Love It or Leave It: Medicaid Expansion and Physician Location Choice

Xuechao Qian*

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Abstract

The health benefits of expansions in Medicaid coverage depend on whether insured patients can find providers. This paper investigates how one important group of providers, Obstetrician-Gynecologists (OB-GYNs) select their practice locations in response to expansions of Medicaid/CHIP coverage to mid-low income pregnant women. Expanding eligibility leads to an overall increase in the total supply of OB-GYNs at the county level, with an inflow of individual OB-GYNs to mid-low income counties. However, in state border counties, expanded eligibility reduces the number of OB-GYNs, as OB-GYNs move to the state with lower eligibility. In keeping with my model, while Medicaid/CHIP eligibility expansions on average increase physician supply, in certain cases, it can reduce access to care as physicians avoid low Medicaid reimbursement rates.

JEL Codes: I13, I18, J22, J61

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*Graduate School of Business, Stanford University, xcqian@stanford.edu. I am very grateful to Michael Andrews, Francisca Antman, Enrico Berkes, Victoria Barone, Nathaniel Breg, Meta Brown, Mark Duggan, Long Hong, Bokyung Kim, Christopher Lowenstein, Felipe Andres Lozano, Gina Li, Kurt Lavetti, Rebecca McKibbin, Zheyu Ni, Tamar Oostrom, Maria Polyakova, Adrienne Sabety, Maya Rossin-Slater, Natalia Serna, Rebecca Staiger, and Bruce Weinberg for generous advice and feedback on this project. I also would like to thank participants of Stanford Health Problem Solving Group, the economics department seminars at University of Maryland, Baltimore County, University of Notre Dame, the Ohio State University, Miami University, and 2024 ASSA Meeting for helpful comments and suggestions.

1 Introduction

As of December 2022, Medicaid (and CHIP) provides coverage for 99 million individuals, including children, pregnant women, low-income adults, and those with disabilities. This number surged by 55% since January 2014. While reduced out-of-pocket costs under Medicaid ought to increase the demand for care (Hadley & Holahan, 2003; Finkelstein et al., 2012; Wray et al., 2021; Coughlin et al., 2016), patients' access to healthcare also relies on the availability of care providers. "Crowding-out", where individuals shift from private to public insurance coverage (Cutler & Gruber, 1996a,b, 1997; Gruber & Simon, 2008; Barnes et al., 2020; Bellerose et al., 2022), might dissuade physicians from offering their services (Alexander & Schnell, 2019) due to the latter's low reimbursement rates.[1] Given that physicians have the autonomy to choose their patient base (Alexander & Schnell, 2019) and practice location (Ricketts & Randolph, 2007; Holmes & Fraher, 2017; McGrail et al., 2017; Molitor, 2018), understanding how they make practice location decisions in response to Medicaid expansion is vital for determining how effectively Medicaid expansions benefit underserved populations.

This study investigates how one important group of providers, Obstetrician-Gynecologists (OB-GYNs), select their practice locations in response to expansions of Medicaid/CHIP coverage to mid-low income pregnant women. Leveraging data on state Medicaid/CHIP income eligibility expansions for pregnant women, as well as multiple datasets, including the Area Health Resource File (AHRF, 2001-2020) for county-level physician counts by specialty and the National Plan and Provider Enumeration System (NPPES, 2007-2023) for identifying the geographical locations of individual National Provider Identifiers (NPIs), I show that, at the aggregate level, expanding income eligibility leads to an increase in the total number of OB-GYNs at the county level. However, when focusing on counties located very close to state borders, higher eligibility is associated with a reduced number of OB-GYNs. These findings are further supported by evidence regarding physician mobility, using individual NPIs' practice addresses from the NPPES database. While physicians in non-border counties tend to relocate closer to mid-low income populations, possibly driven by increased demand, among state border counties, more OB-GYNs move to states with lower eligibility thresholds to avoid low Medicaid reimbursement rates.

I begin by developing a theoretical framework of how individual physicians select practice locations in response to expanding income eligibility lines, following McFadden

[1] According to the Kaiser Family Foundation, Medicaid physician fee is about 73% of Medicare and 51% of private payment for the same services in California in 2020. Sources: https://www.kff.org/medicaid/state-indicator/medicaid-to-medicare-fee-index/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D and https://www.kff.org/medicare/issue-brief/how-much-more-than-medicare-do-private-insurers-pay-a-review-of-the-literature/.

(1981) and Huh (2021). In this model, a representative physician chose a county in which to practice to maximize the utility (profit). The total profit contains revenues from both the Medicaid and private payers and considers the operational costs if practicing in the selected area.[2] As Medicaid income eligibility expands, it has the potential to augment Medicaid revenue by attracting more enrollees to use more care. However, this expansion may concurrently diminish revenue from the private market with a crowding-out effect. Since Medicaid reimbursement rates are not as generous as private prices, the overall marginal revenue change depends on the composition of local demand (e.g., an influx of newly Medicaid-insured individuals) and reimbursement rates. Moving, on the other hand, invariably incurs costs that escalate with geographical distance. Physicians will opt to relocate only when the anticipated gain in revenue offsets the associated moving expenses.

I derive four testable predictions that serve as mechanisms of the effects of Medicaid income eligibility expansion on physician supply. *First*, given that Medicaid reimbursement rates are lower compared to private payments, physicians will experience a positive net revenue change only in areas where there is a substantial increase in demand among Medicaid beneficiaries. Consequently, physician supply is expected to increase with income eligibility. *Second*, more generous Medicaid reimbursement rates will further enhance revenue gains from the Medicaid market, thus prompting a larger positive response in physician supply. *Third*, among counties subject to the same state eligibility expansion, if physicians choose to relocate, they are more likely to be drawn to areas that have experienced a significant increase in demand. *Forth*, among state border counties that exhibit relatively similar socioeconomic and demographic characteristics, physicians are more likely to be attracted to the side with a lower eligibility limit (a higher share of privately insured patients), unless local Medicaid demand is substantially large.

To estimate the overall effect of Medicaid/CHIP income eligibility expansions for pregnant women on OB-GYN supply. I first employ a difference-in-differences (DID) approach based on the state and year level variations in adjusting income eligibility. I examine the extent to which the number of OB-GYNs per 100,000 population in a county changes before and after expansion depending on the change in the expanded eligibility limits.[3] By differencing out the initial level of eligibility, I also account for potential associations between income eligibility levels and state socioeconomic characteristics. For instance, income eligibility might naturally be higher in states with higher income levels. Following Currie & Gruber (1996b), I employ the American Community Survey

[2]Please note that, for simplicity, my model does not take into account the healthcare market for senior people.

[3]In cases where states had multiple expansions, I focus on the first expansion year, as 32 out of 51 states expanded income eligibility for pregnant women only once.

(ACS) to compute the "simulated fraction eligible" out of 20,000 women randomly drawn from the national population each year to instrument for the actual fraction eligible among 15-44-year-old women in each state each year. Both the DID and 2SLS estimates consistently indicate that expanding income eligibility for pregnant women has a positive effect on the county-level total number of OB-GYNs. Specifically, an increase in eligibility line by 0.1 (10% of the current FPL) is associated with a 0.3% increase in the number of OB-GYNs per 100,000 population. Alternatively, 1 percentage point increase in the eligible fraction is associated with a 0.2% rise in the number of OB-GYNs per 100,000 population.

I also examine the relationship between Medicaid/CHIP income eligibility and OB-GYN supply at the county level across state borders, using a border Regression Discontinuity (RD) strategy (Dell, 2010; Imbens & Zajonc, 2011; Kumar, 2018). This analysis particularly focuses on scenarios in which border counties exhibit relatively comparable income and demographic distributions but differ in their Medicaid/CHIP eligibility thresholds. Consequently, border counties with higher income eligibility limits tend to feature a smaller proportion of privately insured patients, who can potentially generate higher profits for healthcare providers. Furthermore, physicians practicing in border counties may have already obtained multi-state licenses, allowing them to serve markets on both sides.[4] Consistent with the hypothesis that physicians prefer the more profitable private payments over Medicaid reimbursement rates, Border RD estimates reveal that, on average, counties on the side with higher income eligibility for pregnant women have fewer OB-GYN physicians compared to their neighboring counties on the other side of the border. This border effect of Medicaid/CHIP income eligibility exposes unintended consequences resulting from the expansion of Medicaid coverage. These consequences become evident under specific conditions: when the change in local demand composition due to eligibility expansion remains consistent but eligibility varies across state border counties, and when physicians exhibit exceptionally high cross-state mobility.

I further test the four theoretical predictions and show consistent empirical evidence. *First*, the increase in OB-GYN physician supply is primarily concentrated in mid-low income counties and in counties exhibiting a high degree of unmet healthcare demand, as measured by the Health Resources and Services Administration (HRSA) Medically Underserved Area (MUA) designations. *Second*, the positive response in physician supply is more pronounced in states with more generous Medicaid reimbursement rates. *Third*, when excluding state border counties and considering counties within the same state, those ranked in the third quartile for poverty rates attract a greater number of OB-GYN physicians following an expansion in Medicaid/CHIP income eligibility for pregnant women. *Last*, among state border counties, there is a notable migration of OB-GYN

[4] Since 2015, the Interstate Medical Licensure Compact (IMLC) has further facilitated physicians in practicing across multiple states within the compact.

physicians toward the side with relatively lower income eligibility limits, especially among low-poverty-rate counties.

In addition to the physician-side evidence, this paper also provides complementary insights from the patient side. After income eligibility expansions for pregnant women, prenatal female patients are more likely to be covered by Medicaid and less inclined to utilize private insurance plans. Moreover, their overall healthcare utilization, particularly in terms of OB visits, experiences a notable increase following these expansions in Medicaid/CHIP income eligibility. The evidence suggests that increased demand for care and the crowding-out effect might coexist, creating multi-dimensional incentives for physicians when making location choices.

This paper contributes to the growing body of literature examining the impact of public health insurance expansions on the supply side of healthcare (Baker & Royalty, 2000; Garthwaite, 2012; Freedman et al., 2015; Buchmueller et al., 2016; Huh, 2021; Barnes et al., 2023; Geddes & Schnell, 2023). A well-established literature has demonstrated that Medicaid expansions improve healthcare utilization and health outcomes (Currie & Gruber, 1996a,b; Card & Shore-Sheppard, 2004; De La Mata, 2012; Finkelstein et al., 2012; Taubman et al., 2014; Wherry & Miller, 2016; Boudreaux et al., 2016; Coughlin et al., 2016; Wherry et al., 2017; Bhatt & Beck-Sagué, 2018; Wherry et al., 2018; Brown et al., 2019; Singer et al., 2019; Wiggins et al., 2020). My study employs a conceptual framework to reconcile both positive (Buchmueller et al., 2016; Huh, 2021) and negative (Geddes & Schnell, 2023) responses on the supply side of healthcare, thereby shedding light on the intricate decision-making processes among healthcare providers.

This paper stands out as one of the first to explore provider-side responses with a specific focus on individual physicians, complementing existing evidence on hospitals (Finkelstein, 2007; Freedman et al., 2015) and clinics (Geddes & Schnell, 2023). With an average relocation rate of approximately 20% (Ricketts & Randolph, 2007; Holmes & Fraher, 2017; McGrail et al., 2017; Molitor, 2018), physicians have greater flexibility in making location decisions compared to healthcare facilities, both within and across states. Consequently, as providers expand their healthcare supply to accommodate new Medicaid patients and extend appointment availability in response to positive financial incentives (Clemens & Gottlieb, 2014; Alexander, 2020; Werbeck et al., 2021; Dunn et al., 2021), they also adapt their practice locations in pursuit of more favorable payment structures according to this study. Simultaneously, they proactively respond to the increased demand among underserved populations by moving closer to them. My paper highlights the complexities involved in shaping state-level public health insurance programs, emphasizing the imperative of achieving policy goals without unintended welfare loss, for example, in border counties.

This paper is structured as follows. In Section 2, I provide an overview of the institutional background related to Medicaid coverage for pregnant women and the Interstate Medical Licensure Compact. Section 3 introduces the theoretical framework that formalizes physicians' decision-making process when selecting practice locations in response to Medicaid expansions. Section 4 covers the empirical strategies employed in this study. Section 5 provides details about the datasets and primary variables used. The main results are presented in Section 6, and the paper concludes in Section 7.

2 Institutional Background

2.1 Medicaid Coverage for Pregnant Women

Medicaid eligibility for pregnant women has evolved over time. Historically, it was linked to the Aid to Families with Dependent Children (AFDC) program. In 1984, the Deficit Reduction Act of 1984 mandated that states must provide Medicaid to pregnant women who, or whose partners, would be eligible for AFDC. However, this eligibility was limited to a small portion of the population with very low income thresholds (Currie & Gruber, 1996b). Additionally, eligible families often faced the social stigma associated with receiving social welfare benefits (Moffitt, 1992). Subsequent legislative changes expanded Medicaid coverage for pregnant women. The Consolidated Omnibus Budget Reconciliation Act of 1985 eliminated employment and marriage restrictions for eligibility. The Omnibus Budget Reconciliation Act of 1986 gave states the option to cover all pregnant women based on family income limits. With the Omnibus Budget Reconciliation Act of 1989, Medicaid was required to cover all pregnant women in families with incomes at or below 133 percent of the Federal Poverty Level (FPL). Since then, all states must provide coverage for pregnant women with incomes up to the federal minimum threshold, while some states have raised their income eligibility levels using state funds (Currie & Gruber, 1996b).

Furthermore, since 2003, 18 states have adopted the Unborn Child Option (UCO), which allows them to provide coverage through the Children's Health Insurance Program (CHIP) to undocumented immigrant pregnant women, considering the fetus as a "targeted low-income child". More recently, in 2009, the Children's Health Insurance Program Reauthorization Act of 2009 established new options for states to offer CHIP-funded coverage to low-income pregnant women, including those lawfully residing in the United States, without regard to the five-year residency requirement.[5]

(Figure 1 here)

[5]Legislative Milestones in Medicaid and CHIP Coverage of Pregnant Women: https://www.macpac.gov/legislative-milestones-in-medicaid-and-chip-coverage-of-pregnant-women/.

This paper focuses on state income eligibility for pregnant women since 2003, generously provided by the Kaiser Family Foundation (KFF).[6] Table A.1 lists specific income eligibility thresholds and the expanded level for each state in the period from 2003 to 2022 for all 50 states and the District of Columbia (D.C.). Figure 1 plots the yearly average eligibility among the 51 states, along with the proportion of states that have been covering undocumented immigrant women since 2003. The historical trends suggest the progressive expansion of Medicaid coverage for pregnant women over time. In 2003, the national average eligibility was set at 180% (1.8) of the FPL, and by 2022, this threshold had risen to approximately 218% (2.18). Furthermore, Figure 2 provides a graphical representation of the average income eligibility by state, where darker colors indicate higher average eligibility. States like California, Colorado, Minnesota, Michigan, Iowa, Tennessee, Maryland, Connecticut, and Rhode Island have some of the highest income eligibility (on average ranging from 229% to 306% of the FPL) for pregnant women, while states in mountainous regions tend to have lower average eligibility thresholds.

(Figure 2 here)

2.2 Physician Mobility and the Interstate Medical Licensure Compact

Physicians are not evenly distributed across the United States. According to the American Medical Association Physician Masterfile and health statistics, the physician-to-population ratio in Washington, D.C. was approximately 3.5 times that of Idaho in 2019.[7] Studies on physician mobility (Ricketts & Randolph, 2007; Holmes & Fraher, 2017; McGrail et al., 2017; Molitor, 2018) have shown that roughly 15% - 25% of physicians move across county borders within a period around 5 years, with the likelihood of relocation diminishing over the course of their careers. The intent to move also varies by medical specialty. Furthermore, various factors such as population density, income levels, rural or urban status, the presence of a teaching hospital, and the overall similarity between the physician's current location and the destination are significantly associated with physicians' decisions to relocate (Holmes & Fraher, 2017).

With the aim of alleviating physician shortages in specific regions and expanding physicians' reach, the Interstate Medical Licensure Compact (IMLC) was launched by state medical boards in 2014. Within this compact, which now includes 37 states

[6] Medicaid and CHIP Income Eligibility Limits for Pregnant Women: https://www.kff.org/medicaid/state-indicator/medicaid-and-chip-income-eligibility-limits-for-pregnant-women/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D. I only use eligibility from 2003 to 2020 for empirical analysis because the Area Health Resource File (AHRF) only provides physician and socioeconomic statistics at the county level up to the year 2020 by now.

[7] Source: https://www.cdc.gov/nchs/hus/topics/physicians.htm

and the District of Columbia, physicians can apply to practice in multiple states by completing just one application. Qualified physicians receive separate licenses from each state they intend to practice in. Although these licenses are still issued by individual states, the compact significantly streamlines the application process, making it faster and more cost-effective.[8] In contrast to Medicaid, which typically restricts benefits to state residents, physicians have much greater flexibility in selecting their practice locations. This enhanced mobility is further facilitated by the cross-state agreements established under the IMLC. This contrast motivates for more rigorous research to investigate how physicians relocate across regions in response to Medicaid policies.

3 Theoretical Framework: a Location Choice Model

I begin with a theoretical model to formalize the probabilistic location choices (McFadden, 1981) made by a representative physician, drawing on prior work on physician migration (Holmes, 2005; Holmes & Fraher, 2017; Huh, 2021). In this study, the model primarily functions as a conceptual framework to derive testable theoretical predictions for the subsequent empirical analysis regarding the association between Medicaid eligibility expansion and physician supply. It's essential to note that this model specifically applies to the relocation decisions of existing physicians and does not account for the entry of new physicians into the U.S. market.[9]

In each period t, the representative physician select a practice location out of a set of counties. The utility of practicing in county i in period t is U_{it}, which consists of a deterministic term v_{it} and a stochastic term ϵ_{it}. Formally,

$$U_{it} = v_{it} + \epsilon_{it} \tag{1}$$

County i will be preferred over county k if $U_{it} > U_{kt}$. Therefore, the probability that county i will be chosen by the representative physician is:

$$P_{it} = Prob(U_{it} > U_{kt}), \forall k, k \neq i \tag{2}$$

If ϵ_{it} is distributed with a Gumbel distribution (Type I extreme value distribution), then P_{it} can be further expressed as:

$$P_{it} = \frac{exp^{v_{it}}}{\sum exp^{v_{kt}}} \tag{3}$$

The deterministic component v_{it} is a profit function of the representative physician. It consists of the total revenue from Medicaid patients $Revenue_{it}^{M}$ and total revenue form non-Medicaid patients $Revenue_{it}^{NM}$ while considering the total cost to practice in county

[8] More information about the IMLC: https://www.imlcc.org/a-faster-pathway-to-physician-licensure/.

