	(0.072)		(0.072)		(0.072)		(0.154)					
% Enrollees Other Race	-0.269	***	-0.263	***	-0.269	***	-0.429	***				
	(0.087)		(0.087)		(0.087)		(0.100)					
% MISSING Race from Survey	-0.285	***	-0.256	***	-0.284	***	-0.616	***				
	(0.097)		(0.097)		(0.097)		(0.152)					
% of Enrollees Married	0.207	***	0.194	***	0.206	***	0.403	***				
	(0.044)		(0.044)		(0.044)		(0.081)					
% MISSING Married from Survey	0.822	***	0.934	***	0.818	***	-0.539					
	(0.214)		(0.213)		(0.214)		(0.521)					
% Private Insurance Coverage (Males 16-64)									0.141		0.179	
									(0.142)		(0.158)	
Unemployment Rate (SAHIE)									0.212		0.175	
									(0.167)		(0.178)	
Household Median Income (SAHIE)									0.000	***	0.000	***
									(0.000)		(0.000)	
PSSG % Age < 40									0.173		0.193	
									(0.364)		(0.365)	
PSSG % Age >= 40, <65									-1.368	***	-1.231	**
									(0.496)		(0.555)	
PSSG % Age >= 65, <75									-1.388	**	-1.198	
									(0.662)		(0.746)	
PSSG % Female									-5.902	***	-5.731	***
									(0.772)		(0.827)	
CDW % Enrollees African American									1.088	**	0.968	**
									(0.447)		(0.492)	
CDW % Enrollees Asian									-3.674	**	-3.334	**
									(1.549)		(1.683)	
CDW % Enrollees Other Race									1.179	*	1.304	*
									(0.677)		(0.714)	
Quarter 2	0.546		0.485		0.599	*	0.741	**	0.881	***	0.940	***
	(0.337)		(0.336)		(0.339)		(0.344)		(0.340)		(0.354)	
Quarter 3	-0.548		-0.781	*	-0.464		2.479	**	1.576	**	1.409	*
	(0.421)		(0.405)		(0.423)		(1.120)		(0.704)		(0.771)	
Quarter 4	-1.473	***	-1.521	***	-1.429	***	-0.625		-0.100		-0.143	
	(0.457)		(0.456)		(0.458)		(0.537)		(0.389)		(0.399)	
FY 12									-0.479		-0.341	
									(0.770)		(0.810)	
FY 13									0.043		0.330	
									(1.410)		(1.502)	
FY 14									-2.237		-1.856	
									(1.856)		(1.988)	
FY 15	-4.084	***	-3.966	***	-4.082	***	-5.396	***	-4.151	**	-4.014	**
	(0.802)		(0.808)		(0.801)		(0.944)		(1.706)		(1.728)	
FY 16	-4.099	***	-3.931	***	-4.093	***	-5.938	***	-1.499		-1.474	
	(1.264)		(1.273)		(1.262)		(1.453)		(1.898)		(1.899)	
FY 17	-7.412	***	-7.237	***	-7.390	***	-8.930	***	-3.368		-3.366	
	(1.543)		(1.554)		(1.542)		(1.663)		(2.071)		(2.070)	
FY 18	-10.282	***	-10.174	***	-10.230	***	-10.958	***	-4.379	*	-4.441	**
	(1.757)		(1.767)		(1.757)		(1.792)		(2.238)		(2.239)	
Constant	7.405	***	-9.046		12.928		288.437	***	216.921	**	190.320	*
	(0.046)		(16.037)		(16.716)		(98.119)		(91.132)		(102.729)	
Observations	6,438		6,438		6,438		6,438		11,531		11,531	
R-squared	0.674		0.674		0.675		0.674		0.560		0.560	

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable in all models is the monthly average primary care wait time for new patients. All models include analytic weights for the number of new patient appointments contributing to the VHA medical center average wait time. Robust standard errors in parentheses.

