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Nurse practitioner oversight ratios and labor market outcomes

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Abstract
Nurse practitioners are important to the US healthcare system; however, many states impose physician oversight ratios, which limit the number of NPs a physician may supervise. In this study, we evaluate the effect of eliminating physician oversight ratios on the supply of NPs by conducting case studies of three states—New York, Nevada, and Pennsylvania—using synthetic control and related approaches. Surprisingly, we find that eliminating oversight ratios had little effect on the labor supply of NPs. For New York, we also analyze the effects of eliminating oversight ratios on wages and hours worked and again find null results.

KEYWORDS
healthcare markets, occupational licensing, regulation

JEL CLASSIFICATION
I11, J44, K20

1 | INTRODUCTION

Practitioner shortages within the U.S. healthcare system are a critical issue with implications for access to care and the quality of care delivered. The U.S. Health Resources and Services Administration (HRSA) currently estimates that 74 million people, or about 22% of the population, live in areas designated as primary care Health Professional Shortage Areas (HRSA, 2024). HRSA also estimates that 12,931 additional primary care practitioners, including physicians, physician assistants (PAs), and nurse practitioners (NPs), are needed to meet the healthcare needs of the population and to remove shortage area designations. Workforce projections for the next decade show the problem may worsen, but they can be mitigated by NPs and PAs (HRSA, 2023). In many states, however, labor markets for these advanced practice providers are hampered by restrictive scope of practice (SOP) laws.

SOP laws are the legal authority given by states to licensed healthcare professionals to provide medical services. These laws specifically define the practitioners' roles, articulate oversight requirements (if any), and govern practice and

Abbreviations: ACS-PUMS, American Community Survey Public Use Microdata Survey; AHRF, area health resource file; APRN, advanced practice registered nurse; ATT, average treatment effect on the treated; BON, board of nursing; CNM, certified nurse midwife; CNS, clinical nurse specialist; COVID-19, coronavirus disease 2019; CPA, collaborative practice agreement; CRNA, certified registered nurse anesthetist; FPA, full practice authority; GP, general practitioner; HIPAA, Health Insurance Portability and Accountability Act; HRSA, Health Resources and Services Administration; MSPE, mean squared prediction error; NP, nurse practitioner; NPAALU, Nurse Practitioner's Annual APRN Legislative Update; NPI, national provider identifier; NPMA, Nurse Practitioner Modernization Act; NPPES, National Plan and Provider Enumeration System; PA, physician assistant; PPSCM, partially pooled synthetic control method; RN, registered nurse; SDID, synthetic difference-in-differences; SOP, scope of practice.

prescriptive authorities. This paper focuses on oversight ratios, a particular type of SOP rule, as they apply to NPs. NPs are the most common type of advanced practice registered nurse (APRN), constituting 76% of APRNs (BLS, 2019). Other types of APRNs include certified nurse midwives (CNMs), clinical nurse specialists (CNSs), and certified registered nurse anesthetists (CRNAs). To become licensed as an NP, one must first become a registered nurse (RN), then complete a master's or doctoral degree and pass a national certification board exam in one of several specialties. NPs can specialize in a range of population foci, including family care, psychiatric/mental health, gerontology, pediatrics, neonatology, and emergency care. While recent evidence suggests that NPs may not be perfect substitutes for physicians in an emergency care setting (Chan & Chen, 2022), the vast majority are certified in (88%) and practice in (70.3%) a primary care specialty (AANP, 2021). NPs perform many of the same tasks as primary care physicians, including examining and diagnosing patients, providing treatments, and prescribing medicine.

To date, 34 states' practice environments for NPs are characterized by "full practice authority" (FPA) where NPs practice without any legal requirement for a formal oversight relationship with physicians. However, in the remaining states, the SOP laws that govern NPs require these nurses to practice under physician oversight. This oversight may be supervisory, delegative, or collaborative in nature; however, all require a collaborative practice agreement (CPA)—a written contract between an NP and the overseeing physician. Note, however, that CPAs do not typically require "supervision," "delegation," or "collaboration" in the common meaning of those words, nor must the NP typically practice at the same location as the supervising physician. Instead, oversight usually takes the form of more detached practices, such as periodic chart review and the physician being available by phone to answer questions or take referrals.

Often the law specifies an oversight ratio that dictates the maximum number of nurses with whom a physician is legally allowed to enter into a supervisory, delegative, or collaborative relationship. Oversight laws and oversight ratios effectively tie the NP practice to physicians and can set up significant barriers to NP practice.