[9] Resident OB-GYNs make up approximately 5% of all OB-GYNs, according to the AHRF data (2001-2020).

i in period t: $Cost_{it}$, as the below expression:

$$v_{it} = Revenue_{it}^{M} + Revenue_{it}^{NM} - Cost_{it} \tag{4}$$

Where, for Medicaid patients, the total revenue depends on the total number of patients $q^M(E_{it}, Z_{it})$, the demand of care per patient $d^M(E_{it}, Z_{it})$, Medicaid reimbursement rate $r^M(Z_{it})$, and is equally shared by the current total supply of physicians S_{it}: $\frac{q^M(E_{it},Z_{it})d^M(E_{it},Z_{it})r^M(Z_{it})}{S_{it}}$. I define E_{it} as the Medicaid eligibility line and Z_{it} as a vector of regional time-variant characteristics, such as economic development, income level, income distribution, etc. While the total revenue from non-Medicaid patients also follows a similar functional form $\frac{q^{NM}(E_{it},Z_{it})d^{NM}(Z_{it})r^{NM}(Z_{it})}{S_{it}}$, the demand for care per non-Medicaid patient d^{NM} does not depend on Medicaid eligibility. The cost to practice in county i, $C(\mu_i, Z_{it})$, depends both on the regional time-invariant characteristics μ_i, such as geographical location, and time-variant socioeconomic characteristics Z_{it}. Relocation always associates with positive costs and increases with distance.

3.1 Total Physician Supply and Medicaid Eligibility

Therefore, the deterministic v_{it} is a function of Medicaid eligibility line E_{it}, local time-variant characteristics Z_{it}, total number of physicians S_{it}, and time-invariant characteristics μ_i:

$$v_{it} = v(E_{it}, Z_{it}, S_{it}, \mu_i) \tag{5}$$

Assume N_t is the national total number of physicians in period t, the physician supply in county i, S_{it}, is then a product between N_t and the probability for a representative physician to practice in county i. Thus, S_{it} can be determined in equilibrium as a function of Medicaid eligibility line E_{it}, local time-variant characteristics Z_{it}, and time-invariant characteristics μ_i:

$$S_{it}^{*} = S(E_{it}, Z_{it}, \mu_i) \tag{6}$$

Based on equation (6), our baseline empirical model estimates the association between the Medicaid eligibility E_{it} and county total physician supply S_{it}.

3.2 Individual Physician Location and Medicaid Eligibility

Now suppose a Medicaid eligibility expansion happens ($E_{t-1} < E_t$). A physician who chose to practice in county j period $t-1$ ($U_{jt-1} \geq U_{it-1}$) will choose to practice in county i in the current period t if and only if $U_{it} - U_{it-1} \geq U_{jt} - U_{jt-1}$. Therefore, the marginal change in v_{it} in response to the change in Medicaid eligibility E_{it} determines whether a physician will relocation and where the practice location is in period t. This marginal change is expressed as below:

$$\frac{\partial v_{it}}{\partial E_{it}} = \frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}} \frac{d^M(E_{it}, Z_{it}) r^M(Z_{it})}{S_{it}} + \frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}} \frac{q^M(E_{it}, Z_{it}) r^M(Z_{it})}{S_{it}} + \frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} \frac{d^{NM}(Z_{it}) r^{NM}(Z_{it})}{S_{it}} \quad (7)$$

Moving always associates with extra cost, therefore, physicians are assume to avoid moving far. However, the representative physician will relocate practice location from county j to county i as long as the marginal increase in total revenue is large enough while additional moving cost $\Delta Cost_{it}$ is minimized.[10] In each period, the moving of physicians across counties always lead to a new equilibrium S^*_{it} in each county.

Existing evidence suggests the number of Medicaid enrollees increases (De La Mata, 2012; Card & Shore-Sheppard, 2004), $\frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}} > 0$, following that Medicaid expansion covers those who were previously uninsured (Finkelstein et al., 2012; Cutler & Gruber, 1996b) and who switched from private plans (Cutler & Gruber, 1996a,b, 1997; Gruber & Simon, 2008; Barnes et al., 2020; Bellerose et al., 2022). As a result of the crowding-out effect, the number of privately insured patients might decrease, $\frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} < 0$, as Medicaid covers the same healthcare service with a cheaper price compared to employer-sponsored insurance (ESI) (Hadley & Holahan, 2003; Coughlin et al., 2016; Wray et al., 2021). Literature also shows that Medicaid coverage induces higher demand for care among low-income population, $\frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}} > 0$ (Finkelstein et al., 2012; De La Mata, 2012; Coughlin et al., 2016; Wherry et al., 2017).

Prediction 1: *Given Medicaid reimbursement rate, r^M, is much lower than private price, r^{NM}, ($\frac{r^{NM}_{it}}{r^M_{it}} \gg 0$)(Zuckerman et al., 2009, 2021), Medicaid eligibility expansion raises the total revenue ($\frac{\partial v_{it}}{\partial E_{it}} > 0$) in counties that experience a substantial rise in new Medicaid enrollees and an increased demand for care among Medicaid patients.*

As equation (7) shows, $\frac{\partial v_{it}}{\partial E_{it}}$ can be substantially positive if some of the below conditions are met:

- $|\frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}}|$ is considerably larger than $|\frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}}|$ with uninsured mid-low income people take up Medicaid in county i.
- A large proportion of population in county i become Medicaid eligible: a big $q^M(E_{it}, Z_{it})$.
- Demand for care per Medicaid patient increases substantially with newly insured Medicaid beneficiaries: a big $\frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}}$.

Prediction 2: *In states with more generous Medicaid reimbursement rate, r^M, the total revenue increase ($\frac{\partial v_{it}}{\partial E_{it}}$) becomes further larger.*

[10] $\Delta Cost_{it} = C(\mu_i, Z_{it}) - C(\mu_j, Z_{jt}) > 0, i \neq j$. When county i is close to j, $\mu_i \approx \mu_j$ and $Z_{it} \approx Z_{jt}$.

Prediction 3: *Within the same state (same eligibility expansion ΔE_{it}), physicians chose county i over other in-state counties, if local social characteristics, Z_{it}, maximizes the marginal revenue increase, $\frac{\partial v_{it}}{\partial E_{it}}$.*

Prediction 4: *Among counties with similar socioeconomic conditions (Z_{it}) but different Medicaid Eligibility (E_{it}), particularly those near state borders, physicians tend to favor markets with lower E_{it} and a higher proportion of privately insured patients (given $\frac{\partial q^{NM}(E_{it},Z_{it})}{\partial E_{it}} < 0$), as long as the effect of "crowding-out" is dominantly large ($\frac{\partial v_{it}}{\partial E_{it}} < 0$).*

Later in this paper, I empirically validate the four theoretical predictions outlined above to offer insights into the observed correlation between Medicaid income eligibility and physician supply.

4 Empirical Strategy

To explore how physicians react to the expansion of Medicaid/CHIP income eligibility, I leverage both time and geographical variations in state Medicaid income eligibility for pregnant women and assess its impact on the supply of OB-GYNs, a medical specialty focused on the care of pregnant women. The empirical analysis is conducted in two different angles, each employing different empirical strategies.

4.1 Overall Relationship between Income Eligibility and Physician Supply

I begin with a difference-in-differences (DID) design and estimate the below event study type of specification:

$$log(MD_{ct}) = \alpha_0 + \sum_{k=-6,k\neq-1}^{11} \beta_k I\{t - T_s^{1stEXP} = k\} EXP_{st} + Z_{ct}\Upsilon + \mu_t + \lambda_s + \epsilon_{ct} \tag{8}$$

where MD_{ct} denotes the total number of OB-GYN per 100,000 population in county c and year t. T_s^{1stEXP} is the eligibility (1^{st}) expansion year in state s. This expansion is staggered across states and involves varying changes in eligibility. While absolute income eligibility is likely associated with local income levels, I calculate EXP_{st} as the annual deviation from the eligibility level in the expansion year to account for local income variations. Z_{ct} represents county-specific yearly characteristics, including poverty rate, log median household income, log per capita income, log total employment (16+), and log total number of non-OB-GYN MDs per 100,000 people, and controls for local income distribution, average income levels, socioeconomic development, and healthcare sector environment. Both state (λ_s) and year (μ_t) fixed effects are controlled for, given that Medicaid is a state-level policy. Taking into account physician mobility both within states and across states, standard errors are clustered at the census division level in the baseline specifications.

The coefficients of interest (β_k) measure how the county level OB-GYN to population ratio changes before and after the expansion year and with the actual amount of eligibility change in each year. The possible casual interpretation relies on whether the "parallel trend" assumption can be met and demands null coefficient of β_k for all years before the expansion.

An alternative way to examine the effect of Medicaid/CHIP income eligibility expansion for pregnant women on the availability of OB-GYNs is to estimate the association between Medicaid population fraction eligible that is determined by Medicaid eligibility and the physician-population ratio. To exclude the effect of Medicaid expansion separately from the local socioeconomic characteristics that are potentially correlated with Medicaid fraction eligible, I follow Currie & Gruber (1996b) to instrument for changes in Medicaid fraction eligible among pregnant women with reproductive ages (15-44 years old) by a "simulated fraction eligible" based on 20,000 women randomly sampled from the national sample using the ACS each year. In this way, the state simulated fraction eligible is generated using the same group of population and depends only on the state legislative in each year. Furthermore, using the same population helps to address the sampling variability in states with small population (Currie & Gruber, 1996b).

The OLS specification estimating the effect of Medicaid fraction eligible on total number of OB-GYNs per 100,000 population is as below:

$$log(MD_{ct}) = \alpha_0 + \beta_1 FRAC_{st} + Z_{ct}\Upsilon + \mu_t + \lambda_s + \epsilon_{ct} \tag{9}$$

where $FRAC_{st}$ is the state level fraction eligible among women between 15 and 44 years in the ACS sample, based on state yearly eligibility limit, yearly FPL, and household incomes. Similar to equation (8), I control for county level time-variant characteristics, state fixed effects, and year fixed effects. To obtain the unbiased estimates for β_1 that measures the percentage change in the number of OB-GYN per 100,000 population with respect to the percentage change in fraction eligible, the main explanatory variable $FRAC_{st}$ will be instrumented by $SIMFRAC_{st}$ that is simulated from the ACS national sample. Below are the two-stage least square (2SLS) specifications:

$$1^{st} stage : FRAC_{st} = \theta_1 SIMFRAC_{st} + Z_{ct}\Phi + \mu_t + \lambda_s + \varepsilon_{ct} \tag{10}$$

$$2^{nd} stage : log(MD_{ct}) = \alpha_0 + \beta_1 \widehat{FRAC}_{st} + Z_{ct}\Upsilon + \mu_t + \lambda_s + \epsilon_{ct} \tag{11}$$

One common concern in using either the event study or the 2SLS strategy is that the state legislature of expanding Medicaid/CHIP eligibility might associate with other socioeconomic determinants that also affect local supply of OB-GYNs. Therefore, I present binned scatter plots between Medicaid/CHIP income eligibility and the state yearly main characteristics in Figure A.1. Regardless of using the absolute eligibility or the yearly expanded eligibility from the level in the (1^{st}) expansion year, the legislature to change Medicaid/CHIP income eligibility has little association with state-year level percentage of population in poverty, log median household income levels, log per capita income levels, and log employment above age 16, after controlling for year and state fixed effects.

4.2 Relationship between Income Eligibility and Physician Supply at State Borderlines

This study also examines the relationship between Medicaid/CHIP eligibility for pregnant women and the county-level number of OB-GYNs per 100,000 population along state borders. This analysis is motivated by two key factors. First, border counties share similar socioeconomic environments, including demographic composition, income distribution, and preferences, all of which are closely related to population demand for healthcare. Therefore, the same changes in eligibility are likely to influence patient demand for care similarly. However, eligibility thresholds are often different between the two sides of the border and, as suggested by prediction 4, the side with lower eligibility typically has a higher proportion of privately insured patients. Second, physicians practicing in border regions are often more mobile than those in the inner parts of the state. While Medicaid beneficiaries are constrained by state boundaries when accessing benefits, physicians can operate in both markets. This asymmetric mobility on both the supply and demand sides can result in unexpected policy impacts and implications at state border areas.

Following Dell (2010), Imbens & Zajonc (2011), and Kumar (2018), I employ the below multidimensional border regression discontinuity (RD) specification:

$$log(MD_{ct}) = \alpha_0 + \beta_1 HIGH_{st} + \sum_{0}^{P}\sum_{0}^{Q} \lambda_{pq} X_c^p Y_c^q + \mu_t + \lambda_s + \epsilon_{ct} \tag{12}$$

where, the discontinuity threshold is, instead of a measure of distance, a multidimensional discontinuity in both latitude and longitude space. Therefore, this approach accounts for location-specific factors using a polynomial function of the vector of running variables: latitude (X) and longitude (Y), as $\sum_0^P \sum_0^Q \lambda_{pq} X_c^p Y_c^q$. $HIGH_{st}$ is an indicator of state with a higher eligibility than the other side of the border. I also control for state λ_s and year μ_t fixed effects. Besides testing the discontinuities of the key county level covariates in Z_{ct} (controlled in equations (8) and (9)), I also generate a "covariate index" and test its discontinuities following Card et al. (2012) and Kumar (2018). Basically, this "covariate index" is the predicated outcome $log\widehat{(MD_{ct})}$ from regressing $log(MD_{ct})$ on the set of variables in Z_{ct}.

5 Data

5.1 Physician Data

This paper employs two primary sources of physician data: the Area Health Resource File (AHRF, 2001-2020) and the National Plan and Provider Enumeration System (NPPES, 2007-2023). These datasets are used to quantify the total physician supply and track their geographical mobility, allowing for a cross-validation of the empirical results. Additionally, both datasets can be linked to publicly available Medicaid eligibility policies (2003-2022), as presented in Section 2.

The AHRF data is provided by the HRSA and contains very detailed information on "health care professions, health facilities, population characteristics, economics, health professions training, hospital utilization, hospital expenditures, and environment at the county, state, and national levels."[11] The AHRF data span from 2001 to 2020 provides information on health care professionals, including residents, office-based, and hospital staff, by specialty, as well as certified nurse practitioners, and demographic and economic statistics at the county level.

The NPPES is developed by the Centers for Medicare & Medicaid Services (CMS) to assign unique identifiers to health care providers. Since May 23, 2007, the National Provider Identifier (NPI) has been standardized for all HIPAA-covered entities, who must get an NPI regardless of individuals or organizations. The NPPES files contain all of the FOIA-disclosable data for active and deactivated providers in NPPES. While the latest NPPES data is refreshed weekly by CMS, historical files (since 2007) are hosted by the National Bureau of Economic Research (NBER).[12] The NPPES data furnishes comprehensive details about the NPI entity. This information encompasses the provider's NPI number, an indicator of whether it is an individual or an organizational entity, provider full name, specialty taxonomy code, business mailing address, and practice location address. In this study, I exclusively focus on individual physicians with any specialty taxonomy classified as OB-GYN. Consequently, I do not include any organizational NPIs or individual NPIs that lack an OB-GYN taxonomy in the NPPES data.[13] I rely on the reported practice address to track the mobility of each individual NPI and construct yearly moving outcomes, such as moving from another in-state county, and moving to an out-state county across state borders.[14] Out of the 59,952 individual

[11]Data source: https://data.hrsa.gov/topics/health-workforce/ahrf

[12]CMS source: https://download.cms.gov/nppes/NPI_Files.html. NBER source: https://www.nber.org/research/data/national-plan-and-provider-enumeration-system-nppes

[13]The OB-GYN taxonomy codes are: 207V00000X, 207VB0002X, 207VC0200X, 207VE0102X, 207VF0040X, 207VG0400X, 207VH0002X, 207VM0101X, 207VX0000X, 207VX0201X, 207VC0300X.

[14]While the representation of physician data and timeliness of updating information, such as location, are possible issues in using NPPES data, DesRoches et al. (2015) suggest that the NPPES data is as good as other physician files in updating address information for physicians billing public and private insurers. Additionally, CMS requires providers to report any NPI-related information within 30 days

OB-GYN NPIs that can be linked to a specific county based on their practice location, approximately 3.1% relocated to another county within one year, 9.3% did so after three years, and 15.7% made a move within six years. In alignment with the primary specifications applied at the county-year level, I further aggregate the data on individual OB-GYN NPIs into county-year units, considering three primary outcomes: the total count of individual OB-GYN NPIs, the count of individual OB-GYN NPIs relocating in from another county within the same state, and the count of individual OB-GYN NPIs moving out across state borders.

(Table 1 here)

In Table 1, Panel (a) summarizes the county-year level total counts of OB-GYNs and some subgroups for residents, office-based physicians, and hospital staff specializing in this field using the AHRF dataset. It also offers summary statistics for midwives, who may serve as substitutes for OB-GYNs with MD degrees, and all other non-OB-GYN MDs.[15] The AHRF includes a complete sample of 3,150 counties each year. Pooling all the county-year observations together, the average number of OB-GYNs per 100,000 population per year in one county is about 6. Column (1) in Panel (a) also suggests that the majority of OB-GYNs primarily practice in private offices.

Panel (b) summarizes for all individual OB-GYN NPIs found in the NPPES dataset. The average at the county-year level is larger than the total reported in the AHRF, primarily due to two key reasons. First, OB-GYN NPI is identified using taxonomy code and might potentially includes some physicians practice in multiple specialties and advanced nurse practitioners. Second, if no physicians are identified using NPPES, I do not code them as zeros to avoid possible reporting errors. Thus, the NPPES sample only includes individual OB-GYN NPIs from 1,888 counties with non-zero counts of OB-GYN NPIs. Nonetheless, we can still utilize the NPPES data to validate the primary patterns identified using the AHRF dataset. Most importantly, the address information in the NPPES data is invaluable for estimating whether individual OB-GYN NPIs alter their practice locations in response to changes in Medicaid eligibility. Panel (b) also summarizes two key mobility measures: yearly number of OB-GYNs moving in from other in-state counties and yearly number of OB-GYNs moving out across state borders. The definition of moving in from other in-state counties is that this NPI's practice address was in another county in the same state last year. Similarly, I define moving-out across state borders if this NPI's address shows up in a county across the nearest state border in the following year. Comparing between border and non-border counties, the average number of OB-GYNs moving-out across state borders in border counties is nearly 3 times that observed in non-border counties.

according to the rules: https://www.cms.gov/medicare/regulations-guidance/administrative-simplification

[15]Data for midwives with NPIs in the AHRF is available from 2010 onwards.

5.2 Supplemental Data

I also use two other supplemental datasets for my empirical analysis: American Community Survey (ACS, 2001-2020) and American Family Cohort data (AFC, 2001-2020) (Vala et al., 2022). The former one is an ongoing nationally representative survey conducted by the U.S. Census Bureau annually. The ACS collects a rich set of information on demographics, education, employment, income, etc. for 1% of the U.S. population each year. Therefore, using the annual FPL and state Medicaid/CHIP eligibility for pregnant women, I can calculate the Medicaid fraction eligible (share eligible for Medicaid if they are pregnant) among all women with reproductive ages (15 to 44 years old). Then, from each years' national sample of all women between 15 to 44 years old, I randomly draw 20,000 women and use them as the fixed base for every state. Based on the household incomes of the 20,000 women and each state's Medicaid eligibility, I obtain the "simulated eligible fraction" that depends only on the state policy and is orthogonal to state yearly socioeconomic characteristics. I use this "simulated eligible fraction" to instrument the actual eligible fraction (Currie & Gruber, 1996b).

