Impact of Physician Supply on Health Outcomes of Underserved Populations

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Abstract

This paper investigates the effect of the Health Professional Shortage Area (HPSA) designation on primary care physician supply and local health outcomes. The federal designation of HPSA offers financial incentives to physicians in these areas. Using an event-study design and data on physicians and regional mortality rates, I find that counties designated as HPSAs attract more new doctors to the regions and experience a decrease of 2.6 percentage points in drug-overdose death rates within two years of receiving the designations. This occurs through the arrival more female and younger doctors to the regions, along with an increase in the frequency of doctor visits.
JEL: H75, I14, I18, I32, I38, J14, J15

1 Introduction

Access to healthcare service and health conditions varies greatly across regions. There are 862 physicians per 100,000 people in rural areas, compared to 2,765 in urban areas. Concurrently, rural residents have an average life expectancy two years lower than urban residents and their drug related death rates have been soaring by 153% despite a 5% decrease in population between 2010 and 2019.

In order to mitigate a health professional supply shortage that rural residents experience, the Health Resources and Services Administration has designated Health Professional Shortage Areas (HPSA). This paper first evaluates whether and how this federal policy targeted at reducing healthcare provider shortages can improve health outcomes.

This paper takes advantage of the variations in HPSA designations across different regions and time periods from 2010 to 2020 to estimate the effect of the policy. HPSA designations designate a specific region that has less than 1 primary care physician for every $3,500$ people as a HPSA, which allows 10% additional Medicare reimbursement for a physician who practices in the region. This simple institutional setting has allowed researchers to explore the relationship between financial incentives and physician location decisions, including Khoury, Leganza, and Masucci 2020 and Chou and Lo Sasso 2009.

Among various health outcomes, this paper particularly aims to find evidence of the effect of the policy on drug overuse deaths. Many existing literature provide evidence that risks of prescription opioid overdose are higher among rural residents. Rural residents have a higher rate of having opioid prescription than urban residents, a higher probability of using opioid non-medically, and lower access to addiction treatment (Andrilla et al. 2019; Prunuske et al. 2014; J. R. Havens, Young, and C. E. Havens 2011). The main finding of this study is a HPSA designation results in an average of 2.6 percentage point decrease in drug-related mortality rates within the population of those over 65 within two years following designation. I demonstrate this is possible through demographic and behavioral changes of doctors as an outcome of the policy. More specifically, I show that the policy attracts primary physicians with different demographic characteristics than local doctors, increasing the proportion of newly arrived, female, and young physicians in an shortage area. In addition, doctors in the designated regions conduct more frequent short patient visits, possibly resulting in more interactions and preventing unintentional drug-overdose deaths. Among the existing literature about the primary care incentivizing policy and health outcomes, this paper is the first to address potential mechanisms of how healthcare supply affect health outcomes of underserved populations.

In addition to an event-study design as the baseline model, I further provide Callaway and Sant'Anna (2021)'s heterogeneity-robust estimator to add to the robustness. I also implement two additional tests. One is to rule out a different channel that the HRSA increases subsidies on health care facilities' operating cost as a result of the designation. If hospitals in the designated regions receive more funds than pre-designation, this can affect patient outcomes (Prunuske et al. 2014). The second test is to rule out a possibility that primary care does not contributed to reduced deaths. I test the effect of policy on unintentional death rates resulting from external causes such as transportation, accidents, assaults, and wars. Those deaths are unrelated to primary care use so that I can rule out the possibility that local health has been improved independently of the policy implementation.[1] There is emphasis on the potential role of primary care physicians in preventing deaths. Primary care providers are the most likely to be in the best position to monitor potential adverse effects of medical treatment from their own care and from specialists (Starfield, Shi, and Macinko 2005, Schnell and Currie 2018).

This study has two important implications in health policy design. First, this setting allows for investigating a relationship between physician supply and unintended health consequences of patients. Since the policy is purely targeting the supply side without prompting patients to respond, it is a valuable opportunity to know the impact of a public health policy on health outcome while controlling for influence from the demand side (Rosen 1974; Rice 1983; Clemens and Gottlieb 2014). Despite this, however, few studies have extended the impact of the policy to health outcomes of underpriviledged populations as well as its mechanism.[2]

Second, it can complement existing policies on drug-overdose by addressing the importance of non-medical inputs. Current opioid prescription policies are mainly focused on clinical guidelines, such as deciding prescription period, monitoring consistently, and assessing the risks of the prescription. However, this study sheds light more on the importance of nonmedical and financial incentives to induce behavioral changes of physicians. Lastly, this paper provides evidence that effects of a change in economic incentives

[1] In this paper, the term "underserved" refers to regions that experience health professional shortages, therefore, it includes both rural and urban areas. Following the Rural-Urban Commuting Area (RUCA) Codes, 60% of the underserved areas in this paper consist of urban areas.

[2] While Clemens and Gottlieb 2014 investigates whether an increase in Medicare fees has a positive impact on mortality and acute myocardial infarction (AMI) probability, they do not shed light on a possible mechanism. Khoury, Leganza, and Masucci 2020 does not study health outcomes as a result of a HPSA designation while they find that physician supply increases as result of the designation.

for physicians might vary across different demographic groups of physicians. Therefore, policies affecting health worker supply should consider demographic changes in the workforce and their potential impact on practice patterns.

The remainder of the paper is organized as follows. Section II reviews existing literature and illustrates the contribution of this paper. Section III demonstrates the policy background and possible effects of the designation. Section IV addresses the empirical strategy and main results, including the mechanisms. Section V concludes this paper and suggests possible policy implications.

2 Literature Review

This paper is related to an ongoing debate on physician incentivizing policies dedicated to underserved areas. A variety of existing literature on physician incentives has centered on the impact of policy intervention on physician location decisions (Chou and Lo Sasso 2009; Goodfellow et al. 2016; Holmes 2005; Khoury, Leganza, and Masucci 2020; Kulka and McWeeny 2019). Among them, Khoury, Leganza, and Masucci 2020 provides the evidence that the HPSA designation increases the supply of young doctors by providing them loan repayment benefits.

Another branch of physician location literature examines medical education with a commitment to serving rural or underserved regions through financial incentives. Numerous medical schools run rural tracks to produce rural physicians Longenecker et al. 2021. Moreover, National Health Service Corps (NHSC) offers tuition and living expenses to prospective primary care physicians in exchange of two or more years of service in a health provider shortage community after they graduate. Studies such as Rabinowitz et al. (2008) and Cullen et al. (1997) show that the NHSC scholarship program plays a role in locating primary care physicians in rural areas.

Many physician location literature finds the physicians' personal characteristics affect their rural service status. Primary care physician practice in underserved areas is associated with racial/ethnicity, being grown in a rural area, and medical education in foreign medical schools (Goodfellow et al. 2016).

The present article also relates to literature linking provider supply, healthcare utilization, and outcome. Clemens and Gottlieb (2014) show that physicians' financial incentives increase healthcare supply and improve patients' outcomes, using regional price shocks caused by Medicare's geographic consolidation across the U.S. in 1997. Alexander and

Richards (2021) show that extended health insurance coverage increases office visits and better self-reported health, using nationwide and exogenous changes in Medicaid reimbursement rates for physicians and the National Health Interview Survey from 2009 to 2014.

Earlier studies support the positive impact of physician supply on health service demand or improved access (Fuchs 1978; Wilensky and Rossiter 1983; Cromwell and Mitchell 1986; Busato and Künzi 2008; Clemens and Gottlieb 2014; Carrillo and Feres 2019). However, Carlsen and Grytten (1998) show there is little evidence that physician supply-induced utilization of medical services exists by implementing a cross-sectional analysis on the Norwegian dataset. Carrillo and Feres (2019) finds no evidence that the increased number of physicians improves infant health outcomes possibly because of the substitution between the use of physicians and nurses by using a quasi-experimental policy design in Brazil. Lower healthcare provider utility is associated with higher opioid prescription rates caused by patients' doctor shopping (Gearhart and Michieka 2021).

This paper's contributions are as follows. First, it contributes to the HPSA literature that investigates the impact of the HPSA designation on patients' health outcomes, which has been understudied so far. Second, this paper contributes to the body of literature on physician incentives and health outcome literature by focusing on more specific regions that are likely to be less privileged than others. This feature of the paper makes a difference from Carrillo and Feres (2019), Alexander and Richards (2021), and Clemens and Gottlieb (2014), whose focus is on a more standard population. The regions studied in this paper are likely to be experiencing lower socioeconomic status, therefore, the effect of incentive of interest might differ from the other regions.

3 Policy Background and Expected Effects of HPSA designation

3.1 What is HPSA and how is it identified?

The Health Services and Resources Administration (HRSA) designate and withdraw the Health Professionals Shortage Areas (HPSA) to identify regions or communities experiencing a health professional shortage since 1978 in their attempt to alleviate the health workers shortage[3].

[3]Many federal programs have widely used the Health Professionals Shortage Areas (HPSA) designations. For example, the National Health Service Corps (NHSC) offers to repay their medical school loan debt for serving a committed period in HPSAs. For a full-time service for a two-year term as a primary-care provider in designated communities, a physician can receive up to $50,000. The Centers for Medicare & Medicaid

The primary determinant of designation is the number of health professionals relative to the population within a rational area. For example, a geographic HPSA is identified as "experiencing a shortage of primary medical care workforce if a corresponding site has a population to full-time-equivalent primary care physician ratio of 1) at least 3,500, or 2) greater than 3,000:1 and has unusually high needs for primary care services". A designation can be made "within a county, a group of contiguous counties, or neighborhoods and communities within metropolitan areas that display a homogeneous socioeconomic or demographic structure (a rational area)". HPSAs can be rural or urban areas and need not conform to the geographic boundaries of a political subdivision[4].

Health Professional Shortage Area (HPSA)[5] designations are used to diagnose areas and population groups that undergo an insufficient number of health professionals within the United States. There are three types of HPSAs, 1) geographic areas 2) population groups and 3) healthcare facilities. Each type of HPSA can have three categories based on the kind of health professionals: 1) primary care; 2) dental; 3) mental health. Because primary care physicians (PCPs) play an essential role in the health care system of the United States, this paper centers on primary care HPSAs.

HPSA designations are prerequisites for various federal and state funding sources for health professionals (physicians, physician assistants, and nurses). National Health Service Corps (NHSC) use geographic, population, and facility HPSAs, to run a school loan-repayment program. An awardee of this program commits to serving at least two years of service to be eligible for up to $50,000 loan repayment. An applicant with a job offer from the NHSC-approved site of the greatest need is selected first, indicated by the HPSA designation score ranging from 0 to 25[6].

The Medicare HPSA Physician Bonus Program includes geographic-primary care HPSAs. The Center for Medicare and Medicaid (CMS) pays a 10% bonus based on the amount

Services (CMS) offers a 10 percent bonus when a physician delivers a Medicare-covered service in health professional shortage areas or HPSAs. CMS also implements the Rural Health Clinic Program to support rural clinicians in HPSAs. A certified rural health clinic is eligible for an enhanced cost-based reimbursement rate for Medicare and Medicaid Services.

[4]https //www.aha.org/lettercomment/2022-01-24-aha-urges-hrsa-delay-effective-withdrawal-date-hpsas-designated-proposed
https //www.ecfr.gov/current/title-42/chapter-I/subchapter-A/part-5#ap42.1.5_14.a

[5]https://nhsc.hrsa.gov/sites/default/files/nhsc/loan-repayment/lrp-application-guidance.pdf
https://nhsc.hrsa.gov/loan-repayment/lrp/service-requirements
https://sgp.fas.org/crs/misc/R44970.pdf

[6]https://nhsc.hrsa.gov/sites/default/files/nhsc/loan-repayment/lrp-application-guidance.pdf
https://nhsc.hrsa.gov/loan-repayment/lrp/service-requirements
https://sgp.fas.org/crs/misc/R44970.pdf

the Medicare patient pays for services to a physician or psychiatrist in only a geographic HPSA[7].