This paper focuses on the labor market effects of physician-to-nurse oversight ratios, which is one aspect of oversight-based SOP laws that has the potential to strongly influence the size of the NP labor force. NPs in seven states are currently restricted by these ratios, and until recently, several others have been as well. Until recently, Oklahoma had the most limiting ratio and only permitted physicians to oversee up to two full-time equivalent APRNs at a time, and no more than four APRNs in total. Economic theory predicts that such ratios would result in a restricted supply of NPs and may generate NP shortages. In the extreme, should no physician wish to or have the capacity to enter into an oversight or collaborative agreement, no NP would be legally allowed to work. More realistically, NPs may find it difficult or costly to enter into a practice agreement with a physician, which could alter incentives to work. Hence our research question: what effect do these oversight ratios have on the labor supply of NPs?

Other aspects of SOP laws that require oversight may also have a chilling effect on the labor supply of nurses, but these do not overtly limit supply. Collaborative practice agreements and required protocols can include limits on the schedule or types of drugs an NP may prescribe. Requirements such as immediate consultation, co-signatures on charts and orders, and periodic chart review can increase administrative burden and result in delays in care. These types of restrictions all may disincentivize nurse labor force participation and generate inefficiencies in practice, but again, these requirements do not have the potential to hinder practice in the same way that oversight ratios do. This is why we focus specifically on the oversight ratios in this paper.

We answer our research question by leveraging several states' decision to eliminate oversight ratios in recent years. Given the relatively small number of states that have eliminated their oversight ratios with sufficiently long pre- and post-treatment years on either side of their policy changes, we conduct case studies using synthetic controls and related methods. Specifically, we look at Nevada, New York, and Pennsylvania. Each state eliminated its oversight ratio as part of a larger legislative or regulatory package, as we discuss below. Nevada and New York did so as part of a broader scope of practice reform that also eliminated all oversight requirements, while Pennsylvania eliminated the oversight ratio but maintained oversight.

We estimate models of NP labor supply using three different yet complementary outcome measures—number of licensed NPs, number of NPs with a National Provider Identifier (NPI) number, and total NPs employed— to draw conclusions. Based on the totality of the evidence, we conclude that eliminating oversight ratios has little effect on the number of NPs working or licensed in a state. We also consider average annual wages and weekly hours worked in New York and again find null effects. These null effects are consistent across states and outcome measures and hold regardless of whether collaborative practice agreements are eliminated or maintained.

Policy debates about SOP laws are active and ongoing. For example, in the thick of the COVID-19 pandemic, several states temporarily expanded NPs' SOP, and some of these states have since made some of these changes permanent. More states are actively considering expanding NP SOP (Ollove, 2023).

Recent research into NP practice generally suggests that there are real benefits to expanding NP practice while the costs are few. The oversight provisions of SOP laws are justified as a way to protect public health and ensure quality of care. However, evidence is mounting that there are no improvements in health outcomes achieved under an oversight environment. For example, greater NP independence has no effect on infant mortality rates (Kleiner et al., 2016); smoking cessation, depression treatment, or statin prescriptions (Kurtzman et al., 2017); or chronic disease management, cancer screening, and preventable hospitalizations (Perloff et al., 2017). Markowitz and Smith (2023) find that eliminating physician oversight requirements of NPs does not result in increased harm to patients as proxied by malpractice cases and adverse actions against practitioners' licenses. By contrast, while it is difficult to measure prices paid in the healthcare setting, what evidence we do have tends to show that liberalizing SOP rules reduces prices and expenditures (Kleiner et al., 2016; Spetz et al., 2013; *but see* Timmons, 2017). This is likely why increasing NP independence tends to increase access to care (Spetz et al., 2013; Stange, 2014; Tracynzki and Udalova, 2018). Adams and Markowitz (2018) and McMichael and Markowitz (2023) provide more extensive reviews of this literature.

Previous research on the effects of the SOP environments on labor market outcomes has produced mixed results. McMichael (2018) and Reagan and Salsberry (2013) find that full practice authority is associated with an increased supply of NPs, and Xue et al. (2018) find a similar result among rural counties and those designated as Health Professional Shortage Areas (HPSA). However, Kandrack et al. (2021) find no effect of FPA on NP supply, and Markowitz et al. (2017) show that the different SOP environments are not associated with changes in the numbers of licensed or employed CNMs. Kleiner et al. (2016) find that independence in practice authority results in no changes in NP hours worked, although independence in prescription authority is associated with small increases in NP hours worked. Markowitz and Adams (2022) find that different levels of SOP restrictions are not associated with probability of employment, part-time work, or multiple job holding, but NPs working in states without oversight requirements are much more likely to be self-employed and work more hours. The result for self-employment is also found in DePriest et al. (2020), and the results for work hours are confirmed in Lou et al. (2021).

Our paper contributes to this literature by being the first to assess the effects of eliminating oversight ratios on NP labor market outcomes. By imposing strict limits on the numbers of NPs that can be supervised by a physician, these ratios have the potential to be more distortive to the NP labor market than do other oversight provisions. And yet—surprisingly—we find that eliminating oversight ratios does not increase (or decrease) the labor supply of NPs in a state relative to its synthetic control.