The latter data source is a research database derived from Electronic Health Record (EHR) data that has already been assembled as part of the ABFM PRIME Registry.[16] The AFC data includes rich patient level information, including demographics, insurance status, health history, procedures, diagnoses, etc. While AFC data mainly covers family medicine and primary care clinicians, an OB-GYN is considered as a primary care doctor when it comes to women's health.[17] Note that this supplemental analysis using AFC data is not to estimate the effect of Medicaid eligibility expansion on how OB-GYNs admit and treat patients. Instead, it offers suggestive evidence that Medicaid expansions may have indeed encouraged greater demand for care among pregnant women, including enrolling in Medicaid and increasing the use of any necessary care, in line with findings from some previous studies (Card & Shore-Sheppard, 2004; De La Mata, 2012; Finkelstein et al., 2012; Wherry & Miller, 2016; Wherry et al., 2017). To do this, I generate a sample of potential pregnant women, who have at least one ICD-10 diagnosis code belonging to the category "Pregnancy, childbirth and the puerperium" category. For each pregnancy related diagnosis, I only keep the patient's EHR records 12 months before and after that diagnosis date to approximately capture all visits around prenatal and postpartum periods.

Additionally, I also use the publicly available data on Medically Underserved Area (MUA) and Health Professional Shortage Areas (HPSA) designations from HRSA, hand-collected data on the federal Area Health Education Centers (AHEC) program, and

[16] I wish to acknowledge and thank the ABFM PRIME Registry participating clinicians and the American Board of Family Medicine, without whom the American Family Cohort would not be possible.

[17] See reference at California Department of Managed Health Care: https://www.dmhc.ca.gov/healthcareincalifornia/yourhealthcarerights/youandyourdoctor.aspx

the information on state participation in the IMLC to investigate heterogeneity effects across geographical regions.[18]

6 Effect of Medicaid/CHIP Eligibility Expansion for Pregnant Women on OB-GYN Supply

6.1 Main Result

(Figure 3 here)

I first investigate whether the Medicaid fraction eligible among women with reproductive ages (15-44 years old) increases with Medicaid/CHIP eligibility expansions, as it is possible that income eligibility was mainly raised to match the growth of incomes. Using a state-year level specification that is slightly updated from equation (8), I estimate the change of state level Medicaid fraction eligible before and after the (1^{st}) expansion year and with the changed level of eligibility line in each year. Figure 3 presents the event study plot and suggests that the state level Medicaid fraction eligible grows by 1.5 percentage points in the expansion year when eligibility expands by 0.1 (10% of the current FPL). This change immediately occurs in the expansion year and persists afterwards. Therefore, Medicaid/CHIP eligibility expansions for pregnant women indeed covers larger share of women, conditional on state time-variant socioeconomic characteristics, and state and year fixed effects.

(Figure 4 here)

I then estimate equation (8) and plot the event study coefficients in Figure 4. Since the expansion year, the total number of OB-GYNs at the county level increases compared to the pre-expansion levels. The magnitude in the post-expansion period ranges around 5 percentage points with significant coefficients in year 0 and after the third year. Once I group the post-expansion periods, the average magnitude of increased county level total number of OB-GYNs per 100,000 is reported in Table 2. Table 2 presents the estimated effect of Medicaid/CHIP eligibility expansions for pregnant women on log county total number of OB-GYNs per 100,000 population using various measures of treatment variable. The coefficient reported in Column (1) is for the actual eligibility limit, in Column (2) is for the expanded eligibility (grouped DID estimator), in Column (3) is for the actual eligible fraction calculated using ACS sample, and in Column (4) is for the 2SLS estimator using the "simulated eligible fraction" as the instrument of

[18]HRSA designation data comes from: https://data.hrsa.gov/tools/shortage-area. Area Health Education Centers Program: https://data.hrsa.gov/data/reports/datagrid?gridName=AHECDirectoryReport. IMLC state level data is at: https://www.imlcc.org/.

the actual eligible fraction. To show validity of the instrument variable, Figure A.2 shows graphical representations of the relevance assumption (first-stage), independence assumption, and the reduced form, following Chan et al. (2022). It suggests a strong correlation between actual fraction eligible and the instrument variable (almost close to 1), simulated fraction eligible. Meanwhile, the proportion of outcome variable that is explained by county time-variant socioeconomic and demographic characteristics has little association with the instrument variable. The first-stage F statistics for the 2SLS estimation is 525.50. All four columns of Table 2 suggest that Medicaid/CHIP eligibility expansion is positively associated with the county total number of OB-GYNs per 100,000 population. More specifically, an increase in eligibility line by 0.1 (10% of the current FPL) is associated with a 0.3 percentage points increase in the number of OB-GYNs per 100,000 population. Alternatively, 1 percentage point increase in the eligible fraction is associated with a 0.2 percentage points rise in the number of OB-GYNs per 100,000 population. Both Figure 4 and Table 2 provide evidence that expanding Medicaid/CHIP eligibility for pregnant women overall increases the county level total number of OB-GYNs per 100,000 population.

(Table 2 here)

6.2 Effect at State Borders

(Figure 5 here)

I then estimate the border RD specification in equation (12) to pinpoint the relationship between Medicaid/CHIP eligibility and total supply of OB-GYNs across state borders. In this scenario, Medicaid patients can only access benefits within the current state and tend to prefer providers located in closer proximity (Chan et al., 2006), while physicians are flexible to choose which side of the border to serve.

(Figure 6 here)

I first test the discontinuities in all county level covariates at the state borderlines to verify the assumption that counties along state borders are very similar to each other. Figure 5 presents the binned means of county yearly controls conditional on year and state fixed effects as well as the fitted value for a local linear regression on each side in a 200-mile bandwidth. Visual inspection suggests little evidence on substantial discontinuities in county level time-variant covariates. Following Card et al. (2012) and Kumar (2018), I predict a “covariate index” that is the predicted outcome variable using a single regression of log total number of OB-GYNs per 100,100 population on all the county time-variant covariates. Then, I test discontinuity in the “covariate index” in various bandwidths as Figure 6 displays. Figure 6 plots the binned means of the “covariate index” with 95 percent confidence intervals as well as local linear regression fitted lines. It shows that discontinuities in this “covariate index” are all insignificant with bandwidths from 50 to 200 miles.

(Figure 7 here)

Figure 7 presents the discontinuities of log total number of OB-GYNs per 100,000 population using bandwidths of 50, 100, 150, and 200 miles (conditional on state and year fixed effects). Different from Figure 6, the confidence intervals of the binned means of the outcome variable do not overlap with each other across the 0 distance lines (borderlines) and the local linear regressions suggest relatively large and significant discontinuities in the outcome variable regardless of the length of bandwidth. Based on equation (12), Table 3 reports the multidimensional RD estimates of the effect of Medicaid/CHIP eligibility for pregnant women on log total number of OB-GYNs per 100,000 population at the county level. Quadratic polynomial in latitude and longitude, state and year fixed effects are controlled for. Columns (1) to (4) present estimates using various bandwidths and consistently suggest that counties on the side with higher Medicaid/CHIP eligibility on average have 8 percentage points fewer number of OB-GYNs per 100,000 population.

(Table 3 here)

Both Figure 7 and Table 3 provide evidence that Medicaid/CHIP eligibility has a negative impact on the number of OB-GYNs per 100,000 population in counties near state borders. This effect is particularly noticeable when physicians can easily access multiple markets with different Medicaid eligibility criteria simultaneously. While a significant portion of physicians practice in non-border counties and face relatively higher relocation costs across states, this effect among physicians in border counties suggests potential unintended consequences of Medicaid expansion on access to care availability in state border areas.

6.3 Mechanisms

To understand and reconcile the patterns in the relationship between Medicaid/CHIP eligibility for pregnant women and the county-level total supply of OB-GYNs when examining all counties versus border counties, I empirically test the four conceptual predictions outlined in Section 3 to demonstrate key mechanisms and heterogeneity in how physicians make location choices in response to Medicaid expansions.

6.3.1 Physician Supply by Demand of Medicaid Beneficiaries

While the overall association between Medicaid/CHIP eligibility and the number of OB-GYNs is positive, Prediction 1 suggest that this relationship might be contributed by certain types of counties, where eligibility expansions induced a large demand surge among Medicaid enrollees. To test this hypothesis, I estimate the effect of eligibility expansions on county total number of OB-GYNs per 100,000 population by two classifications.

(Figure 8 here)

Mediciad/CHIP eligibility for pregnant women is a household income threshold. While people with lowest household incomes are already covered by Medicaid, the marginal population that is affected by eligibility expansions are people with mid-low level incomes. Therefore, I first rank all the counties in a state each year into quartiles based on percentage of population in poverty. Therefore, the first quartile includes the richest counties, while the forth quartile is the group of poorest counties. For each quartile by poverty rate, I estimate the effect of Mediciad/CHIP eligibility on log total number of OB-GYNs per 100,000 population. Figure 8 shows the point estimates of all four specifications by the ranking of poverty rate. While the positive effects mainly come from 2nd and 3rd quartiles, the magnitudes are overall largest in the 3rd quartile counties. For example, the eligibility expansion of 0.1 FPL (10% of the current FPL) corresponds to 0.6 percentage points more OB-GYN per 100,000 pop in the 2nd quartile and 0.65 percentage points more in the 3rd quartile counties. Equivalently, increasing Medicaid fraction eligible by 1 percentage point raises the county total OB-GYNs by 0.3 percentage points in the 2nd and by 0.4 percentage points in the 3rd quartiles. Figure 9 then present the event study version estimates and suggests similar patterns as Figure 8. While the coefficients for the richest and poorest quartiles are most of the time insignificant, the 3rd quartile counties experience an immediate and largest increase in the number of OB-GYNs per 100,000 population in the expansion year. The effects among the 2nd quartile counties also become significant since year 3. The yearly pattern in the 2nd and 3rd quartile counties is almost the opposite of that in the 1st and 4th quartiles, thus suggesting a concentration effect towards mid-low population. As mid-low income population is the target group of Medicaid/CHIP eligibility expansion, the strongest positive effect of eligibility expansion on the number of OB-GYNs per 100,000 population in the mid-low income counties is consistent with Prediction 1 and is very likely driven by the large demand for care from the new enrollees.

(Figure 9 here)

An alternative exercise is utilizing the Medically Underserved Area (MUA) designation, which identifies areas with a lack of access to primary care service, as a rough measure of areas with potential unmet demand for care. The algorithm of determining MUA designation weights heavily on the demand-side population need for care.[19] Using the historical time information on designating MUA from HRSA, I compare the effect of Medicaid/CHIP eligibility expansions on the county level log total number of OB-GYNs per 100,000 population between MUA counties versus non-MUA counties. Table 4 suggests that the positive effect on OB-GYN supply is strongly driven by counties when they were designated as a MUA. The effect is not significant among counties that are not MUAs.

So far, I show evidence that the positive effect of Medicaid/CHIP eligibility expansions on county level total supply of OB-GYNs are statistically stronger among mid-low income counties and counties with MUA designation. Although I am not able to calculate the county level change in demand for care, these empirical findings support Prediction 1 that the demand induced by Medicaid/CHIP expansions can be a positive incentive for physician supply.

(Table 4 here)

6.3.2 Physician Supply by Medicaid reimbursement rate

Prediction 2 emphasizes the importance of Medicaid reimbursement rate, which is much lower than private payment for the same type of service. Therefore, more generous Medicaid reimbursement rate could potentially further amplify the revenue from the Medicaid market and help to positively encourage physician supply following Medicaid expansions.

(Table 5 here)

While state-year level Medicaid reimbursement rate is hard to obtain, KFF provides a Medicaid-to-Medicare fee index to measure each state's Medicaid physician fees relative to Medicare fees in each state for the same services (Zuckerman et al., 2021). The higher the index is, the more generous the Medicaid reimbursement rate is in this state. Based on the state level Medicaid-to-Medicare Fee index for all services, I group the sample into two groups by higher versus lower index. Table 5 reports the estimated effect of Medicaid/CHIP eligibility on log total number of OB-GYNs in two groups of states. It shows positively significant effects in states with higher Medicaid physician fee relative to Medicare, but negatively insignificant coefficients in states with lower Medicaid-to-Medicare fee indexes. Therefore, Table 5 is consistent with Prediction 2.

[19]The established criteria for determining eligibility of a MUA is based on the Index of Medical Underservice (IMU), which is 0 to 100 score by adding weighted values of 4 variables: the rate of primary medical care physicians per 1,000 population, the infant mortality rate, the percentage of the population with incomes below the poverty level, and the percentage of the population age 65 years or older. Detailed information: https://www.michigan.gov/mdhhs/doing-business/providers/hpsa/hpsa-and-mua-p-program-overview.

6.3.3 In-state Physician Moving by Demand of Medicaid Beneficiaries

Prediction 3 hypothesizes in-state physician moving in order to further explain observed changes in total physician supply. Under the same state Medicaid eligibility and reimbursement rate, the relative demand change among Medicaid beneficiaries compared to privately insured patients solely determines where physicians prefer to practice in.

(Figure 10 here)

I use the practice addresses in the NPPES data to identify individual NPIs' relocation across counties. Specifically, in this analysis, I exclude border counties that are potentially also affected by neighboring states, and generate the outcome: log yearly individual OB-GYN NPIs moving in from other in-state counties. The definition of moving in from other in-state counties is that this NPI's practice address was in another county in the same state last year. Similar to Figure 8, Figure 10 presents estimated effects using four measures of Medicaid eligibility expansions by poverty rate. While in-state moving is measured across counties, I control for county and year fixed effects and cluster standard errors at the state level. Consistent with Figure 8 and Figure 9 showing the increased OB-BYNs is largest and most prompt in 3rd quartile counties, the number of moving-in OB-GYN NPIs from other in-state counties within one year substantially increases among the same quartile of counties.

Therefore, evidence supports the hypothesis that, within the same state, counties with largest demand response to Medicaid expansion attract physicians to relocate in. In this study, these counties are areas where most mid-low income population live in.

6.3.4 Cross-border Physician Moving by Medicaid Eligibility

The last prediction is about physician relocation across state borders and is highly relevant to the border effect showing eligibility is negatively associated with the number of physicians. As Medicaid eligibility expansions cover more mid-low income population partially through crowding out private patients, physicians earn higher profits on the side with lower eligibility, unless increased demand for care among Medicaid enrollees exceeds the revenue drop in the private market. Meanwhile, moving across state borders to practice also depends on the availability of multi-state licenses.

(Table 6 here)

I define moving-out across state borders if this individual NPI's address locating across the nearest state borders next year. Within border counties, Table 6 estimates the effect of relative eligibility on log number of individual OB-GYN NPIs' yearly moving-out across state borders per 100,000 population. Adapted from equation (8), I control for borderline-year fixed effect instead of year fixed effect to conduct the within border comparison. Therefore, counties bordering multiple counties are duplicated to the number of pairs. Table 6 first report the aggregated effect among border counties and suggest that higher eligibility line is associated more individual OB-GYN NPIs relocating to the other side of the border within a year. Then, I estimate this relationship by separating all the post-2015 years of states participating IMLC from the rest of the sample. Columns (3) and (4) shows that these IMLC member-states on average have even higher number of OB-GYNs moving-out across state borders, while Columns (5) and (6) present negative coefficients. Therefore, the IMLC which streamlines multi-state licence applications for physicians further helps physicians to move across state borders toward low eligibility states.

I also rank the county yearly poverty rate within each borderline and classify counties into higher versus lower poverty rate groups. Since Medicaid/CHIP expansions likely target mid-low income population as Prediction 1 and its empirical evidence highlight, higher-poverty counties within the border area would have larger demand increase following eligibility expansions. As Columns (7) to (10) reveal, the effect on moving-out across state borders is more pronounced among lower-poverty counties where people are more likely to earn higher incomes and less likely to respond to Medicaid/CHIP expansions.

These findings are very consistent with Prediction 4 and the border RD analysis. Even within a short range of one year, physicians relocate to practice in counties with very similar socioeconomic and demographic characteristics but lower Medicaid/CHIP eligibility to embrace more privately insured patients. Moreover, enhanced physician mobility and small demand response to eligibility expansion in the original county further increase the rate of moving-out across state borders.

6.4 Additional Heterogeneous Effects

I further explore the heterogeneous treatment effects of Medicaid/CHIP eligibility expansions for pregnant women by local market competition, population size, demographic composition, and urbanization.

Market Competition Dunne et al. (2013) suggest that the entry cost faced by physicians in undeserved markets is comparatively lower. To study whether the effect of Medicaid/CHIP eligibility expansions for pregnant women on the supply of OB-GYNs depends on local market competition among OB-GYNs. Table 7 presents the estimated effects on the probability of whether the county reaches a given number of OB-GYNs. The realizing outcomes include non-zero, at least five, and at least ten OB-GYNs per 100,000 population. While both the effects on reaching non-zero and larger than five OB-GYNs per 100,000 population are substantially large and positive, the null effect on reaching at least ten OB-GYNs per 100,000 population suggests that the response of the supply of OB-GYNs becomes more inelastic with growing number of OB-GYNs per population, possibly due to increasing entry cost.

(Table 7 here)

Population Size As population size potentially affects local market size, Table 8 compares the effects of Medicaid/CHIP eligibility expansions on the total supply of OB-GYNs in counties categorized based on population sizes. "Small" counties are defined if the county population is lower than 20,000, and "Large" counties are those with a population larger than 50,000. The rest of the counties are grouped as middle-sized. All four specifications consistently indicate that while the positive effect of eligibility expansions on the county's total number of OB-GYNs is primarily driven by counties with a population smaller than 50,000 people, it is mostly significant among middle-sized counties with 20,000 to 50,000 people.

(Table 8 here)

Share of Minority Population Compared to White women, black women are nearly twice as likely to delay or miss prenatal care (Hill et al., 2022). Table 9 examines whether the effect of Medicaid/CHIP eligibility expansions on the total supply of OB-GYNs differs by the county's share of minority population. Using the yearly national share of the non-Hispanic white population as a threshold, I separate all the counties into two groups. I categorize counties as the "Minority" group if the county's share of the non-Hispanic white population is lower than the national level; otherwise, as the "White" group. Table 9 shows that, compared to counties with a relatively higher white population, Medicaid/CHIP eligibility expansions for pregnant women increase the total number of OB-GYNs in areas with higher representations of minority populations more substantially. This suggests that Medicaid/CHIP eligibility expansions for pregnant women potentially address healthcare access disparities between areas with different demographic compositions.

(Table 9 here)

Share of Urban Population According to Lewis et al. (2019), "fewer than half of all rural counties have a practicing OB/GYN." To explore potential heterogeneity effects between rural and urban counties, I categorize counties into "Low," "Middle," and "High" urbanized categories based on thresholds of urban population share: 30% and 60%, according to the 2010 census. Table 10 compares the effect of Medicaid/CHIP eligibility expansions for pregnant women on the supply of OB-GYNs at the county level among the three sub-sample categories. It suggests that the positive effect is more pronounced among counties with fewer than 60% urban population, but is particularly significant in counties with urban populations between 30% and 60%.