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APPENDIX A

Below is a copy of a working (unpublished) policy brief that is intended for VHA policymakers regarding the application of an earlier version of our model to address Section 401 of the MISSION Act.

Introduction

Effective health care reform is contingent on adequate access. Health systems can offer the highest quality care but if their patients cannot access it, the benefits are lost. The Institute of Medicine deems access to care a critical dimension of care quality, noting that patients must have access to high quality care whenever they need it and through whatever delivery method necessary (e.g., telehealth, face-to-face care). The American health care system has struggled with access for decades, with the best care often restricted by high prices. The Affordable Care Act was passed in 2010 to expand access to care through more affordable health insurance options.

Adequate access to care leads to improved health outcomes. However, health systems operating under fixed budgets without substantial fees for service typically develop waiting times. For example, the Veterans Health Administration (VHA) strives to provide timely, high-quality care to Veterans within a budget established by Congress. However, in 2014, VHA was under heavy scrutiny for long waiting times and scheduling data manipulated to hide access problems. Inadequate VHA access can result in longer waiting times and increased Veteran mortality. As a result, Congress and VHA launched several initiatives to reduce waiting times and increase Veteran access to non-VHA care when necessary, including the passage of the Veterans Access, Choice, and Accountability Act of 2014 (VACAA). These initiatives did improve VHA waiting times while, interestingly, private sector waiting times remained stagnant.

While VACAA and other VHA initiatives improved Veteran access to care, they did not address every barrier Veterans face. Another approach is to identify VA medical centers (VAMCs) whose Veterans have the greatest difficulties accessing care and subsequently target national and local resources to those facilities. In this paper, we describe how VHA implemented a standardized program to identify VAMCs underserved in primary care through statistical modeling. The underserved program fulfilled a mandate within the VA Maintaining Internal Systems and Strengthening Integrated Outside

Networks Act of 2018 (MISSION Act). The MISSION Act was passed to maintain and build upon existing efforts to improve Veteran access to care by strategically investing in VHA care and strengthening relationships with non-VHA providers.

Methods

Section 401 of the MISSION Act directed VHA to establish criteria to evaluate underservedness so that local VHA leadership could create targeted plans to improve access to care. The VHA Office of Veterans Access to Care (OVAC) spearheaded Section 401 and now executes the underserved program in consultation and collaboration with the Health Resources and Services Administration, local VHA leadership, the Office of Rural Health, and several VHA research offices, including the Program Evaluation and Resource Center (PERC) and the Partnered Evidence-based Policy Resource Center (PEPReC).

In the first year after the law's passage, PERC and PEPReC developed methodologies to measure underservedness at VAMCs in mental health and primary care services, respectively. PERC has published on the cornerstone components of the mental health methodology and their approach will not be discussed in this paper. , The primary care model developed by PEPReC employed a novel approach to measuring access to care through statistical modeling using the economic principles of supply and demand.

Data

128 VAMCs that provide primary care services across the United States were included in the model. Data from FY14 through FY16 were gathered from VHA and public data sources to measure the supply of and demand for VHA care; 17 variables were included (Table 2). Eleven variables changed over time and were considered time-varying characteristics. Seven did not and were used to predict static facility characteristics.

A key access measure used in VHA is new patient create date waiting time: the time between the date the Veteran calls to make an appointment and the actual appointment date. Any mention of waiting times in this paper refers to new patient waiting times, calculated using VHA appointment scheduling system data. Waiting times for primary care have been validated through comparison to access related questions in patient experience surveys.

Waiting times are affected by various factors that can be categorized into two groups: a VAMC's capacity (i.e., supply) and Veteran need (i.e., demand). Our model estimated empirical relationships between supply and demand variables and waiting times, which were then used to calculate underserved scores.

VHA supply variables included: primary care provider (PCP) full-time equivalents (FTEs) per 1000 Veteran enrollees, number of unique community care patients per Veteran enrollee, average dollars spent per community care patient, work relative value units (RVUs) per FTE, mental health program complexity, ICU/surgical program complexity, complex clinical program complexity, and average drive time. These data were collected from VHA sources.