The Rural Health Clinics Program is another branch of programs operated by CMS[8]. It certifies a health clinic located in geographic and population HPSA. CMS pays Rural Health Clinics (RHCs) a bundled payment, or All-Inclusive Rate (AIR) per patient visit, for qualified primary care and preventive health services an RHC practitioner provides.

Lastly, a visa waiver program removes the requirement for J-1 visa-holding foreign physicians to return to their home country for two years in exchange for working in a HPSA region.

3.2 The Possible Outcomes of HPSA

The purpose of designating a health professional shortage area is to increase primary care supply, which can be made possible in two ways. The first is at an extensive margin, by increasing the total number of primary care physicians within a region. The second is to increase the volume of healthcare at an intensive margin, without changing the number of doctors.

The first channel can be shown easily by the new inflow of physicians(Khoury, Leganza, and Masucci 2020). Primary care physicians can be motivated to enter the region because designated areas provide them with financial incenctives, including medical school loan repayment and additional payment for Medicare services[9]. Alternatively, existing physicians can decide not to exit or retire later, but the willingness to locate or retire is difficult to observe. Therefore, counting the new number of physicians makes it possible to observe physician location decisions more directly. CMS' Medicare Fee-For-Service Provider Utilization & Payment Data provides all Medicare practitioners' locations, making it possible to disaggregate the effect of the entering physicians from the overall number of physicians in a county.

In order to investigate the effect of HPSA designation on local health outcomes, I select

[7]https://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNProducts/Downloads/HPSAfctsht.pdf

[8]https://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNProducts/Downloads/RuralHlthClinfctsht.pdf

[9]However, this channel may not be pervalent as the New York Residency Training exit surveys report that in several many years a large portion of doctors who completed their residency and found a job in the shortage areas did not know that their upcoming practice region is designated as the HPSA. Additionally, Khoury, Leganza, and Masucci 2020 finds the evidence of effectiveness of the policy only on less experienced doctors. Their analysis shows that the supply of experienced doctors does not respond to the policy. Therefore, the impact on overall supply may not be notable

relevant health outcomes based on previous research about primary care workforce supply and health outcomes. Since my policy variable incentivizes primary care providers who serve Medicare beneficiaries, it is reasonable to select the primary care related outcomes. One of the most reliable and approachable health outcomes available by economists is mortality rate. For example, Bailey and Goodman-Bacon 2015 use the all-cause mortality rate of population aged 50 and over because their deaths are more preventable than infants and children. Alternatively, several papers on the impact of health insurance generosity on health outcomes such as Finkelstein et al. 2012 and Alexander and Richards 2021 use self-reported health outcome from various surveys. However, the surveys used in those papers do not sufficiently cover populations in my treatment and control counties[10].

Even if the role of a primary care physician in preventing deaths and diseases ranges very widely, from a chronic to acute diseases, I focus on the role of primary care providers on drug-related deaths (Starfield, Shi, and Macinko 2005, Macinko, Starfield, and Shi 2007, Buchmueller and C. Carey 2017), one of the preventable deaths if patients are attended well. In fact, misuse of prescription drugs has been a prevalent problem in the U.S. for the last couple of decades. I pay attention to the fact that the decline in opioid prescriptions in the U.S. is a relatively recent development, with institutions such as the CDC and American College of Physicians (ACP) continuing to issue recommendations. There is recent evidence of possibility that doctors contribute to the opioid epidemic. Research shows that prescription drug monitoring programs (PDMPs) are effective to reduce the possibility of opioid abuse when states require physicians to advise the opioid-taking patients(Buchmueller and C. Carey 2017 Dave, Deza, and Horn 2021).

This implies that communications between physicians and patients play an important role in managing risks drugs safely, shedding a light on the possibility that HPSA, a healthcare supply policy, is associated with the drug-induced mortality. Whether primary care physicians increase communications regarding the prescribed opioid with patients is related to the first outcome mentioned, especially the intensive marginal increase in healthcare supply. Despite being the gatekeepers of the legal opioid supply, little is known about the physician staffing policy and drug-related deaths.

It is impossible to rule out the possibility that the policy increases the drug claims due to the increased number of physicians if the first round outcome, physician supply, is affected by the policy. However, in my analysis the number of primary care physicians

[10]Finkelstein et al. 2012's analysis is based on Oregon populations and Alexander and Richards 2021 uses the National Health Interview Survey which does not guarantee the balanced distribution of observations to treatment and control counties of the current paper.

and opioid prescription rates(The number of opioid claims per population) do not change after HPSA designation, which means that this channel is not likely to work.

4 Empirical strategy

I use a difference-in-difference event study with lags and leads of treatment timing to estimate the causal effect of designation on physician supply and drug-related mortality rates. In addition to the baseline event study, I show the two-way fixed effect estimator with a coefficient of post-treatment indicator of treated counties. There are two key assumptions to validate these methods. First, the timing of HPSA designation must be uncorrelated with determinants of the outcome variables. Second, HPSA classification timing must be uncorrelated with pre-designation trends.

4.1 Model assumption

The first assumption is supported by the characteristics of counties classified as HPSA for the first time between 2010 and 2020 failing to predict the timing of the designation in Table 1. I regress the years of HPSA designations on pre-designation factors of physician supply and health outcomes (population, percentage of uninsured, unemployment rate) and on state-fixed effects to control statewide demographic characteristics. Table 1 shows that the past determinants that affect my current outcomes variables of interest do not affect the timing of HPSA designations. For example, the first column represents the estimation result of regressing designation years from 2013 to 2020 on the set of determinants before 2013. In addition, the administrative process also supports that socioeconomic determinants of my outcomes of interest do not affect the designation timing. HPSA eligibility is having a population-to-provide ratio of 3,500:1 or more, and a score index based on poverty rate, infant health index, and travel time to care outside of the proposed HPSA is considered. Moreover, physicians' locating determinants suggested in the existing literature indicate there is a low possibility that such determinants affect the timing of the designation[11].

[11]Many papers have investigated the roles of both financial and non-financial incentives in locating physicians. Some suggest the importance of financial incentives such as capped malpractice damage premiums (Chou and Lo Sasso 2009) and opportunities for higher earnings in urban areas (Mohammadiaghdam et al. 2020). Loan repayment benefits from locating rural areas do not play a major role (Falcettoni 2018). There are also papers that focus on the role of amenities (Falcettoni 2018) and personal experiences in communities (Paladine et al. 2020) and in residency program (Taati Keley et al. 2016).

	Designation year(> 2013)	(> 2014)	(> 2015)	(> 2016)	(> 2017)
Past determinant year	2013	2014	2015	2016	2017
% of uninsured	0.0534	-0.0383	-0.0541	-0.0515	0.0106
	(0.0597)	(0.0410)	(0.0460)	(0.0543)	(0.0434)
% of uninsured $\times D_{p50}$	0.0810	0.163	0.117	-0.0465	-0.0874
	(0.251)	(0.166)	(0.144)	(0.124)	(0.124)
% Unemployed	0.0200	0.0705	-0.0678	0.0335	-0.155
	(0.0911)	(0.102)	(0.105)	(0.105)	(0.200)
% Unemployed $\times D_{p50}$	0.0957	0.259	0.386	0.265	0.0255
	(0.396)	(0.254)	(0.250)	(0.291)	(0.277)
100K Population	0.000461	0.000377	0.00000548	-0.000301	-0.000991
	(0.00111)	(0.000889)	(0.000860)	(0.000665)	(0.00173)
100K Population $\times D_{p50}$	0.0190	-0.00558	0.0179	0.0125	-0.0234
	(0.0527)	(0.0361)	(0.0334)	(0.0351)	(0.0315)
N	186	171	157	140	93
R^2	0.272	0.384	0.388	0.359	0.474

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

Table 1: Regressing the timing of treatment on past determinants of physician supply and local health

$Designationyear_c = \%unemployed_{ct} + \%uninsured_{ct} + 100Kpop_{ct} + State_c$
$Designationyear_c$ is a year designated of county c, $\hat{X_{ct}}$ is variable X of county c at t represented at the top of each column, $state_c$ is state. Each variable is multiplied by a dummy indicator of whether the value of the variable is above the median.

The second assumption is about the no pre-trend assumption that the outcome variables must show a no specific trend before the treatment or be consistently biased from non-treated communities. I plot the physician supply variables and drug-related mortality rate against the year of HPSA initiations in treated counties in Figure 1 and 2 find no violations in the non pre-trend assumption in both outcomes.

4.2 Event-study Specification

Based on these assumptions, I use the event study with interaction terms of years-since-treatment and eventual treatment dummies and additionally two-way fixed effects with interaction terms of post-designation and eventual treatment dummies.

Following a flexible event-study framework (Jacobson et al. 1993; Bailey and Goodman-Bacon 2015), the baseline event-study regression is as follows, exploiting variation in

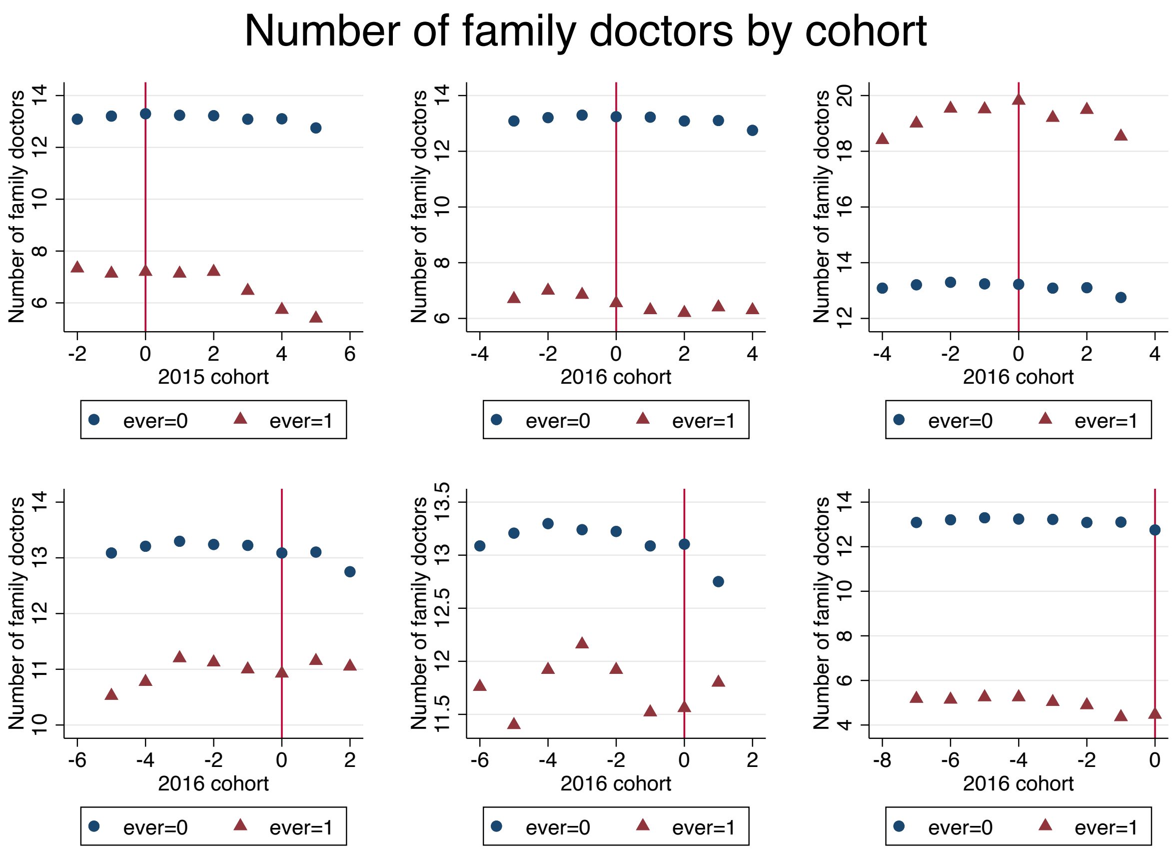

Figure 1: Trend in the number of family doctors by cohort

Method: For each cohort (ever = 1), I assign the same time-to-treat values (from -5 to 5) to never-treated (ever = 0) counties as the treated cohort. Then I plot averages of the outcome against their according time-to-treat.
Source: The Centers for Medicare & Medicaid Services

region and timing of HPSA designations:

$$Y_{ct} = \alpha_c + year_t + \sum_{m=-5}^{5} \delta_m \mathbf{1}(t - T_c = m) + \mathbf{W'}_{ct}\tau + \epsilon_{ct} \tag{1}$$