(Table 10 here)

6.5 Robustness Checks

To probe the robustness of the main findings, I conduct various additional analysis in this section. I first estimate the effect of Medicaid/CHIP eligibility expansion on different sub-groups of OB-GYNs and a special group of nurse practitioners, the mid-wives. Figure A3 suggests that the positive response of increasing supply mainly comes from office-based physicians, who are more likely to run small-scale business and more mobile. Meanwhile, Columns (1) to (4) in Table A.2 further suggest there is no significant correlation between the Medicaid/CHIP eligibility expansions for pregnant women and the total number of other physicians who do not specifically treat this group of population. After separating one specialty that might substitute OB-GYNs, the family medicine doctors, from all the non-OB-GYN physicians, Columns (5) to (8) in Table A.2 show that Medicaid/CHIP eligibility expansions do not have a positive effect on the supply of family medicine physicians at the county level.

Table A.3 shows, regardless of whether the county total population is used as the sample weight or for dividing the total number of OB-GYNs per county as a per capita measure, the estimates consistently match the coefficients in Table 2. One concern of the effect of Medicaid/CHIP expansions for pregnant women is other confounding Medicaid reforms in the similar period of time. For example, the Unborn Child Option to extend coverage for undocumented immigrant women since 2003 and ACA expansions since 2014. Meanwhile, confounding factors could come from the supply side, as other programs also make effort to attract physicians to underserved areas. For example, the AHEC program is a federally funded program to make medical training (including residency and student rotations) locally available, on the hope that physicians are more likely to practice where they train (Qian, 2023). To attract physicians to the HPSA areas, physicians who provide professional services in a HPSA are eligible for a 10-percent bonus payment. Table A.4 controls for the state level time-variant adaption of UCO and ACA, while Table A.5 accounts for the other incentive programs offered to physicians, both table show very similar estimates compared to Table 2 for all estimators. Furthermore, Table A.6 controls for state year trends and health service area year trends to capture all possible regional time-variant institutional changes, and present robust but slightly higher estimated effects. Methodologically, I address the concern of timing varying treatment effects and plot the event study estimates, following Callaway & Sant'Anna (2021) in Figure A.4.[20] Meanwhile, I redefine the expansion year for states with multiple expansions

[20]The estimation automatically drops years beyond 2013 due to the absence of time variation in

as the year with the largest change in eligibility. I compare the DID estimates for both a continuous measure of expanded eligibility and an indicator of post-expansion based on either 1st expansion or the largest expansion in Table A.7. The estimates in Columns (2) and (3) are very consistent with Column (1), which is my baseline result. Lastly, I use the NPPES individual OB-GYN NPIs to replicate the main estimates in Table A.8 and Figure A.5. To address possible sample selection issue in NPPES data, I control for county and year fixed effects. Although the 2SLS estimates in Table A.8 is not significant, the sizes of the magnitudes are still comparable with those in Table 2. Moreover, Figure A.5 shows very consistent pattern as Figure 8 that strongest supply side response to Medicaid/CHIP eligibility expansions comes from the 3rd quartile counties ranked by poverty rate.

I also provide a variety of robustness checks for the border RD estimates. First, I separately estimate the multidimensional RD for all IMLC member states after 2015 versus the rest of the sample. As IMLC facilitates physicians in the member states to get multi-state licences more smoothly to practice in any of the participating states, the border effect that higher Medicaid/CHIP eligibility negatively associates with the supply of OB-GYNs might be more severe within the compact after its establishment. As Table A.9 shows, the negative effect is much stronger among states within the compact since 2015. Different from the main RD strategy in equation (12), Table A.10 uses the conventional one-dimensional border RD to replicate the analysis, it shows consistently negative effect right at the borderlines as Table 3. Since one-dimensional border RD only uses the discontinuities in distance, the coefficients in Table A.10 show a bit larger magnitudes than what the multidimensional RD estimates. To verify that the border effect is stronger when the local demand rarely respond to Medicaid expansion, I also rerun the main analysis after excluding all the 3rd quartile counties. Evidence in Table A.11 shows stronger negative effects than Table 3 and corresponds to Table 6 that the intent to move towards lower eligibility states is stronger among counties with less poverty issue (higher income counties). Additionally, I estimate the border effect of Medicaid/CHIP eligibility expansions on county level total OB-GYN supply using within border pair comparison strategy. Different from equations (8) and (9), it controls the year fixed effects for each border county pair. Counties bordering multiple counties are duplicated to the number of pairs. Table A.12 presents the within border pair estimates that all suggest a negative association between Medicaid/CHIP eligibility and county level total number of OB-GYNs.

treatment. The final year of the state level first expansion occurred in 2013.

6.6 Demand Side Supplemental Evidence

Although I focus on supply side response to Medicaid/CHIP eligibility expansions in this study, I also show some evidence on whether Medicaid take-up rate and the intent to use care among pregnant women increase after Medicaid expansions. While the observed patient outcomes are not purely demand change, an equilibrium where the quantity of care increases provides suggestive evidence.

Therefore, I use the AFC data to construct a pregnant women sample who has at least one pregnancy-related visit detected in the data, and match this patient to her visits 12 months before and after that prenatal diagnosis date. I then aggregate the visit level data to patient-month level for two main outcomes: an indicator of insurance status in that month: Medicaid, private, or uninsured, and the total number of visits per month and by main procedure codes. Particularly, I look at the total number of OB visits. Note that, Medicaid coverage of pregnant women includes all medically necessary care, dental, mental health, and all prenatal care. [21]

(Figure 11 here)

Consist with previous demand-side study (Card & Shore-Sheppard, 2004; De La Mata, 2012; Finkelstein et al., 2012; Wherry & Miller, 2016; Wherry et al., 2017), Panel (a) in Figure 11 shows some evidence that the probability of being covered by Medicaid increases while the rate of using private plans decreases among the sample of pregnant women, following the expansions of Medicaid/CHIP eligibility for pregnant women. Meanwhile, Panel (b) shows that the total number of care visits, especially OB visits, increases with Medicaid/CHIP eligibility. These findings on the demand side support the fundamental basis for this study. 1) Following Medicaid expansions, the total demand among Medicaid beneficiaries grows with both increased number of Medicaid patients ($\frac{\partial q^M}{\partial E_{it}} > 0$) and the use of care per patient ($\frac{\partial d^M}{\partial E_{it}} > 0$). 2) "Crowding-out" effect exists as $\frac{\partial q^{NM}}{\partial E_{it}} < 0$. Moreover, corresponding to the evidence that physician supply respond negatively to Medicaid expansions within border counties, Table A.13 shows that these pregnant women actually become less likely to use Medicaid benefits and do not increase total amount of care use after Medicaid/CHIP eligibility expanded, exclusively in these border counties.

6.7 Discussion: Workforce Distribution and Medicaid/CHIP Eligibility Expansions

Given limited patient-level data, this study is constrained in providing a comprehensive welfare calculation. However, Figure 12 illustrates changes in the distribution of the

[21] The limitation of using AFC data is that it covers mainly primary care and family medicine clinicians. However, when related to women's health, an OB-GYN can be regarded as a primary care doctor and AFC does include a fair amount of OB visits. Moreover, Medicaid covers pregnant women's all necessary use of care, not just pregnancy-related visits.

OB-GYN workforce before and after Medicaid/CHIP Eligibility Expansions, comparing non-border and border counties. As the supply and mobility of OB-GYNs in state border areas are affected by Medicaid/CHIP eligibility expansions in unintended ways that the total number of county OB-GYNs reduces following eligibility expansions as OB-GYNs move towards lower income eligibility across state borders. In Figure 12(a), the share of counties with an extremely low number of OB-GYNs decreases with Medicaid/CHIP eligibility expansions among non-border counties. Conversely, in Figure 12(b), among border counties, it might even slightly increase after the income eligibility becomes more generous. This comparison between non-border and border counties suggests possible different welfare implications of Medicaid/CHIP eligibility expansions within different ranges of local healthcare markets.

(Figure 12 here)

7 Conclusion

This paper is among the first to investigate provider-side response to Medicaid eligibility expansion with a particular focus on physician relocation decision. Different from programs that merely expand the scope of services covered by Medicaid (Buchmueller et al., 2016; Huh, 2021), Medicaid/CHIP eligibility extensions broaden the pool of people eligible for Medicaid benefits. This expansion affects both the number of patients and the level of care they receive per patient when income eligibility is extended. It's worth noting that these expansions target mid-low-income individuals, who may rely on employer-sponsored insurance rather than being uninsured. Research, including the patient-level evidence in this study and prior work (Cutler & Gruber, 1996a,b, 1997; Gruber & Simon, 2008; Barnes et al., 2020; Bellerose et al., 2022) suggests that the shift from private to public insurance, known as "crowding-out," can potentially discourage healthcare providers from offering services due to the limited Medicaid reimbursement rates.

Taking into account the multi-dimensional incentives created by Medicaid/CHIP eligibility expansions — increased demand among Medicaid patients and altered payments due to private patients switching to Medicaid — this paper formalizes how physicians adapt their practice locations to changes in Medicaid eligibility criteria. Four theoretical predictions together demonstrate that if Medicaid expansions generate a substantial demand increase, particularly in mid-low income counties, physician supply can respond positively as some doctors relocate towards the newly eligible population. However, when physicians have the flexibility to choose from multiple markets with different eligibility thresholds, they tend to practice in states with lower eligibility but a higher proportion of private patients to maximize their profits unless local demand growth resulting from

Medicaid expansions is significant.

Following the conceptual framework, I estimate the impact of Medicaid/CHIP eligibility for pregnant women on the supply and relocation of OB-GYNs at the county level. My empirical findings highlight the trade-off faced by physicians and provide clear support for the predictions. In summary, increasing Medicaid/CHIP eligibility by 10% of the federal threshold results in a 0.3 percentage points increase in the number of OB-GYNs per 100,000 population in a county. Alternatively, covering 1 percentage point more women of reproductive age increases the number of OB-GYNs per 100,000 population by 0.2 percentage points. This positive association between Medicaid/CHIP eligibility for pregnant women and the supply of OB-GYNs is most pronounced in mid-low income counties, where the largest share of the population becomes newly Medicaid eligible and sees a concentration of OB-GYNs. However, the analysis of border counties reveals a decrease in the number of OB-GYNs in counties with higher eligibility along the same state border. As the demand increase resulting from new Medicaid enrollees does not necessarily offset the negative profit reduction due to "crowding-out" in every counties, physicians in border counties, on average, relocate to areas with lower eligibility to serve more private patients.

This study sheds light on the significant policy implications of Medicaid expansions. While the aim of Medicaid expansions is to enhance access to care and improve health outcomes among low-income and disadvantaged populations, a positive supply-side response can help achieve these policy goals and enhance social welfare. However, being a state-level policy, the mobility of physicians across state boundaries, disparities in Medicaid eligibility, and low Medicaid reimbursement rates collectively contribute to unintended consequences arising from Medicaid expansions. In specific cases, such as in state border areas, these expansions have the potential to reduce access to care for Medicaid beneficiaries since they are restricted to using Medicaid benefits only within their own state.

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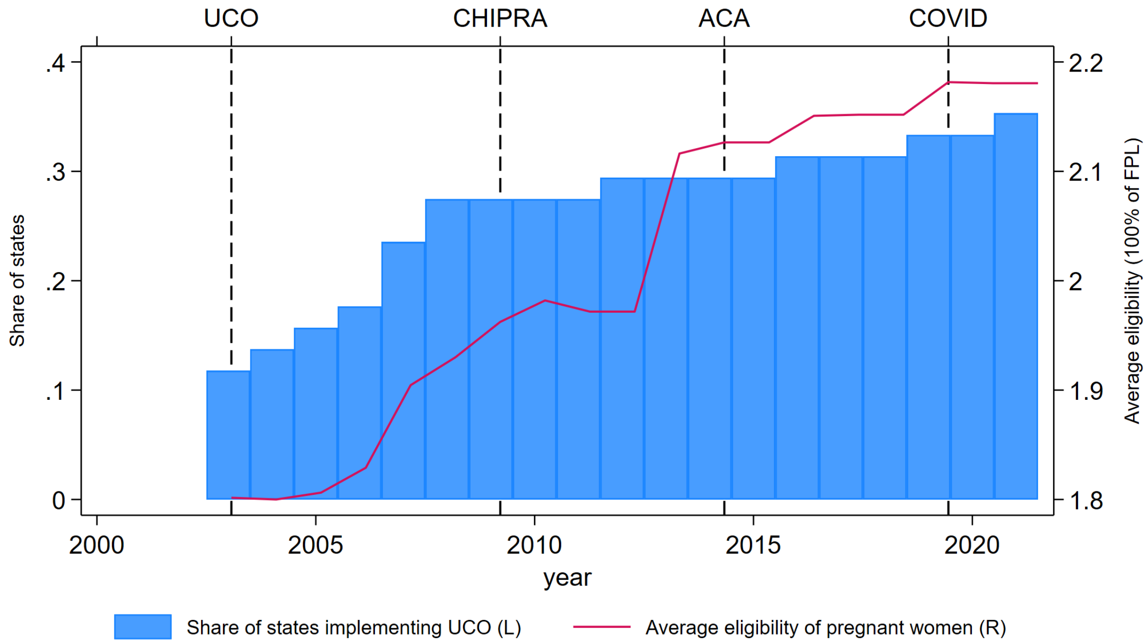
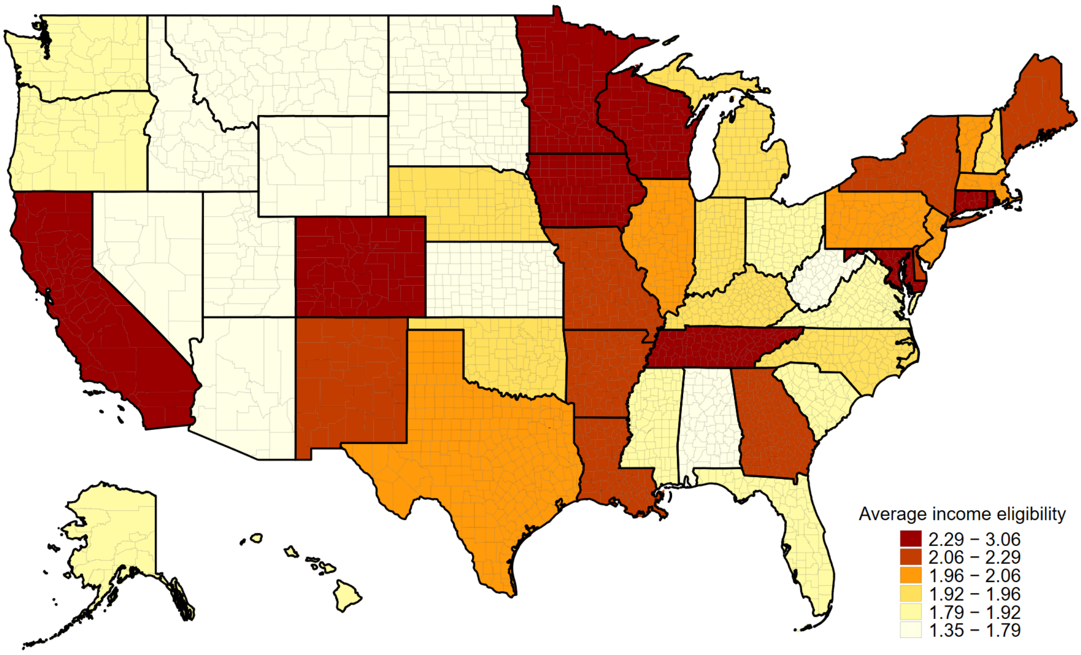
Figure 1: Medicaid/CHIP coverage for pregnant women over time



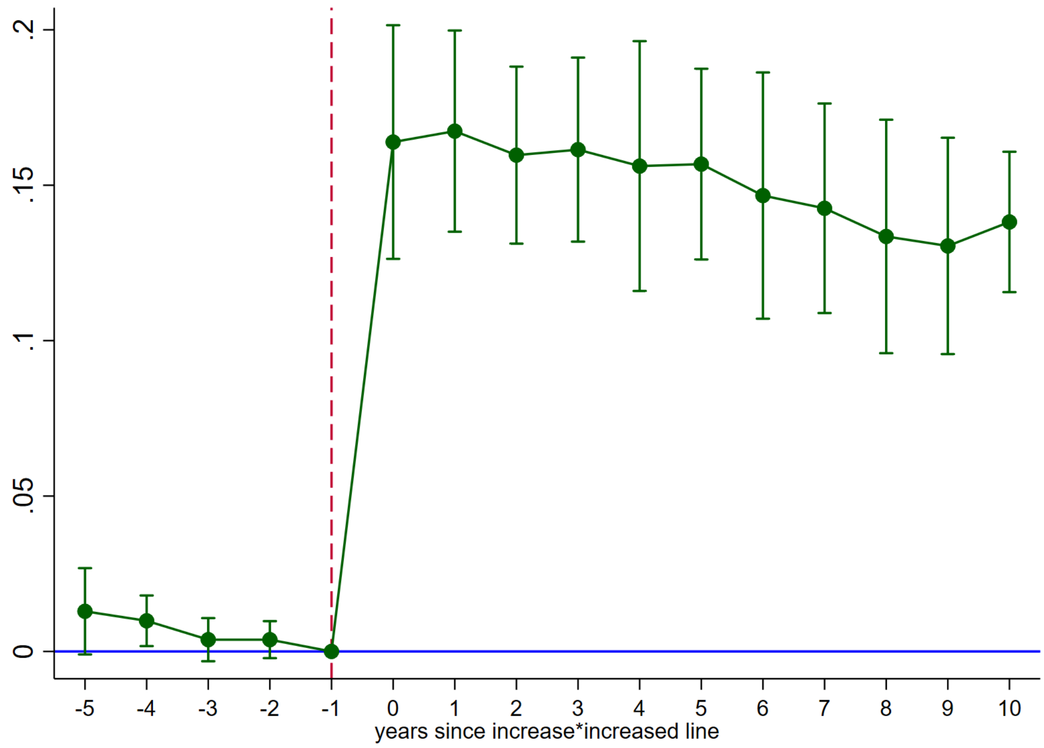
Notes: This figure describes how states expand Medicaid/CHIP coverage for pregnant women. The line plots the yearly average income eligibility (right axis) while the bars show the share of states that have adopted the Unborn Child Option (left axis).