VHA demand variables included: percentage of enrolled Veterans in Priority Groups 7 or 8 (Veterans with higher incomes), percentage of enrolled Veterans over 65 years old, Medicare Advantage market penetration rate, percentage of Veterans unemployed, percentage of males (18-64 years old) with private health insurance coverage, household median income, house price index, Nosos risk score, and Health Provider Shortage Area (HPSA) score. These data were collected from both VHA and public data sources.

The VHA data were reported at the VAMC level but most of the public data were reported at the county level. To aggregate county-level data to the VAMC level, we multiplied county-level data by county weights (based on the number of VHA enrollees in the area) and summed by VAMC. For variables reported at an annual frequency, linear interpolation was used to create VAMC-month level data. The analytic dataset included 33 months of data for each VAMC. All variables were z-scored so relative values of the coefficients could be directly compared with each other and interpreted as weights.

Analysis

Economic theory suggests waiting times for primary care services are determined by the equilibrium of changes in VHA supply and VHA demand. Holding all else constant, an increase in the supply of primary care appointments will decrease waiting times and an increase in the demand for primary care appointments will increase waiting times. The model estimated waiting times for primary care services (i.e., underservedness) with this relationship and included two separate linear regressions: one for time-varying characteristics, which fluctuated between FY14 and FY16, and one for static facility characteristics, which remained constant.

In the time-varying model, we implemented an instrumental variables technique because capacity (i.e., PCP FTEs per 1000 enrollees) and waiting time are simultaneously determined. VAMCs often hire short-term staff to reduce waiting times (waiting time causes staff change) and understaffed VAMCs often have longer waiting times (staff shortage causes waiting time).11, To combat this issue, we used the density of non-VHA specialists in the geographical area served by a VAMC to estimate the effect of changes in VHA staffing on waiting times, theorizing that this exogenous source of variation is indicative of the labor market for physicians, which influences VHA primary care capacity. Specifically, we estimated a two-stage least squares regression with density of non-VHA specialists as an instrument for VHA primary care capacity, controlling for time-varying supply and demand variables, fiscal year, month, and VAMC fixed effects.

The fixed effects coefficients were then extracted from the time-varying model to be used as dependent variables in the static facility model. We used a linear regression to measure the association between VAMC fixed effects coefficients and static facility variables.

An underserved score was calculated for each VAMC using the coefficients from both models (time-varying and static facility) as weights and applying those to the most recent data available for each variable. We multiplied the associated weight by a VAMC's z-scored value of that variable. Overall, scores for each variable were distributed around zero (the national average) for all VAMCs and this roughly translated to the overall scores also being distributed around zero. Once the model was finalized, VAMCs were ranked by relative underservedness in primary care. This allows rankings to shift over time in response to changes in the supply of and demand for VHA care while still guaranteeing that VHA targets resources to the facilities with the highest relative needs.

Results

In our analysis, we estimated linear regressions to obtain a coefficient for each independent variable based on the variable's relationship to the dependent variable, waiting time. Table 1 shows the output of the regression models, the variables' coefficients, interpreted as weights. (The R-squared value for time-varying model was 0.68.) The weights were adjusted estimates, scaling the smallest coefficient up to 1.00 for ease of interpretability. A larger absolute value numerical weight indicated a larger impact on the dependent variable and, thus, underservedness. Variables with a positive weight increased a VAMC's likelihood of being underserved while those with a negative weight reduced it. A VAMC's capacity (i.e., PCP FTEs per 1000 enrollees), the percentage of Veterans in Priority Groups 7 or 8, the percentage of Veterans over 65 years old, and patient complexity (i.e., Nosos risk score) were found to have the most influence on waiting times and underservedness.

For the first year of the program, the top seven VAMCs most underserved in primary care were reported to Congress in June 2019. PEPReC calculates and OVAC reports underserved scores annually along with the mitigation strategies planned by those facilities.