Y_{ct} is one of three outcomes in year t of county c, each of which is estimated independently. The first outcome variable is the number of family doctors. The second outcome is the number of newly entered family doctors to county c in year t. The last one is the mortality rate in year t of county c, measured by the number of deaths of population over 65

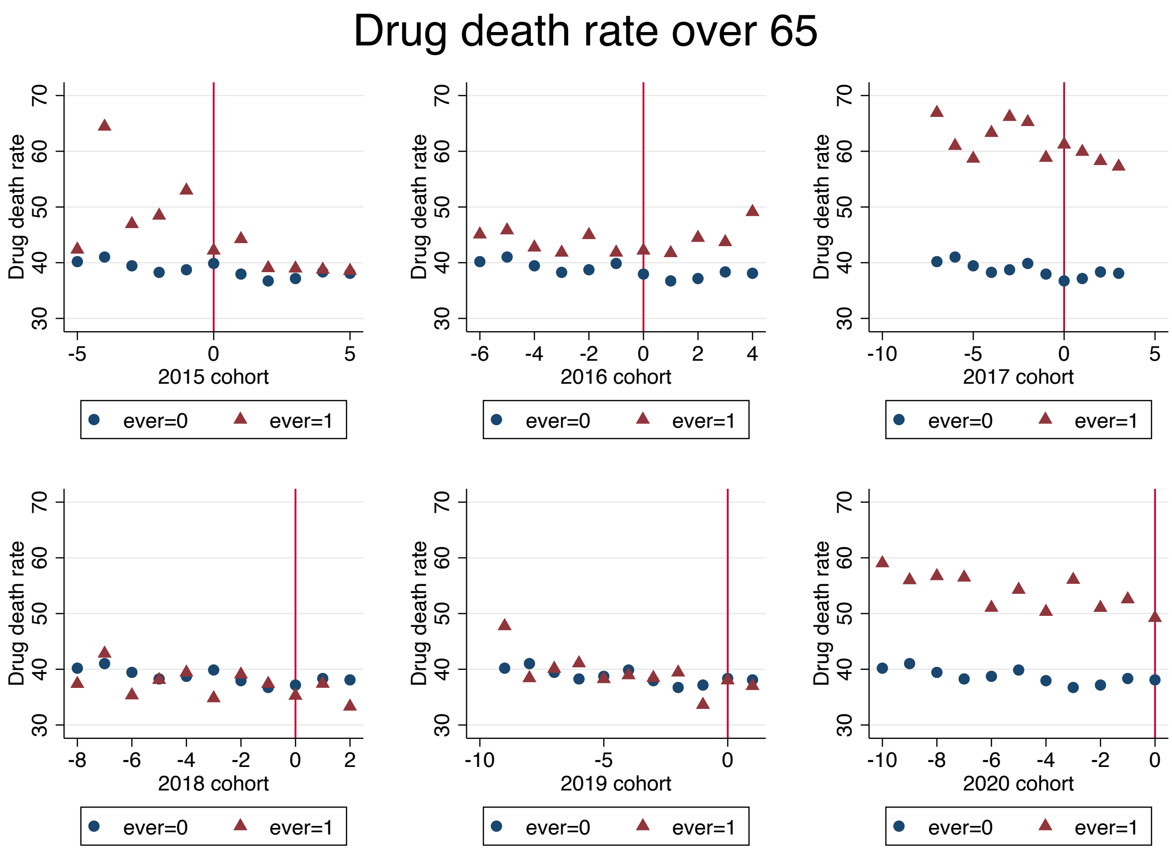

Figure 2: Trend in local health outcome by cohort
Death rate = Number of drug-poisoned deaths per 100K population
Source: The National Center for Health Statistics

from drug misuse following the classification by the International Causes of Deaths(ICD), defined as codes X40–X44 (unintentional), X60–X64 (suicide), X85 (homicide), or Y10–Y14 (undetermined intent), per $100,000$ population of the same age group.

α_c is county fixed effects to control time-invariant differences in observable and unobservable characteristics across regions. It also captures state-wise health policies, underlying health conditions and time-consistent factors that affect physician's location decisions, such as the number of medical schools within each state. My sample is not large enough to have enough treated and untreated units per each state, allowing both county and state-fixed effects are not feasible.

$year_t$ is year-fixed effects capturing nationwide changes in health policies. m is the time since treatment (year - designated year), having 0 for all control counties, negative values for pre-treatment of treated counties, and positive values for post-treatment of treated counties. The set of point estimates δ_ms represents the evolution of the outcome variable of interest in ever-treated counties across time. The evolution is relative to two: before-treatment of ever-treated and never-treated, after eventually adjusting for all variables in W_{ct}. Lag and lead dummies **1** for all m range from -5 to 5 and are all 0 if a county was never treated between 2013 and 2020. $m = -1$ was dropped for reference.

W_{ct} is a vector of observed, time-varying county covariates, including unemployment rate, population, and the percentage of uninsured people to capture different adoption of Medicaid and Medicare by state and the median age.

Since this model allows treatment to be assigned non-randomly based on characteristics that affect the level of the outcome such as physician supply or mortality, I need two assumptions of which validity is supported by Table 1 and Figure 2. The first assumption is that HPSA designation timing is uncorrelated with physician location decisions and health determinants related to drug-related mortality. The second assumption is that the selection bias into treatment from non-designated counties must be consistent across time. By assuming that an underlying difference in outcomes is consistent before the treatment, I can estimate the causal effect of the treatment even with a quasi-random setting. One possible violation is that a county's residents are interested in promoting their own health and are motivated to designate their county as HPSA. However, since HPSA is a health policy that affects physician supply, not health demand directly, it is reasonable to say that the mortality will be unaffected by the expectation of future designations.

I make the following attempts for robustness check. First, I replicate the analysis using Callaway and Sant'Anna (2021) to attain average treatment effects of different lengths of time being treated to circumvent negative weighting problems. In addition, I implement a placebo test to estimate the effect of HPSA designation on unpreventable mortality. If it is true that HPSA designation affects primary care doctors and therefore relevant health outcomes, then outcomes irrelevant to PCP use should not be affected by the designation. It can support the casual interpretation of my analysis. All robustness check results are provided in Appendix.

4.3 Data

Health Resources & Services Administration (HRSA) provides a historical dataset of designations and withdrawal of ever-treated regions. The designations can be made for an entire county or a portion of the county. Even if the policy has designated 1051 full counties as geographic HPSA and high-need geographic HPSA since its rollout in 1978 to 2022, I limit my analysis to from 2010 to 2020 because another primary dataset, the Medicare Fee-For-Service Provider Utilization & Payment, is currently available from 2013 to 2020. Also, some counties were withdrawn and re-designated multiple times, therefore, complexity rises when it comes to which treatment effects must be identified. For the best estimation of the policy effect, I consider only the first designation in each county's history as treatment.

Considering the available time range of additional data sources, a treatment group consists of only 329 counties whose first designations[12] occurred between 2010 and 2020. The rest 670 counties are excluded from the treatment group due to one of two reasons. First, 562 counties are simply omitted from the analysis because they were designated before 2010 or withdrawn and re-designated after 2010. The frequent withdrawal and re-designations make it hard to identify the valid treatment effect, so I decided to omit these counties with "noisy" treatments. The remaining 160 counties are those whose designations occurred in 2021 or 2022. I use these not-yet-treated counties as a control group Goodman-Bacon 2021 because these counties share similar traits with the treated ones that lead to the treatment in the future, increasing the likelihood of being a randomized control trial.

Selecting a control group is more complex because the rest 2,097 counties units are possibly partially designated, meaning that a partial county is sometimes eligible for the bonus payment even if not included in the treated group. I want to omit these partially designated counties because my health outcomes are not available at the level of regions smaller than a county. To do so, I first start with 2,097 counties with no history of being fully designated out of 3,148 counties in the U.S. Among them, 1,913 counties experienced partial designation between 2010 and 2020. I opt out of these partially designated counties because including them in the analysis can mislead the true effect of the designation if the

[12]In this paper, treatment and designation are used interchangeably. Further, a designation refers to a primary-care shortage designation. One concern is that a primary care HPSA can be also designated as mental or dental, or both. This can be problematic when my treatment and control regions are newly designated as mental HPSA or dental HPSA between 2010 and 2020. Especially regarding my health outcomes, a change in mental HPSA designation status during the sample period can affect my analysis outcome. Regarding this concern, I check if how many of my treatment and counties are newly designated as mental geographic HPSA. I find that only 20 out of 329 treatment counties were treated after their primary care HPSA designation between 2010 and 2020. Furthermore, only 14 out of 366 control counties were designated between 2010 and 2020. This small fraction of "spoiled counties" implies that mental HPSA designation will not affect the analysis significantly. In fact, because of high correlation(0.25***), including an indicator of mental HPSA designation status in the estimation equations results in omitting the variable.

size of the population from partially treated regions is unknown. In other words, including these incompletely treated counties either in the control group or treatment group can be problematic since there is no way to figure out what percentage of the population is truly under the treatment. Therefore, I select only the remaining 184 counties that have never experienced the designation in part between 2010 and 2020, adding to the previously selected 160 control counties that are first designated after 2020.

I come to have 329 counties in the treatment group as the first fully treated counties and 344 counties in the control group. Even if I select the control group such that the treatment group can be distinctive the best from the control group, 160 counties end up being designated after 2020. Those counties will help the control group to keep similar traits to the treated, leading to group-specific confounders varying little across the groups.

The control group and treatment group may have been other types of HPSA designation other than geographic primary care HPSA, for example, a county might have experienced only a specific racial group, not the entire county, having a shortage problem. It is not problematic for identification because only geographic HPSA offers the bonus program for doctors.

Another important data source comes from Medicare Fee-For-Service Provider Utilization & Payment (MSPUP) Data from the Center for Disease Control & Prevention (CDC) available since 2013. This dataset provides extensive information about Medicare utilization on a provider-by-year level. Providers are identified using their own National Provider Identifiers with their geographic information, sex, credentials, and the amount of Medicare services measured by the number of patients and charged amount. Geographic information on a zip code level allows for knowing the aggregated number of physicians serving in a specific county and matching it with a county-level panel dataset in the previous dataset. Since MSPUP dataset is available from 2013, the scope of analysis on the number of physicians is restricted to the period from 2013 to 2020. This is the reason why the first stage analysis has a smaller size of observations than the health outcome analysis.