Figure 2: Geographical variation in state Medicaid/CHIP eligibility for pregnant women



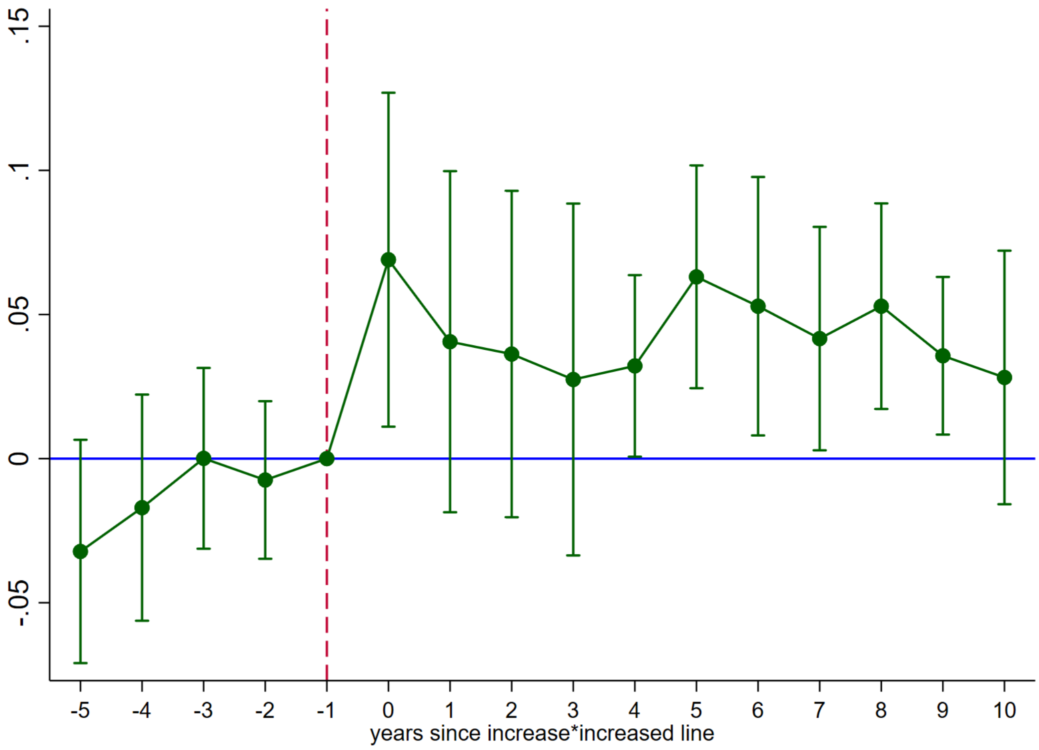
Notes: This figure presents the state level average Medicaid eligibility for pregnant women from 2003 to 2022. The darker the state is, the higher eligibility this state has. For example, in the highest group, the average state Medicaid/CHIP eligibility ranges from 229% to 306% of the FPL.

Figure 3: Effect of Medicaid/CHIP eligibility on state fraction eligible among women (15-44)



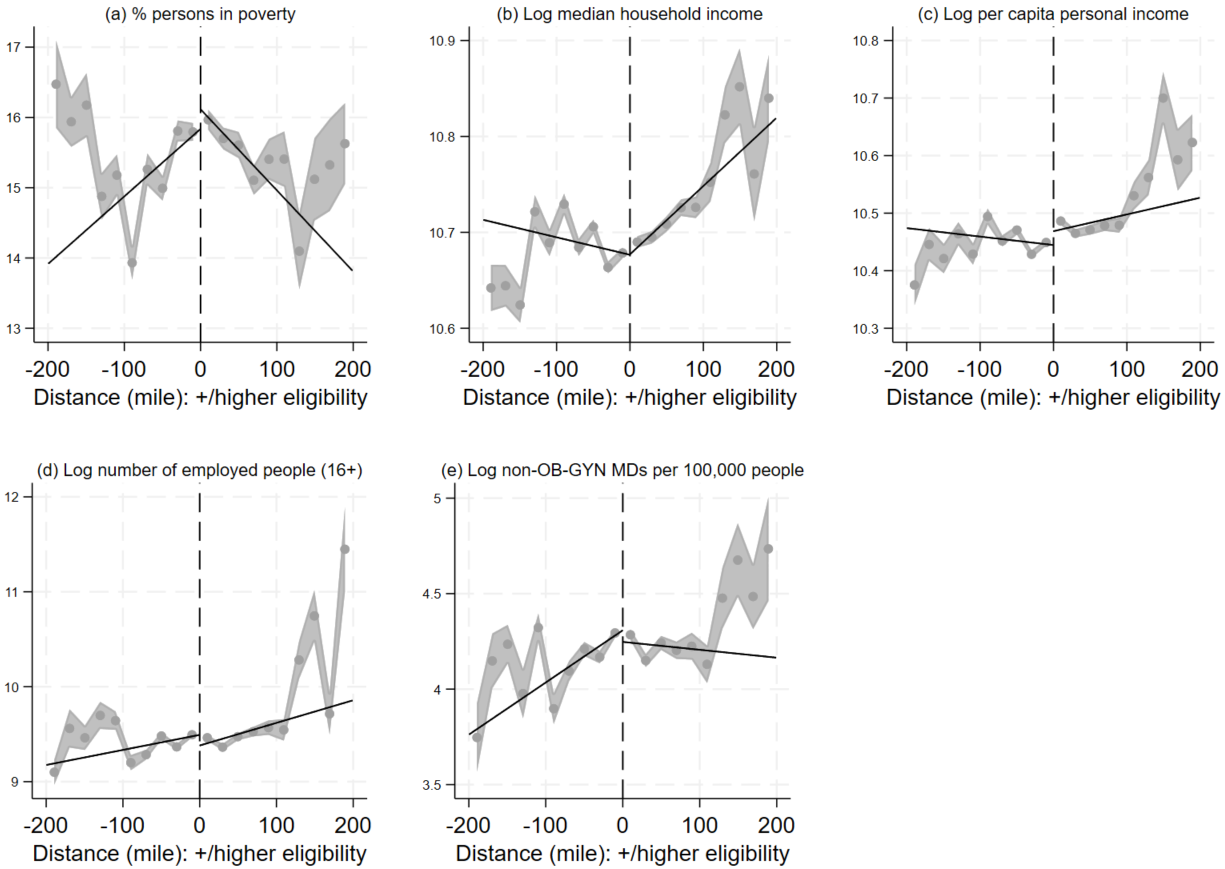
Notes: This figure presents the event-study plot of the effect of Medicaid/CHIP eligibility expansion on state fraction eligible among women (15-44). State fraction eligible among women (15-44) is calculated using the ACS sample (2003-2020). State yearly characteristics come from AHRF (2001-2020). State-yearly controls include poverty rate, log median household income, log per capita income, and log total employment. State and year fixed effects are controlled for. Standard errors are clustered at census division level and presented with 95% confidence intervals.

Figure 4: Effect of Medicaid/CHIP eligibility on the supply of OB-GYNs



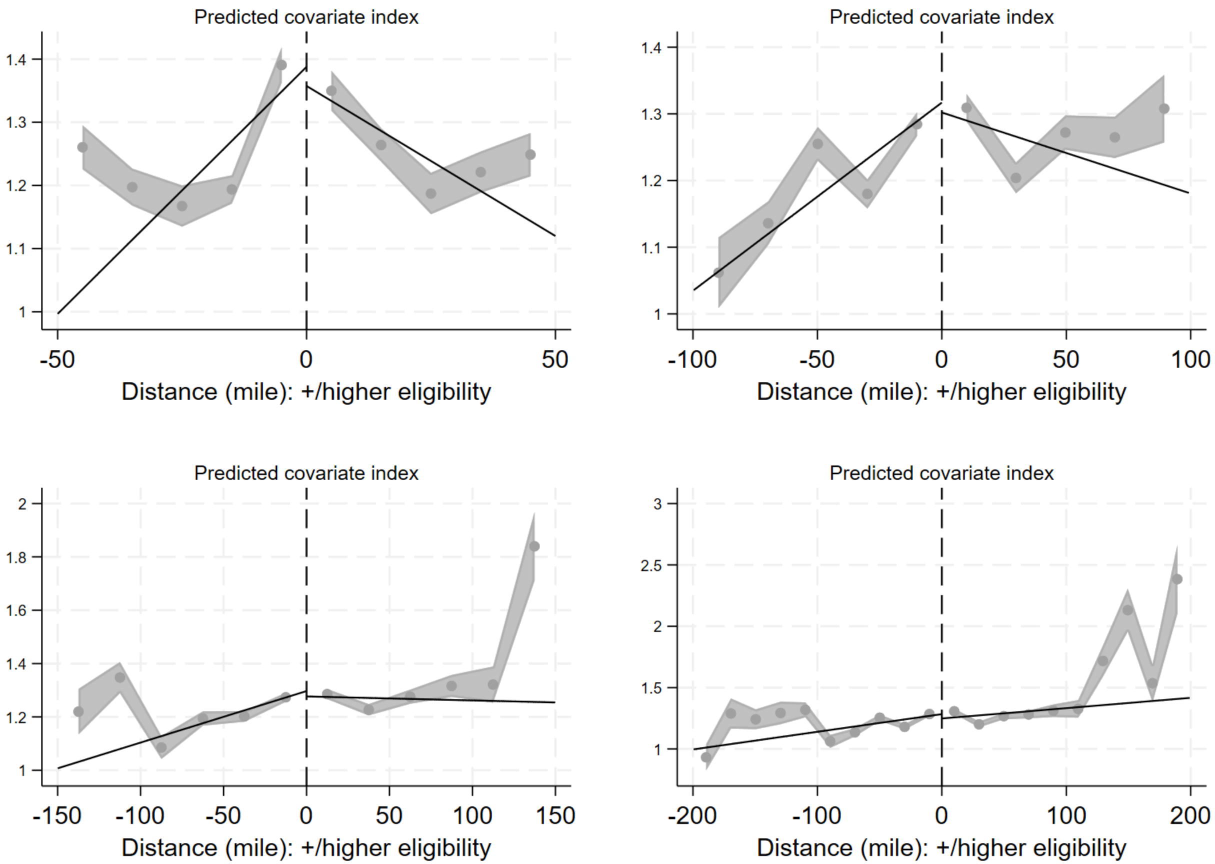
Notes: This figure presents the event-study plot of the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level and presented with 95% confidence intervals.

Figure 5: Discontinuity in county yearly covariates



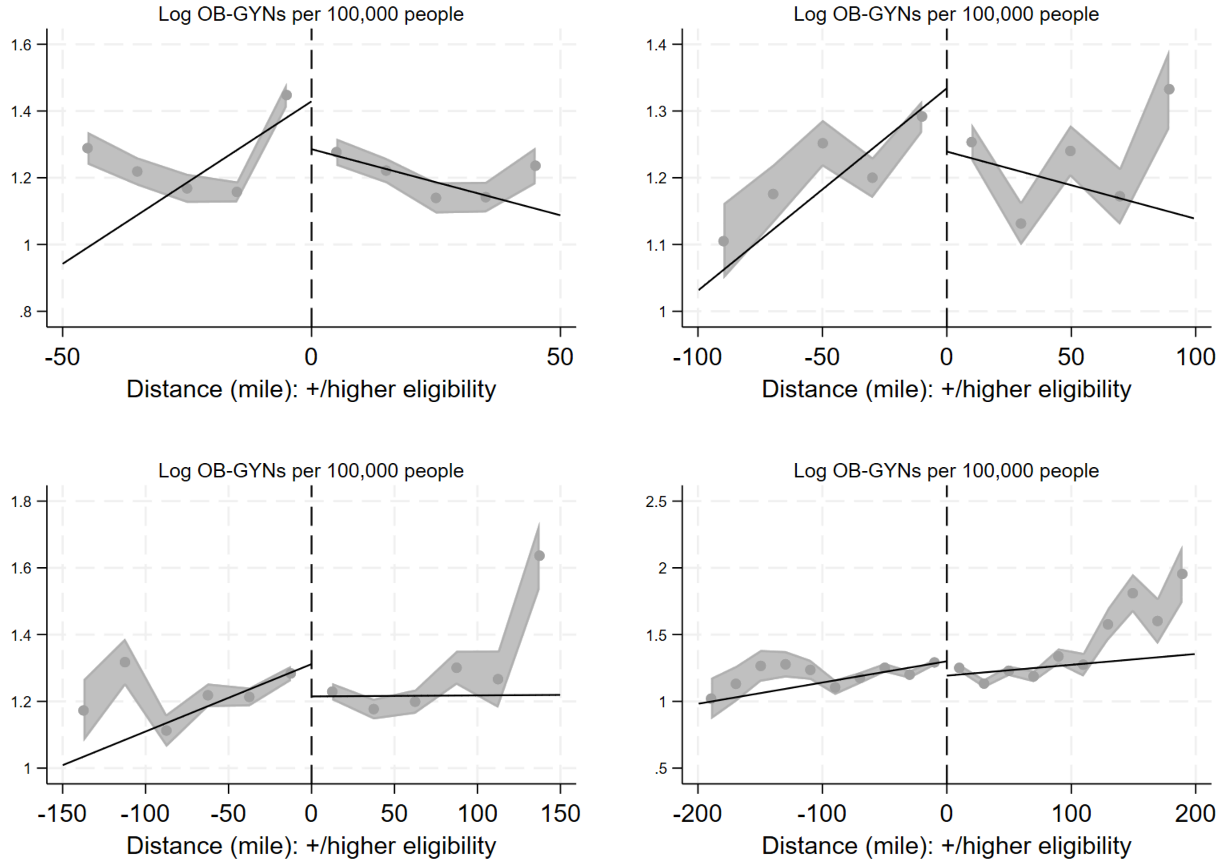
Notes: This figure plots binned means of county yearly covariates conditional on year and state fixed effects within 10-mile bins with 95 percent confidence intervals displayed. The solid line represents the fitted values for a local linear regression on each side. The bandwidth is 200 miles. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County time-variant characteristics are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people.

Figure 6: Discontinuity in "covariate index" within various bandwidths



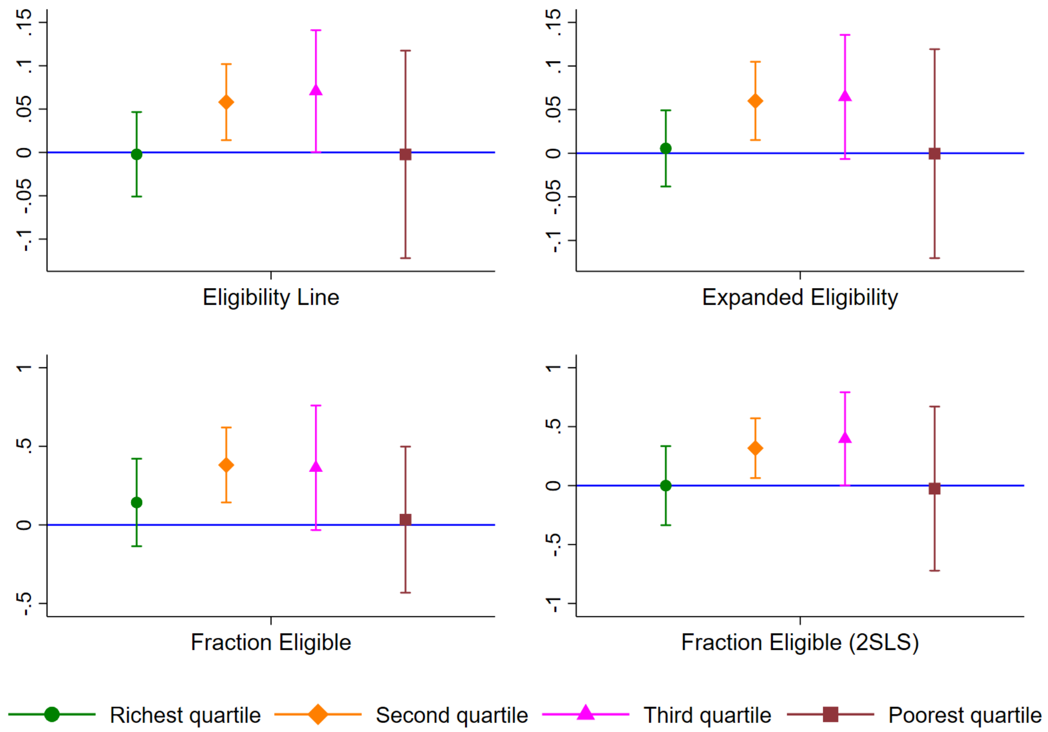
Notes: This figure plots binned means of the "covariate index" conditional on year and state fixed effects with 95 percent confidence intervals displayed. The solid line represents the fitted values for a local linear regression on each side. The bandwidths are 50, 100, 150 and 200 miles with respective numbers of bins. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). "Covariate index" is the predicted outcome from a simple regression of the log total number of OB-GYNs per 100,000 people on the set of covariates. County time-variant covariates are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people.

Figure 7: Discontinuity in the supply of OB-GYNs within various bandwidths



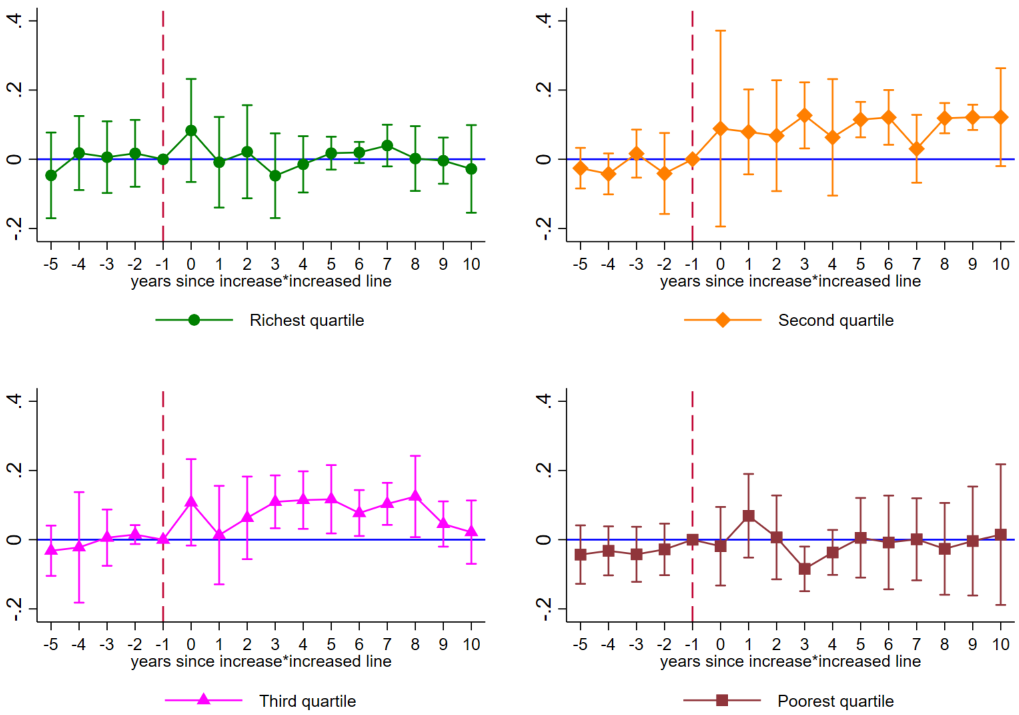
Notes: This figure plots binned means of log total number of OB-GYNs per 100,000 population conditional on year and state fixed effects with 95 percent confidence intervals displayed. The solid line represents the fitted values for a local linear regression on each side. The bandwidths are 50, 100, 150 and 200 miles with respective numbers of bins. County total number of physicians by specialty per 100,000 population comes from the AHRF (2001-2020).

