The Impacts of TRAP Laws on the Supply of Maternal Care Providers[*]

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November 18, 2024

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Abstract

This study examines the impacts of Targeted Regulation of Abortion Providers (TRAP laws) on the supply of maternal care providers by exploiting the staggered enactment of TRAP laws across states. Our findings indicate a significant decrease in the number of Obstetrician-Gynecologists (OB/GYNs) by 3.38 to 3.55 per 100,000 females aged 15-44 following the enactment of TRAP laws. Furthermore, the enactment of TRAP laws affects the composition of OB/GYNs. The decline in response to TRAP laws is particularly pronounced among OB/GYNs under the age of 34 and those between the ages of 55 and 64. Newly graduated OB/GYNs, especially those from lower-ranked medical schools, also reduce their presence in states enacting TRAP laws. Although we do not find significant changes in applicants to OB/GYN residency programs or medical schools in response to TRAP laws, in-state applicants tend to shift their applications from public medical schools, which are often higher-ranked, to private medical schools.

Keywords: Maternal care, Healthcare workforce, Targeted Regulation of Abortion Providers

JEL: I11 I18

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[*]This research was supported by NIH Grant: Effect of Losing Hospital-Based Obstetric Services on Maternal Health in Rural Communities (1R03HD10621501A1). The content is solely the responsibility of the authors and does not reflect the official views of the NIH.

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1. Introduction

Maternal healthcare remains a critical concern in the U.S. On average, 859 maternal deaths occurred annually between 2018 and 2022,[1] a figure nearly three times higher than that of most other developed countries and continues to widen over time.[2] Moreover, this disparity has continued to widen over time.[2] In addition to maternal mortality, the U.S. experiences approximately 50,000 cases of severe maternal morbidity annually, which involve life-threatening complications or require urgent surgical intervention during or immediately after childbirth (Kozhimannil et al., 2019).

In 2022, over 2.2 million women of childbearing age lived in areas without a hospital or birth center offering obstetric care and without any obstetric providers which are defined as maternity care deserts by March of Dimes (Brigance et al., 2022), and the number of these deserts continues to grow.[3] Research suggests that the shortage of physicians contributes to elevated mortality rates, particularly in rural areas where healthcare access is limited (Gong et al., 2019). This shortage has significant implications for maternal and infant health outcomes. Specifically, rural residents not only face a 9% greater probability of severe maternal morbidity and mortality for inpatient admissions, but also an increased risk for ICU admissions during delivery, which are associated with a fourfold increase in healthcare costs. Furthermore, Sullivan et al. (2005) found that an increase of five maternal-fetal specialists per 10,000 live births resulted in a 27% reduction in maternal death risk. Understanding the supply of maternal healthcare providers is therefore critical to improving access to consistent, high-quality maternity care.

A significant recent factor influencing the landscape of maternal healthcare providers is the Targeted Regulation of Abortion Providers, or TRAP laws. TRAP laws are state-level regulations that impose stringent requirements on abortion facilities and personnel, such as mandating that abortion clinics operate as ambulatory surgical centers and requiring physicians to have admitting privileges and transfer agreements. Between 2010 and 2017, the number of states enacting these restrictions increased by 59%, leading to the closure of many abortion clinics and likely hindering the establishment of new ones (Jones and Pineda-Torres, 2024). These laws also affect maternal care providers, as abortion procedures are sometimes necessary to treat miscarriages and pregnancy-related medical complications. Additionally, TRAP laws

[1] Source: Maternal Mortality Rates in the United States, 2022

[2] Source: Rural Maternal Health Overview, by Rural Health Information Hub

[3] Source: PBS news: Maternity care deserts grow across the US as obstetric units shut down

limit training opportunities for obstetricians and gynecologists (OB/GYNs).[4] In this paper, we investigate the critical but understudied impacts of TRAP laws on the supply of maternal care providers.

Our empirical analysis employs a novel dataset that combines various data sources. For the treatment variable, we compile data on the enactment and enforcement of TRAP laws across states from 2010 to 2017, based on Austin and Harper (2019), Jones and Pineda-Torres (2024), and official legal websites. Counties located in states enacting TRAP laws are considered treated counties. We use the propensity score matching (PSM) method to find a set of control counties that are comparable to our treated counties based on observed socioeconomic characteristics. For the outcome variables, we collect county-level data of existing OB/GYNs, nurse practitioners (NPs) and physician assistants (PAs), both specializing in maternal health care, and midwives from the Area Health Resources Files (AHRF). For OB/GYNs in pipeline, we collect state-level data on newly graduated OB/GYNs from OneKey IQVIA, OB/GYN residency applicants from the Association of American Medical Colleges' (AAMC) Electronic Residency Application Service (ERAS), and medical school applicants from the AAMC's FACT report.

We employ a stacked difference-in-difference (DID) approach to account for the staggered treatment timings at the county level. Our findings indicate a significant decrease in the number of OB/GYNs by 3.38 to 3.55 per 100,000 females aged 15-44 after the enactment of TRAP laws. This represents approximately 10.1% to 10.6% of the average OB/GYN density and suggests a corresponding increase of 11.6% to 12.1% in maternal death risk in counties with TRAP law. Additionally, we find that the negative impacts of TRAP law enactment are stronger for counties that are less profitable for physician practice. Specifically, TRAP laws have stronger negative effects in counties with a high uninsured rate, a high poverty rate, a competitive maternal care market, and Health Professional Shortage Area (HPSA) designation.

Furthermore, the enactment of TRAP laws impacts the composition of the OB/GYN workforce. First, it reduces the existing OB/GYN workforce, particularly affecting the supply of OB/GYNs aged under 34 and between 55 and 64, with minimal impact on mid-career physicians. Second, it reduces the number newly graduated OB/GYNs by 0.33 per 100,000 females

[4] Bernstein et al. (2023) reported that a majority of surveyed physicians preferred to work or train in states with preserved abortion access after the U.S. Supreme Court overturned *Roe v. Wade* in the case of *Dobbs v. Jackson Women's Health Organization* (hereafter, *Dobbs*), with 76.4% actively avoiding states that imposed legal consequences for providing abortion care.

aged 15-44 one year after the enactment of TRAP laws. This decline is particularly driven by graduates from low-ranked medical schools, which may potentially lead to an increase in OB/GYN quality despite the reduced supply of new OB/GYNs. Third, we find no significant change in the total number of applicants to OB/GYN residency programs or medical schools. However, three years after the enactment of TRAP laws, there is a 1.46% reduction in the share of in-state applicants applying to private schools and a corresponding 1.29% increase in the share of in-state applicants applying to public schools. The decrease in in-state applicants to often higher-ranked private schools may have an unintended long-term quality effect on OB/GYNs. Fourth, we do not find NPs, PAs and midwives substitute for the decline in OB/GYNs.

Our work contributes to the literature in several aspects. It builds on a growing set of studies that examine the impacts of TRAP laws. The majority of these studies examine the impacts of TRAP laws on abortion and fertility. Earlier studies employed a single state setting such as Texas (Grossman et al., 2017, Fischer et al., 2018, Lindo et al., 2020) and Wisconsin (Venator and Fletcher, 2021). Recent studies, such as Arnold (2022), Jones and Pineda-Torres (2024), and Gardner (2024), employ a similar setup to ours to exploit the staggered implementation of TRAP laws across states. These three studies focus on the impacts on young females and infant health. The examined outcomes include abortion use, fertility, pregnancy-associated hypertensive disorders, education, and measures of infant health.

However, there is limited attention on the impacts of TRAP laws on the supply side. Previous studies cited above focus on the closure of abortion clinics as the sole supply-side impact. In fact, the abortion restrictions from TRAP laws also affect OB/GYNs, who need to apply abortion procedures to treat miscarriage and pregnancy-related medical complications. These restrictions may discourage OB/GYNs from practicing and medical students from training in restrictive states. Our work extends the literature by examining the supply-side effects of TRAP laws on the maternal care workforce, including current OB/GYNs, newly graduated OB/GYNs, OB/GYN residency applicants, medical school applicants and alternative providers, including NPs, PAs, and midwives. Our approach provides a comprehensive analysis of how TRAP laws affect the landscape of maternal care providers. This is an important question as an estimated 2.2 million U.S. women live in maternity care deserts, and 4.7 million more live in areas with limited access in 2022 (Brigance et al., 2022).

Our paper also relates to the broader literature that studies the effect of public policies on physician supply. For demand-side policy, Huh and Lin (2024) found that Medicaid eligibility expansion for pregnant women increased OB/GYNs per capita by 6.58%, particularly among early-career OB/GYNs in rural or poor counties. Similar effects were observed with Medicaid dental benefits and the supply of dentists in poor counties (Huh, 2021). Turning to supply-side policy, counties designated as HPSAs had incentives such as scholarships, loan repayment and physician bonus. Falcettoni (2018), Khoury et al. (2024), and Costa et al. (2024) showed that those policy incentives promote physician supply. Further, more lenient malpractice reform promoted physician supply (Encinosa and Hellinger, 2005), and an expansion of the cap on J-1 visa waivers increased the supply of international medical graduates (IMGs) (Braga et al., 2024). We add to this literature in two aspects. First, we are the first to examine the impacts of TRAP laws on physician supply. Second, unlike most previous studies that focus only on the current supply of physicians, we extend the analysis to consider the effects on residency applicants, medical school applicants, and alternative providers. Our approach provides an analysis of how public policy affects the short-term and long-term supply of healthcare providers.

The paper proceeds as follows: Section 2 provides an overview of the policy context. Section 3 describes the data and empirical strategy. Section 4 reports the results. Section 5 discusses the findings, and Section 6 concludes.

2. TRAP laws

In 1973, the United States Supreme Court legalized abortion nationwide in the landmark case of *Roe v. Wade*, affirming that abortion during the first trimester is a constitutional right. In 1992, the Court's decision in *Planned Parenthood v. Casey* allowed states to impose restrictions on abortion, provided that these restrictions do not place an undue burden on women seeking the procedure. Following this ruling, state and local legislatures began to enact more laws to limit abortion access. The most rapidly increasing restrictions were parental involvement laws, requiring minors to notify or obtain consent from a parent before an abortion. More recently, but less common, are mandatory waiting period laws, which mandate a 24- to 48- hour wait after consulting a physician before an abortion can be performed.

Since 2010, there have been more efforts to use TRAP laws to limit access to abortion. By 2021, TRAP laws had become more common than parental involvement laws and, as of mid-2023, were more prevalent than post-*Dobbs* abortion bans (Jones and Pineda-Torres, 2024). TRAP laws require abortion providers to adhere to a series of regulations, such as obtaining specific facility licenses or operating as ambulatory surgical centers. There are four main types of TRAP laws: (1) Admitting privileges: This regulation mandates that some or all providers at an abortion clinic must have admitting or staff privileges at a hospital. This means that providers must be able to admit patients to the hospital and provide specific medical services. (2) Transfer agreements: This regulation requires clinics to have a written agreement with a hospital to transfer patients in case of emergencies. (3) Hospital proximity regulations: This regulation mandates that clinics be located within a certain distance from a hospital, such as within 30 miles or 30 minutes of driving time. (4) Building regulations: These include various requirements for the clinic's physical environment, such as minimum hallway widths, ventilation levels, emergency power sources, and the presence of operating and recovery rooms.

While these regulations are designed to ensure patient safety, many are difficult to meet and are considered medically unnecessary by leading healthcare organizations (Mercier et al., 2016; Austin and Harper, 2019; Jones and Pineda-Torres, 2024). For instance, there is often no hospital near an abortion clinic, making it difficult to comply with admitting privileges, transfer agreements, and hospital proximity regulations. Additionally, hospitals may be hesitant to grant these privileges or enter into agreements with abortion providers due to concerns about public image and social reputation. Furthermore, fewer than 0.5% of abortion patients in the U.S. experience complications requiring hospitalization,[5] meaning abortion providers may not see enough patients in a year to meet the minimum requirements set by local hospitals. These challenges highlight the burdensome nature of TRAP laws and their potential impact on the availability of abortion services, particularly in underserved areas.

Due to the inability of some clinics and providers to comply with the stringent requirements, TRAP laws have led to the closure of many abortion clinics and have become a significant barrier to the opening of new ones. In 2017, 95% of abortions were performed in clinics (Jones and Pineda-Torres, 2024), yet the number of abortion providers declined from 2,908 in 1982 to 1,603 in 2020. According to a report by Guttmacher Institute (2019),[6] between 2011 and 2017, 86% of abortion regulations were enacted in the Southern and Midwestern regions of the United States. Consequently, the South saw the closure of 50 abortion clinics, while the Midwest experienced the closure of 35 clinics.

The TRAP laws also impose burdens on OB/GYN practice and training. OB/GYNs need

[5] Source: Guttmacher Institute (2020), Targeted Regulation of Abortion Providers (TRAP) Laws

[6] Source: Guttmacher Institute (2019): The U.S. Abortion Rate Continues to Drop: Once Again, State Abortion Restrictions Are Not the Main Driver

to comply with these laws to perform abortions for miscarriages and medical complications. Medical schools need to comply with these laws to provide abortion training to their residents and students. Consequently, the TRAP laws impact the sustainability of the OB/GYN workforce.