Health outcomes are county-level drug overuse mortality estimated by the National Center for Health Statistics. [13] Mortality rates are a widely used proxy for health status due to their reliability and consistent availability over years (Bailey and Goodman-Bacon 2015; Deschênes and Greenstone 2011; Mullins and White 2020). Primary care physicians

[13]Mortality estimates are based on the National Vital Statistics System's multiple cause-of-death mortality files. CDC states "Drug overdose deaths are defined as having the International Classification of Disease, Tenth Revision (ICD–10) underlying cause-of-death codes X40–X44 (unintentional), X60–X64 (suicide), X85 (homicide), or Y10–Y14 (undetermined intent)."

are the most likely to observe the adverse events that result both from their own care and from other specialists the patient may see, leading them to be in the best position to monitor potential adverse effects of the medical treatment (Starfield, Shi, and Macinko 2005).

Lastly, county-level covariates are collected from various resources. Unemployment data is from Local Area Unemployment Statistics of the United States Bureau of Labor Statistics. Income, poverty ratio, insured and uninsured population come from the American Community Survey of Census Bureau from 2010 to 2020.

Table 2 shows summary statistics of primary indicators of local health and socioeconomic status.

Before the treatment, as indicated by column 2, one family doctor in a county covers 5,926 people, and it increases to 6,209 on average after the treatment. The number of newly entered physicians decreases from 0.332 to 0.367, both of which are lower than the control group.

Health status is represented by mortality rates of drug-induced, all-age, and age over 65 mortality attained from the Center for Disease Control & Prevention. All types of mortality rates before and after treatment are both higher in treated counties than in control counties.

Determinants of physician supply and health outcome are mixed. The unemployment rate slightly decreases from 5.4 to 4.585 after treatment, and the number of people in poverty decreases from 17.13 to 15.29.

One important feature is that all figures are constantly worse than controlled counties, indicating that treated counties are systematically underprivileged regions compared to untreated counties, causing a simple comparison between treated and controlled is likely to misleadingly interpret the effect of the policy.

4.4 Estimation result

Figure 3 and 4 present the first-stage estimation results of the effect of designation on the inventory and inflow of physicians. Each figure represents the coefficients of the time-since-treatment for the numbers of physicians. Figure 3 and 4 are estimated using Poisson regression method. The pre-designation coefficients do not show significant differences from zero. Treated and untreated having similar trends before and diverging after the treatment supports that such changes must have been driven mainly by the designation rather than area-specific factor.

	Control	Treatment		Total
		Pre	Post	
Population per family doctor	4844.4	5926.3	6209.0	5322.7
	(3767.3)	(4974.6)	(4535.8)	(4237.0)
Number of new family doctor	0.534	0.332	0.367	0.460
	(1.129)	(0.993)	(1.095)	(1.099)
Population (in 1000)	58.07	50.06	47.61	54.46
	(86.48)	(100.0)	(99.97)	(92.13)
Drug-related death rate (deaths per 100K pop)	15.82	16.26	17.68	16.25
	(9.745)	(12.29)	(11.13)	(10.61)
All-age death rate	1039.4	1110.0	1117.5	1068.6
	(271.9)	(275.2)	(299.2)	(280.0)
Age over 65 death rate	4339.0	4546.7	4387.8	4392.4
	(753.0)	(816.7)	(828.9)	(785.2)
% of pop in poverty	12.75	17.13	15.29	14.15
	(6.326)	(6.682)	(6.135)	(6.624)
Median age	41.21	40.77	41.35	41.14
	(4.330)	(4.913)	(4.451)	(4.485)
Unemployment rate	4.294	5.400	4.585	4.584
	(1.622)	(2.024)	(1.728)	(1.789)
% of uninsured	9.894	12.80	11.95	10.89
	(4.180)	(5.697)	(5.240)	(4.905)
N	1648	585	491	2724

Table 2: Summary statistics

Death rates = The number of deaths per 100,000, age-adjusted.
Source: The number of family doctors; Centers for Medicare & Medicaid Services
Death rates; Center for Disease Control & Prevention
Poverty, age, population by sex: American Community Survey
Unemployment; Bureau of Labor Statistics;

Figure 3 shows that the total number of doctors does not change in response to designation. The joint test for the non-existence of pretrend is not rejected even after I change

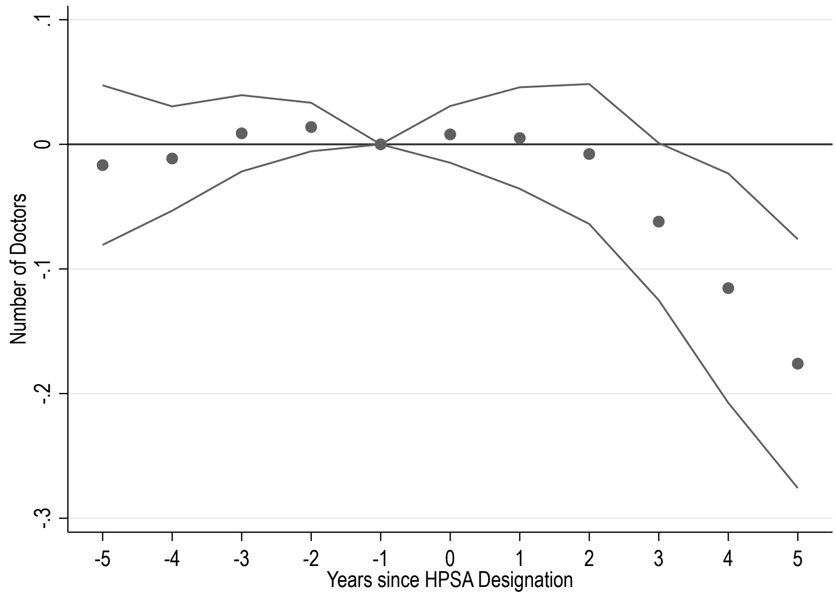

Figure 3: The effect of HPSA designation on physician supply
The outcome is the number of doctors whose specialty is classified as "Family practice"

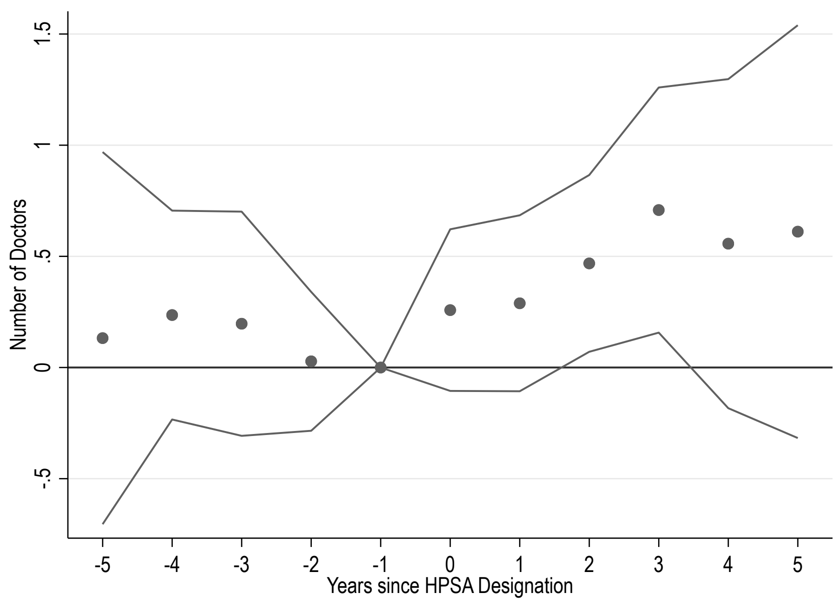

Figure 4: The effect of HPSA designation on the number of new physicians
The outcome is the number of family doctors who enter the county c in year t while being observed in a different county in year $t-1$.

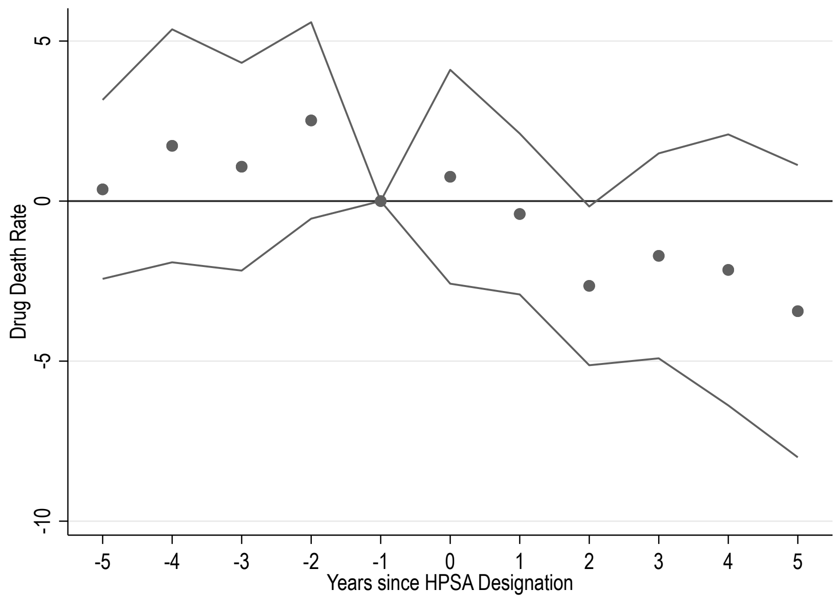

Figure 5: The effect of HPSA designation on drug-related death rate
Drug death rate is the number of drug-induced deaths per 100,000 population over 65.

the range of sample analysis from using 5 year ($0+-5$) window to 4 years window ($0+-4$), before and after treatment. However, negative signs of the designation coefficients indicate that the policy does not increase supply of primary care physicians to communities. It rather indicates that the number of primary care physicians keeps decreasing after the intervention. Several explanations are possible. First, the policy's incentive is not strong enough to retain the existing physicians and promote entry. Second, physicians exit the region for better living quality and higher-paying jobs. These explanations are not necessarily exclusive. It is hard to distinguish the two in the current analysis environment.

Figure **??** shows that the policy attracts new physicians even with large standard errors. In the first year of treatment ($m = 0$), there is 0.26 more just-arrived family doctors in the region and the inflow grows gradually, having 0.5 more newly-arrived doctors in the third year ($m = 2$) and 0.7 more in the region in the fourth year ($m = 3$) since designation. This result implies that the policy induces turnover, substituting 0.6 doctors for every 13 doctors serving an average-sized counties of 48,000 people in three years since the event.

Finally, figure 5 represents the effect of the designation on the drug-induced death rate of population over 65. Even with large standard errors, the policy has a decreasing impact on drug-related mortality rate of designated counties. In the first and second year($m = 0, 1$), the impact is small, but in the third year($m = 2$) it reduces the mortality by 1.9 percentage point. As primary care doctors account for approximately 50% of opioid prescriptions written by physicians[14], investigating the relationship between the local family doctors' practices and drug overuse deaths is a reasonable next step.

Such changes in drug misuse death rate can be driven by the policy under several mechanisms. One explanation is that newly entered primary care physicians prevent drug-induced deaths by becoming reluctant to prescribe risky drugs such as opioids to patients they inherited. It is known that doctors tend to avoid accepting new patients who are being treated with opioids after a clinic closes, making it challenging for patients to keep opioid use or inducing doctors to pay more careful attention when prescribing it (Lagisetty et al. 2019; Coffin et al. 2022). Replacing the current doctors with new doctors can have a similar impact on local patients. Figure 6 illustrates the evolution of a binary indicator equal to 1 if more than 10% of doctors in a region is newcomers and 0 if not. A newcomer is defined as a family doctor who is found to practice in a county during the current year, while practicing in a different county in the previous year. Since many of the observations of ratio of new to total doctors have zero values, I use such a binary variable for the circumstance that many counties face-zero new doctors. The probability that a treated region experiences more than 10% of the total family doctors being newcomers increases up to 50% the pre-treatment level. This could lead to more frequent rotation of doctors within an area.