This paper proceeds as follows. Section 2 describes oversight ratios in greater detail and explains why we would expect oversight ratios to restrict the number of working NPs and why we would therefore expect eliminating oversight ratios to boost their labor supply. Section 3 discusses our outcome measures, and Section 4 explains how we use synthetic control and synthetic difference-in-differences (SDID) to estimate the effect of eliminating oversight ratios in our case studies. Next, Section 5 discusses our case studies state-by-state. For each state—New York, Nevada, and Pennsylvania—we describe the institutional context for the state's elimination of oversight ratios and the results from our synthetic control estimates for each outcome where an analysis is feasible. We also discuss our findings from (partially) pooled analysis of multiple states where feasible. These overall results are consistent with the null findings from our case studies. Section 6 briefly concludes.

2 | OVERSIGHT RATIOS

Oversight ratios dictate the number of full-time equivalent NPs with whom a physician may legally enter into a supervisory, delegative, or collaborative relationship. If present, the oversight ratio is part of a broader set of rules encompassed in states' SOP laws. The oversight ratios are specified as part of the requirements for CPAs with physicians. States may have no oversight requirements and therefore no ratios; oversight requirements without ratio; and oversight requirements with ratios. Table 1 lists the states that have ever had oversight ratios along with the date and status of the laws. Information on the legislated oversight ratio is gathered directly from each state's statutes and administrative codes. This table shows that over time, six states eliminated their ratios, five changed the levels, and three currently maintain the ratios. Of the states that changed or eliminated their ratios, most have done so very

TABLE 1 States with physician-to-NP ratios, 1998–2019.

State	Physician:NP ratio	Year changed or eliminated
Alabama	1:4; 1:9	In effect during sample period. Changed in 2021 to allow for supervision of up to nine FTE NPs, CNMs, and/or physician assistants
California	1:4	In effect during sample period. Requirement for physician supervision eliminated effective in 2023
Georgia	1:4	Still in effect
Missouri	1:3; 1:6	Changed 2018
Nevada	1:3	Eliminated 2013
New York	1:4	Elminated 2015
Ohio	1:5	Still in effect
Oklahoma	1:2; 1:6	In effect during sample period. Changed in 2020 to allow for supervision of up to six APRNs and/or physician assistants
Pennsylvania	1:4	Eliminated 2010
South Carolina	1:3; 1:6	In effect during most of sample period. Changed to 1:6 effective July 1, 2018
South Dakota	1:4	Eliminated 2017
Texas	1:7	Still in effect
Virginia	1:4, 1:6	Changed 2012; eliminated 2018

recently, leaving three states—New York, Nevada, and Pennsylvania—as viable case studies for evaluation.[1] Details on these three states' laws are provided below.

Oversight ratios may impact the labor supply of NPs in several ways. Most directly, oversight ratios can form a hard cap on the number of NPs allowed to practice in a state. For example, in Georgia, where the oversight ratio is 1:4, the maximum number of NPs that could practice would be four times the number of doctors eligible to enter into CPAs. Admittedly, this restriction may not be binding in the strictest sense. Even limiting the pool of doctors to general practitioners (GPs), the average ratio GPs to NPs across our data's state-year observations is 1:2.16. However, the pool of doctors willing to enter into CPAs with NPs on reasonable terms is likely smaller than the total number of GPs. Physicians have, for instance, expressed a reluctance to enter into CPAs out of fear of additional malpractice liability risk. In this case, bindingness may be possible, even though the number of NPs does not technically exceed the ratio's multiple of doctors in a state. To the extent the restrictions are binding, removing the caps would allow markets to clear and should cause the quantity of NP labor supplied to increase.

In addition, oversight ratios may exacerbate the costs associated with collaborative practice requirements. All states that dictate oversight ratios also require NPs to have a CPA with a physician. These CPAs specify the rights and responsibilities of each party along with the requirements for physician consultation. Some states require written protocols as part of the collaborative practice agreement. These outline the specific details of the NP's permitted practice, such as the medical conditions the NP may treat, the treatments that may be provided, and the drug therapies that may be prescribed. Many NPs subject to CPA requirements have to pay physicians for the privilege, and the monthly payments can be quite large. In a survey, those NPs listing a dollar value reported paying physicians an average of \$1048.47 per month to participate in a CPA, which represents an average of 12.5% of NP's self-reported salary (Ritter et al., 2020). Imposing an oversight ratio could create a shortage of doctors available to enter CPAs, which could drive up the contract prices faced by NPs looking to practice and disincentivize work.

More generally, CPA requirements can impose significant search costs on NPs—they must first find a doctor willing to enter into a CPA and then negotiate with the doctor for acceptable contract terms. Legal restrictions on the number of NPs a doctor may supervise would likely increase these search costs by making it harder for an NP to find doctors willing and available to enter into the contract. By increasing search costs, states may make practicing independently—and getting the advanced training necessary to do so—a less attractive option for current and aspiring nurses. This can result in job lock and inhibit migration to states with oversight ratios.