Figure 8: Effect of Medicaid/CHIP eligibility on the supply of OB-GYNs: by poverty rate (DID and 2SLS)



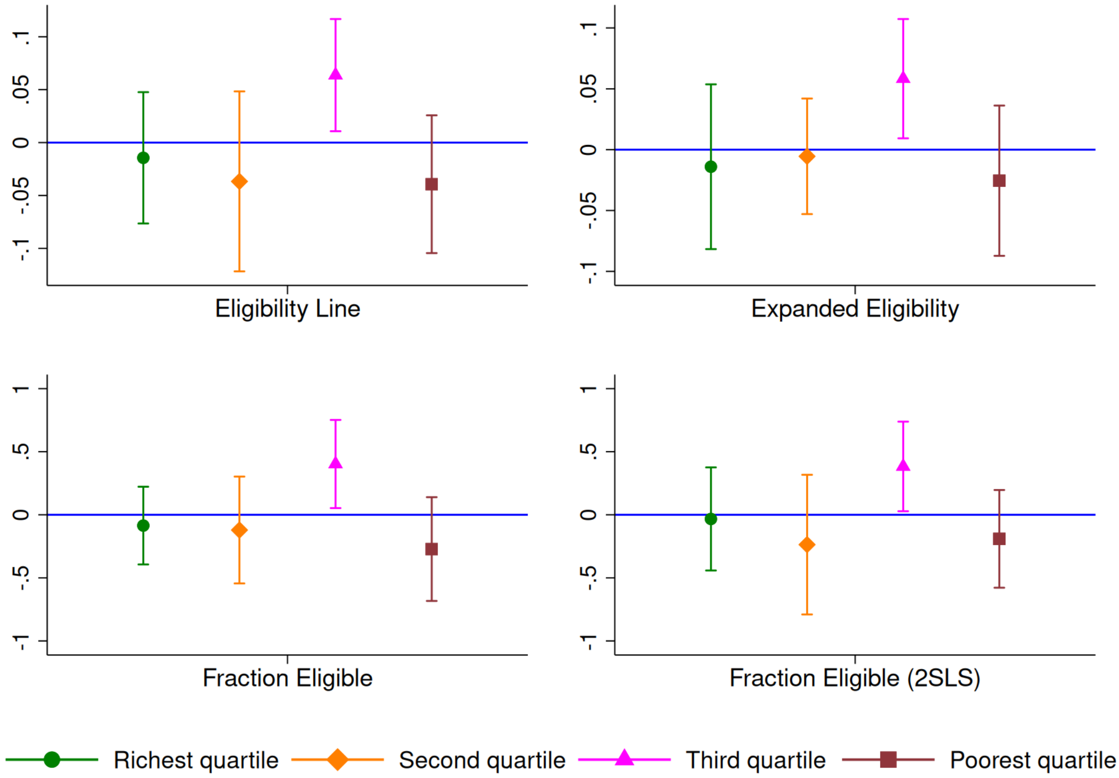
Notes: This figure plots the coefficients of the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population by county level poverty rate. All four estimators in Table 2 are reported. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level and presented with 95% confidence intervals.

Figure 9: Effect of Medicaid/CHIP eligibility on the supply of OB-GYNs: by poverty rate (Event Study)



Note: This figure presents the event-study plot of the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population by county level poverty rate. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level and presented with 95% confidence intervals.

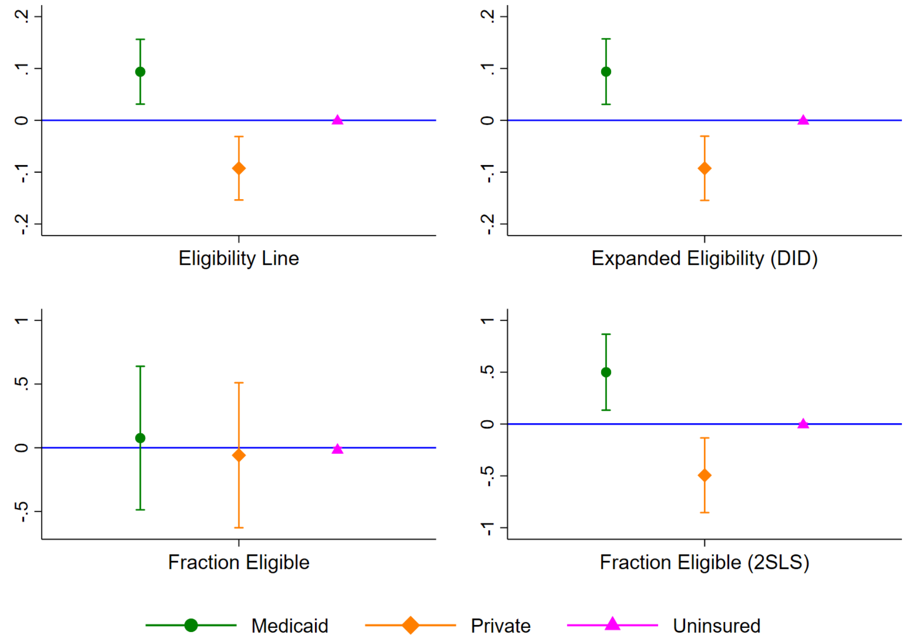
Figure 10: Effect of Medicaid/CHIP eligibility on OB-GYN NPIs' yearly moving-in from other in-state counties: by poverty rate (DID and 2SLS)



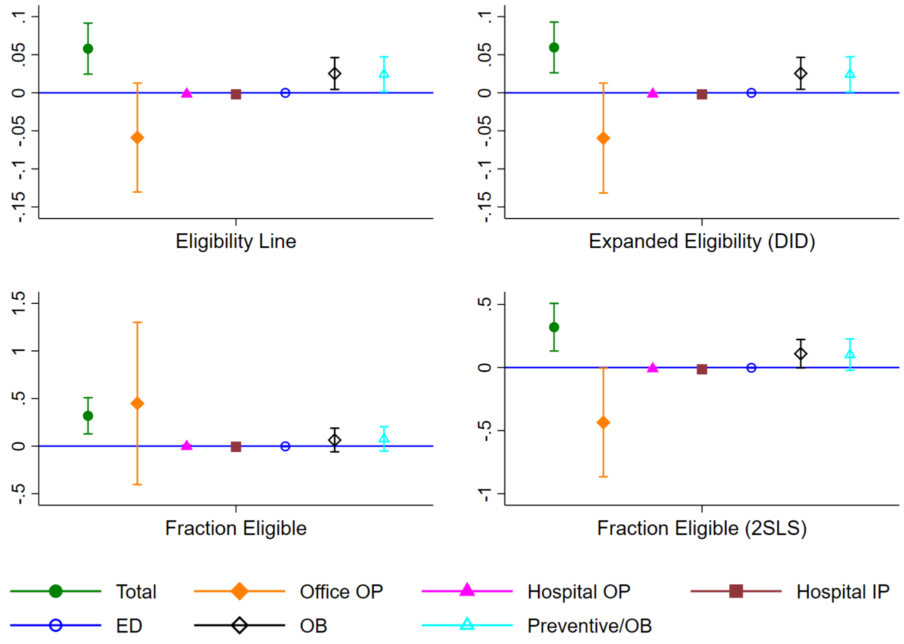
Notes: This figure plots the coefficients of the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYN NPIs' yearly moving-in from other in-state counties per 100,000 population by county level poverty rate. All four estimators in Table 2 are reported. NPI practice addresses come from the NPPES (2001-2023). County time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. County and year fixed effects are controlled for. Standard errors are clustered at state level and presented with 95% confidence intervals.

Figure 11: Effect of Medicaid/CHIP eligibility on pregnant women's insurance status and healthcare utilization

(a) An indicator of insurance status per patient per month



(b) Log number of care in total and by category

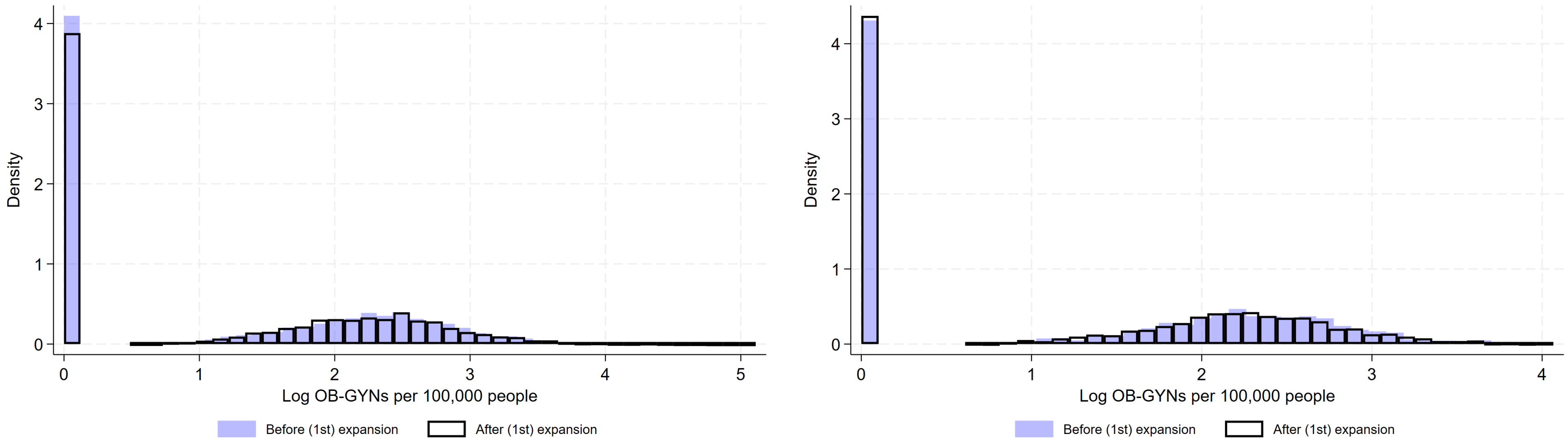


Note: This figure plots the coefficients of the effect of Medicaid/CHIP eligibility expansion on patient level outcomes using a pregnant women sample. Patient outcomes and demographics come from the AFC (2001-2023). County time-variant characteristics come from the AHRF (2001-2020). All four estimators in Table 2 are reported. County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. Individual level controls include race and birth year fixed effects. Insurance status indicators are controlled in Panel (b). County, visit calender month, and visit year fixed effects are controlled for. Standard errors are clustered at state level and presented with 95% confidence intervals.

Figure 12: OB-GYN Workforce Distribution Before and After Medicaid/CHIP Eligibility Expansion for Pregnant Women

(a) Non-border Counties

(b) Border Counties



Note: This figure displays histograms of the log county total number of OB-GYNs per 100,000 population before and after the (1st) expansion year of Medicaid/CHIP eligibility for pregnant women, comparing non-border and border counties.

Table 1: County-year level summary statistics

(a) Area Health Resource File (2001-2020)

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled N=59,686		Non-border counties N=37,191		Border counties N=22,495	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
# of OB-GYNs/100,000 pop	5.86	8.18	5.87	8.62	5.84	7.40
# of resident OB-GYNs/100,000 pop	0.34	1.53	0.37	1.68	0.30	1.26
# of office OB-GYNs/100,000 pop	4.87	6.65	4.89	7.00	4.83	6.03
# of hospital OB-GYNs/100,000 pop	0.53	1.48	0.48	1.46	0.59	1.51
# of midwifes/100,000 pop	1.26	3.23	1.24	3.35	1.29	3.02
# of non-OB-GYN MDs/100,000 pop	118.89	152.06	118.89	167.52	118.91	122.29
% persons in poverty	15.41	6.23	15.42	6.17	15.38	6.34
Household median income ($)	44,826	13,157	44,907	12,949	44,692	13,494
Income per capita ($)	35,590	12,074	35,474	11,789	35,779	12,523
Total employment (16+)	46,168	149,095	46,511	161,567	45,602	125,801

(b) NPPES (2007-2023): individual OB-GYN NPIs

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled N=24,032		Non-border counties N=14,517		Border counties N=9,515	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Total #/100,000 pop	11.87	10.60	12.12	11.66	11.47	8.74
# of yearly in-state moving-in/100,000 pop	0.18	0.93	0.20	1.03	0.15	0.76
# of yearly across-border moving-out/100,000 pop	0.03	0.30	0.02	0.30	0.05	0.31

Notes: This table presents county-year level summary statistics for the pooled sample, non-border counties, and border counties. Panel (a) summarizes the county-year level number of physicians by specialty and category and main socioeconomic characteristics that come from the AHRF (2001-2020). Data for midwives with NPIs in the AHRF is available from 2010 onwards. While Panel (b) summarizes the county level individual OB-GYN NPIs' total number, in-state and across-border movements, using the NPPES data (2007-2023).

Table 2: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs

	(1)	(2)	(3)	(4)
	Log OB-GYNs per 100,000 people			
Eligibility line	0.030**			
	(0.009)			
Expanded eligibility (DID)		0.031***		
		(0.007)		
Fraction eligible			0.201***	
			(0.057)	
Fraction eligible (2SLS)				0.163**
				(0.054)
Observations	52,893	52,568	52,893	52,893
R-squared	0.580	0.580	0.580	0.506
First-stage F statistics				525.50

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population. The independent variable in Column (1) is the actual eligibility limit, in Column (2) is the expanded eligibility, in Column (3) is the actual eligible fraction calculated using ACS sample, and in Column (4) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 3: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: Multidimensional RD

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
	Border RD				Donut RD			
Bandwidth	<=50 miles	<=100 miles	<=150 miles	<=200 miles	50-400 miles	100-400 miles	150-400 miles	200-400 miles
Higher line	-0.071	-0.078*	-0.081*	-0.080*	-0.067	0.047	0.204	0.190
	(0.039)	(0.038)	(0.041)	(0.041)	(0.090)	(0.157)	(0.138)	(0.127)
Observations	34,237	47,259	50,115	51,271	18,411	5,389	2,533	1,377
R-squared	0.166	0.153	0.155	0.157	0.190	0.304	0.344	0.284

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population using equation (12). County total number of physicians by specialty per 100,000 population comes from the AHRF (2001-2020). Quadratic polynomial in latitude and longitude, state and year fixed effects are controlled for. Standard error clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 4: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: by MUA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
	MUA	Non-MUA	MUA	Non-MUA	MUA	Non-MUA	MUA	Non-MUA
Eligibility line	0.033**	0.034						
	(0.010)	(0.032)						
Expanded eligibility (DID)			0.035***	0.030				
			(0.010)	(0.035)				
Fraction eligible					0.228***	0.106		
					(0.044)	(0.225)		
Fraction eligible (2SLS)							0.186**	0.171
							(0.062)	(0.182)
Observations	42,821	10,072	42,563	10,005	42,821	10,072	42,821	10,072
R-squared	0.589	0.575	0.590	0.575	0.589	0.575	0.510	0.482
First-stage F statistics							453.01	971.30

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population by MUA designation. The independent variable in Columns (1) and (2) is the actual eligibility limit, in Columns (3) and (4) is the expanded eligibility, in Columns (5) and (6) is the actual eligible fraction calculated using ACS sample, and in Columns (7) and (8) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 5: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: by state Medicaid-to-Medicare Fee Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
	Higher	Lower	Higher	Lower	Higher	Lower	Higher	Lower
Eligibility line	0.073**	-0.028						
	(0.023)	(0.036)						
Expanded eligibility (DID)			0.081***	-0.028				
			(0.019)	(0.036)				
Fraction eligible					0.433**	-0.084		
					(0.164)	(0.176)		
Fraction eligible (2SLS)							0.436**	-0.166
							(0.162)	(0.211)
Observations	25,751	25,527	25,426	25,527	25,751	25,527	25,751	25,527
R-squared	0.564	0.598	0.564	0.598	0.564	0.598	0.494	0.521
First-stage F statistics							121.87	2449.32

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population by state Medicaid-to-Medicare Fee Index. Higher VS lower reimbursement rate is defined based on the Medicaid-to-Medicare Fee Index (Zuckerman et al., 2021). The independent variable in Columns (1) and (2) is the actual eligibility limit, in Columns (3) and (4) is the expanded eligibility, in Columns (5) and (6) is the actual eligible fraction calculated using ACS sample, and in Columns (7) and (8) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 6: Effect of Medicaid/CHIP eligibility for pregnant women on OB-GYN NPIs' yearly moving-out across state borders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log OB-GYN NPIs' moving-out across state borders per 100,000 people									
	All		IMLC states since 2015		Non-IMLC states and years		Lower poverty rate		Higher poverty rate	
Higher line	0.009**		0.023*		-0.001		0.015***		-0.002	
	(0.003)		(0.012)		(0.007)		(0.006)		(0.009)	
Gap of line		-0.001		0.031***		-0.016**		0.010		-0.004
		(0.006)		(0.004)		(0.007)		(0.007)		(0.009)
Observations	18,556	18,556	6,145	6,145	12,406	12,406	10,368	10,368	8,112	8,112
R-squared	0.293	0.293	0.395	0.395	0.354	0.354	0.402	0.402	0.484	0.484

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log OB-GYN NPIs' yearly moving-out across state borders per 100,000 people, using a within border comparison updated from equation (8), which replaces year fixed effect with a borderline-year fixed effect. NPI practice addresses come from the NPPES (2001-2023). County time-variant characteristics come from the AHRF (2001-2020). Counties bordering multiple counties are duplicated to the number of pairs. County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. County and year fixed effects are controlled for. Standard errors are clustered at state level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 7: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: by market competition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Prob (reaching a given number of OB-GYNs per 100,000 population (sample mean:5.86))											
	Above 0	Above 5	Above 10	Above 0	Above 5	Above 10	Above 0	Above 5	Above 10	Above 0	Above 5	Above 10
Eligibility line	0.012**	0.015**	-0.004									
	(0.005)	(0.005)	(0.007)									
Expanded eligibility (DID)				0.012**	0.016***	-0.004						
				(0.004)	(0.004)	(0.007)						
Fraction eligible							0.055*	0.102***	0.021			
							(0.028)	(0.021)	(0.030)			
Fraction eligible (2SLS)										0.058*	0.085**	-0.009
										(0.026)	(0.029)	(0.037)
Observations	52,893	52,893	52,893	52,568	52,568	52,568	52,893	52,893	52,893	52,893	52,893	52,893
R-squared	0.513	0.451	0.368	0.513	0.451	0.367	0.513	0.451	0.368	0.421	0.382	0.319
First-stage F statistics										525.50	525.50	525.50

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on the probability of that the county total number of OB-GYNs per 100,000 population is above 0, 5, and 10. The independent variable in Columns (1) to (3) is the actual eligibility limit, in Columns (4) to (6) is the expanded eligibility, in Columns (7) to (9) is the actual eligible fraction calculated using ACS sample, and in Columns (10) to (12) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 8: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: by population size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
					Log OB-GYNs per 100,000 people)							
	Small	Middle	Large	Small	Middle	Large	Small	Middle	Large	Small	Middle	Large
Eligibility line	0.039	0.064**	-0.003									
	(0.027)	(0.024)	(0.029)									
Expanded eligibility (DID)				0.039	0.063**	-0.006						
				(0.027)	(0.026)	(0.029)						
Fraction eligible							0.231	0.269*	0.002			
							(0.151)	(0.142)	(0.156)			
Fraction eligible (2SLS)										0.227	0.313*	-0.025
										(0.147)	(0.136)	(0.171)
Observations	22,083	14,346	16,464	21,931	14,257	16,380	22,083	14,346	16,464	22,083	14,346	16,464
R-squared	0.137	0.455	0.751	0.137	0.454	0.750	0.137	0.455	0.751	0.087	0.407	0.732
First-stage F statistics										599.15	669.86	347.62