Discussion

In efforts to continually improve how VHA measures and addresses Veteran access to care, and guided by Section 401 of the MISSION Act, OVAC established the underserved program to systematically identify imbalances in the supply of and demand for VHA care. One benefit of using statistical modeling to identify underserved VAMCs and, subsequently, underserved populations, is that it fosters evidence-based policymaking and equitable resource allocation. This is currently a critical priority for VHA leadership, particularly with the passage of the Foundations for Evidence-Based Policymaking Act in 2019.

Geographical Distribution of Underservedness

Figure 1 shows the geographical distribution of the top seven VAMCs underserved in primary care for the first year of the program. Two important patterns are apparent. First, underservedness is not synonymous with rurality and impacts urban and metropolitan areas as well. The resources and tactics needed to address underservedness in these different environments will vary but it's critical to acknowledge them all as possible areas of need.

Second, the geographical distribution of underserved VAMCs partly reflects the influence of variables outside local VHA leadership's control. For instance, there is a cluster of underserved VAMCs on the southeastern coast of the United States. There are market forces and demographic factors unique to this region impacting Veteran access to VHA care. Nearby military bases lead to younger, less wealthy Veteran populations who rely more heavily on VHA care. Additionally, provider recruitment can be difficult, resulting in understaffed VAMCs. Local leaders may not be able to control these variables. This may affect their ability to mitigate underservedness and, thus, meet their enrolled Veterans' demand for VHA care.

Mitigation Strategies

VHA used the underserved scores produced by the model in several ways. First, the top seven VAMCs most underserved for primary care in the first year received national guidance and resources to improve access for their enrolled Veterans. Several sections of the MISSION Act and other established programs also offered resources and opportunities to underserved facilities, both identified in Section 401 and beyond.

Telehealth-focused Interventions

Section 402 authorized VHA to pilot Mobile Deployment Teams (teams of telehealth providers providing primary care or mental health care) at underserved facilities to increase capacity and access to VHA care. These teams were targeted in response to the needs identified in Section 401 (e.g., type and number of providers) and are managed regionally. Mobile Deployment Teams are nested within VHA's existing Clinical Resource Hubs.

A Clinical Resource Hub is a virtual care resource center physically located at one VAMC but serving many other facilities through telehealth. Telehealth providers work from the hub but virtually treat patients throughout a specific geographical region. Clinical Resource Hubs have been particularly helpful in rural areas where the supply of VHA and non-VHA care is often low, but they also represent an opportunity for VHA to rapidly respond to geographical shifts in demand for care. Mental health hubs were established in 2016 and the same framework has since been extended to primary care. In 2019, there were 11 of each.

There are many other telehealth-focused strategies that were not mandated by the MISSION Act but can still address underservice. For example, VA Video Connect connects Veterans and their VHA providers via a smartphone, tablet, or computer for an encrypted video appointment. The store-and-forward telehealth modality allows a provider to assist another provider in a different location by remotely interpreting clinical information. The clinical video telehealth modality allows for the same remote interpretation of clinical information but in real time. Through public-private partnerships, the Advancing Telehealth Through Local Access Stations (ATLAS) program installs private telehealth exam rooms in community establishments in rural areas where Veterans often have long drive times and poor bandwidth connectivity at home.

Personnel- and Infrastructure-focused Interventions

Several sections of the MISSION Act aimed to address underservedness by building upon current personnel strategies. Sections 302 and 306 targeted VHA's Education Debt Reduction Program, increasing the maximum amount of debt that VHA will forgive and expanding which employees are eligible. Section 403 required that VHA pilot at least 100 new residency slots based on need at various types of facilities.

OVAC and the VHA Office of Workforce Management and Consulting are working together on these endeavors. Other personnel-focused strategies include recruitment and retention incentives, utilizing non-physician providers, maximizing providers' time available for patient care, and using direct hiring authority. VAMCs are also encouraged to build more clinical space, if appropriate, to address underservice.