The likely effect of eliminating oversight ratios, therefore, would be to reduce NPs' reservation wages and shift their labor supply curve outward. It should also increase the wage elasticity of their labor supply; lowering search and transition costs would likely allow NPs to be more responsive to changes in wages. The exact overall effect would depend on the nature of competition in the NP labor market. In a competitive market, the aforementioned responses to eliminating oversight ratios would tend to lower NP wages and increase their employment in equilibrium.

However, there is evidence that the market for RNs—a similar occupation to NPs— is highly monopsonistic, and moving costs like those described above are a classic source of labor market monopsony (Boal & Ransom, 1997; Staiger et al., 2010). In monopsonistic markets, eliminating the oversight ratios—and thereby reducing NPs' reservation wages and increasing their wage elasticity—would tend to increase NP employment but have ambiguous effects on their wages. Yet despite the contradictory effects on wages, total quantity of NP labor in equilibrium should increase regardless of whether the NP labor market is competitive or monopsonistic.

Of course, the above discussion assumes that eliminating oversight ratios would not affect the demand for NPs. Eliminating the oversight ratios could increase the demand for NPs by allowing physician-employers who currently employ the maximum allowed number of NPs to hire more. This would, however, require that the ratios be binding, at least for some number of physicians.

In light of these considerations, theory suggests that eliminating oversight ratios should increase the equilibrium quantity of NP labor. Both supply and demand effects should move in this same direction, under both perfect competition and monopsony conditions. By contrast, theory does not generate any clear predictions about wages to test. Accordingly, we focus our empirical analysis on testing the clear theoretical prediction, whether eliminating oversight ratios increases NP labor supply, though we also analyze wages.

3 | LABOR MARKET OUTCOMES

We primarily assess the effect of eliminating oversight ratios on the extensive margin of NP labor supply, and we do that using three alternative measures. Specifically, we estimate the effect on the number of licensed NPs, employed NPs, and NPs who have received an NPI. After completing graduate-level training, an aspiring NP must pass a national certification exam and apply to a state agency for a license. At that point, an NP is free to practice, either independently or as an employee of a healthcare entity. In either case, the NP will count as "employed." If the NP wishes to bill patients in his or her own name, then HIPAA requires that the NP apply to the National Plan and Provider Enumeration System (NPPES) for an NPI, a number unique to each provider.

Data on the number of licensed NPs come from the Nurse Practitioner's Annual APRN Legislative Update (NPAALU). The NPAALU provides information on the number of APRNs licensed in each state as reported by state nursing associations, state boards of nursing, or similar state agencies (Phillips, 2020). The primary benefit of these data is the long timeframe over which the data are available: we use data from 1999 through 2019.[2] This source provides information on total APRNs—which includes NPs, CNMs, CRNAs and CNSs—and counts each type separately. We only evaluate the count data for NPs since the SOP laws we examine pertain specifically to NPs. The strength of this data source is its relatively long coverage period. However, because states maintain their nurse licensing data in different ways and not necessarily for the purpose of tracking NP labor supply over time, the NPAALU data set is missing about 12% of state-year observations.[3] In addition, not all licensed NPs work. Between 2010 and 2019, 91.62% of NPs were employed, with the majority of the rest not in the labor force.

In addition to licensed NPs as reported in the NPAALU, we also use NPs with NPIs as a dependent variable. We get this information from the Area Health Resource File (AHRF), which summarizes data on NPs with NPIs from the NPPES. The NPPES collects information directly from healthcare providers. Data on NPs from the AHRF are available annually from 2010 to 2019. Despite the shorter time frame, the advantage of the NPI data is the completeness of the state-year data and the fact that this data represents a population of NPs. Researchers including McMichael (2018) and Xue et al. (2018) have used this data in their studies of NP labor supply, so using this variable allows us to compare our results to theirs. While providers have an incentive to acquire an NPI, they have less incentive to provide the NPPES with up-to-date, accurate information. As a result, the NPPES data include nurses who are employed, unemployed, and out-of-the-labor force.

While the AHRF and the NPAALU sources provide administrative data on NPs, they do not necessarily capture shorter movements in and out of NP employment. To address this limitation, we rely on a third data source, the American Community Survey Public Use Microdata Sample (ACS-PUMS) data. We use these data to generate annual state-level counts of NPs who are actively employed by limiting the sample to all individuals with the occupational code for "Nurse Practitioners and Nurse Midwives" (code 3258) and using the appropriate sample weight to generate annual state-level counts. Rates per 100,000 people in the state population are analyzed. The ACS-PUMS does not provide the occupation code for NP/CNMs until 2010, so these data span the years 2010–2019. The inclusion of nurse midwives in this data is not problematic since they constitute a small fraction of the total count (around 4%) and in many states the SOP laws pertain to all APRNs, including NPs and CNMs.[4]

Unfortunately, we are limited to using data derived from the ACS-PUMS to New York. The survey nature of the ACS-PUMS dataset, combined with the relatively small proportion of the population that works as NPs, means that the ACS-PUMS data are more volatile and less reliable than those in the other data sets. In Nevada, aggregate values are calculated using an average of 9.5 and as few as 5 survey respondents for each year. This results in some highly erratic aggregate values for Nevada. For New York, this does not appear to be as much of a problem as for Nevada. Observations from all years are based on at least 76 and an average of 124.1 survey respondents.