I also find that the new doctors to the treated regions experience an increase in a share of female doctors and young doctors. Lazkani et al. (2015) and Rochon et al. (2018) suggest that female doctors tend to prescribe safer, long-acting pain drugs than male counterparts. Therefore, it can be inferred that a region where women doctors are prevalent may experience fewer prescriptions of risky substance per person, with all other health determinants equal, and substitute it toward safer but similarly effective drugs. It is also likely for the local patients to receive more quality consultations if the woman doctors tend to be more cautious when prescribing drugs. Also, it is known that young doctors are less likely to prescribe opioids (Baker, Kessler, and Vaska 2022). Even if the authors do not explicitly illustrate the mechanism, one explanation is that aged doctors are less likely to adopt a new standard of care. Howard and Hockenberry 2019 and Tsugawa et al. 2017 find that older physicians can be less likely to have updated information about medical practice

[14]Schnell and Currie 2018 use more broader definition for primary card doctors, including general practice, family practice, and internal medicine. In my sample, family doctors account for more than 50 percentage of total primary care doctors in 75 percent of observations.

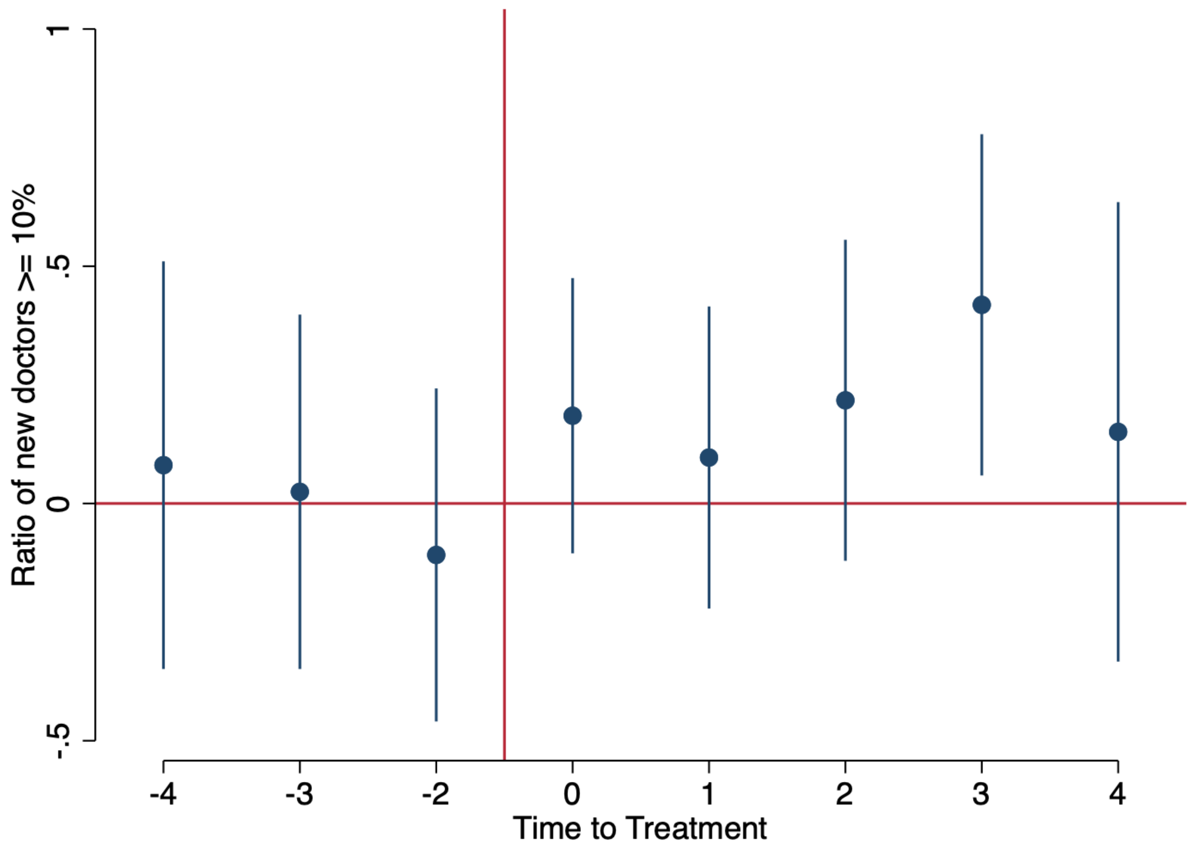

Figure 6: New doctors' entry

Outcome variable is an indicator of whether more than 10% of total doctors are newly arrived ones to county c during year t, equal to 0 if less than 10 and 1 if more than 10%.

and adhere to appropriate treatment. As the decline in opioid prescriptions in the U.S. is a relatively recent development, with institutions such as the CDC and American College of Physicians (ACP) continuing to issue recommendations, the increasing proportion of young doctors is likely to associated with local patients' better health outcomes. Newly arrived and young doctors in HPSAs may provide a patient with an option to switch from high-risk medications to safer alternatives or provide more frequent consultations on prescription use to patients, compared to existing and old doctors, thereby contributing to a reduction in drug-related mortality rates in the HPSAs.

Figure 7 left panel implies that the logged ratio of female doctors in the designated regions increases by 4.5-5.8 percent in the following two years after designation, even with limited statistical significance, compared to their comparison group averaged over years and one year before their designation, after controlling population, uninsured population ratio, and unemployment rate. The right panel shows that the percentage of early-to-mid career (less than or equal to 15 years in year t) doctors compared to total doctors increases in a couple of years after the designation, meaning that the doctors on average in the treated areas become younger in terms of their professional experience than they used to be in the previous year, and also than those in untreated regions. From the second year of HPSA designation, the percent of doctors experienced up to 15 years increases by 4 percentage point.

One thing to note is that this gender and years-of-experience analysis is based on a simple snapshot of each county during a year, meaning that there is no consideration of dynamics of entrance and exit of physicians. In other words, the increasing proportion of women doctors and early-to-mid-career physicians may be either due to the inflow of woman/young physicians or retention of existing woman/early-to-mid career physicians, or both. It is unclear that the left panel of Figure 7 is either an outcome of more woman doctors entering or exit of male doctors, or both. Likewise, the right panel of Figure 7 may result from either an inflow of younger doctors or existing young doctors' retention to exit. If the former is correct, so that young physicians newly entering to the regions is a major factor, their up-to-date skills combined with the newness to the patients would jointly impact on the reduction of mortality rate than existing young doctors sticking to the region. On the other hand, if this is an outcome of young doctors continuing to serve in the regions, then their up-to-date skill set is the only major determinant of health outcomes. This paper will not extend the analysis to such dynamics because the primary interest of this paper is whether HPSA status affects health outcome or not.

In order to determine whether changes in composition cause a lower volume of risky drug prescriptions, I regress the opioid prescription rate(Medicare Part D opioid claims divided by population) on the same set of regressors in Equation 1. I do not observe changes in opioid prescription rates after treatment (Figure 8). Therefore, more new, women and younger doctors might bring changes in quality of prescription, e.g., patients having longer consultation with doctors, which is unobserved and not identified in the dataset.

Another explanation for the reduced drug misuse mortality is through more frequent visits to doctors as doctors can receive 10% higher reimbursement when they practice in HPSA areas. This explanation is in line with the goal of HPSA designation policy, which is to increase access to healthcare services by attracting more physicians. Primary care

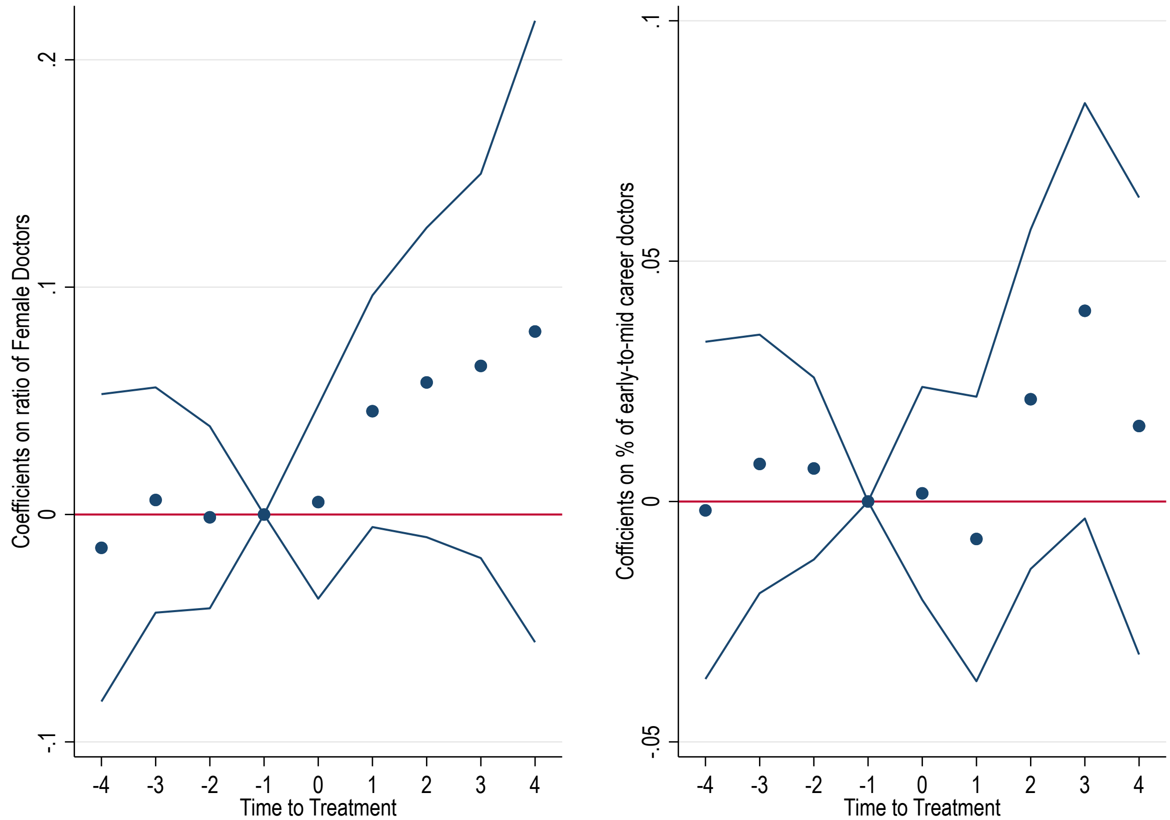

Figure 7: The effect of HPSA designation on the ratio of women doctors and the ratio of doctors with less than 15 years of experience

Outcome variable is $\log\left(\frac{\text{number of female doctors}}{\text{Total doctors}}\right)$ and $\log\left(\frac{\text{doctors with less than 15 years of experience}}{\text{Total doctors}}\right)$.

physicians play a crucial role in observing patients' adverse health outcomes(Starfield, Shi, and Macinko 2005, Macinko, Starfield, and Shi 2007). Even though the total number of doctors remain unchanged (Figure 3), an individual doctor may respond to the policy by increasing healthcare supply in their clinics. In order to test this mechanism, I use an additional dataset, Medicare Physician & Other Practitioners by Provider and Service listed as Healthcare Common Procedure Coding System (HCPCS) and Current Procedural Terminology (CPT) codes from CMS. I aggregate the number of Medicare services claimed per capita under the two CPT codes, "New patient office or other outpatient visit (HCPCS code 99201-99205)" and "Established patient office or other outpatient(99211-99215)"[15] (C. M. Carey, Miller, and Wherry 2020). To control statewide and yearly impact on patient