3. Empirical Strategy

3.1. Data

3.1.1. TRAP Laws

We collect state-specific information on TRAP laws from Jones and Pineda-Torres (2024) and supplement it with the year of passage for each state's TRAP laws. The passage year is defined as the first year in which a state enacted at least one TRAP law. To obtain this information, we refer to Austin and Harper (2019) and review regulatory texts on WestLaw, LexisNexis, Justia Law, and Case-Text.com. For Kansas and Illinois, where the exact passage year was unavailable, we assume it to be one year before the effective year, following conventions observed in other states. Table 1 presents the enforcement and passage years of TRAP laws between 2010 and 2017 and traces their block years to 2020.

3.1.2. Maternity Care Providers

We obtain county-level data on existing OB/GYNs from Area Health Resources Files (AHRF) from 2010 to 2019. Our main outcome focuses on non-federal OB/GYNs holding Doctor of Medicine (MD) degrees.[7]

Data on new OB/GYNs comes from IQVIA OneKey database, which provides individual-level characteristics such as national provider identifier (NPI), gender, specialty, practice title, practice location, graduated medical school, graduate year, etc. We define new OB/GYNs as those who graduated four or five years before their first appearance in the IQVIA dataset, considering that OB/GYNs residency usually lasts four years. We supplement any missing information using data from Physician Compare and Google searches, cross-referencing NPI, first name, last name, specialty, and practice location.

[7]Federal OB/GYNs account for approximately 2.15% of all OB/GYNs between 2010 and 2019. We also include regression results on federal OB/GYNs in Figure 9.

For the analysis of alternative providers, we consider OB/GYNs with Doctor of Osteopathic (DO) degrees, as well as certified advanced midwives, nurse practitioners, and physician assistants. Data on the first two groups is sourced from AHRF, while the latter two are obtained from the IQVIA OneKey dataset.

3.1.3. Residency and Medical School Applicants

The Association of American Medical Colleges (AAMC) collects data from its member medical schools and related organizations. We obtain data on OB/GYN residency program applicants from 2010 to 2019 through AAMC's Electronic Residency Application Service (ERAS).[8] ERAS is a centralized online application service through which medical students apply for residency and fellowship programs. Our dataset includes information on the total number of OB/GYN residency applicants, self-reported degree types (MD, DO, or IMG), and self-reported gender.[9] In addition, we use the FACTS Report to obtain data on medical school applicants, including the percentage of in-state versus out-of-state applicants and the percentage of women and men for each medical school by state from 2010 to 2019.[10]

3.1.4. Socioeconomic Variables

We include a set of county-level socioeconomic characteristics as control variables. These characteristics include the percentage of the population that is non-Hispanic white, non-Hispanic Black, and Hispanic; the share of the population receiving Supplemental Nutrition Assistance Program (SNAP) benefits; birth rates per 100,000 females of childbearing age; poverty rate; median income; unemployment rate for individuals aged 16 and older; and the

[8] Hammoud et al. (2024) used the same dataset to examine trends in OB/GYN residency applications following the *Dobbs v Jackson*.

[9] The AAMC does not release ERAS data that could potentially identify a specific program, including exact applicant counts. Data is only provided for states with five or more OB/GYN residency programs. All states that enacted TRAP laws during our sample period meet this criterion, except for North Dakota, which has none. For control states with fewer than five OB/GYN residency programs, we group them into three categories: Never-treated West Region (Colorado, Nevada, New Mexico, Oregon, Washington), Never-treated South and Northeast (Delaware, D.C., West Virginia, Maine, New Hampshire, Vermont), and Never-treated Midwest (Iowa, Minnesota, Wisconsin).

[10] The AAMC does not provide versions of the FACTS Tables prior to 2013. We obtain data for 2011 from "Diversity in Medical Education: Facts & Figures 2012". Data for 2010 and 2012 is unavailable, leaving us with only one pre-period for the DID analysis on medical school applicants.

total population of females aged 15-44, all sourced from AHRF. For state-level analyses, we use the corresponding state-level data for these characteristics.

3.2. Descriptive Statistics

Table 2 presents summary statistics for existing OB/GYNs (Panel A), county-level characteristics (Panel B), and new OB/GYNs (Panel C) for both treatment and control groups. Panel A shows that the average number of OB/GYNs per 100,000 females aged 15 to 44 is 33.48 in treatment counties and 36.46 in control counties. OB/GYNs aged 45-54 and 55-64 account for over 50% of the total OB/GYNs in both groups.[11] Panel B indicates that the county-level characteristics after PSM are similar between the treatment and control counties.

Panel C reports that the average number of new OB/GYNs per 100,000 females aged 15-44 is 0.65 in treatment states and 0.64 in control states. Over 90% of new OB/GYNs graduated from U.S. medical schools. A higher proportion of new OB/GYNs graduated from low-ranked medical schools in treatment states compared to control states (55% vs 31%). Additionally, a higher proportion of new OB/GYNs graduated from in-state medical schools in treatment states than in control states (46% vs 28%). The ratio of female to male new OB/GYNs is 3.8 in the treatment group and 5.2 in the control group.[12]

Table 3 presents summary statistics for applicants to OB/GYN residency programs (Panel A) and medical schools (Panel B) in both treatment and control states. In treatment states, the average number of OB/GYN residency applicants is 1,265, compared to 1,302 in control states. Approximately 59% of applicants in both groups are graduates of U.S. medical schools, with 49% holding an MD degree. Additionally, 76% of the applicants are female.

Panel B shows that the average number of medical school applicants is 26,468 in treatment states and 17,979 in control states. In treatment states, 58% of applicants apply to private schools, whereas only 37% do so in control states. Over 85% of applicants are from out-of-state. The distribution of female and male applicants is similar across both groups.

[11] The combined share of OB/GYNs aged 45-54 and 55-64 in treatment groups is $53\% = \frac{8.67+9.09}{33.48} \times 100\%$ and in control groups is $55\% = \frac{10.39+9.50}{36.46} \times 100\%$.

[12] Calculated as $3.8 = \frac{0.50}{0.12}$ for the treatment group and $5.2 = \frac{0.52}{0.10}$ for the control group.

3.3. Empirical Strategy

To estimate the impact of TRAP laws on the location decisions of practicing OB/GYNs, we employ a DID framework to compare outcomes in treated states that enacted TRAP laws with counterfactual outcomes in control states that did not. We use the year of enactment rather than the year of enforcement as the treatment year as we hypothesize that OB/GYNs begin to react when they first become aware of the law's enactment. Specifically, we apply a PSM approach to select control states and, following Cengiz et al. (2019) and Deshpande and Li (2019), implement a stacked DID framework to ensure the robustness of our DID estimates. The stack DID approach is particularly suitable in our setting as it addresses biases arising from heterogeneous treatment timing (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021).

3.3.1. Propensity Score Matching

We use the PSM approach to ensure similarity between counties in treated and control states. Specifically, we select a range of county-level demographic characteristics from 2010, the first year of our study period, as matching variables because previous studies have identified these characteristics as important determinants for selecting control counties (Brown et al., 2020). The variables include the percentage of the population that is non-Hispanic white, non-Hispanic Black, and Hispanic; the share of the population receiving SNAP benefits; birth rates per 100,000 females of childbearing age; poverty rate; median income; and the unemployment rate for individuals over 16. These variables also serve as covariates in our main regression. Recognizing that the passage of TRAP laws may be influenced by political party control, we additionally include the state-level percentage of people who voted for the Democratic candidate in the most recent presidential election (Brown et al., 2020).[13] To estimate the propensity score, we assume that whether a county passes a TRAP law is governed by a logit model:

$$Treat_c = z_c\gamma + \eta_c \tag{1}$$

where $Treat_c$ is an indicator of whether county c passed a TRAP law during our sample period. z_c represents the matching variables discussed above. Following the recommendations of Callaway and Sant'Anna (2021), we select the never-treated group as the control group and

[13] Data comes from https://uselectionatlas.org/

choose matched counties from within this group. Overall, selection bias is significantly reduced after matching (see Figures A1 and A2 in Appendix A).

3.3.2. Difference-in-Difference Estimation

We define each treatment timing as a "stack." For each stack, we create a mini-dataset consisting of all counties in the treatment states and a matched group of control counties obtained through the PSM method. We then stack these mini-datasets to form a single dataset and perform the DID estimation.

The empirical model for our main analysis as follows:

$$y_{ctd} = \sum_{j=\underline{j}, j\neq -1}^{\bar{j}} \beta_j (Treat_{cd} \times 1[\tau_{td} = j]) + X'_{ctd}\alpha + \mu_{cd} + \sigma_t + \varepsilon_{ctd} \tag{2}$$

where y_{ctd} is the number of OB/GYNs per 100,000 females aged between 15 and 44 for county c in year t within mini-dataset d. $Treat_{cd}$ is a binary indicator for whether county c in mini-dataset d is a treatment county, and τ_{td} represents the number of years relative to the TRAP law enactment for treated counties in mini dataset d in year t. The interaction term for these two variables indicates whether a TRAP law in county c within mini dataset d turns on j years away from t, where $j \in [\underline{j}, \bar{j}]$, $j \neq -1$ and $\underline{j} = -3, \bar{j} = 3$. The final TRAP law in our sample was enacted in 2015 in Illinois, so the sample period spans from 2010 to 2018.

The vector of control variables X_{ctd} includes the percentage of populations that is non-Hispanic white, non-Hispanic Black, and Hispanics; the share of the population receiving SNAP benefits; birth rates per 100,000 females of childbearing age; poverty rate, median income, and the unemployment rate for those over 16.[14] μ_{cd} denotes county fixed effect and σ_t represents year fixed effect. Standard errors are clustered at the state level to account for dependence in the residuals across counties within a state (Brown et al., 2020; Huh and Lin, 2024).

The identification strategy assumes that OB/GYN density trends in treated states are parallel to those in control states. Equation (2) offers a way to assess the validity of this parallel trends assumption. Specifically, we test whether β_j for all $j < 0$ is equal to zero. If any β_j for $j < 0$ is significantly different from zero, it would indicate the presence of pre-trends, which

[14] To impute missing values for county-level characteristics in certain years, we apply a linear trend based on data from the preceding and following years. This imputation method is used for variables such as the number of unemployed individuals over 16 and SNAP recipients.

could bias our DID estimation.

For the analyses of new OB/GYNs, OB/GYN residency applicants, and medical school applicants, we conduct them at the state level due to the limited number of new OB/GYNs each year and the unavailability of more granular data of the other two variables. The empirical model at the state level is specified as follows:

$$y_{std} = \sum_{j=\underline{j}, j\neq -1}^{\bar{j}} \beta_j (Treat_{sd} \times 1[\tau_{td} = j]) + X'_{std}\alpha + \mu_{sd} + \sigma_t + \varepsilon_{std} \tag{3}$$

where the outcome variables include the number of new OB/GYN per 100,000 females aged 15-44, the number of OB/GYN residency and medical school applicants in state s in stack d in year t. $Treat_{sd}$ is an indicator for whether state s enacted a TRAP law during the sample period.[15] All other aspects of the empirical model follow those in Equation (2), and we continue to estimate the model using the stacked DID approach.

4. Results

4.1. Impacts on Total OB/GYNs

4.1.1. Event Study Result

Figure 1 plots the estimated coefficients for β_j along with their 95% confidence intervals from Equation (2). The horizontal axis represents the number of years relative to the enactment year, which is indicated as zero on the axis. We observe a marked reduction in the supply of OB/GYNs two years following the enactment of TRAP laws. Specifically, the OB/GYN supply decreases significantly by 3.38 per 100,000 females aged between 15 and 44 two years after enactment, and the decline persists into the third year. These reductions account for approximately 10.1% to 10.6% of the average OB/GYN density in treatment counties.

4.1.2. Robustness Checks

We conduct a series of robustness checks to test the reliability of our results. First, we re-estimate Equation (2) using alternative methods, including the traditional two-way fixed effect (TWFE) model, as well as the modern approaches developed by Borusyak et al. (2024),

[15] We use all never-treated states as control states in each stack. Since there are only seven treated states, applying a PSM approach at the state level would result in a small sample size.

Callaway and Sant'Anna (2021), and Sun and Abraham (2021). Figure B1 shows the event study results. Across all methods, we find a consistent and statistically significant decline in OB/GYN density two and three years after the enactment of TRAP laws.

Second, we conduct placebo tests by estimating Equation (2) using per capita counts of cardiologists, dermatologists, gastroenterologists, and plastic surgeons as outcome variables, with data sourced from AHRF. Figure B2 presents the corresponding event study results. Encouragingly, we do not observe significant changes in physician density for any of these specialties following the enactment of TRAP laws. Since these physicians provide services unrelated to maternal care, these findings support our main conclusion that the decline in OB/GYN supply after the enactment of TRAP laws is primarily attributable to the laws themselves.

Third, we test whether other contemporary laws confound our findings. Specifically, we examine the potential effects of two additional types of laws: malpractice reforms and demand-side abortion laws. State-level malpractice reforms, which are designed to reduce malpractice pressure on physicians, could influence physician supply in states with such reforms (Kessler et al., 2005). We consider two types of demand-side abortion laws: parental involvement laws and mandatory waiting period laws. Parental involvement laws require parental consent for minors seeking abortions, asserting that they do not impose an undue burden. Mandatory waiting period laws require women to wait a specified period—most often 24 hours—between receiving information and undergoing the abortion procedure. Previous studies have shown that these two laws affect the demand for maternal care (C. Myers and Ladd, 2020; C. K. Myers, 2021; Jones and Pineda-Torres, 2024).[16] We add malpractice reforms and demand-side abortion laws as a separate control in Equation (2). The results, presented in Figure B3, are consistent with those shown in Figure 1, indicating that our main findings are robust to the inclusion of these additional legal factors.