To summarize, there are pros and cons to each source of data. The NPAALU license data provide the longest time series but with missing values. The counts of NPs with NPIs are complete and comparable to estimates from previous literature but span a shorter time frame. Neither the NPAALU nor the NPI data distinguish among employed, unemployed, and out of the labor force, whereas the ACS-PUMS does. In addition to data considerations, the variables we consider measure slightly different outcomes. Licensed NPs represent the number of persons either currently working as NPs or who could be mobilized to work in some capacity without clearing any additional legal hurdles. NPs with an NPI have completed a further bureaucratic requirement that allows them to bill independently for their services. And as discussed above, employed NPs measures the NPs that are actively employed. Given these advantages and disadvantages and the fact that the variables measure slightly different outcomes, we rely on the weight of evidence from these different sources to draw conclusions.

Figures 1–3 show the time series of licensed NPs, NPs with an NPI, and employed NPs (per 100,000 people in the population) over the sample periods for the states considered in our synthetic control analyses below. The thicker, darker lines are for the states that eliminated their oversight ratios during the sample period, and the thinner gray lines are for the donor pool states. The overall trend is an increase in licensed NPs between 1999 and 2019 and an increase in employed and NPI-possessing NPs between 2010 and 2019.[5]

In addition to the extensive measures of NP labor supply discussed above, we also consider average wages and hours worked per week for NPs in New York. Because hours per week and wages come from the ACS-PUMS, we are only confident evaluating these outcomes for New York for the same reasons as employed NPs, discussed above. The time series for average wages and average weekly hours for the treated and donor pool states are shown in Figures 4 and 5. Unlike the number of NPs, however measured, real wages and weekly hours appear relatively flat.

4 | METHODS

To evaluate the effect of eliminating oversight ratios, we primarily rely on the synthetic control method for comparative case studies developed by Abadie et al. (2010) and Abadie and Gardeazabal (2003). However, for reasons we discuss below, synthetic control is not a viable method for Nevada, so we use synthetic difference-in-differences there instead (Arkhangelsky et al., 2021). Where applicable, we also combine states using the partially pooled synthetic control method (PPSCM) of Ben-Michael et al. (2022) to obtain an overall average treatment effect on the treated (ATT).

New York and Nevada eliminated their ratios early enough in the time frames of the available datasets to provide multiple pre and post periods, which allows us to analyze the effects on licensed NPs and NPs with an NPI in each of these states. We further analyze the effects on employed NPs, average annual wages, and average weekly hours for New York. Pennsylvania eliminated its oversight ratio in 2010, the first year that data on NPs are available in the AHRF or ACS-PUMS. Thus, we can only estimate the effect of Pennsylvania eliminating its oversight ratio on the rate of licensed NPs from the NPAALU.

To test the hypothesis that eliminating oversight ratios had a causal effect on the labor supply of NPs in New York, Nevada, and Pennsylvania, we use the Fisher (1935) p-value test suggested by Abadie et al. (2010). This test applies the synthetic control method to each state in the donor pool, calculates the mean squared prediction error (MSPE) for each state before and after the principal state's treatment time, calculates the ratio of the post-to the pretreatment MSPE, and then plots these ratios in a distribution. The p-value here is essentially the treated state's location within this distribution. For each synthetic control estimate, we also plot each of these placebo states along with the treated state to see how they compare visually. These figures produce compelling, easily interpretable evidence for our conclusions.