The annual report of underserved scores and forthcoming program evaluation offer the opportunity to assess the effectiveness of the interventions mentioned above as well as make regular refinements to the model as mentioned below. We anticipate the implementation of interventions and model refinements will lead to changes in rankings as Veteran access to VHA care improves and the model becomes more precise.

Subsequent Model Improvements

This paper reflects the methods applied in the first year of the underserved program. To continually improve VHA's estimations of underservedness, PEPReC recalculates scores and rankings each year, improving the model each time (e.g., adding new variables, revising weights, adding more data). Consequently, details of the model can change over time. For example, in the second year of the program, we were able to source more granular data for several static facility characteristics and move them into the time-varying model. This makes the overall scoring mechanism more accurate and sensitive to time trends.

Further, the underserved model is meant to guide VHA operational decisions. To that end, OVAC and PEPReC regularly brief VHA national and local leadership, requesting feedback on the variables included and model design. Connecting with the Office of Primary Care is of particular importance. After our first briefing, primary care leadership suggested both new variables and new ways to measure existing variables. These changes were included in the second year's model and we continue to build on their suggestions for future iterations as well.

Going forward, PEPReC will expand similar statistical modeling approaches to both primary care at VHA's community-based outpatient clinics and specialty care at VAMCs.

Conclusion

Addressing underservedness has long been a priority of VHA and the development of a standardized national program is another tool. Under OVAC's leadership, PEPReC developed a statistical model to measure underservedness in primary care, supporting an evidence-based and equitable allocation of national and local resources. The underserved program fulfilled Section 401 of the MISSION Act, passed to expand VHA's internal capacity, strengthen relationships with non-VHA providers, and thus, improve Veteran access to care. Going forward, PEPReC will continue to improve the model and expand it to other areas of care. VHA will use this foundation to keep Veteran access to high-quality health care at the forefront of its resource allocation decisions.