4.1.3. Heterogeneity analyses

We estimate the heterogeneous effects of TRAP laws by county characteristics. These analyses help us better understand the potential mechanisms through which OB/GYNs respond to TRAP laws.

[16]C. Myers and Ladd (2020) found that parental involvement laws increased teen births by 3% in more recent decades, while C. K. Myers (2021) showed that two-trip waiting periods increased second-trimester abortions by 19.1%, reduced resident abortion rates by 8.9%, and increased births by 1.5%.

By County Socioeconomic Characteristics. We hypothesize that the effect of TRAP laws on OB/GYN supply is stronger in areas that are less preferable for physicians to practice, as the additional costs imposed by TRAP laws lead physicians to re-evaluate the viability of their practices. Specifically, we employ three measures to classify locations as more or less preferable for physicians to practice.

First, physicians are less likely to practice in rural area for various reasons, such as their specialties, family backgrounds, and financial needs (Rabinowitz and Paynter, 2002). The enactment of TRAP laws may impose additional costs on physicians practicing in rural areas and steer them toward other locations. To examine this heterogeneity, we divide our sample into rural and urban counties based on Rural-Urban Commute Area Codes and estimate Equation (2) for each subsample.

Second, populations residing in areas with higher poverty rates often struggle to finance their medical needs, leading to an increased likelihood of uncompensated care. TRAP laws may further exacerbate financial pressures on physicians serving in these areas, making it less viable for them to maintain their practices. To examine this heterogeneity, we estimate Equation (2) using subsamples based on higher and lower poverty rates, defining high-poverty counties as those in the top quartile for poverty rates.

Third, following similar reasoning to the previous measure, we suggest that areas with higher uninsured rates are less attractive for physicians to practice. We estimate Equation (2) using subsamples based on higher and lower uninsured rates, defining high-uninsured counties as those in the top quartile for uninsured rates.

Figure 2 presents the event-study results. The figures in the first row show the effects of TRAP laws in rural and urban counties. In rural areas, the number of OB/GYNs significantly declines starting in the second year after the enactment of TRAP laws, with a magnitude ranging from -3.24 to -3.41 per 100,000 females aged 15-44. In urban areas, the decline begins in the first year after enactment, with a magnitude ranging from -3.44 to -3.50 per 100,000 females aged 15-44. The timing and magnitude of OB/GYN responses to TRAP laws are similar across rural and urban areas.

The figures in the second row show the effects of TRAP laws in counties with higher and lower poverty rates. The effect is stronger in high-poverty counties, with a magnitude of -5.36 per 100,000 females aged 15-44, which is larger than that depicted in Figure 1. In low-poverty counties, we also observe a negative effect of TRAP laws on OB/GYN supply, but the magnitude is about half of that in high-poverty counties.

The figures in the third row illustrates the effects of TRAP laws in counties with higher and lower uninsured rates. In high-uninsured counties, the effect is more pronounced, with a decline of 4.38 per 100,000 females aged 15-44, exceeding the effect shown in Figure 1. In low-uninsured counties, the decline is more moderate, ranging from -3.60 to -3.69 per 100,000 females aged 15-44.

By Local Healthcare Infrastructure. First, we consider the size of the existing OB/GYN supply. In areas with a higher supply, competition among OB/GYNs may be more intense. TRAP laws could raise costs, prompting physicians to relocate to states with less competitive pressure. To explore this heterogeneity, we re-estimate Equation (2) by comparing counties with high and low OB/GYN supply. Low-supply counties are defined as those in the bottom quartile, while the remaining counties are classified as high-supply counties.

Second, OB/GYNs benefit from policy incentives such as scholarships, loan repayment, and physician bonus programs if they practice in areas designated as primary care Health Professional Shortage Area (HPSA).[17] These HPSA-tied programs provide financial incentives for physicians to serve in areas of need, but their effectiveness has been found to be mixed (Huh, 2021; Khoury et al., 2024; Markowski et al., 2023). Therefore, we examine whether HPSA-tied policy incentives mitigate the effect of TRAP laws on OB/GYN supply by dividing the sample into two subsamples: counties with primary care HPSA designation and those without it.

Figure 3 presents the event-study results. First, we find that the effects of TRAP laws are stronger in counties with a high existing supply of OB/GYNs, with $\beta_2 = -5.87$ and $\beta_3 = -5.81$. In contrast, there is no significant effect in counties with a low existing supply. Second, TRAP laws affect both HPSA-designated and non-designated counties, but the impact is more pronounced in HPSA-designated counties, with declines of -4.97 versus -3.21 at t = 2 and -7.13 versus -3.08 at t = 3. However, we cannot rule out the possibility of pre-existing trends in areas with the designation.

In summary, we find that TRAP laws significantly affect OB/GYN supply in both rural and

[17] HPSAs for primary care are granted by the Health Resources and Services Administration (HRSA) to identify geographic areas with potential shortages in primary care. HRSA determines HPSA eligibility based on a score that incorporates factors such as the population-to-provider ratio, the fraction of the population below the federal poverty line, the infant health index, and travel time to the nearest source of care outside the proposed HPSA.

urban counties. The impact of TRAP laws is stronger in high-poverty areas compared to low-poverty areas, in high-uninsured areas compared to low-uninsured areas, in areas with greater competition among OB/GYNs, and in areas with HPSA designation.

4.2. Compositional Impacts on Maternal Care Providers

First, we examine how OB/GYNs' responses to TRAP laws vary by age or career stage. Second, we analyze how the supply of new OB/GYNs, OB/GYN residency applications, and medical school applications respond to TRAP laws. Third, we explore how alternative maternal care providers respond to TRAP laws.

4.2.1. Impacts on OB/GYNs at different Age/Career Stage

Young physicians may be more sensitive to state regulations when choosing their practice locations (Chatterji et al., 2018; Huh and Lin, 2024; Khoury et al., 2024). They tend to prefer states with fewer regulations and greater autonomy, as these environments are seen as more conducive to establishing new practices. In contrast, experienced physicians may be less responsive to TRAP laws due to the higher opportunity costs associated with relocation (Huh and Lin, 2024). For physicians nearing retirement, previous research suggests that regulations such as malpractice reform affect retirement decisions (Kessler et al., 2005). Thus, OB/GYNs' responses to TRAP laws are likely to vary based on their age and career stage.

To test these effects, we estimate Equation (2) by categorizing OB/GYNs into different age groups: under 34, 35-44, 45-54, 55-64, and over 65. This classification also reflects the different career stages of OB/GYNs. Following Huh and Lin (2024) and Khoury et al. (2024), OB/GYNs under 34 are classified as early-career OB/GYNs, those in the middle two groups as mid-career, and those in the last two groups as late-career. Figure 4 presents the event-study estimates.

We find a significant reduction in the number of early-career OB/GYNs starting in the first year after the enactment of TRAP laws, with declines ranging from -0.70 to -1.46 per 100,000 females aged between 15-44. However, the treated counties exhibit a downward trend in early-career OB/GYN supply even before the TRAP law, suggesting a violation of the parallel trend assumption for this group. This pre-event reduction may reflect uncertainty surrounding the passage of TRAP laws before their actual enactment. We will further explore the responses of new OB/GYNs in a later section.

Additionally, we find significant reductions in the number of OB/GYNs aged 55-64, who are in the later stages of their careers, with declines ranging from -1.45 to -2.06 per 100,000 females aged 15-44. This reduction accounts for approximately half of the total decline in OB/GYN supply, and the parallel trend assumption holds for this group. For OB/GYNs over 65, although the changes are not statistically significant (p-value ranging from 0.139 to 0.406), there is a noticeable increase in their supply after the enactment of TRAP laws. Some retired OB/GYNs return to practice in affected counties to address gaps left by the reduction in early-career and experienced OB/GYNs.

Our findings suggest that TRAP laws significantly reduce the supply of both early-career and late-career OB/GYNs, with insignificant impact on mid-career OB/GYNs aged 35-44 and 45-54.

4.2.2. Impacts on New OB/GYNs

New OB/GYN graduates are at a critical juncture in their career planning, as their first job placements can have lasting impacts on their career development. Previous studies suggest that state-level policy environment affects the entry of new physician, see Kessler et al. (2005) for tort law and Huh (2021) for Medicaid expansion. The policy uncertainty surrounding TRAP laws may have a stronger impacts on new OB/GYN graduates in terms of where they choose to provide maternal care. Second, Figure 4 shows a significant reduction in the supply of OB/GYNs aged 34 and under following the enactment of TRAP laws, but there is a presence of pre-trends. To better understand the behavior of young OB/GYNs, it is prudent to conduct further analysis focused on this group.

To address this, we utilize a unique database, OneKey IQVIA, which has been used in previous studies on physician supply and behavior (Baker et al., 2016; Lin et al., 2021). We examine whether the enactment of TRAP laws affects the first job location choices of newly graduated OB/GYNs after completing their residency. We estimate Equation (3) and present the event-study results in Figure 5. Encouragingly, there is no evidence of pre-trends (all pre-period coefficients are insignificant). We find a significant decline of 0.33 new OB/GYNs per 100,000 females aged 15-44 (p-value: 0.09) one year after the enactment of TRAP laws.

Next, we examine which types of newly graduated OB/GYNs are more responsive to the effects of TRAP laws. Previous research finds that the selectivity of medical schools influences physicians' responsiveness to policy changes (Chatterji et al., 2018, Khoury et al., 2024, Costa et al., 2024). Physicians prefer to work in the same area where they attended medical school (Costa et al., 2024). Additionally, U.S. medical school graduates and IMGs face different constraints in their location preferences. IMGs, in particular, encounter additional challenges, such as visa barriers and licensing processes. For instance, Braga et al. (2024) found that expanding the cap on J1 visa waivers increased the supply of IMGs in underserved communities. Thus, new OB/GYNs' responses to TRAP laws are likely influenced by their educational and demographic backgrounds.

To test these effects, we estimate Equation (3) across eight sub-samples: new OB/GYNs who graduated from low-ranked medical schools (defined as ranked outside the top 100 and including all IMGs) versus high-ranked medical schools (those ranked within the top 100); U.S. medical school graduates versus IMGs; new OB/GYNs practicing within the states where they graduated versus those practicing outside their graduation state; and female versus male OB/GYNs. The event-study results are shown in Figure 6. The first two graphs indicate a decline of 0.22 new OB/GYNs per 100,000 females aged 15-44 (p-value: 0.075) from low-ranked medical schools in the year of law enactment, while there is no significant effect for graduates from high-ranked medical schools. In the remaining six sub-samples, we do not find any significant effects.

4.2.3. Impacts on OB/GYN Residency Applications

Recent analysis of 2023 ERAS data indicates a continued decline in residency program applicants in states with comprehensive abortion bans.[18] Applications to OB/GYN residency programs decreased by 5.2% during the 2022-2023 cycle compared to the previous year, followed by a modest increase of 0.6% in the 2023-2024 cycle. OB/GYNs are required to learn basic abortion techniques, which are also essential for managing miscarriages and certain pregnancy complications. However, in states with abortion bans and restrictions, residents must travel out of state for these trainings, increasing the opportunity cost of completing a residency in those states. As a result, states with TRAP laws may experience a decline in applicants to OB/GYN residency programs.

We estimate Equation (3) with OB/GYN residency applicants as the outcome variable and present the results in Figure 7. We also present the event study results of Equation (3) with the

[18] AAMC data snapshot, States With Abortion Bans See Continued Decrease in U.S. MD Senior Residency Applicants

following outcome variables in Figure C1: the share of U.S. graduates, IMGs, U.S. graduates with MD degrees, U.S. graduates with DO degrees, male applicants, and female applicants. None of these results are statistically significant. There are several potential reasons for these insignificant results. First, medical graduates often apply to as many residency programs as possible to minimize the risk of rejection. Second, they incur costs associated with their chosen specialty, making them more likely to prioritize program reputation and resources over state-level policies. Third, geographic preferences, such as proximity to their medical school or home, may outweigh the concerns about TRAP laws.

4.2.4. Impacts on Medical School Applications

Nearly 40% of physicians end up practicing in the state where they attended medical school (Hess, 2024). A reduction in medical school applications weakens the physician pipeline and could potentially affect the availability of maternal care providers. In this section, we examine the effect of TRAP law enactment on medical school applicants.

Figure 7 presents the estimation results using the number of medical school applicants as the outcome variable. We do not observe any significant effects. Figure 8 explores these effects across three categories: school type (private vs. public schools), in-state share to private vs. public school, and out-of-state share to private vs. public school. The first row of Figure 8 shows a downward trend in the share of applicants to private schools, prompting further analysis by residency status and school type. We find a significant decline in the in-state share of applicants to private schools (β_2=-0.98%, p-value=0.104 at t=2 and β_3=-1.46%, p-value=0.019 at t=3) and a significant increase in the in-state share to public schools (β_2=1.00%, p-value=0.096 at t=2 and β_3=1.29%, p-value=0.027 at t=3) after TRAP law enactment. No other results are statistically significant, see Figure C2.

4.2.5. Impacts on Alternative Providers

NPs and PAs specializing in maternal health care, along with midwives can help address the shortage of OB/GYNs, particularly in rural areas.[19] Therefore, we investigate whether TRAP laws affect these alternative providers, potentially offsetting the decline in OB/GYNs with an increase in these providers. We re-estimate Equation (2) by replacing the outcome vari-

[19]See newsletter from Commonwealth Fund: Restoring access to maternity care in rural America, and Sheffield et al. (2024)

able with the number of NPs, PAs, and nurse advanced midwives per 100,000 females aged 15-44, and report the results in the first three sub-figures in Figure 9. However, we do not find any significant effects on these groups.