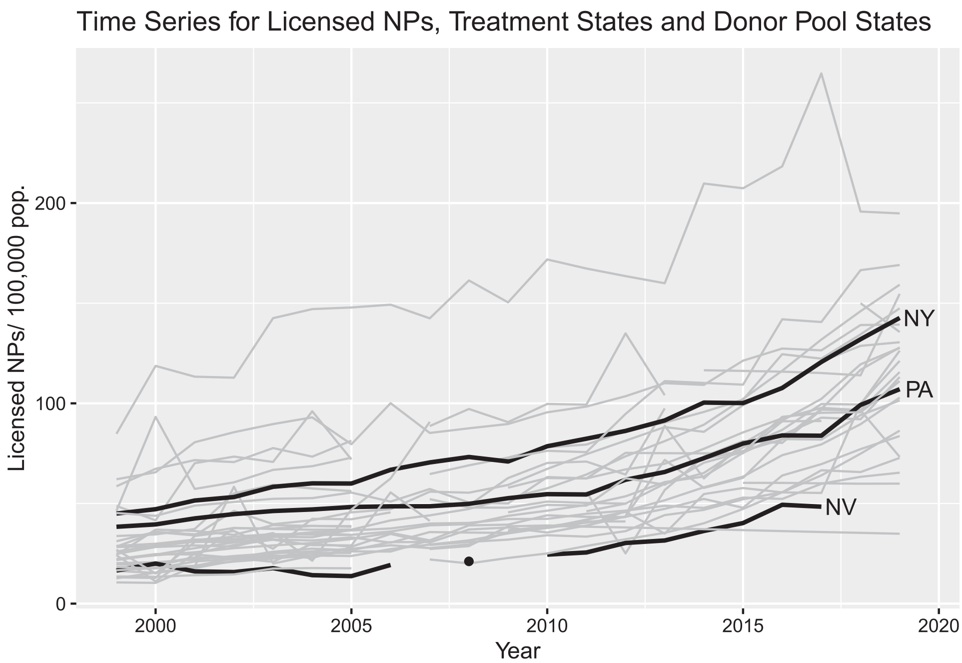

FIGURE 1 Time series of licensed NPs in the treatment states—those that eliminate their oversight ratios—and the donor pool states. The three treatment states—Nevada, New York, and Pennsylvania—are in bold. Nevada is missing the years 2007, 2009, 2018, and 2019.

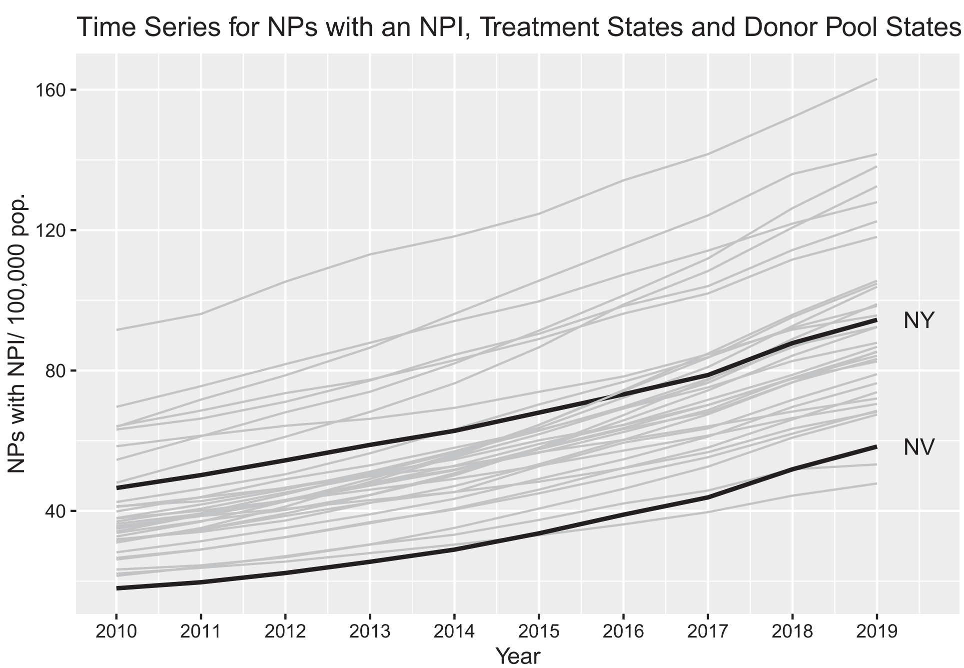

FIGURE 2 Time series of NPs with NPIs in the treatment states—those that eliminate their oversight ratios—and the donor pool states. The two treatment states—Nevada and New Yorkare in bold.

The synthetic control method is particularly appropriate in this context because of the relatively few states that are treated over the course of our sample. In addition, considering each treated state individually allows us to account for heterogeneous treatment effects explicitly and thereby avoid many of the potential problems raised by Borusyak and Jaravel (2018), de Chaisemartin and D'Haultfoeuille (2020), and Goodman-Bacon (2021).