[15]See appendix for description for the codes

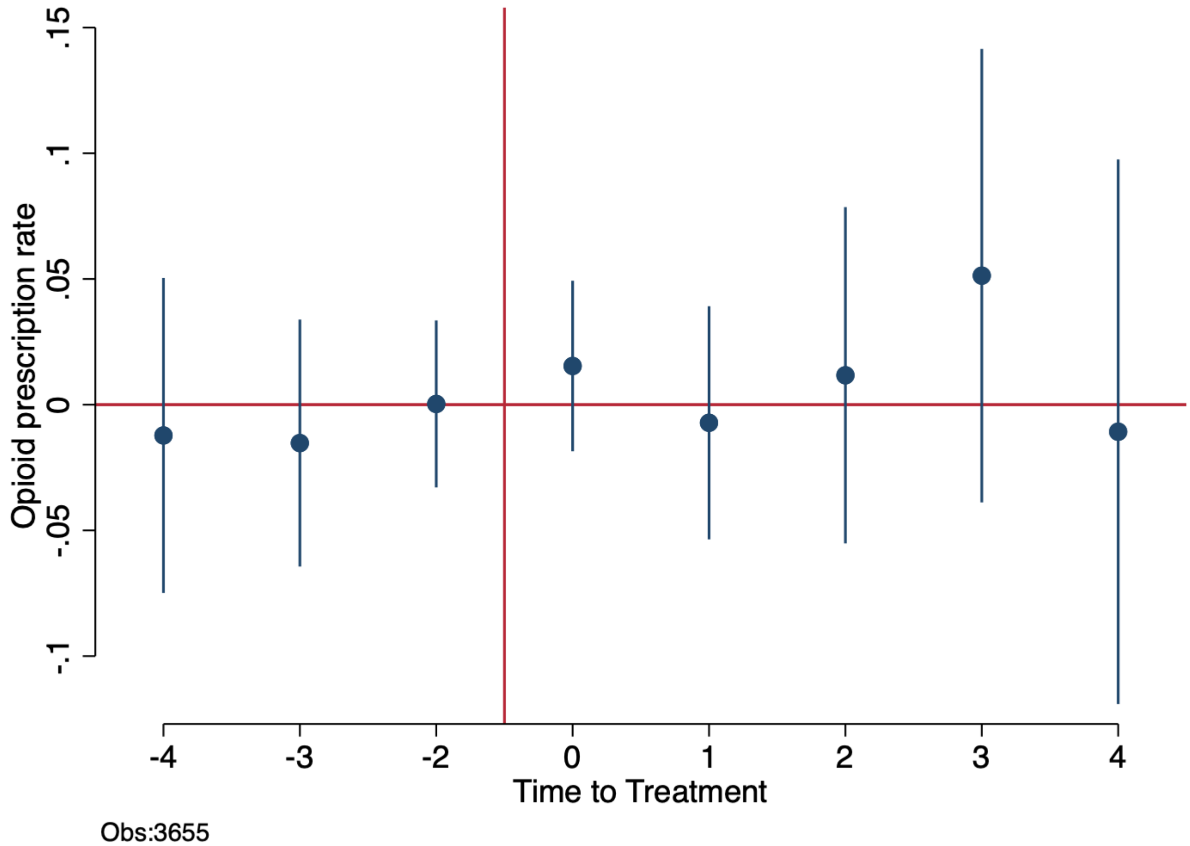

Figure 8: The effect of HPSA designation on OPR

Opioid Prescription Rate (OPR) = $\frac{\#\ of\ opioid\ claims}{Population}$, regressed on the same set of covariates in Equation 1.

visits, I subtract state-year averages of each service from each observation.

In every service code, there exists a significant gap in local PCP use between control and treatment regions in pre-treatment period. The top left graph in Figure 10 illustrates that in the pre-designation period from 2013 to 2020, there are approximately 140 of 100,000 fewer 10-minute PCP visits than the national level in HPSA counties while the control group has 25 of 100,000 fewer visits than the national level. However, the difference becomes smaller after treatment. The gap between control group (blue bar) and treatment group before treatment (red) significantly narrows, as represented by the bar graph of treatment group after being treated (green). In the post-designation period, this gap reduces approximately to 50 compared to the national level. Reduced gap is also found in 20-minute visits but not in longer visits. This is also supported by Fleming 1997 that show short visits of 10-15 minute to doctors are able to reduce drinking problems.

Figure 11 shows the similar analysis but for established patients instead of new patients. While the decreasing gap between control and treatment is not as significant as new patients' visit per population, it is still observable for shorter visits of 5 minutes. This finding is in line with Figure 10. Of course, it might be questionable that people become ill as they experience shortage of heatlh workers and make more frequent visits. The limitation of the analysis from Figure 10 and 11 is that it is not possible to control the people's health conditions that affect frequency of visits to a doctor.

However, the mean of number of longer visits per capita does not vary across treatment status, as illustrated the bottom panels of Figure 10 and 11. Therefore, it is unlikely that people getting sicker since designation results in more frequent shorter visits to doctors.

To further check if a HPSA designation impacts mortality through increased short visits, I estimate Equation 1 with extra controls-visits to doctor per capita. The estimated coefficients are plotted in Figure 9. The top right figure of Figure 9 indicates that adding the count of 10-minute visits per capita reduces the absolute values of δ_m for $0 \leq m \leq 3$. On the other hand, the bottom figures shows adding 20- and 30-minute visits per capita does not critically affect δ_ms. The comparison of results can be summarized that short-visit frequency highly correlates with treatment status, while long-visits do not. This indicates that an increased short-term visits can connect a HPSA designation to better health.

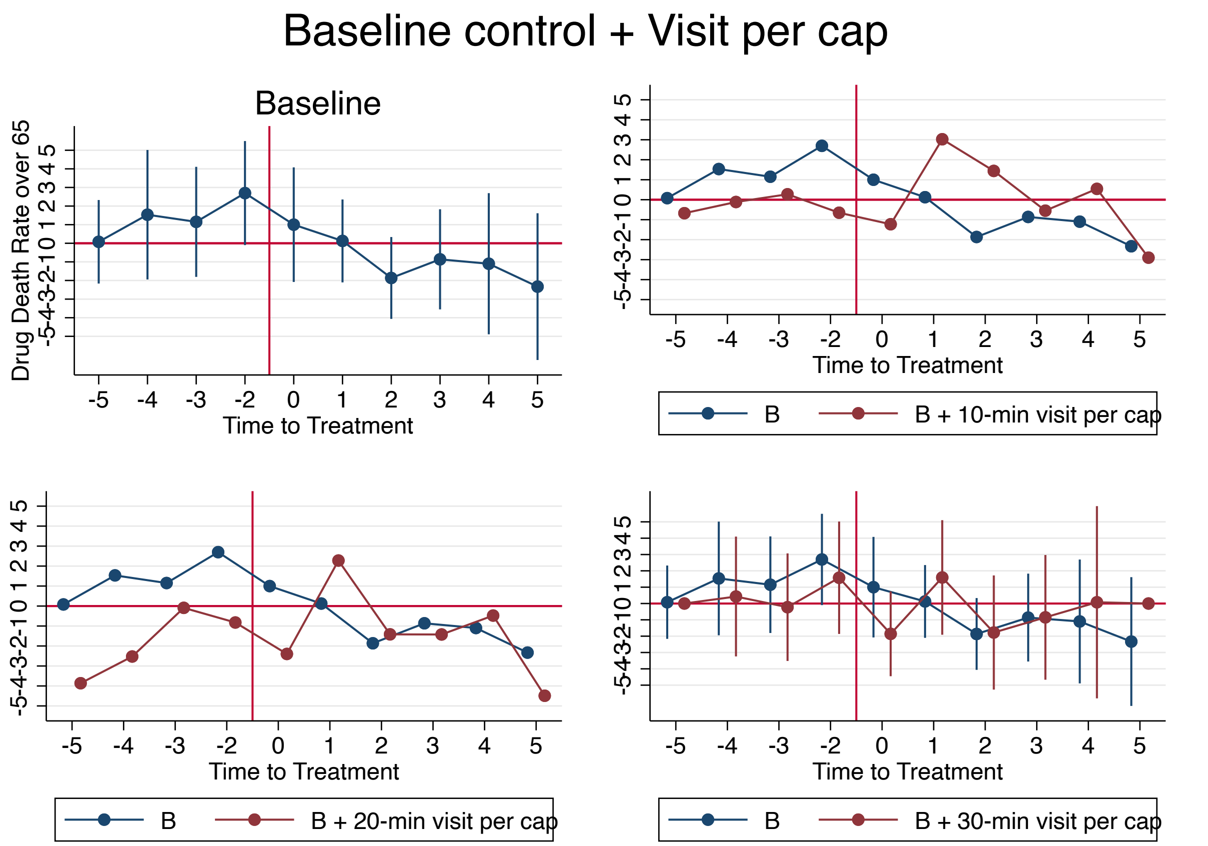

Figure 9: Comparison of estimation results: Baseline vs. Baseline+Visits per capita
B denotes the baseline equation. In the baseline equation, I additionally control for the visits per capita variable(=total number of services practice/population) to represent how often average people make visits to doctor and plot the estimates for coefficients δ_m

5 Conclusion

This paper investigates whether a financial incentive for physicians to increase labor supply in underprivileged communities can improve local health outcomes. Using a policy variation across regions between 2010 and 2020, I find that a HPSA designation leads to a 0.5 unit increase in the number of new physicians coming into a county and 2.6% point decrease in drug-induced death rates after two years of the designation. The 0.5 unit increase in the number of new doctors is equivalent to a 3.8% turnover rate of physicians. The effect on mortality corresponds to saving 2,600 people in a community of

Figure 10: New patient visit (total visitpopulation) gap, by length of visit
Source: Medicare Physician & Other Practitioners by Provider and Service, Center for Medicare & Medicaid Services I match doctors' location to counties using HUD-USPS Crosswalk Files 2013Q1 version, aggregate the number of total services by CPT codes (99201-99205, 99211-99215) within a county, divide the summed services by total population and multiplied by 100,000. for each code. Then I subtract state-by-year average from each observation to consider state and year fixed effects. The reason why all groups are below average is that the state-by-year average is calculated using almost entire population while the graphs take into account only control and treatment groups. Control groups are close to 0, meaning that control groups represent the average of the state in each year. Panels are accompanied by a count of valid observations by each group.

100,000 populations every year. I support the analysis by showing the policy changes in physician characteristics and increases quick PCP visits in disadvantaged communities. I conclude that providing doctors with financial incentives for paying attention to patients more frequently can discourage drug-related and preventable deaths.