In addition to our main analysis, which focuses on non-federal MDs, we also examine the impacts of TRAP laws on DO OB/GYNs and federal OB/GYNs, as shown in the last two sub-figures in Figure 9. While there is no significant effect on DO OB/GYNs, we observe a slight decline in the number of federal OB/GYNs in the year of enacting TRAP laws and the following year (β_0=-0.12, p-value=0.072 at t=0, β_1=-0.50, p-value=0.049 at t=1). In sum, we do not find the decline of OB/GYNs in states with TRAP laws is offset by an increase in alternative providers.

5. Discussion

The main finding in this paper is that there is a decline of 3.38 to 3.55 OB/GYNs per 100,000 females aged 15-44 in counties after the enactment of TRAP laws, relative to comparable counties without enacting such laws. Sullivan et al. (2005) found that an increase of five maternal-fetal specialists per 10,000 live births resulted in a 27% reduction in the risk of maternal death. Given that the average birth rate in our treated group is 6,338 per 100,000 females aged 15-44, a back-of-the-envelope calculation suggests an increase of 11.6% to 12.1% in maternal death risk in counties with TRAP laws.

Even within states that enacted TRAP laws, the impact on OB/GYN supply is stronger in high-poverty areas compared to low-poverty areas, in high-uninsured areas compared to low-uninsured areas, in more competitive maternal care markets, and in areas with HPSA designation.

Moreover, the enactment of TRAP laws affects the composition of the maternal care workforce. These laws reduce the existing OB/GYN workforce, particularly affecting the supply of early- and late-career OB/GYNs, with minimal impact on mid-career OB/GYNs. This difference is driven by two key factors: early-career OB/GYNs may be more likely to relocate in response to regulatory laws due to their lower opportunity costs, whereas late-career physicians, despite facing high opportunity costs of relocating, may feel less pressure to move given their established reputations and strong bargaining power. Additionally, some retired OB/GYNs return to practice in counties affected by TRAP laws, potentially filling gaps in maternal care.

We also find that fewer newly graduated OB/GYNs, especially those from lower-ranked medical schools, choose to practice in states enacting TRAP laws. Asch et al. (2014) show that OB/GYNs from the lowest-ranked programs had one-third higher maternal complication rates compared to those from the best programs. Thus, the decline in OB/GYNs from lower-ranked schools suggests a potential increase in the quality of maternal care provided by new OB/GYNs, as the higher barrier to entry may improve the overall standard of care. However, it is important not to overlook the decline in the quantity of new OB/GYNs following the enactment of TRAP laws. The reduction in new OB/GYNs, particularly those from lower-ranked medical schools, raises concerns about the accessibility of maternal health care, especially in underserved regions already experiencing a shortage of maternal care providers.

Considering the future supply of maternal care providers, we do not find any significant change in the total number of applicants to OB/GYN residency programs or medical schools following the enactment of TRAP laws. However, we find that enacting the TRAP laws has a significant negative impact on the in-state share of applicants to private medical schools, while the out-of-state share remains unchanged. This suggests that in-state applicants are more sensitive to state policies, as they are more likely to practice within the state. In an uncertain policy environment, where implicit opportunity costs are higher, some in-state students might opt to reduce costs by applying to public schools. Since medical school marks the beginning of the physician pipeline, this unintended effect of TRAP laws could divert students from private schools to public schools—where private schools are typically higher-ranked than public schools. This shift could have some implications for healthcare delivery, potentially lowering the overall quality of physicians in the future.

6. Conclusion

This study examines the impacts of TRAP laws on the supply of maternal healthcare providers. By employing a stacked DID approach with staggered treatment timings, our findings show a significant decrease in the availability of OB/GYN by 3.38 to 3.55 per 100,000 females aged 15-44 post-TRAP laws. The impact is stronger in counties with high uninsured rates or high poverty rates, in competitive maternal care markets and in areas with the HPSA designation. Additionally, the enactment of TRAP laws affects the composition of the OB/GYNs workforce. OB/GYNs under 34 and those aged 55-64 disproportionately reduce their supply. Newly graduated OB/GYNs, especially those from low-ranked medical schools, are discouraged from practicing. Moreover, in-state applicants to medical schools shift their applications from private to public schools.

Our findings have several policy implications for potential shifts in the maternal care workforce in the post-*Dobbs* era. First, policymakers should be mindful of the unintended effects of TRAP laws and reassess the balance between regulatory burdens and benefits. Regular evaluations of the impact of TRAP laws on medical school applications, residency placements, and physician distribution are essential to ensure a robust and high-quality OB/GYN workforce. Second, policymakers could take a more active role in expanding the roles of NPs, PAs, and certified midwives in maternal care, helping to alleviate the pressure caused by the decline in OB/GYNs.

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7. Figures and Tables

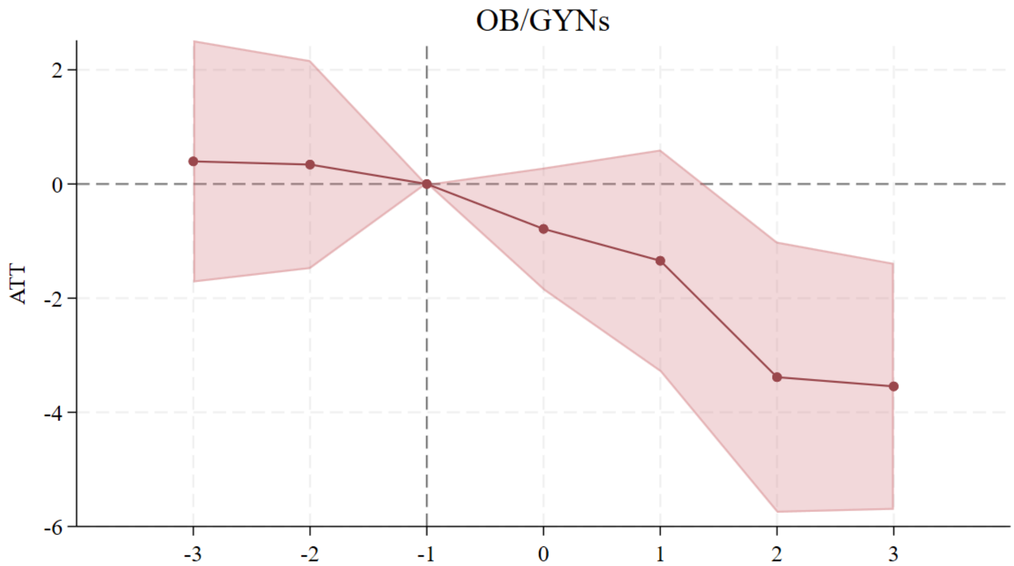

Figure 1: Effect of TRAP laws on OB/GYN supply

Notes: This figure plots the event study coefficients for the effect of TRAP law passage on the supply of nonfederal OB/GYNs with medical doctor degrees using the stacked DID method. The dependent variable is the number of nonfederal OB/GYNs per 100,000 females of childbearing age. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level. At t=2, the coefficient is -3.38 with a p-value of 0.009; At t=3, the coefficient is -3.55 with a p-value of 0.003. The average OB/GYN density for treatment counties is 33.48, and these coefficients represent 10.1%-10.6% of the average density.

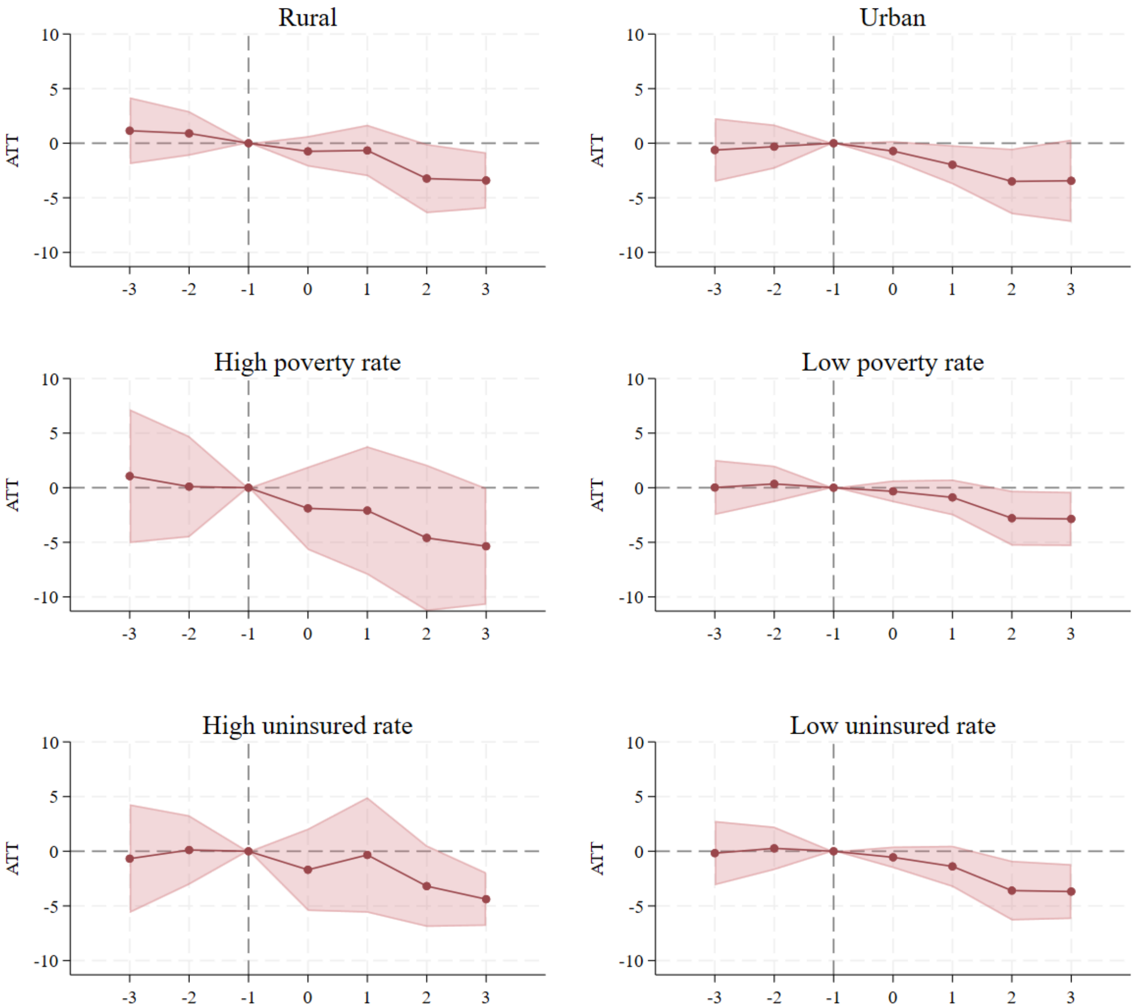

Figure 2: Effect of TRAP laws on OB/GYN supply by county socioeconomic characteristics
Notes: The dependent variables for the figures are the number of OB/GYNs per 100,000 females of childbearing age across different subsamples: rural counties versus urban counties, counties with high poverty rates versus low poverty rates, and counties with high uninsured rates versus low uninsured rates. Rural/urban classification is based on the Rural-Urban Commuting Area (RUCA) primary codes, with codes 1–3 categorized as urban and codes 4–10 as rural. High poverty rate counties are those with poverty rates ranked in the top quartile, while the rest are classified as low poverty rate counties. Similarly, high uninsured rate counties are defined as those with uninsured rates in the top quartile, and the remainder are classified as low uninsured rate counties. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.

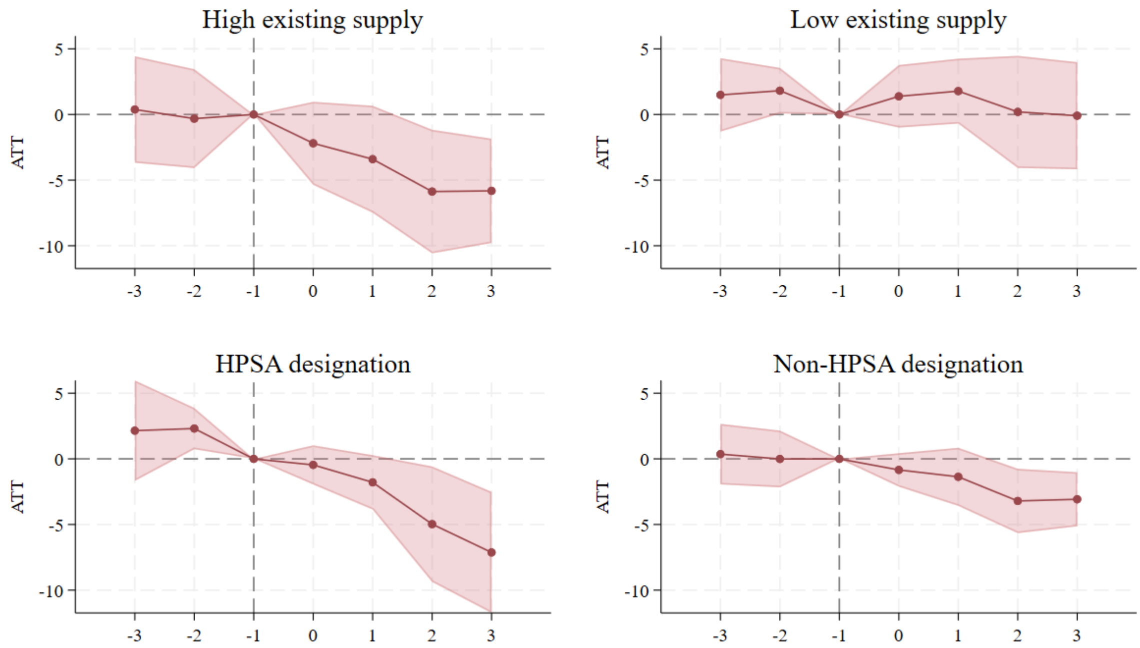

Figure 3: Effect of TRAP laws on OB/GYN supply by county healthcare infrastructure

Notes: The dependent variables for the figures represent the number of OB/GYNs per 100,000 females of childbearing age across different subsamples: counties with high versus low existing OB/GYN supply, and counties with versus without a Health Professional Shortage Area (HPSA) designation. Counties with low existing OB/GYN supply are defined as those where the OB/GYN supply ranks in the bottom quartile, while the rest are classified as high existing OB/GYN supply counties. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.