However, the bias in synthetic control methods is inversely proportional to the number of pretreatment periods. Synthetic control can be further biased by high data volatility. For both the AHRF (NPPES) and the ACS-PUMS, data on

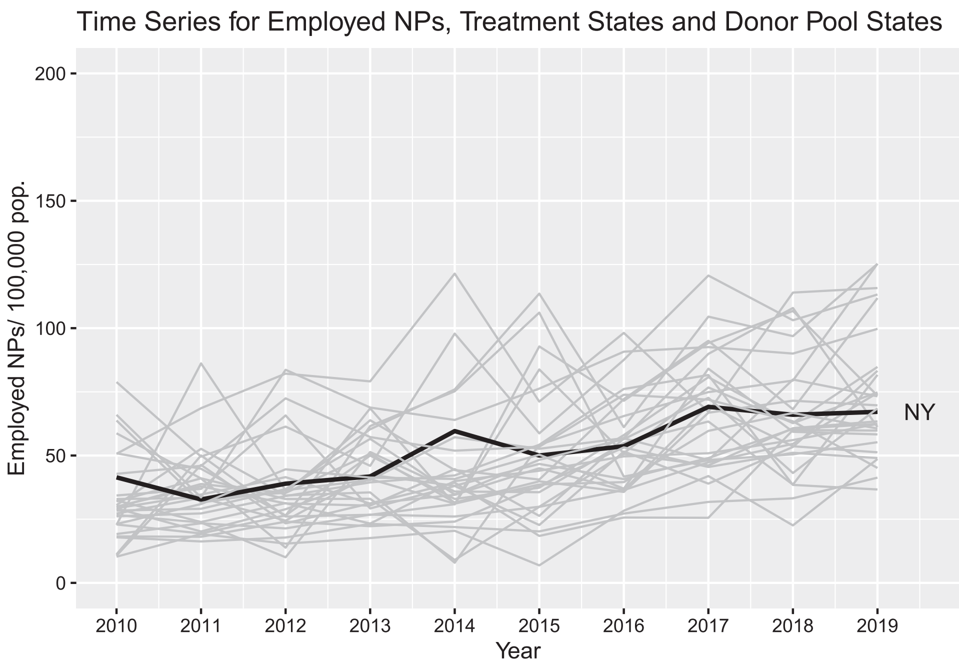

FIGURE 3 Time series of employed NPs in the treatment states—those that eliminate their oversight ratios—and the donor pool states. The treatment state, New York, is in bold.

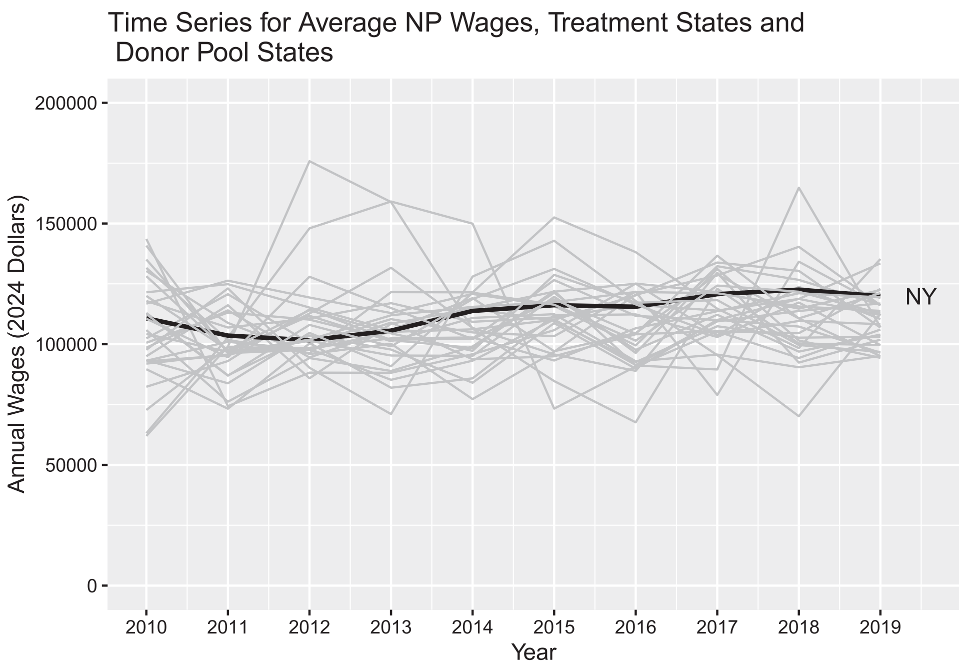

FIGURE 4 Time series of average annual wages of NPs in treatment states—those that eliminate their oversight ratios—and the donor pool states. The treatment state, New York, is in bold.

NPs do not become available until 2010, which limits the number of pretreatment periods. In addition, since the ACS-PUMS is survey based, whether and how many NPs are surveyed in a given state-year can expose the NP counts we generate from this data source to some volatility.