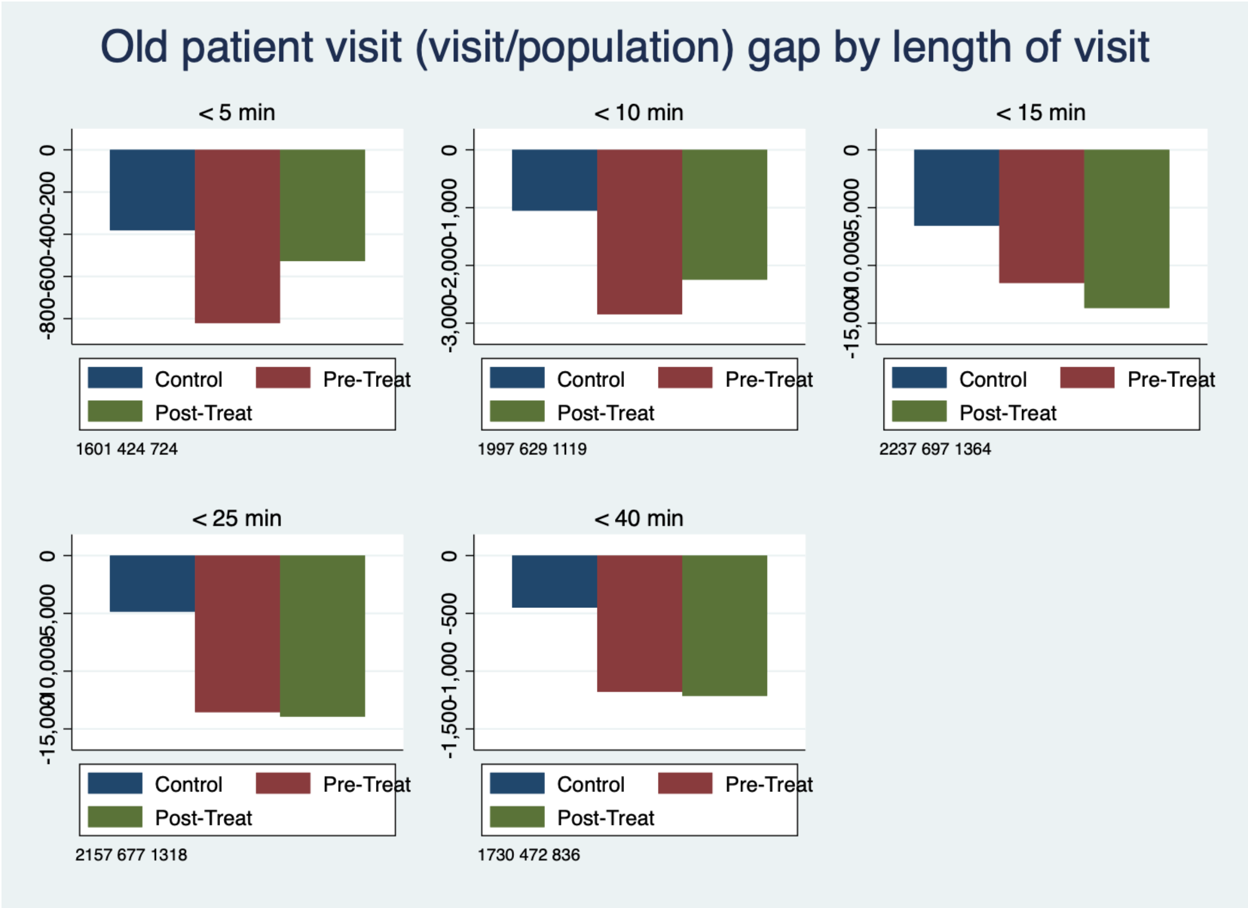

Figure 11: Old patient visit (total visitpopulation) gap, by length of visit
Source: Medicare Physician & Other Practitioners by Provider and Service, Center for Medicare & Medicaid Services

Lastly, this study has three implications in health policy design. First, the intervention allows investigating physician-induced health demand of specific population group. Since different population groups may have heterogeneous response to health supply, it is important for policy makers to focus on specific regions to evaluate an impact of health policy. Second, since the policy does not target any specific health outcome, it can help an existing public policy which is designed to improve specific health outcomes relate to non-medical inputs. Lastly, this paper provides evidence that effects of a change in economic incentives might vary across different demographic groups of physicians, such as gender and age. Therefore, policies affecting health professionals should consider these demographic changes and potential impact on practice patterns.

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A Distribution of hpsa designation years

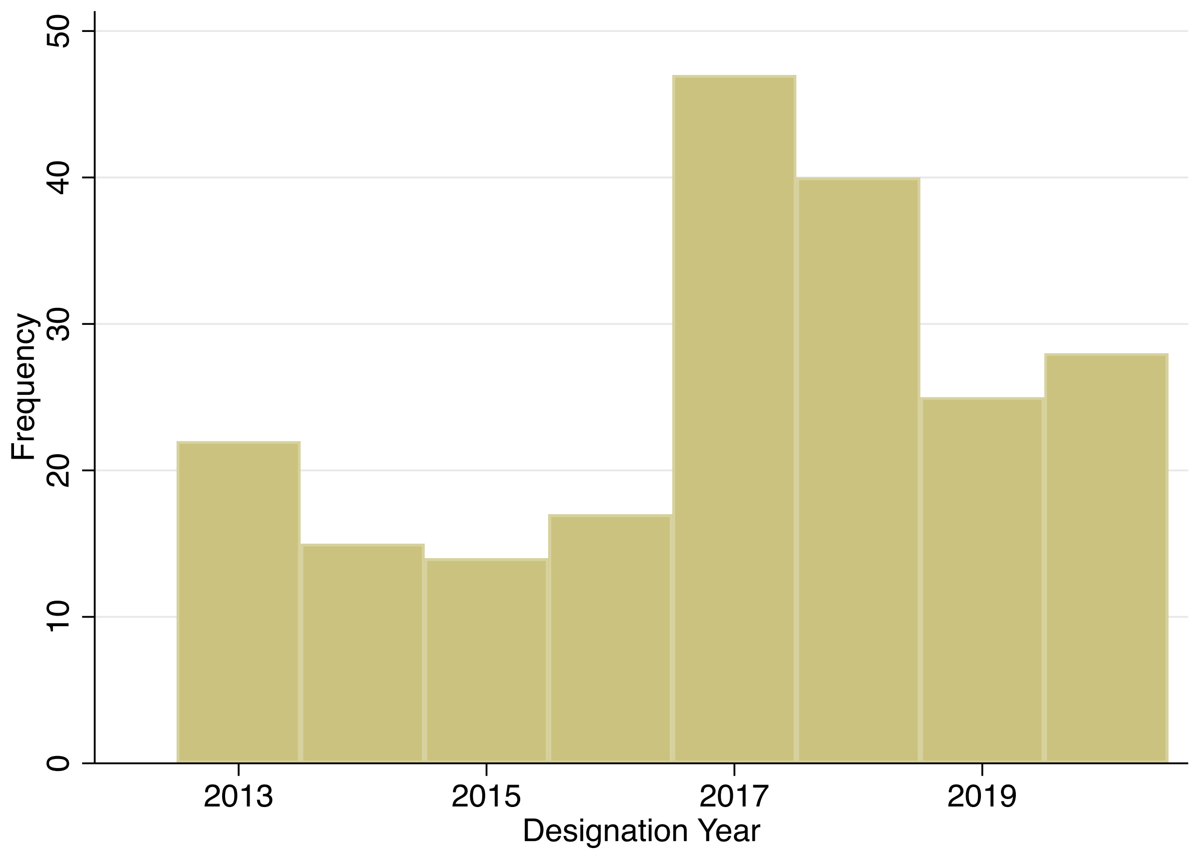

Figure 12: Distribution of designation years

B Estimation Result table

	(1)	(2)	(3)
m = Time since designation			
$m = -5$	-0.0167	0.132	0.366
	(0.0327)	(0.427)	(1.423)
$m = -4$	-0.0114	0.236	1.726
	(0.0214)	(0.240)	(1.853)
$m = -3$	0.00883	0.197	1.074
	(0.0156)	(0.257)	(1.652)
$m = -2$	0.0139	0.0278	2.520
	(0.00993)	(0.159)	(1.562)
$m = -1$	ref	ref	ref
$m = 0$	0.00797	0.258	0.760
	(0.0116)	(0.185)	(1.701)
$m = 1$	0.00506	0.289	-0.403
	(0.0208)	(0.202)	(1.280)
$m = 2$	-0.00774	0.468**	-2.648**
	(0.0286)	(0.203)	(1.263)
$m = 3$	-0.0620*	0.708**	-1.710
	(0.0322)	(0.281)	(1.630)
$m = 4$	-0.115**	0.557	-2.150
	(0.0470)	(0.378)	(2.155)
$m = 5$	-0.176***	0.611	-3.440
	(0.0509)	(0.474)	(2.324)
% of uninsured	-0.00230	-0.00286	0.987***
	(0.00395)	(0.0339)	(0.268)
% of uninsured ≥ p50	0.0415	-0.173	13.89***
	(0.0661)	(0.710)	(3.647)
% of uninsured × p50	-0.00587	0.0228	-0.958***
	(0.00500)	(0.0564)	(0.274)
% of unemployed	0.00681	0.0600*	0.140
	(0.00497)	(0.0337)	(0.219)
% of unemployed ≥ p50	0.0214	-0.290	-4.515
	(0.0446)	(0.459)	(3.067)
% of unemployed × p50	-0.00462	0.0351	0.761
	(0.00842)	(0.0852)	(0.622)
population	0.00000362***	-0.00000220	0.000243***
	(0.000000791)	(0.00000586)	(0.0000611)
population ≥ p50	-1.073	1.322	96.69***
	(1.052)	(7.209)	(29.14)
population × p50	0.0000573	0.0000102	-0.00459***
	(0.0000517)	(0.000354)	(0.00146)
Year-fixed effects	Y	Y	Y
County-fixed effects	Y	Y	Y
N	3615	2046	4733

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

Table 3: Estimation result

(1) = Total number of family doctors
(2) = Number of family doctors who practice in county c during in year t while practicing in a different county in $t-1$
(3) = $\frac{Number\ of\ Drug\!-\!induced\ deaths\ over\ 65}{populationover65} \times 100,000$ of county c in year t
Sample: 2010-2020(2013-2020 for column 1 and 2) 342 control and 208 treatment counties

C Callaway & Sant'Anna (2021) Estimation

Using DiD to estimate treatment effects with different treatment timing (staggered DiD) challenges researchers to come to a single treatment parameter that can summarize time-varying treatment effects. Also, it is necessary to balance different treatment cohort groups so that at all lengths of exposure a fixed set of groups can be used. I adopt Callaway & Sant'Anna (2021)'s event-study estimator with balanced groups for robustness check.