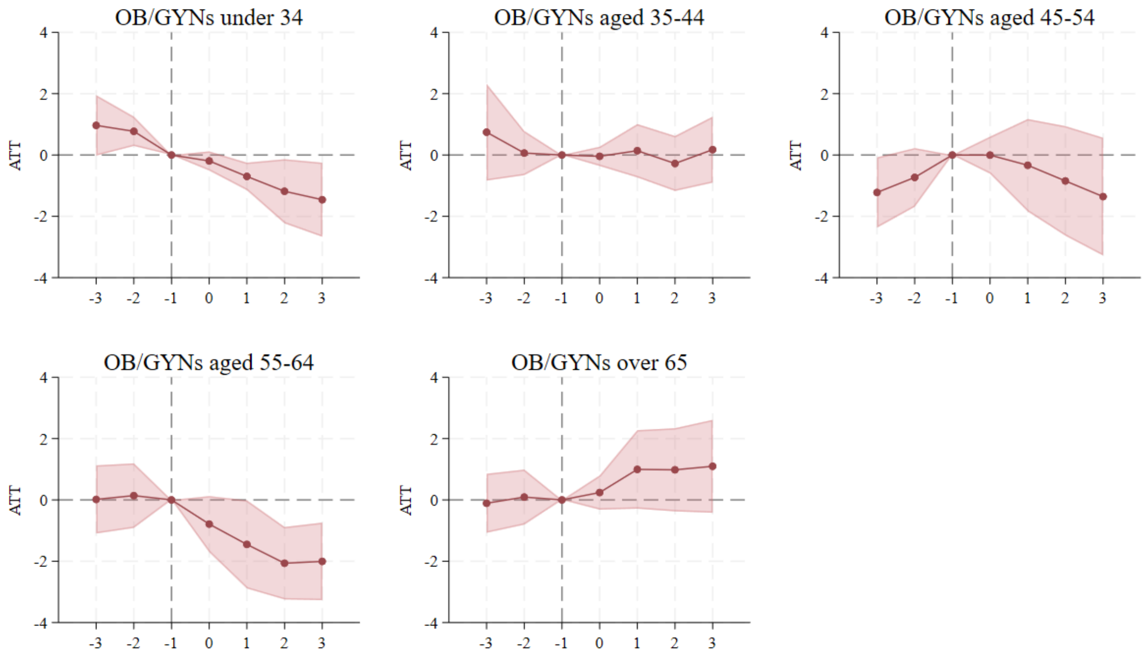

Figure 4: Effect of TRAP laws on OB/GYN supply by age groups/career stages

Notes: The dependent variables are the number of OB/GYNs aged under 34, 35–44, 45–54, 55–64, and over 65 per 100,000 females of childbearing age. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.

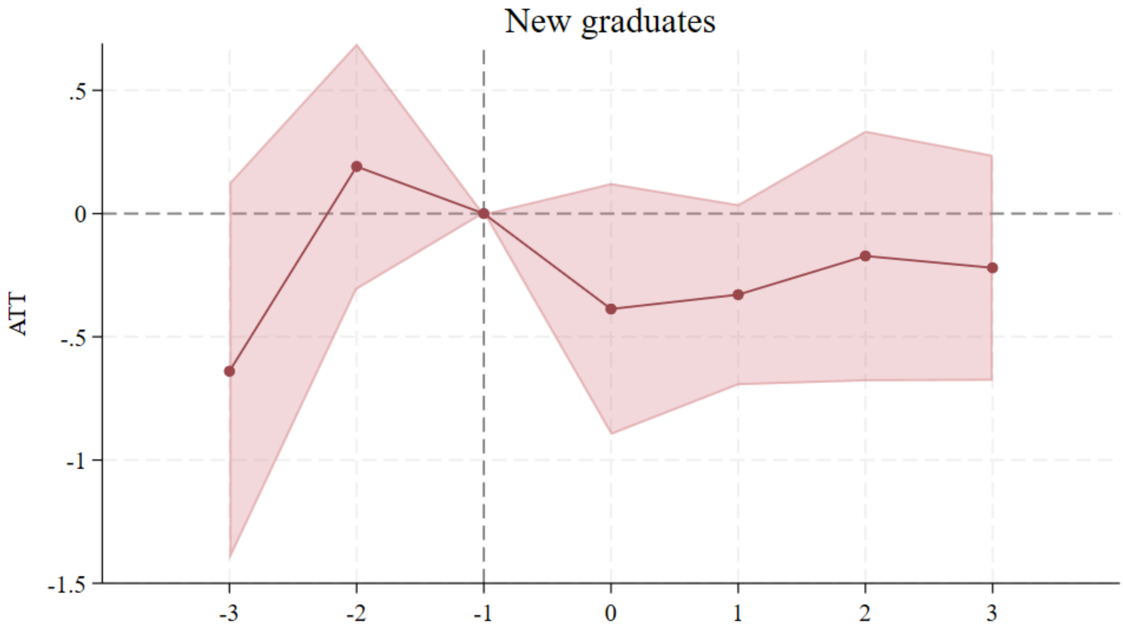

Figure 5: Effect of TRAP laws on supply of newly graduated OB/GYNs

Notes: This figure plots the event study coefficients for the effect of TRAP law passage on newly graduated MD OB/GYNs using the state-level stacked DID method. The dependent variable is the number of newly graduated OB/GYNs per 100,000 females of childbearing age. Lousiana was excluded from the treated group because the law was enforced in 2014 and blocked in 2016. States that never adopt a TRAP law serve as the control group. The vertical lines show 95% confidence intervals. Regressions include state fixed effects, year fixed effects, and the following state-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics, share of family receiving SNAP, number of births per 100,000 females of childbearing age, family median income, poverty rate, and the unemployment rate for people under 65. Standard errors are clustered at the state level. At t=1, the coefficient is -0.33 with a p-value of 0.090.

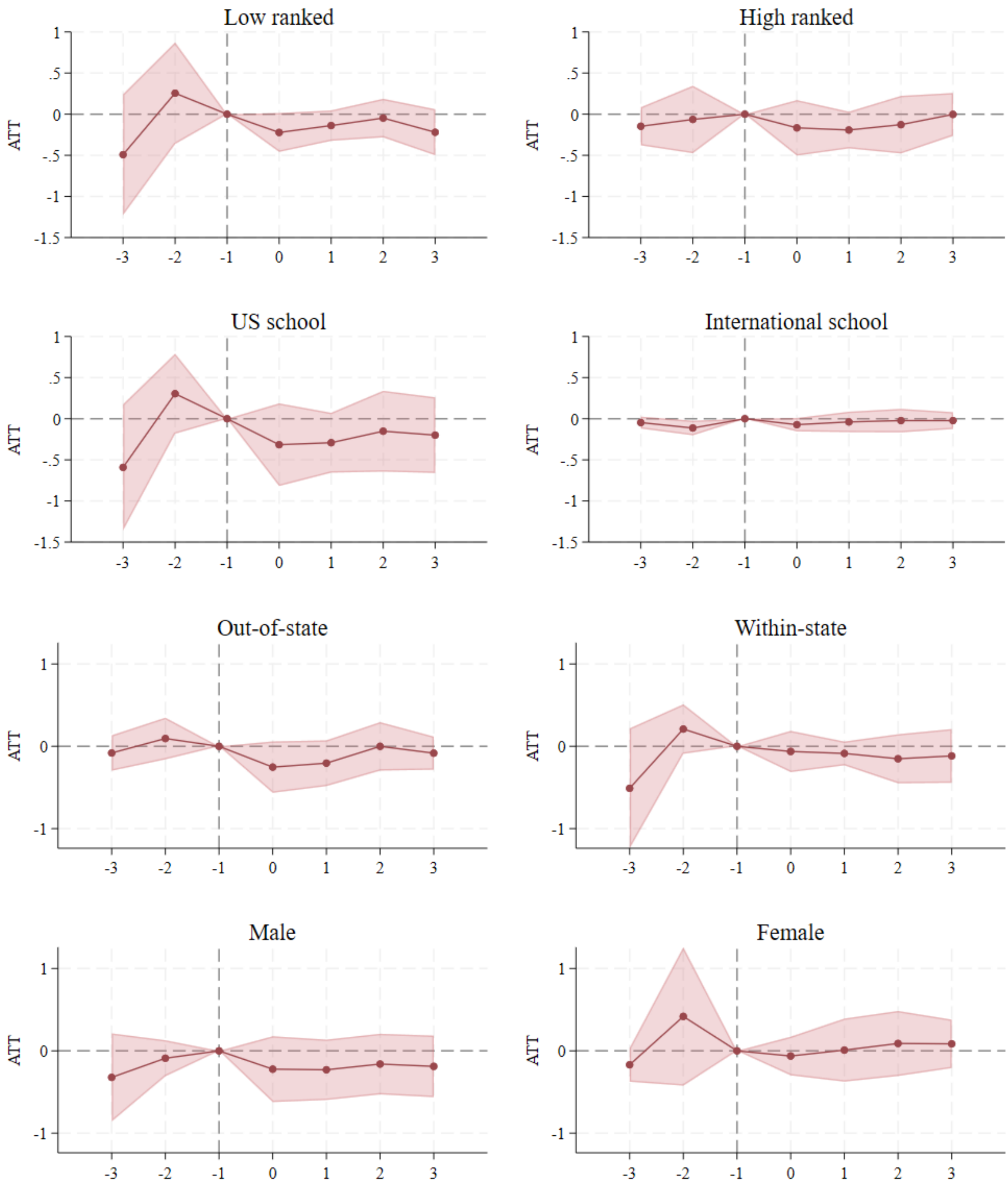

Figure 6: Effect of TRAP laws on supply of newly graduated OB/GYNs by school characteristics and gender

Notes: The dependent variables are the number of newly graduated MD OB/GYNs, categorized as follows: those whose medical schools are ranked below 100 or from non-U.S. medical schools, those whose schools are ranked above 100, graduates from U.S. medical schools, graduates from international medical schools, those practicing in a different state from their medical school, those practicing in the same state as their medical school, males, and females, all measured per 100,000 females of childbearing age. Lousiana was excluded from the treated group because the law was enforced in 2014 and blocked in 2016. States that never adopt a TRAP law serve as the control group. The vertical lines show 95% confidence intervals. Regressions include state fixed effects, year fixed effects, and the following state-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics, share of family receiving SNAP, number of births per 100,000 females of childbearing age, family median income, poverty rate, and the unemployment rate for people under 65. Standard errors are clustered at the state level. At t=1, the coefficient is -0.33 with a p-value of 0.090.