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population by county population size. Counties are categorized into "Small," "Middle," and "Large" based on population thresholds: 20,000 and 50,000 people. The independent variable in Columns (1) to (3) is the actual eligibility limit, in Columns (4) to (6) is the expanded eligibility, in Columns (7) to (9) is the actual eligible fraction calculated using ACS sample, and in Columns (10) to (12) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 9: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: by share of non-Hispanic white

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
	Minority	White	Minority	White	Minority	White	Minority	White
Eligibility line	0.042*	0.017						
	(0.019)	(0.017)						
Expanded eligibility (DID)			0.041*	0.020				
			(0.020)	(0.015)				
Fraction eligible					0.262**	0.151*	0.282**	0.082
					(0.090)	(0.077)	(0.121)	(0.100)
Fraction eligible (2SLS)								
Observations	26,275	26,618	26,011	26,557	26,275	26,618	26,275	26,618
R-squared	0.627	0.504	0.628	0.504	0.627	0.504	0.557	0.396
First-stage F statistics							101.11	2417.70

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population by county population share of non-Hispanic white. Counties with shares of the non-Hispanic white population lower than the national level are categorized as the "Minority" group; otherwise, as the "White" group. Columns (1), (3), (5), and (7) are counties where the share of non-Hispanic white population is lower than the national level. The independent variable in Columns (1) to (2) is the actual eligibility limit, in Columns (3) to (4) is the expanded eligibility, in Columns (5) to (6) is the actual eligible fraction calculated using ACS sample, and in Columns (7) to (8) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table 10: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: by 2010 census share of urban population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Log OB-GYNs per 100,000 people)											
	Low	Middle	High	Low	Middle	High	Low	Middle	High	Low	Middle	High
Eligibility line	0.022	0.092***	-0.007									
	(0.027)	(0.019)	(0.012)									
Expanded eligibility (DID)				0.025	0.091***	-0.010						
				(0.024)	(0.019)	(0.012)						
Fraction eligible							0.212*	0.347*	-0.030			
							(0.102)	(0.164)	(0.074)			
Fraction eligible (2SLS)										0.109	0.478***	-0.039
										(0.161)	(0.133)	(0.079)
Observations	20,583	16,507	15,786	20,440	16,417	15,697	20,583	16,507	15,786	20,583	16,507	15,786
R-squared	0.274	0.469	0.648	0.274	0.468	0.647	0.274	0.468	0.648	0.129	0.364	0.570
First-stage F statistics										503.35	860.82	340.96

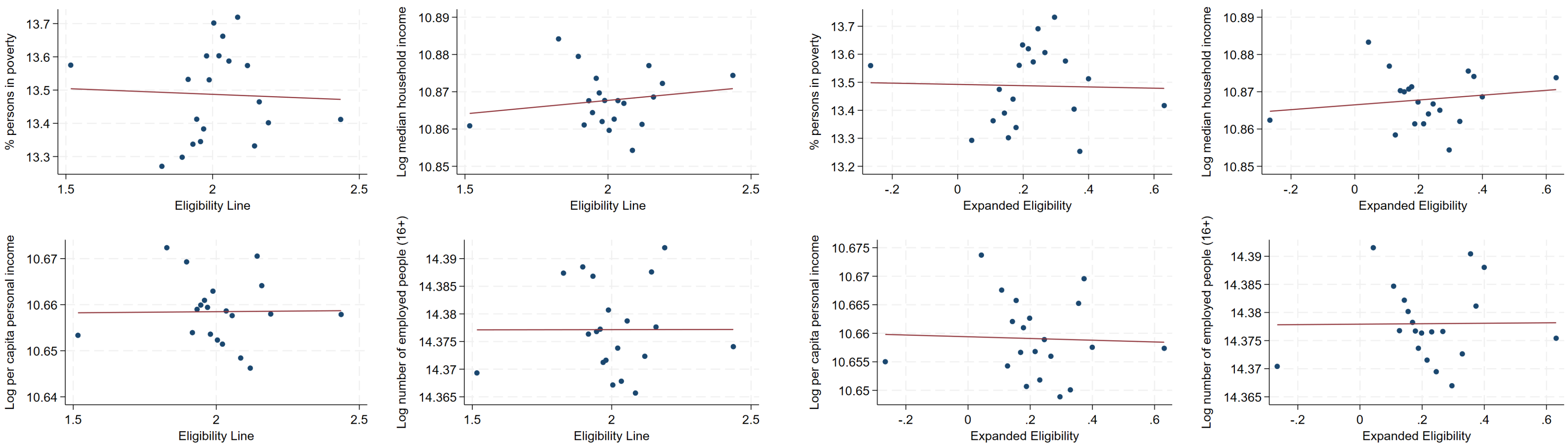
Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population by county share of urban population in 2010 census. “Low”, “Middle”, and “High” urbanized counties are defined based on thresholds of urban population share: 30% and 60%, according to the 2010 census. The independent variable in Columns (1) to (3) is the actual eligibility limit, in Columns (4) to (6) is the expanded eligibility, in Columns (7) to (9) is the actual eligible fraction calculated using ACS sample, and in Columns (10) to (12) is the actual eligible fraction that is instrumented by the “simulated eligible fraction”. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Appendix A

Figure A.1: Medicaid/CHIP eligibility and state yearly characteristics

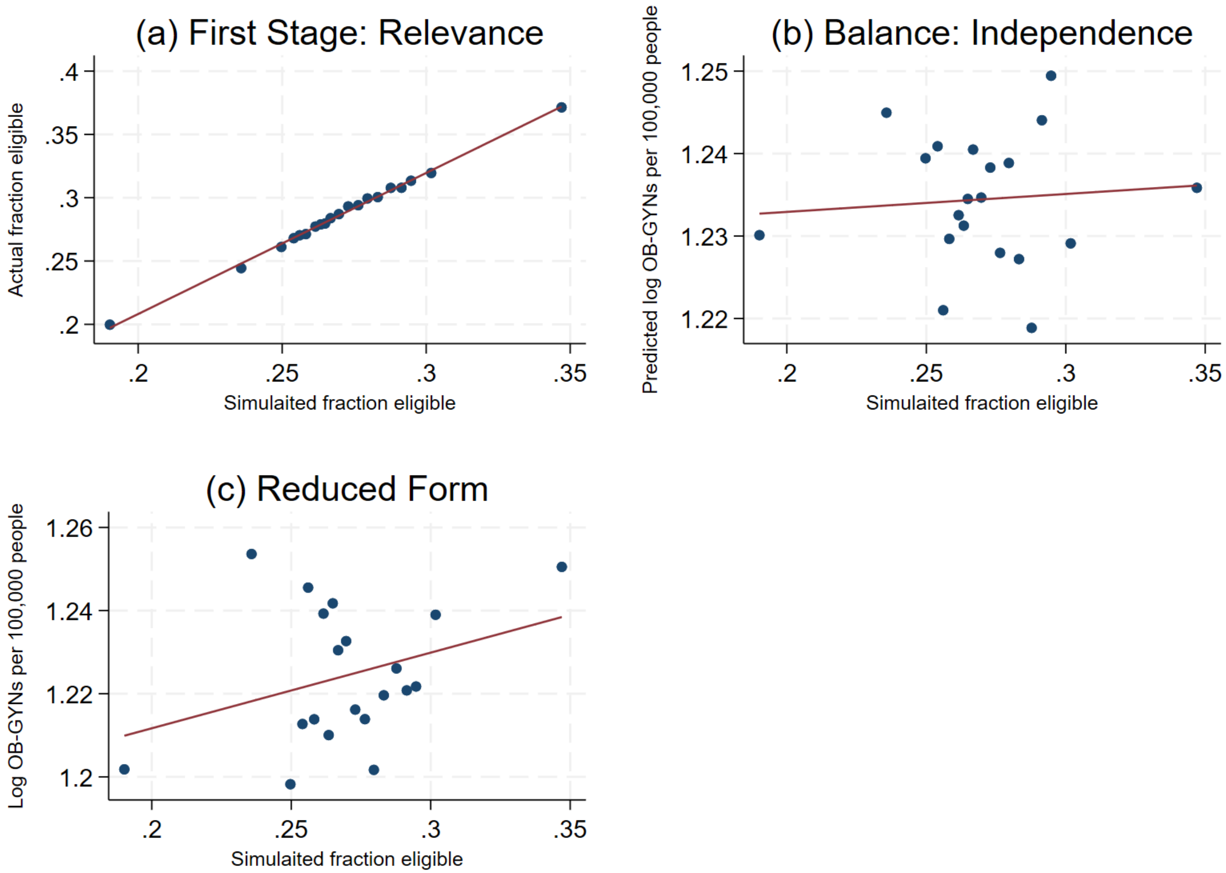
(a) Absolute eligibility and state yearly characteristics

(b) Expanded eligibility and state yearly characteristics



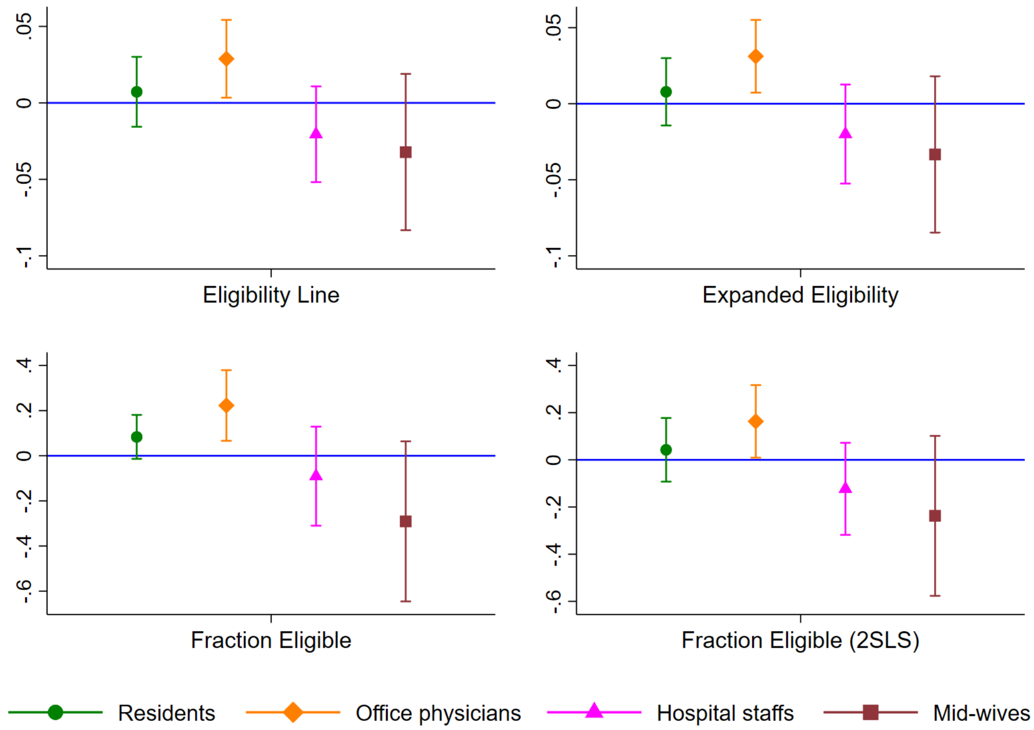
Note: Panel (a) shows binned scatter plots of each state yearly against the absolute level of Medicaid/CHIP income eligibility. Panel (b) replaces the absolute eligibility with the expanded eligibility from the level in the (1^{st}) expansion year. In each figure, both variables on the x- and y-axis are residualized conditional on state and year fixed effects.

Figure A.2: Relevance, independence, and reduced form



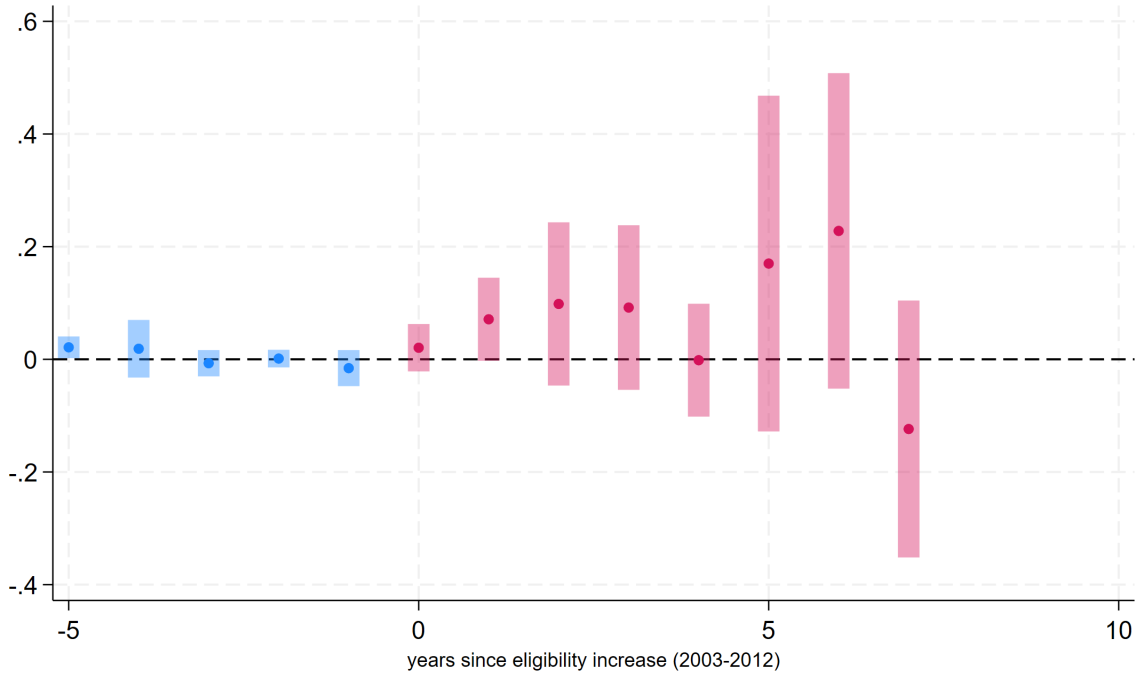
Notes: This figure presents the binned scatter plot for relevance, independence, and reduced form of IV estimation. Panel (a) is the visual representation of the first-stage estimate using equation (10). It shows the binned scatter plot between the actual fraction eligible and the simulated fraction eligible. Panel (b) is the binned scatter plot of predicted log total number of OB-GYNs per 100,000 population against the simulated fraction eligible. Predicted log total number of OB-GYNs per 100,000 population is obtained by regressing log total number of OB-GYNs per 100,000 population on county poverty rate, log median household income, log per capita income, and log total employment, while all the rest control variables in equation (9) including fixed effects are covariates in Panel (b). Panel (c) shows a binned scatter plot of log number of OB-GYNs per 100,000 people against simulated fraction eligible as a graphical representation of the reduced form regression.

Figure A.3: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: by category



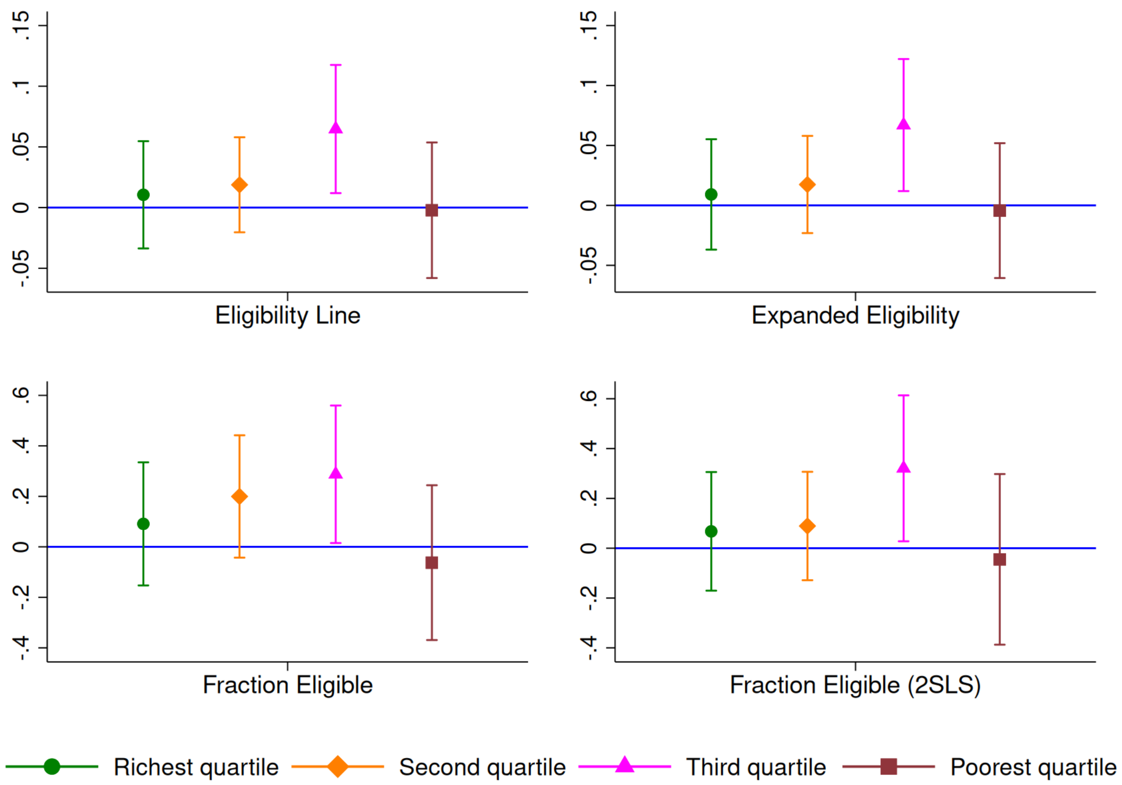
Notes: This figure plots the coefficients of the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs in each sub-group per 100,000 population. The sub-group OB-GYN categories are residents, office physicians, and hospital staffs. I also estimate the effect on mid-wives who are substitute of MDs. All four estimators in Table 2 are reported. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020).County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level and presented with 95% confidence intervals.

Figure A.4: Effect of Medicaid/CHIP eligibility on the supply of OB-GYN: before 2013 (Callaway & Sant'Anna, 2021)



Notes: This figure plots the Callaway & Sant'Anna (2021) event study estimates of the effect of Medicaid/CHIP eligibility expansion on log county total number of individual OB-GYN NPIs per 100,000 population by county level poverty rate, for all years before 2013. The estimation automatically drops years beyond 2013 due to the absence of time variation in treatment. The final year of the state level first expansion occurred in 2013. County total number of individual OB-GYN NPIs come from NPPES (2007-2023). County time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. County and year fixed effects are controlled for. Standard errors are clustered at state level and presented with 95% confidence intervals.