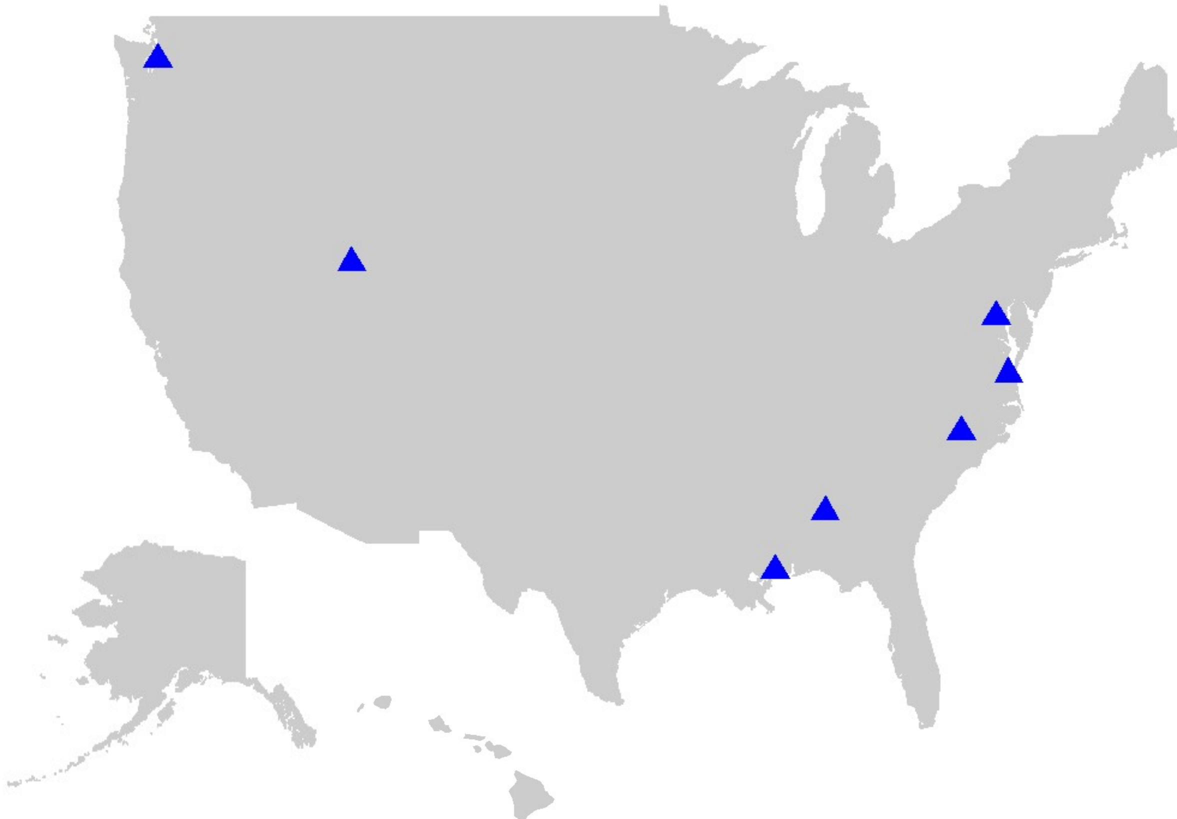
Appendix Table 1. Numerical variable weights in primary care model in the first year of the underserved program (June 2019).		
Variable	Numerical Weight	Nonnumerical Weight[*]
Time-varying independent variables		
1. PCP FTEs per 1000 enrollees[‡§]	- 2590	- HIGH
2. Percentage of Veterans in Priority Groups 7 or 8	- 1449	- HIGH
3. Percentage of Veterans over 65 years old	- 1223	- HIGH
4. Medicare Advantage penetration	- 465	- MED
5. Percentage of Veterans unemployed	- 171	- MED
6. Unique community care patients	- 98	- MED
7. Dollars spent on community care	+ 96	+ MED
8. Percentage of Veterans (18-64 years old) with alternative insurance coverage	+ 50	+ LOW
9. RVUs per FTE[‖]	+ 16	+ LOW
10. Household median income	- 11	- LOW
11. House price index	+ 10	+ LOW
Static facility independent variables		
12. Nosos risk adjustment score	+ 1218	+ HIGH
13. Mental health program complexity[†]	+ 1	+ LOW
14. ICU/surgical program complexity[†]	+ 1	+ LOW
15. Complex clinical program complexity[†]	+ 1	+ LOW
16. HPSA score[†¶]	+ 1	+ LOW
17. Drive time[†]	+ 1	+ LOW

[*] Numerical weights were translated into nonnumerical weights to be more helpful for national and local VHA leadership. The numerical weights were divided into three non-numerical weight categories: low, medium (med), and high. These were absolute value categories and did not demonstrate the direction of influence. A positive or negative sign was included for clarity.

[†] Variables with a weight of +1 had no influence in the model. However, in order to accurately demonstrate the relationship between variables and comply with statutory requirements, these factors were left in and assigned a weight of +1.

[‡] *PCP*, primary care provider; [§] *FTE*, full-time equivalent; [‖] *RVU*, relative value unit; [¶] *HPSA*, health provider shortage area

Appendix Figure 1. Geographical distribution of top seven VAMCs underserved in primary care during the first year of the underserved program (June 2019).



Note: Each triangle represents a VAMC.