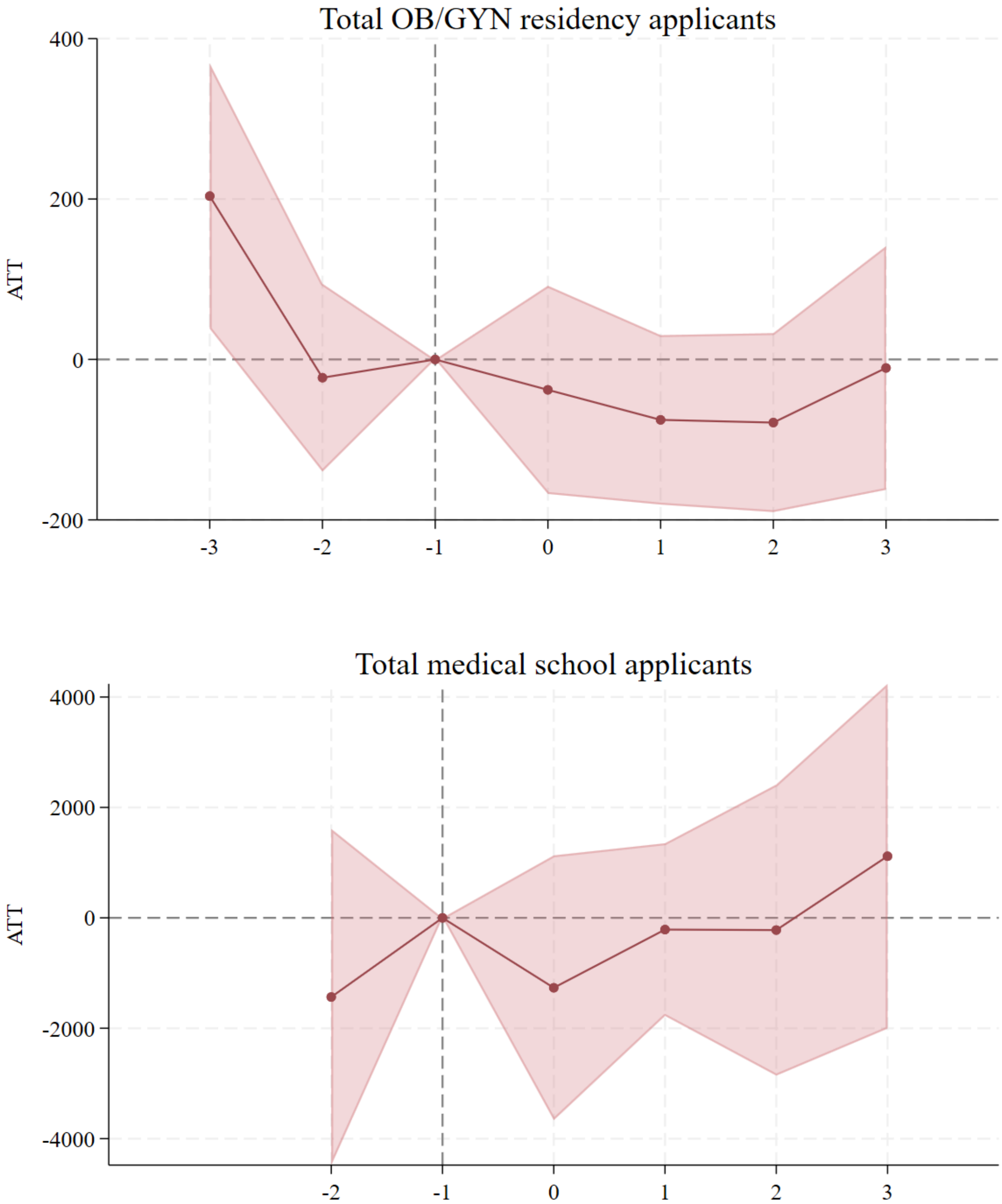

Figure 7: Effect of TRAP laws on OB/GYN residency program applicants and medical school applicants

Notes: This figure plots the event study coefficients for the effect of TRAP law passage on OB/GYN residency program applicants and total medical school applicants using the state-level stacked DID method. The dependent variables are the total number of OB/GYN residency program applicants and the total number of medical school applicants. Lousiana was excluded from the treated group because the law was enforced in 2014 and blocked in 2016. States that never adopt a TRAP law serve as the control group. The vertical lines show 95% confidence intervals. Regressions include state fixed effects, year fixed effects, and the following state-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics, share of family receiving SNAP, number of births per 100,000 females of childbearing age, family median income, poverty rate, and the unemployment rate for people under 65. Standard errors are clustered at the state level.

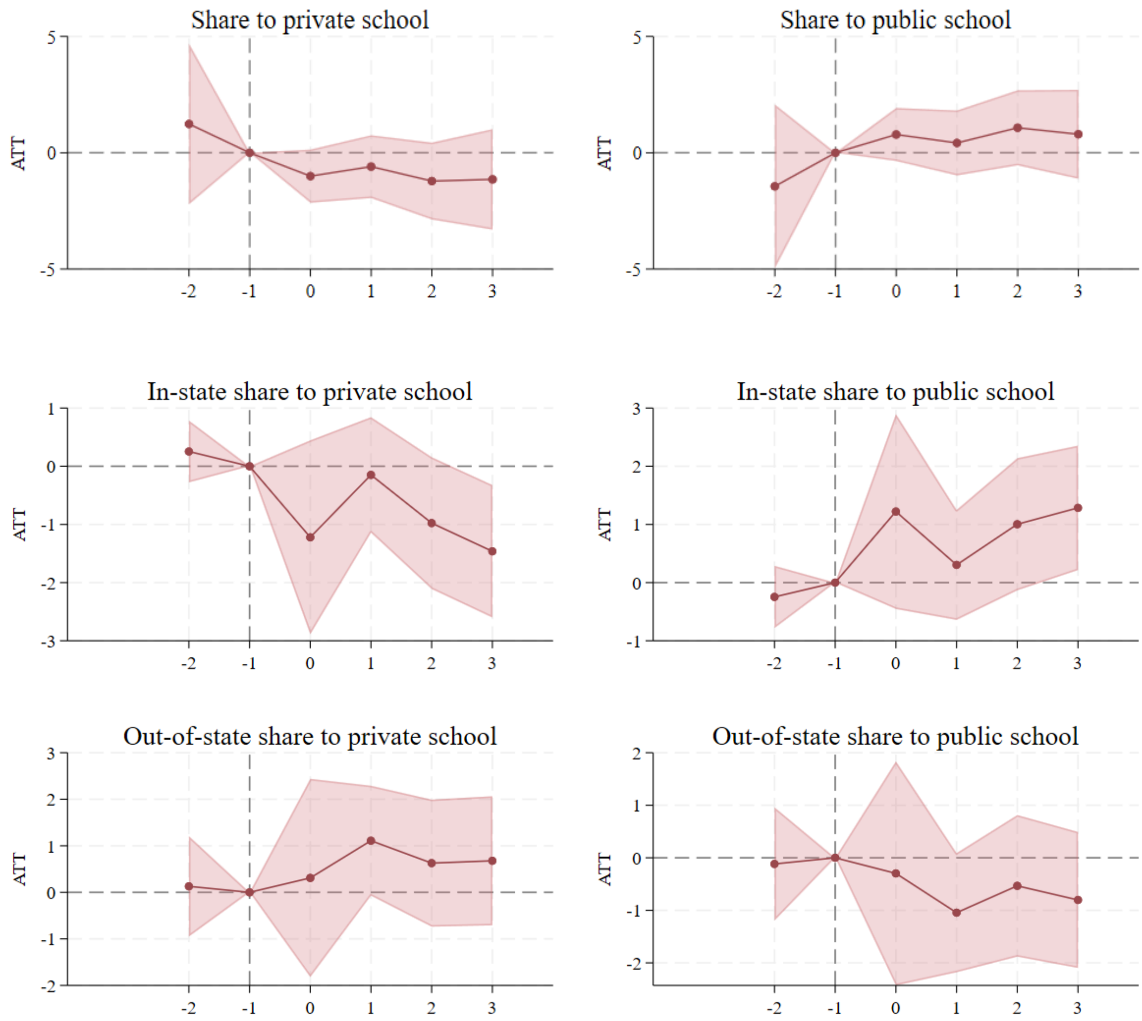

Figure 8: Effect of TRAP law on the number of medical school applicants by share to private school and public school

Notes: This figure plots the event study coefficients for the effect of TRAP law passage on medical school applicants by school type using the state-level stacked DID method. The dependent variables include the share of applicants to private schools, the share of applicants to public schools, the share of in-state applicants to private vs. public schools, and the share of out-of-state applicants to private vs. public schools. Lousiana was excluded from the treated group because the law was enforced in 2014 and blocked in 2016. States that never adopt a TRAP law serve as the control group. The vertical lines show 95% confidence intervals. Regressions include state fixed effects, year fixed effects, and the following state-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics, share of family receiving SNAP, number of births per 100,000 females of childbearing age, family median income, poverty rate, and the unemployment rate for people under 65. Standard errors are clustered at the state level.

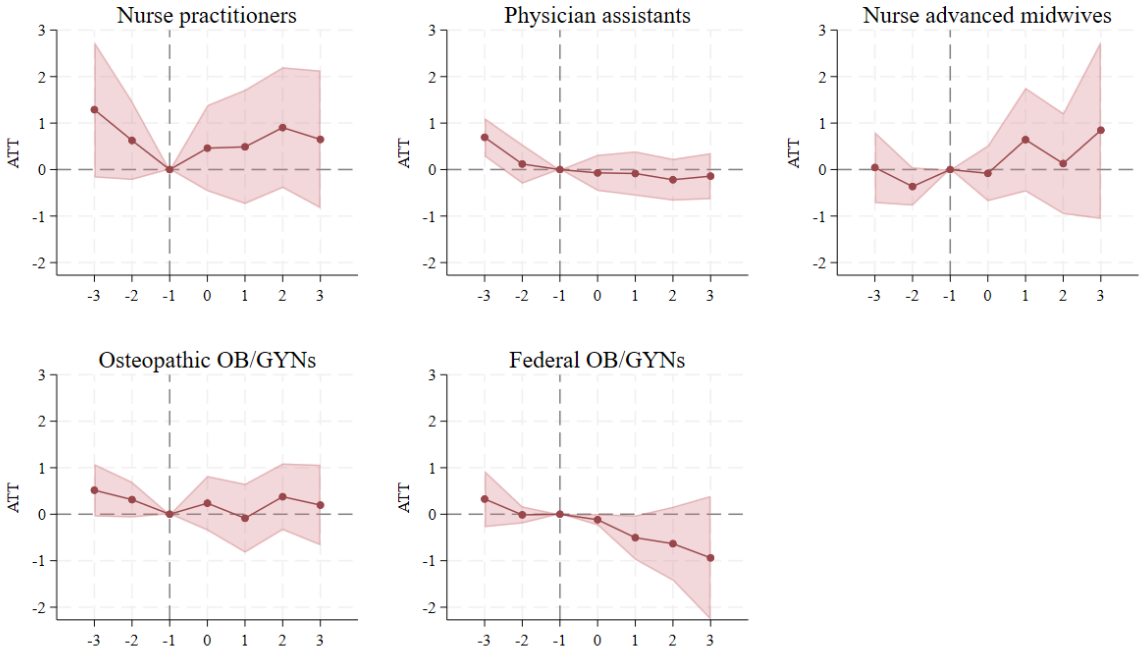

Figure 9: Effect of TRAP laws on alternative providers

Notes: The dependent variables for the figures are the number of nurse practitioners, physician assistants, nurse advanced midwives, osteopathic OB/GYNs, and OB/GYNs working in federal agencies, each measured per 100,000 females of childbearing age. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.

Table 1: Number of counties and states by treatment timing groups

Passage year	Enforce year	Number of county	Number of state	State name
2010	2010	29	1	Utah
2010	2011	105	1	Kansas
2011	2012	132	1	Virginia
2011	2012	67	1	Pennsylvania
2012	2012	95	1	Tennessee
2012	2012	24	1	Maryland
2013	2013	153	1	Georgia
2013	2013	53	1	North Dakota
2014	2014	60	1	Louisiana
2015	2016	102	1	Illinois
	Never treated	299	22	California, Colorado, Connecticut, Delaware, DC, Idaho, Iowa, Maine, Massachusetts, Montana, Minnesota, New Hampshire, New Jersey, New York, North Carolina, Oregon, Vermont, Washington, West Virginia, Wisconsin, Wyoming

Notes: Tennessee: blocked in 2017; Louisiana: blocked in 2016; Illinois: blocked in 2020. In our analysis, Utah and Kansas are excluded because they are part of the already-treated group. Louisiana is excluded because it was blocked one year after its passage.

Table 2: Summary statistics for OB/GYN supply and covariates

Variable	Treatment group Mean	Treatment group Std. dev.	Control group Mean	Control group Std. dev.
Panel A: Existing OB/GYNs				
OB/GYNs per 100,000 females aged 15-44	33.48	48.08	36.46	40.56
OB/GYNs under 34	3.32	10.60	4.12	10.28
OB/GYNs aged 35-44	7.14	13.29	7.70	11.19
OB/GYNs aged 45-54	8.67	16.28	10.39	14.42
OB/GYNs aged 55-64	9.09	15.84	9.50	12.54
OB/GYNs over 65	5.25	12.33	4.75	8.66
Observations	3967		3967	
Panel B: County characteristics				
Population Non-Hispanic Whites (%)	78.36	17.93	78.74	18.82
Population Non-Hispanic Black (%)	13.40	15.47	12.69	16.95
Population Hispanics (%)	4.71	4.87	4.61	4.22
Population receiving SNAP (%)	16.48	7.71	17.61	8.42
Births per 100,000 females aged 15-44	6338.20	1270.36	6177.52	1003.54
Median income ($, in 2010 value)	44587.87	13059.13	43447.68	13473.25
Poverty rate (%)	16.79	6.85	17.30	6.58
Unemployment rate (%)	7.57	2.67	7.74	2.82
Observations	3967		3967	
Panel C: New OB/GYNs				
New OB/GYNs per 100,000 females aged 15-44	0.65	0.50	0.64	0.55
New OB/GYNs from low-ranked medical schools	0.36	0.49	0.20	0.27
New OB/GYNs from high-ranked medical schools	0.29	0.18	0.44	0.42
New OB/GYNs from U.S. medical schools	0.61	0.49	0.58	0.52
New OB/GYNs from non-U.S. medical schools	0.04	0.06	0.05	0.19
New OB/GYNs from out-of-state medical schools	0.31	0.20	0.40	0.47
New OB/GYNs from within-state medical schools	0.30	0.40	0.18	0.25
Male new OB/GYNs	0.12	0.24	0.10	0.16
Female new OB/GYNs	0.50	0.34	0.52	0.47
Observations	44		598	

Table 3: Summary statistics for applicants to OB/GYN residency programs and medical schools

	Treatment group		Control group	
Variable	Mean	Std. dev.	Mean	Std. dev.
Panel A: OB/GYN residency applicants				
Total number of OB/GYN residency applicants	1265.08	293.52	1302.49	316.23
Applicants who are:				
U.S. graduates (%)	58.42	7.06	59.03	14.19
IMG graduates (%)	41.58	7.06	40.97	14.19
U.S.-trained MD graduates (%)	49.06	5.66	49.13	13.18
U.S.-trained DO graduates (%)	9.36	2.09	9.91	2.26
Males (%)	23.94	2.52	23.98	3.52
Females (%)	76.05	2.51	76.00	3.52
Observations	37		234	
Panel B: Medical school applicants				
Total number of medical school applicants	26468.42	20982.51	17979.30	22649.34
Applicants to private schools (%)	57.57	37.48	36.99	39.83
Applicants to public schools (%)	39.86	37.14	63.01	39.83
In-state applicants (%)	14.73	4.87	14.91	13.05
Out-of-state applicants (%)	85.27	4.87	85.09	13.05
Males (%)	47.97	4.05	47.59	4.48
Females (%)	46.54	2.89	45.81	2.88
Observations	31		342	

Appendix A Data Appendix

A.1 Geographic Aggregation

Data from Bedford County, VA and Bedford city, VA was aggregated into a new "county". Bedford was designated as an independent city in 1968 but remained the county seat of Bedford County. Its status as an independent city ended on July 1, 2013, when it returned to being a town within Bedford County.