Figure A.5: Effect of Medicaid/CHIP eligibility on the supply of OB-GYN NPIs: by poverty rate (DID and 2SLS)



Notes: This figure plots the coefficients of the effect of Medicaid/CHIP eligibility expansion on log county total number of individual OB-GYN NPIs per 100,000 population by county level poverty rate. All four estimators in Table 2 are reported. County total number of individual OB-GYN NPIs come from NPPES (2007-2023). County time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. County and year fixed effects are controlled for. Standard errors are clustered at state level and presented with 95% confidence intervals.

Table A.1: Medicaid income eligibility by state from 2003 to 2020

State name	2003 Eligibility	2020 Eligibility	Increased Level
Alabama	1.33	1.46	.13
Alaska	2	2.05	.05
Arizona	1.33	1.61	.28
Arkansas	2	2.14	.14
California	2	3.22	1.22
Colorado	1.33	2.65	1.32
Connecticut	1.85	2.63	.78
Delaware	2	2.17	.17
District of Columbia	2	3.24	1.24
Florida	1.85	1.96	.11
Georgia	2.35	2.25	-.1
Hawaii	1.85	1.96	.11
Idaho	1.33	1.38	.05
Illinois	2	2.13	.13
Indiana	1.5	2.13	.63
Iowa	2	3.8	1.8
Kansas	1.5	1.71	.21
Kentucky	1.85	2.18	.33
Louisiana	2	2.14	.14
Maine	2	2.14	.14
Maryland	2.5	2.64	.14
Massachusetts	2	2.05	.05
Michigan	1.85	2	.15
Minnesota	2.75	2.83	.08
Mississippi	1.85	1.99	.14
Missouri	1.85	3.05	1.2
Montana	1.33	1.62	.29
Nebraska	1.85	2.02	.17
Nevada	1.33	1.65	.32
New Hampshire	1.85	2.01	.16
New Jersey	2	2.05	.05
New Mexico	1.85	2.55	.7
New York	2	2.23	.23
North Carolina	1.85	2.01	.16
North Dakota	1.33	1.62	.29
Ohio	1.5	2.05	.55
Oklahoma	1.85	2.1	.25
Oregon	1.85	1.9	.05
Pennsylvania	1.85	2.2	.35
Rhode Island	2.5	2.58	.08
South Carolina	1.85	1.99	.14
South Dakota	1.33	1.38	.05
Tennessee	1.85	2.55	.7
Texas	1.85	2.07	.22
United States	1.85	2.07	.22
Utah	1.33	1.44	.11
Vermont	2	2.13	.13
Virginia	1.33	2.05	.72
Washington	1.85	1.98	.13
West Virginia	1.5	3.05	1.55
Wisconsin	1.85	3.06	1.21
Wyoming	1.33	1.59	.26

Notes: Data for this study was generously provided by the Kaiser Family Foundation (KFF). It's worth noting that the eligibility data for Georgia in 2003 is an outlier, as it remained constant at 200% from 2004 to 2012, and then it was expanded to 225% for all the years afterwards. Similar outliers include Alaska in 2003, Nevada in 2011 and 2012, and Virginia in 2013. All these outliers are excluded when conducting the difference-in-differences analysis.

Table A.2: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of non-OB-GYNs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log non-OB-GYN MDs per 100,000 people				Log family medicine MDs per 100,000 people			
Eligibility line	-0.007				-0.050***			
	(0.013)				(0.014)			
Expanded eligibility (DID)		-0.003				-0.049***		
		(0.011)				(0.015)		
Fraction eligible			0.076				-0.182*	
			(0.085)				(0.090)	
Fraction eligible (2SLS)				-0.020				-0.276***
				(0.084)				(0.081)
Observations	52,893	52,568	52,893	52,893	52,893	52,568	52,893	52,893
R-squared	0.481	0.481	0.481	0.402	0.263	0.262	0.263	0.205
First-stage F statistics				525.44				525.50

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of all non-OB-GYN MDs per 100,000 population in Columns (1) to (4) and on log county number of family medicine MDs per 100,000 population in Columns (5) and (8). The independent variable in Columns (1) and (5) is the actual eligibility limit, in Columns (2) and (6) is the expanded eligibility, in Columns (3) and (7) is the actual eligible fraction calculated using ACS sample, and in Columns (4) and (8) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of MDs per 100,000 population by specialty and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, and log total employment. In Columns (5) to (8), log total number of non-family-medicine MDs per 100,000 people is also controlled for. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.3: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: influence of county population

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people				Log OB-GYNs			
Eligibility line	0.030***				0.017**			
	(0.008)				(0.006)			
Expanded eligibility (DID)		0.031***				0.018***		
		(0.007)				(0.005)		
Fraction eligible			0.190***				0.136***	
			(0.052)				(0.039)	
Fraction eligible (2SLS)				0.160***				0.096**
				(0.046)				(0.034)
County population weights	Y	Y	Y	Y				
Observations	52,893	52,568	52,893	52,893	52,897	52,572	52,897	52,897
R-squared	0.599	0.599	0.599	0.531	0.874	0.874	0.874	0.839
First-stage F statistics				504.73				526.57

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population, weighted by the county population size, in Columns (1) to (4), while on log net county total number of OB-GYNs in Columns (5) to (8). The independent variable in Column (1) and (5) is the actual eligibility limit, in Column (2) and (6) is the expanded eligibility, in Column (3) and (7) is the actual eligible fraction calculated using ACS sample, and in Column (4) and (8) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, and log total employment. In Columns (1) to (4) log total number of non-OB-GYN MDs per 100,000 people and in Columns (5) to (8) log total number of all non-OB-GYN MDs is controlled for. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.4: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: other Medicaid reforms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
Eligibility line	0.033**				0.031***			
	(0.011)				(0.009)			
Expanded eligibility (DID)		0.034***				0.033***		
		(0.009)				(0.007)		
Fraction eligible			0.216**				0.206***	
			(0.067)				(0.056)	
Fraction eligible (2SLS)				0.181**				0.167**
				(0.066)				(0.052)
Unborn Child Option	Y	Y	Y	Y				
ACA					Y	Y	Y	Y
Observations	52,893	52,568	52,893	52,893	52,893	52,568	52,893	52,893
R-squared	0.580	0.580	0.580	0.506	0.580	0.580	0.580	0.507
First-stage F statistics				529.76				518.568

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population, controlling for the implementation of Unborn Child Option and ACA expansion. The independent variable in Column (1) is the actual eligibility limit, in Column (2) is the expanded eligibility, in Column (3) is the actual eligible fraction calculated using ACS sample, and in Column (4) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.5: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: other physician incentive program

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
Eligibility line	0.030***				0.029**			
	(0.008)				(0.011)			
Expanded eligibility (DID)		0.031***				0.030***		
		(0.007)				(0.009)		
Fraction eligible			0.201***				0.199**	
			(0.058)				(0.064)	
Fraction eligible (2SLS)				0.164**				0.157**
				(0.052)				(0.062)
AHEC program	Y	Y	Y	Y				
HPSA Designation					Y	Y	Y	Y
Observations	52,893	52,568	52,893	52,893	52,893	52,568	52,893	52,893
R-squared	0.580	0.580	0.580	0.506	0.580	0.581	0.580	0.507
First-stage F statistics				495.08				526.22

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population, controlling for other physician incentive programs. The AHEC program is a federally funded program to make health care education (including residency and student rotations) locally available, in order to preserve healthcare professionals in the local areas. Meanwhile, Physicians who provide professional services in a HPSA are eligible for a 10-percent bonus payment. The independent variable in Column (1) is the actual eligibility limit, in Column (2) is the expanded eligibility, in Column (3) is the actual eligible fraction calculated using ACS sample, and in Column (4) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.6: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
Eligibility line	0.036***				0.039**			
	(0.010)				(0.013)			
Expanded eligibility (DID)		0.038***				0.042**		
		(0.009)				(0.013)		
Fraction eligible			0.267***				0.312***	
			(0.062)				(0.071)	
Fraction eligible (2SLS)				0.219***				0.247***
				(0.049)				(0.061)
State year trend	Y	Y	Y	Y				
Health service area year trend					Y	Y	Y	Y
Observations	52,893	52,568	52,893	52,893	52,893	52,568	52,893	52,893
R-squared	0.580	0.581	0.580	0.507	0.666	0.666	0.666	0.503
First-stage F statistics				688.85				526.22

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population, controlling for additional regional time trends. The independent variable in Column (1) is the actual eligibility limit, in Column (2) is the expanded eligibility, in Column (3) is the actual eligible fraction calculated using ACS sample, and in Column (4) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.7: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYN: various DID

	(1)	(2)	(3)	(4)
	Log OB-GYNs per 100,000 people			
Expanded eligibility (1st)	0.031***			
	(0.007)			
Post 1st expansion		0.021*		
		(0.010)		
Expanded eligibility (largest)			0.030**	
			(0.011)	
Post largest expansion				0.016
				(0.012)
Observations	52,568	52,568	52,568	52,568
R-squared	0.580	0.580	0.580	0.580

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population using different verions of DID estimates. The independent variable in Column (1) is the expanded eligibility from the year of 1st expansion, in Column (2) is an indicator of post-1st-expansion year, in Column (3) the expanded eligibility from the year of largest expansion, and in Column (4) is an indicator of post-largest-expansion year. County total number of B-GYNs per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. County and year fixed effects are controlled for. Standard errors are clustered at state level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.8: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYN NPIs

	(1)	(2)	(3)	(4)
	Log OB-GYN NPIs per 100,000 people			
Eligibility line	0.022*			
	(0.012)			
Expanded eligibility (DID)		0.022*		
		(0.012)		
Fraction eligible			0.127	
			(0.076)	
Fraction eligible (2SLS)				0.106
				(0.069)
Observations	20,597	20,534	20,597	20,597
R-squared	0.913	0.913	0.913	0.005
First-stage F statistics				1087.72

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYN NPIs per 100,000 population. The independent variable in Column (1) is the actual eligibility limit, in Column (2) is the expanded eligibility, in Column (3) is the actual eligible fraction calculated using ACS sample, and in Column (4) is the actual eligible fraction that is instrumented by the "simulated eligible fraction". County total number of individual OB-GYN NPIs come from NPPES (2007-2023). County time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. County and year fixed effects are controlled for. Standard errors are clustered at state level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.9: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: Multidimensional RD

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log OB-GYNs per 100,000 people							
	<=50 miles		<=100 miles		<=150 miles		<=200 miles	
	IMLC states since 2015	Non-IMLC states and years	IMLC states since 2015	Non-IMLC states and years	IMLC states since 2015	Non-IMLC states and years	IMLC states since 2015	Non-IMLC states and years
Higher line	-0.182*	-0.049	-0.197**	-0.057	-0.211**	-0.057	-0.209**	-0.056
	(0.079)	(0.041)	(0.060)	(0.039)	(0.064)	(0.041)	(0.064)	(0.040)
Observations	8,820	25,417	12,180	35,079	12,972	37,143	13,332	37,939
R-squared	0.156	0.172	0.147	0.157	0.149	0.159	0.152	0.160

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population using equation (12). States participating IMLC in post-2015 years are saperated from the rest of the sample. County total number of physicians by specialty per 100,000 population comes from the AHRF (2001-2020). Quadratic polynomial in latitude and longitude, state and year fixed effects are controlled for. Standard error clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.10: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: one-dimensional border RD

	(1)	(2)	(3)	(4)
	Log OB-GYNs per 100,000 people			
	<=50 miles	<=100 miles	<=150 miles	<=200 miles
Higher line	-0.115	-0.153**	-0.153**	-0.167**
	(0.089)	(0.056)	(0.049)	(0.054)
Observations	34,237	47,259	50,115	51,271
R-squared	0.155	0.143	0.146	0.148

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population using the conventional one-dimensional border RD. County total number of physicians by specialty per 100,000 population comes from the AHRF (2001-2020). Distance to the borderline, its interaction with an indicator of higher eligibility, state and year fixed effects are controlled for. Standard error clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.11: Effect of Medicaid/CHIP eligibility for pregnant women on the supply of OB-GYNs: excluding 3rd quartile counties

	(1)	(2)	(3)	(4)
	Log OB-GYNs per 100,000 people			
	<=50 miles	<=100 miles	<=150 miles	<=200 miles
Higher line	-0.089**	-0.096**	-0.101**	-0.100**
	(0.038)	(0.039)	(0.042)	(0.042)
Observations	25,462	35,368	37,496	38,315
R-squared	0.177	0.163	0.166	0.167

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population using the conventional one-dimensional border RD. County total number of physicians by specialty per 100,000 population comes from the AHRF (2001-2020). Quadratic polynomial in latitude and longitude, state and year fixed effects are controlled for. Standard error clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.12: Effect of Medicaid/CHIP eligibility on OB-GYN supply: within border pair comparison

	(1)	(2)	(3)	(4)	(5)	(6)
	Log OB-GYNs per 100,000 people					
Eligibility line	-0.078*					
	(0.038)					
Expanded eligibility (DID)		-0.079*				
		(0.039)				
Fraction eligible			-0.465**			
			(0.151)			
Fraction eligible (2SLS)				-0.429*		
				(0.205)		
Higher line					-0.053*	
					(0.027)	
Gap of line						-0.051**
						(0.019)
Observations	44,390	43,898	44,390	44,390	43,812	43,812
R-squared	0.816	0.816	0.816	0.470	0.816	0.816
First-stage F statistics				628.49		

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on log county total number of OB-GYNs per 100,000 population, only among border counties. Counties bordering multiple counties are duplicated to the number of pairs. The independent variable in Column (1) is the actual eligibility limit, in Column (2) is the expanded eligibility, in Column (3) is the actual eligible fraction calculated using ACS sample, in Column (4) is the actual eligible fraction that is instrumented by the "simulated eligible fraction", in Column (5) is an indicator of higher eligibility side, and in Column (6) is the gap in eligibility relative to the other side of the border. County total number of physicians by specialty per 100,000 population and time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. State and border-pair specific year fixed effects are controlled for. Standard errors are clustered at census division level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Table A.13: Effect of Medicaid/CHIP eligibility on pregnant women's insurance status and healthcare utilization: within border pair comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Prob(Covered by Medicaid)						Log total monthly visits					
Eligibility line	-0.050**						0.010					
	(0.024)						(0.016)					
Expanded eligibility (DID)		-0.050**						0.010				
		(0.024)						(0.016)				
Fraction eligible			-0.378**						0.124			
			(0.153)						(0.100)			
Fraction eligible (2SLS)				-0.271**						0.143		
				(0.119)						(0.112)		
Higher line					-0.021						0.002	
					(0.016)						(0.010)	
Gap of line						-0.025**						0.005
						(0.012)						(0.008)
Observations	562,074	561,992	562,074	562,074	562,074	562,074	562,074	561,992	562,074	562,074	562,074	562,074
R-squared	0.149	0.149	0.150	0.004	0.149	0.149	0.073	0.073	0.073	0.000	0.073	0.073
First-stage F statistics				1998.85						2000.91		

Notes: This table reports the effect of Medicaid/CHIP eligibility expansion on patient level outcomes using a pregnant women sample, only among border counties. Counties bordering multiple counties are duplicated to the number of pairs. The independent variable in Column (1)/(7) is the actual eligibility limit, in Column (2)/(8) is the expanded eligibility, in Column (3)/(9) is the actual eligible fraction calculated using ACS sample, in Column (4)/(10) is the actual eligible fraction that is instrumented by the "simulated eligible fraction", in Column (5)/(11) is an indicator of higher eligibility side, and in Column (6)/(12) is the gap in eligibility relative to the other side of the border. Patient outcomes and demographics come from the AFC (2001-2023). County time-variant characteristics come from the AHRF (2001-2020). County yearly controls are poverty rate, log median household income, log per capita income, log total employment, and log total number of non-OB-GYN MDs per 100,000 people. Individual level controls include race and birth year fixed effects. Insurance status indicators are controlled in Columns (7) to (12). County, visit calender month, and visit year fixed effects are controlled for. Standard errors are clustered at state level. Significant level at ***p<0.01, **p<0.05, *p<0.1.

Appendix B

In this section, I provide further mathematical details for the section of theoretical framework.

As the specific expression of v_{it} is as blow:

$$v_{it} = \frac{q^M(E_{it}, Z_{it})d^M(E_{it}, Z_{it})r^M(Z_{it})}{S_{it}} + \frac{q^{NM}(E_{it}, Z_{it})d^{NM}(Z_{it})r^{NM}(Z_{it})}{S_{it}} - C(\mu_i, Z_{it}) \tag{13}$$

The probability that the representative physician will choose to practice in county i can be further expressed as:

$$P_{it} = \frac{exp^{v(E_{it}, Z_{it}, S_{it}, \mu_i)}}{\sum exp^{v(E_{kt}, Z_{kt}, S_{kt}, \mu_k)}}, \forall k, k \neq i \tag{14}$$

Therefore, the number of physicians in county i period t is the product between P_{it} and national total number of physicians N_t, as for each county:

$$S_{it} = P_{it}N_t = \frac{exp^{v(E_{it}, Z_{it}, S_{it}, \mu_i)}}{\sum exp^{v(E_{kt}, Z_{kt}, S_{kt}, \mu_k)}} N_t, \forall k, k \neq i \tag{15}$$

Then, the equilibrium number of physicians in each county S^*_{it} can be obtained by solving the k equations above.

Given equation (7), when $\frac{\partial v_{it}}{\partial E_{it}} > 0$, we have:

$$\frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}} \frac{d^M(E_{it}, Z_{it})r^M(Z_{it})}{S_{it}} + \frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}} \frac{q^M(E_{it}, Z_{it})r^M(Z_{it})}{S_{it}} + \frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} \frac{d^{NM}(Z_{it})r^{NM}(Z_{it})}{S_{it}} > 0 \tag{16}$$

Given that $\frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}} > 0$, $\frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} < 0$, and $\frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}} > 0$, we can modify the equation to be:

$$\frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}} \frac{d^M(E_{it}, Z_{it})r^M(Z_{it})}{S_{it}} + \frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}} \frac{q^M(E_{it}, Z_{it})r^M(Z_{it})}{S_{it}} > - \frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} \frac{d^{NM}(Z_{it})r^{NM}(Z_{it})}{S_{it}} \tag{17}$$

After Multiplying both sides with S_{it} and then dividing both sides with $-\frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} d^{NM}(Z_{it})r^M(Z_{it})$, we obtain:

$$\frac{\frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}} d^M(E_{it}, Z_{it}) + q^M(E_{it}, Z_{it}) \frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}}}{-\frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} d^{NM}(Z_{it})} > \frac{r^{NM}(Z_{it})}{r^M(Z_{it})} \tag{18}$$

Since $\frac{r^{NM}(Z_{it})}{r^M(Z_{it})} \gg 0$, we must have:

$$\frac{\frac{\partial q^M(E_{it}, Z_{it})}{\partial E_{it}} d^M(E_{it}, Z_{it}) + q^M(E_{it}, Z_{it}) \frac{\partial d^M(E_{it}, Z_{it})}{\partial E_{it}}}{-\frac{\partial q^{NM}(E_{it}, Z_{it})}{\partial E_{it}} d^{NM}(Z_{it})} \gg 0 \tag{19}$$