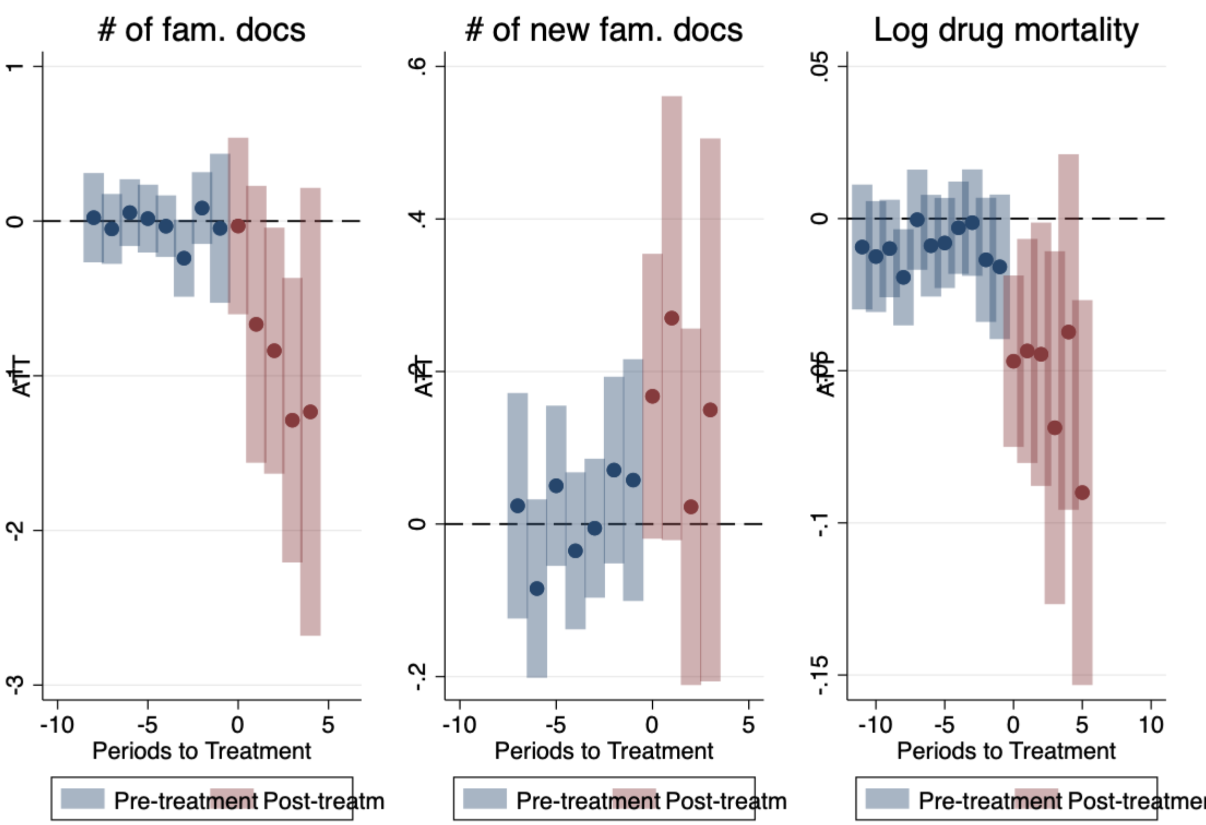

Figure 13: CSDiD results: Primary outcome

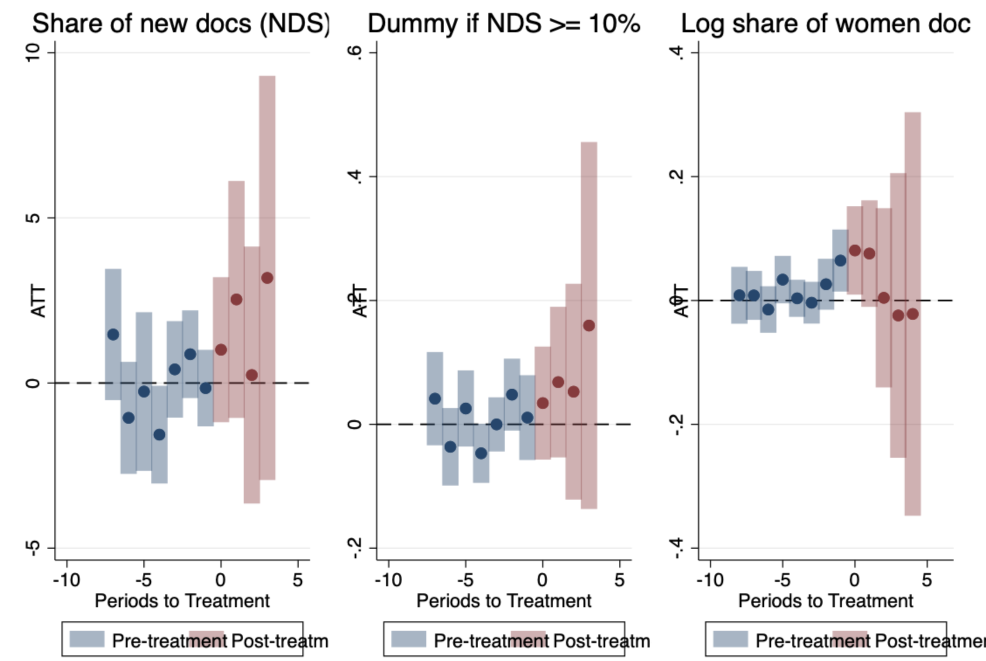

Figure 14: CSDiD results: Physician characteristics

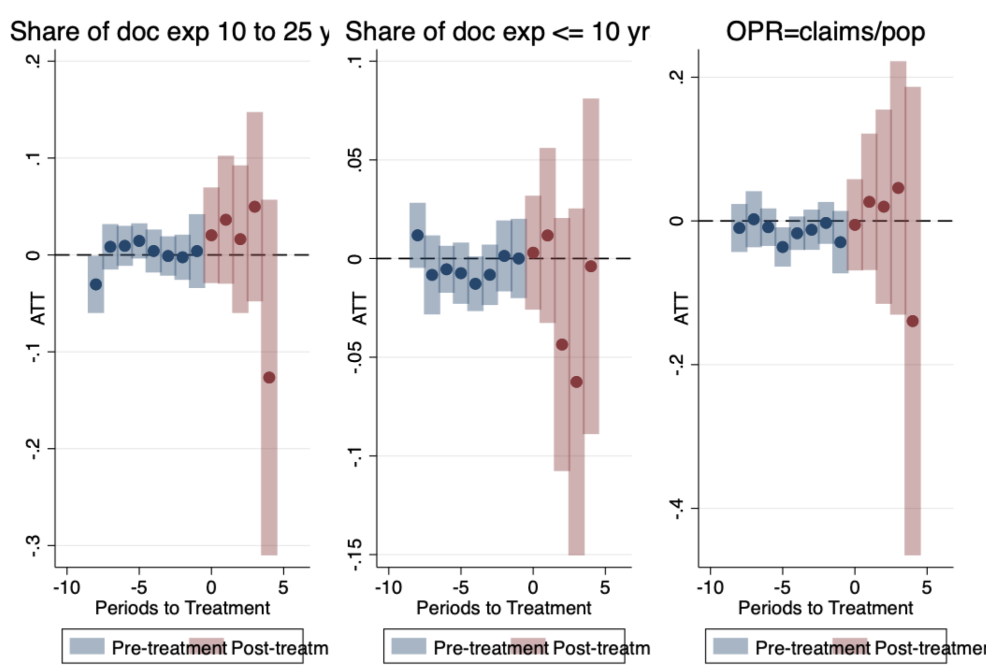

Figure 15: CSDiD results: Physician age and OPR

D Placebo test

The main finding of this paper is that the HPSA identification policy, motivating primary care physicians to attend patients more frequently, improves drug-misuse mortality. The role of a primary care physician in preventing deaths and diseases is extensive, from a chronic to acute diseases. However, the primary interest of this paper is whether the locating motive reduces preventable deaths, not an extensive range of health outcome.

I can further ensure that the policy influences death related mortality mainly through primary care physicians by implementing two placebo tests. First, the Health Resources & Services Administration (HRSA), the organization in charge of managing the designation and withdrawal of HPSA, can prioritize HPSAs in awarding HRSA grants to cover direct and indirect costs of health care facilities. This might misinterpret the effect of HPSA designations on the health outcome through the channels I mentioned in Section D. To rule out this possibility, I test the effect of HPSA designation on HRSA grant amount to local health care facilities and find no evidence that a county's HRSA grant amount responses to the treatment.

Second, I replicate the analysis with a different outcome irrelevant to the role of primary care physicians to rule out the possibility that overall mortality advances regardless of HPSA certification[16]. To do so, I select mortality rates of which ICD-10 codes are V01-V99, W00-X59, X85-Y09, Y10-36 because those codes are unrelated with primary care use. I find that such mortality rates are unaffected therefore not associated with HPSA designation in Figure 16.

ICD-10 Codes	Description
V01-V99	Transport accidents
W00-X59	Other external causes of accidental injury
X85-Y09	Assault
Y10-36	Event of undetermined intent, Legal intervention and operations of war

Table 4: Causes of death ICD-10 codes description

[16] See Cruz and Schneider 2017; Hainmueller and Hangartner 2019; Eggers, Tuñón, and Dafoe 2021 for similar falsification tests

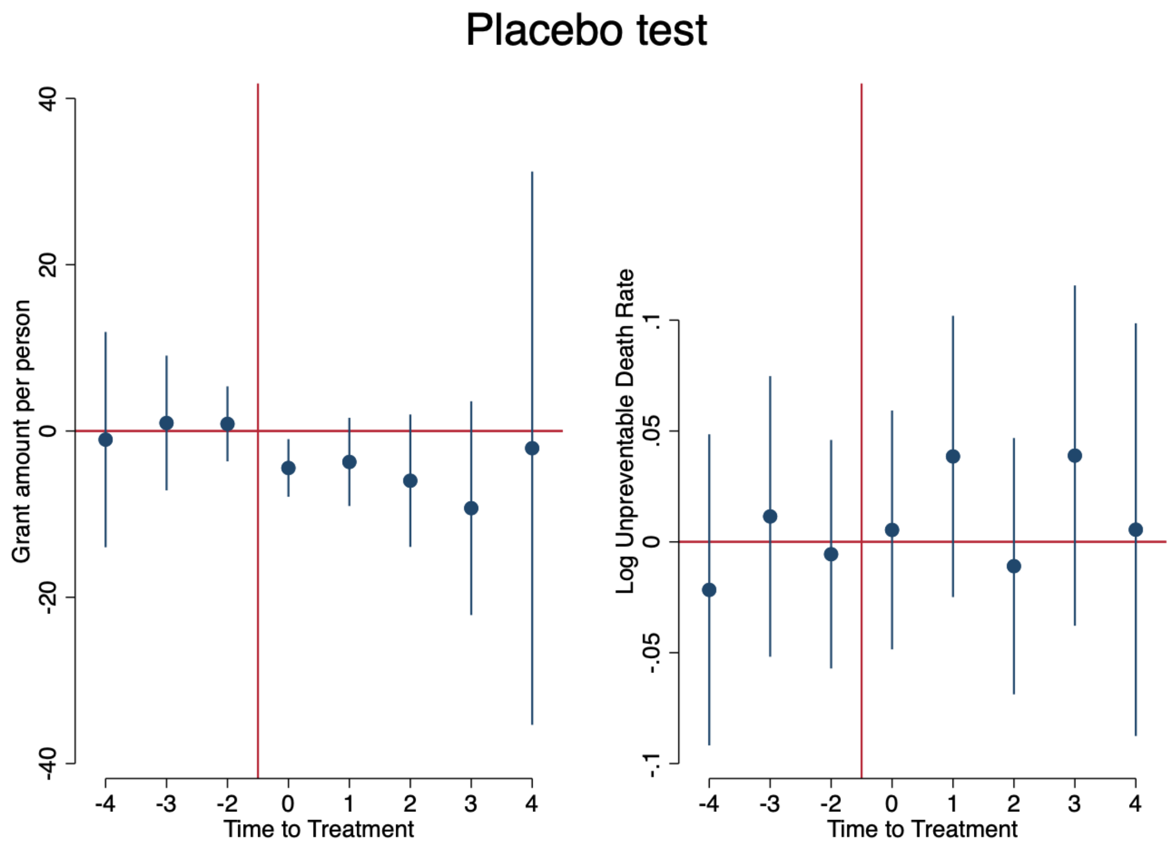

Figure 16: The effect of HPSA designation on false outcomes

CPT code	History	Exam	Decision making	Requirement	Face-to-face time (minutes)
99201	Problem-focused	Problem-focused	Straightforward	5*All three components	10
99202	Expanded problem-focused	Expanded problem-focused	Straightforward		20
99203	Detailed	Detailed	Low		30
99204	Comprehensive	Comprehensive	Moderate		45
99205	Comprehensive	Comprehensive	High		60
99211	Not required	Not required	Not required	5*Two of three components	5
99212	Problem-focused	Problem-focused	Straightforward		10
99213	Expanded problem-focused	Expanded problem-focused	Low		15
99214	Detailed	Detailed	Moderate		25
99215	Comprehensive	Comprehensive	High		40

Table 5: CPT Codes Description