Data from Alleghany County, VA and Clifton Forge City, VA was aggregated into a new "county". On July 1, 2001, the city of Clifton Forge reincorporated as a town within Alleghany County. As such, the town is subject to the county's jurisdiction, while also being governed by the new charter for the town of Clifton Forge.

Data from Adams, Boulder, Broomfield, Jefferson, and Weld counties in CO was aggregated into a new "county". Broomfield County in Colorado was created in November 2001 from parts of Adams, Boulder, Jefferson, and Weld counties.

A.2 Medical School and Graduation Year of New OB/GYNs

There are missing values for medical school and graduate year in the IQVIA data. To address this, we merge the IQVIA data with the Physician Compare data, as 95% of OB/GYNs accept Medicare patients according to this KFF report. The Centers for Medicare & Medicaid Services (CMS) began publishing the Physician Compare dataset in 2014 to identify doctors who accept Medicare patients. We use this data to fill in the missing information on graduated medical school and graduation year in the IQVIA data. Since medical school graduation and year of graduation are time-invariant, we can still obtain this information for physicians who graduated prior to 2014 using the CMS data.

After merging, 10.5% of physicians had both their medical school and graduation year missing, and we exclude these observations from the analysis. For physicians with either their medical school or graduation year missing, or who reported "Other" as their medical school in the Physician Compare dataset, we manually collect the missing information through Google searches. We cross-reference their first name, last name, job title, practice location, NPI, and any available details on medical school or graduate year. The results are sourced from official workplace websites, Healthgrades, US News Health, LinkedIn, WebMD, Doximity, and Sharecare. Only individuals whose primary specialty and job title are listed as OB/GYNs were included, excluding those in other roles such as nurse practitioners and physician assistants.

Ultimately, we obtain the medical school and graduation year for all new OB/GYNs except for one whose medical school was listed as "Other" and we are unable to identify the specific medical school.

A.3 Sample Matching

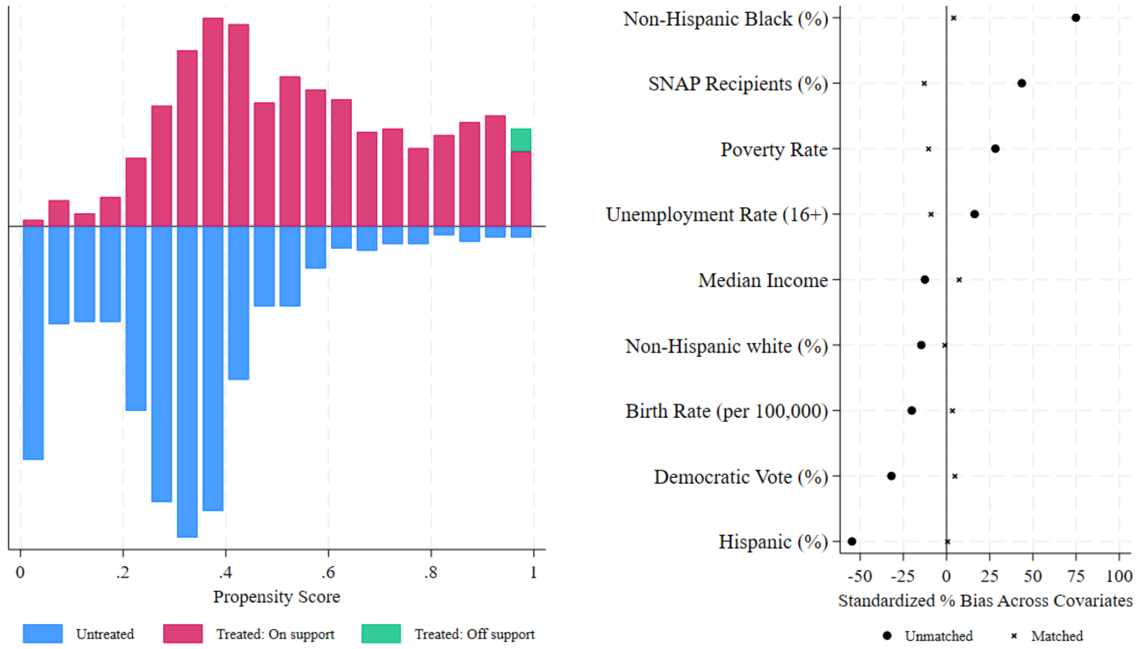

Figure A1: Common support (left) and balancing test (right) for PSM method

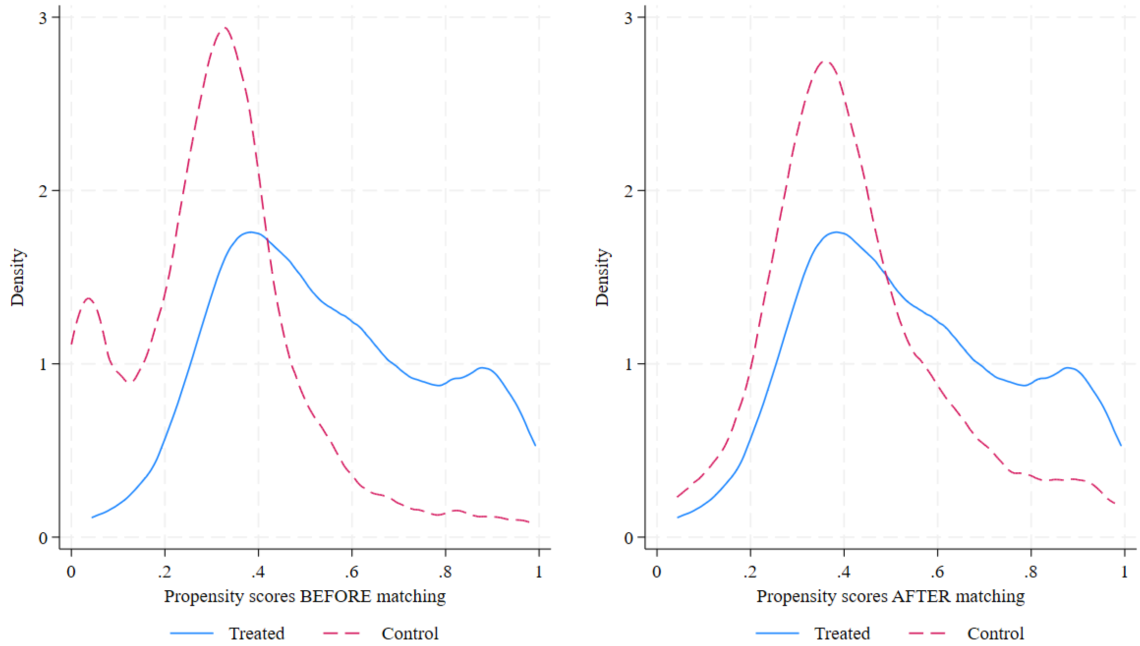

Figure A2: Propensity score before (left) and after (right) matching

Appendix B Robustness Checks

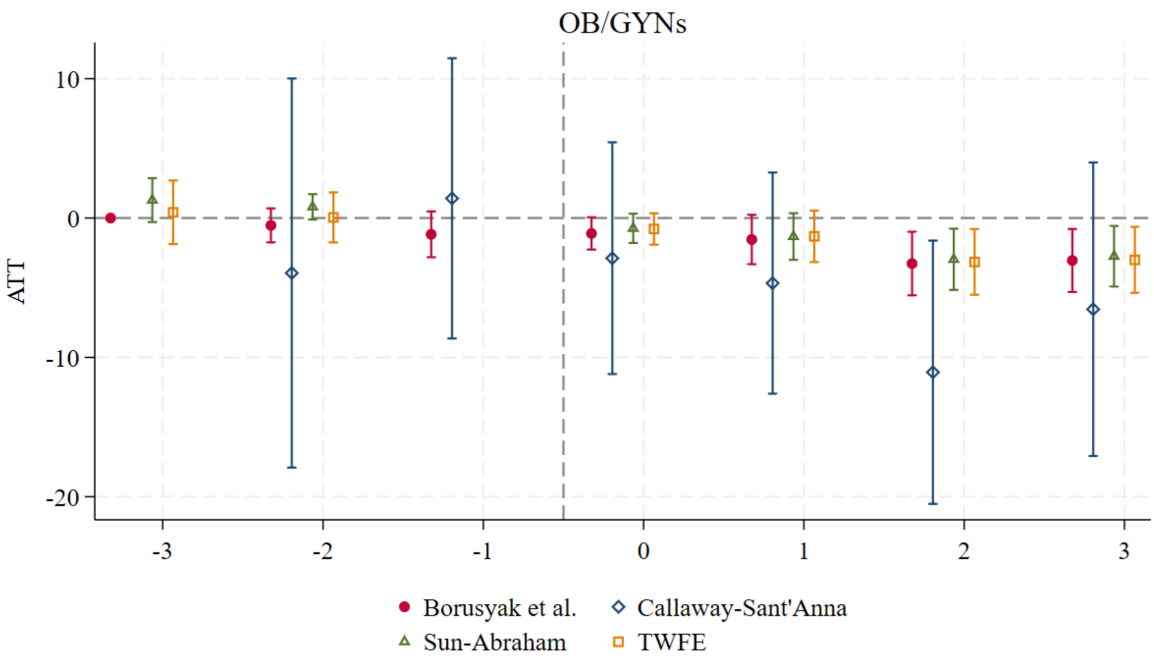

Figure B1: Effect of TRAP law passage on OB/GYN supply using other DID methods

Notes: This figure plots the event study coefficients for the effect of TRAP laws on the supply of nonfederal OB/GYNs with medical doctor degrees using two-way fixed effect (TWFE) method as well as methods developed by Borusyak et al. (2024), Callaway and Sant'Anna (2021), and Sun and Abraham (2021). The dependent variable is the number of nonfederal OB/GYNs per 100,000 females of childbearing age. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.

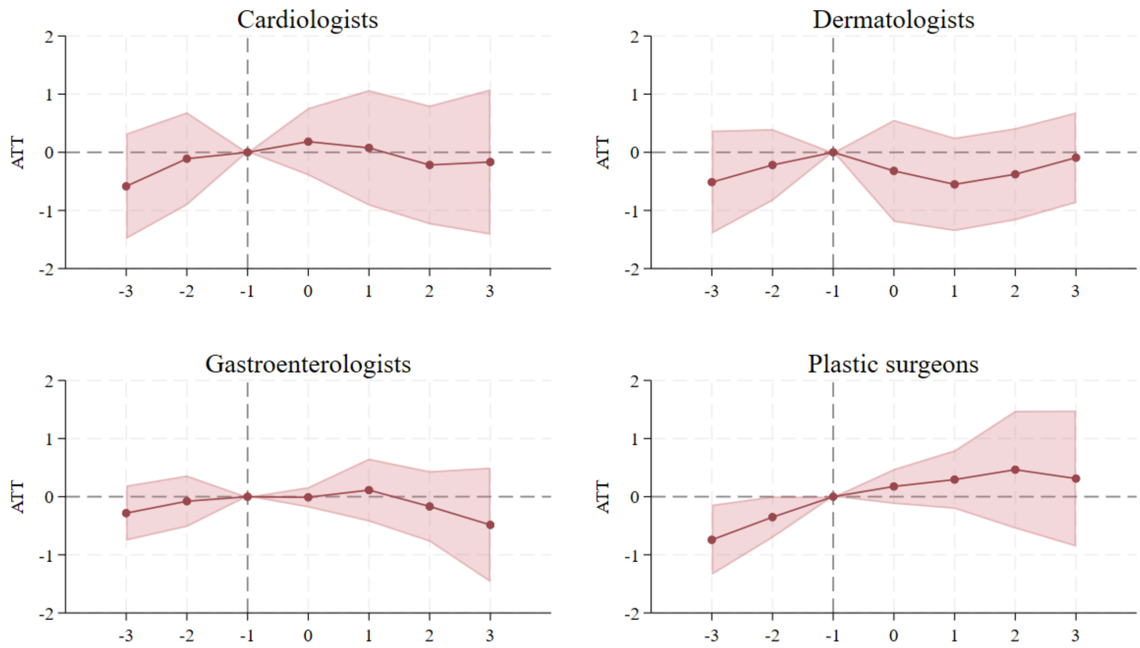

Figure B2: Effect of TRAP laws on specialties less likely to be affected by TRAP laws

Notes: This figure plots the event study coefficients for the effect of TRAP laws on the supply of medical specialties that are less likely to be affected by these laws. The dependent variables are per-capita physician counts for the following specialties: cardiologists, dermatologists, gastroenterologists, and plastic surgeons. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.