Appendix Table 2. Variables included in primary care model in the first year of the underserved program (June 2019).			
Variable	Data Source	Time Varying (Y/N)	Definition
PCP FTEs per 1000 enrollees*†	VHA‡	Y	The number of primary care physician (PCP) full-time equivalents (FTEs) per 1000 enrollees at each VAMC. Used to measure capacity.
Percentage of Priority Groups 7 or 8 Veterans	VHA	Y	The percentage of enrollees who are considered Priority 7 or 8 at each VAMC.§ Veteran enrollees are placed in one of eight priority groups based on need, affluence, and eligibility for VHA care. Veterans in Priority 7 and 8 are required to financially contribute to their VHA care and may be less reliant on VHA care.
Percentage of Veterans over 65 years old	VHA	Y	The percentage of enrollees who are 65 years old and older. Medicare eligibility typically begins at 65 years old. This variable is a proxy for the proportion of enrollees with Medicare coverage. These Veterans may be less reliant on VHA for health care.
Medicare Advantage penetration	Centers for Medicare and Medicaid Services	Y	The percentage of eligible individuals who have Medicare Advantage insurance coverage in the area surrounding a VAMC. Medicare Advantage offers more tailored insurance coverage than traditional Medicare. Veterans may be less reliant on VHA care, and even less reliant than those with traditional Medicare insurance coverage.
Percentage of unemployed Veterans	American Community Survey	Y	The percentage of veterans between age 18 and 64 years old who are unemployed in the area surrounding a VAMC. Studies have shown unemployment are associated with reduced utilization of health care.
Unique community care patients per enrollee	VHA	Y	The number of unique patients referred to community care at a VAMC. Under the MISSION Act, Veterans are eligible to use community care under certain circumstances. A measure of capacity to care for patients.
Dollars spent on community	VHA	Y	The dollars spent on community care per patient at a VAMC. Under the MISSION Act, Veterans are eligible to use community care under certain

care per patients			circumstances.[‖] The measure of capacity to care for its patients.
Percentage of health insurance coverage	Small Area Health Insurance Estimate	Y	The percentage of population younger than age 65 years old with health insurance coverage in the area surrounding a VAMC.
RVUs per FTE[¶]	VHA	Y	The number of work relative value units (RVUs) completed per primary care FTE at each VAMC. RVUs is a measure how much clinical work providers complete. More RVUs per FTE signifies a more productive staff.
Household median income	American Community Survey	Y	The median household income in the area surrounding at each VAMC. This is a measure of affluence. Veterans in higher median household income area are wealthier and less reliant on VHA care.
Housing Price Index	Federal Housing Finance Agency	Y	The Housing Price Index is a broad measure of the movement of single-family house prices in the area surrounding at each VAMC. This is a measure of affluence. Veterans who own will increase and who rent will decrease their affluence, influencing their reliance on VHA care.
Nosos risk score	VHA	N	The Nosos risk score is a risk adjustment to adjust for clinical differences in patients at each VAMC. A higher Nosos score signifies a sick and more complex patient population that utilize more VHA care.
Mental health program complexity	VHA	N	The complexity of the mental health services provided at a VAMC. Mental health program complexity is scored in two parts: the percentage of a VAMC's enrollees who using mental health services and the number and types of mental health programs available. Mental health program complexity may influence the facility's capacity to care for its patients.
ICU/surgical program complexity	VHA	N	The availability and complexity of both ICU care and surgical care provided at a VAMC. ICU and surgical program availability and complexity may influence the facility's capacity to care for its patients.
Complex clinical	VHA	N	The number of complex clinical programs provided at a VAMC. Twelve clinical programs, such as blind rehabilitation and polytrauma, are determined to

program complexity			increase the administrative and clinical complexity of a VAMC. The number of complex clinical programs a VAMC offers may influence the facility’s capacity to care for its patients.
HPSA score#	Human Resources and Services Administration	N	The score of geographical areas with an insufficient number of providers based on population size as well as accounting for overutilization or inaccessibility of existing providers. A VAMC in a shortage area may have higher demand for VHA care and reduced capacity for care.
Drive time	VHA	N	The average drive time to a primary care community-based outpatient clinic for enrollees at a VAMC. Drive time and distance are associated with rurality and can influence access to care. VAMCs in rural areas may have higher demand for care as it may be their only option for care.

**PCP*, primary care provider; †*FTE*, full-time equivalent; ‡*VHA*, Veterans Health Administration; §*VAMC*, Veterans Affairs medical center; ||*MISSION*, VA Maintaining Internal Systems and Strengthening Integrated Outside Networks Act of 2018; ¶*RVU*, relative value unit; #*HPSA*, health provider shortage area