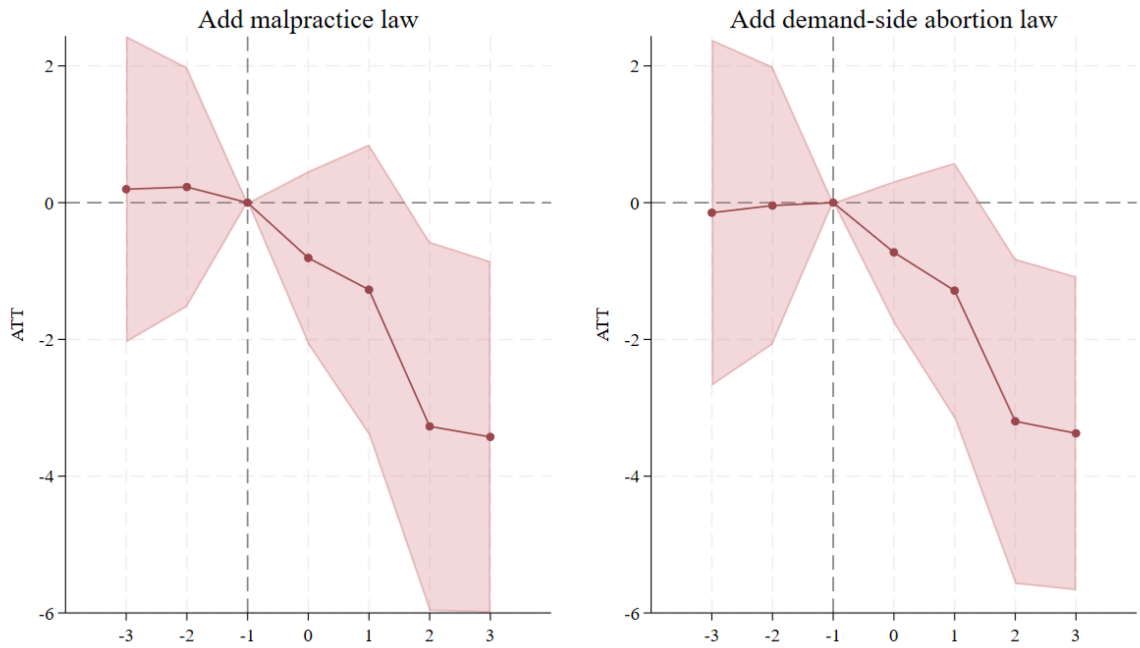

Figure B3: Effect of TRAP laws on OB/GYN supply adding malpractice laws and demand-side abortion laws

Notes: This figure plots the event study coefficients for the effect of TRAP laws on the supply of nonfederal OB/GYNs with medical doctor degrees, with malpractice laws (left) and demand-side abortion laws (right) separately included as controls. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.

Appendix C Further Results

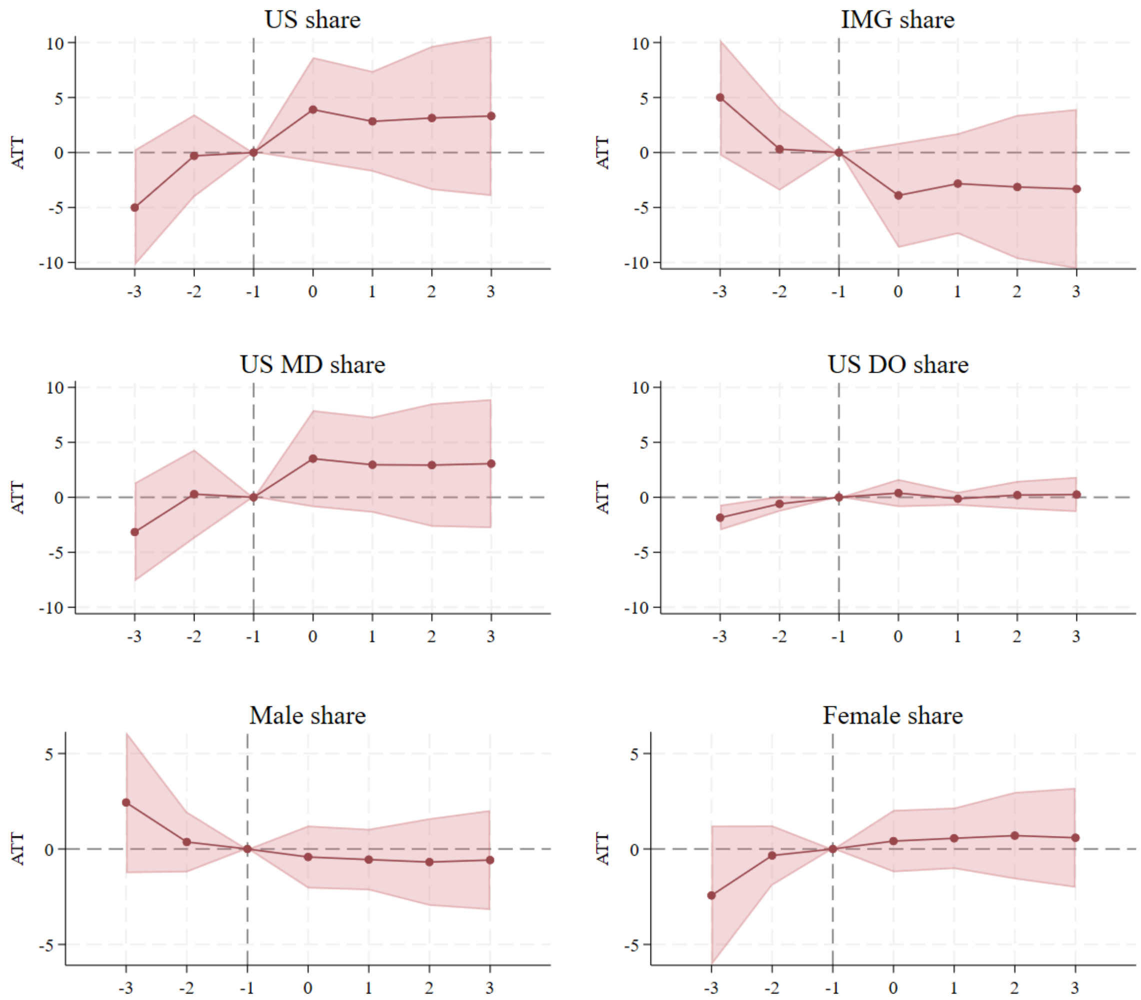

Figure C1: Effect of TRAP laws on total number of OB/GYN residency program applicants by school characteristics, degree and gender

Notes: This figure plots the event study coefficients for the effect of TRAP law passage on OB/GYN residency program applicants by school type, degree, and gender using the state-level stacked DID method. The dependent variables are the share of applicants who are U.S. graduates, international medical graduates, U.S. graduates with an MD degree, U.S. graduates with a DO degree, males, and females, respectively. Lousiana was excluded from the treated group because the law was enforced in 2014 and blocked in 2016. States that never adopt a TRAP law serve as the control group. The vertical lines show 95% confidence intervals. Regressions include state fixed effects, year fixed effects, and the following state-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics, share of family receiving SNAP, number of births per 100,000 females of childbearing age, family median income, poverty rate, and the unemployment rate for people under 65. Standard errors are clustered at the state level.

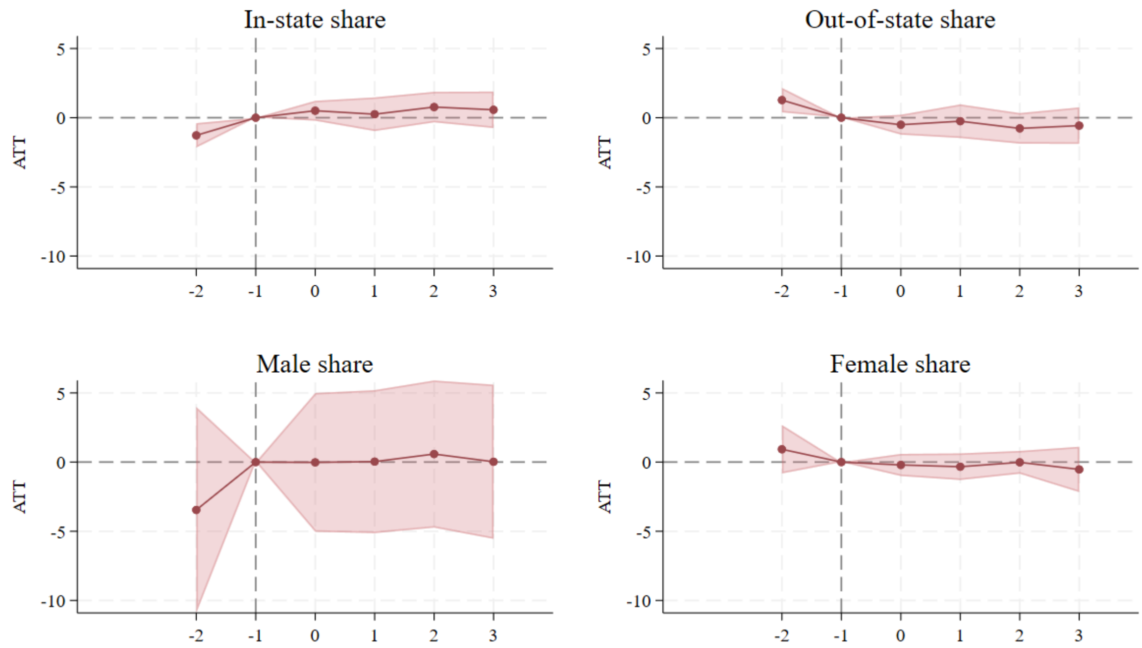

Figure C2: Effect of TRAP laws on the number of medical school applicants by resident status and gender

Notes: This figure plots the event study coefficients for the effect of TRAP law passage on medical school applicants by resident status and gender using the state-level stacked DID method. The dependent variables are the share of in-state applicants, the share of out-of-state applicants, the share of males, and the share of females. Lousiana was excluded from the treated group because the law was enforced in 2014 and blocked in 2016. States that never adopt a TRAP law serve as the control group. The vertical lines show 95% confidence intervals. Regressions include state fixed effects, year fixed effects, and the following state-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics, share of family receiving SNAP, number of births per 100,000 females of childbearing age, family median income, poverty rate, and the unemployment rate for people under 65. Standard errors are clustered at the state level.

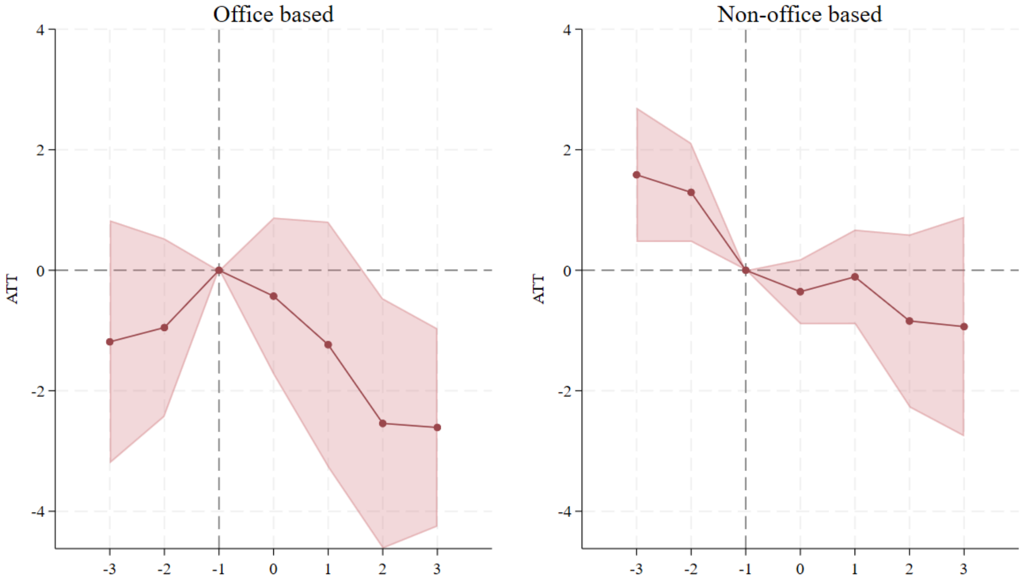

Figure C3: Effect of TRAP laws on OB/GYN: office-based vs non-office based

Notes: The dependent variables are the number of office-based OB/GYNs and non-office-based OB/GYNs, each measured per 100,000 females of childbearing age. Lousiana is excluded from the treated group because this law was enforced in 2014 and blocked in 2016. Vertical lines show 95% confidence intervals. Regressions control for county fixed effects, year fixed effects, and the following county-level characteristics: percentage of non-Hispanic whites, non-Hispanic Blacks, and Hispanics; share of families receiving SNAP; number of births per 100,000 females of childbearing age; family median income; poverty rate; and the unemployment rate for people over 16. Standard errors are clustered at the state level.