To construct the donor pools for each state, we first drop all other states that either eliminated their oversight ratios, transitioned to FPA, or both during the sample period. The donor pool therefore consists of states that maintain a constant SOP environment over the sample periods. Table 2 lists the states that transitioned to FPA during the sample period. In

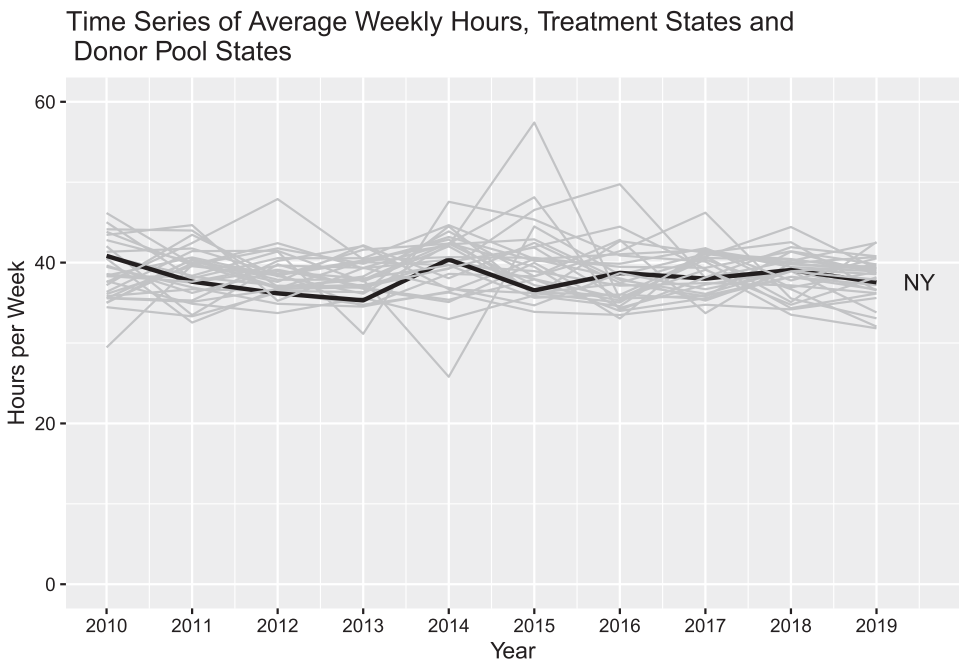

FIGURE 5 Time series of average annual wages of NPs in treatment states—those that eliminate their oversight ratios—and the donor pool states. The treatment state, New York, is in bold.

TABLE 2 States that transition to full practice authority, 1998–2019.

State	Date transitioned to FPA
Arizona	December 1999
Colorado	July 2010
Connecticut	July 2014
Delaware	September 2015
Hawaii	July 2009
Idaho	July 2004
Illinois	January 2018
Maryland	October 2010
Minnesota	January 2015
Nebraska	March 2015
Nevada	July 2013
New York	January 2015
North Dakota	October 2011
Rhode Island	February 2012
South Dakota	February 2017
Utah	May 2016
Vermont	June 2011
Virginia	April 2018
Washington	July 2005
West Virginia	June 2016

Note: For a more extensive description of when states changed their NP SOP rules, see McMichael and Markowitz (2023).

addition, missing values for the number of NPs in the various data sets for some state-years necessitates dropping either years or states from the donor pools. Here, because the bias of the synthetic control estimator is inversely proportional to the number of pretreatment periods, we opt to drop states. Table 3 lists the donor pools for licensed NPs for each state we analyze as well as the contribution of each donor state. Table 4 does the same for NPs with an NPI, and donor weights for employed NPs, annual wages, and weekly hours (all for New York only) are reported in Table 5.

As a robustness check, we repeat our analysis while dropping all states that have always had FPA for NPs and present this analysis in an online Appendix. Dropping these states makes no difference for most of our results and does not affect our overall conclusions.

For predictors, we include variables related to the concurrent economic conditions and socioeconomic status of the area. Unlike in many other applications, the purpose of including covariates in synthetic control is not so much to address confounding variables; rather it is to best predict the pretreatment outcome in the treated unit using observed variables. Mechanically, the fewer observed predictors one includes, the more the synthetic control algorithm depends on unobserved factors in fitting the synthetic control, which increases the bias bounds of the estimator (Abadie, 2021). Ultimately, it is not known which factors are best predictive of NP labor market outcomes—hence, our research question. We therefore include variables describing the economic circumstances of each state.

Specifically, in addition to the pretreatment values of the outcome variable, the predictors we use include unemployment rates, real income per capita, and the percentage of the area population living in poverty. The AHRF and U.S. Census Bureau provide these data. The AHRF also provides information on the supply of general practice physicians, both hospital- and office-based. These variables are likely important to include to reflect the availability of physicians for which NPs can enter into a collaborative practice agreement where required. Table 6 reports the predictor weights used for each model we estimate using synthetic control. For many, though not all, of our estimates, the pretreatment outcome has the greatest weight. Tables 7 and 8 present the sample averages for these variables for the treated states, their synthetics, and the overall sample.

As mentioned above, synthetic control is not an appropriate method for Nevada. The reason for this can be seen in Figures 1 and 2. Nevada (in bold) has the lowest rate of NPs in its population, however measured, in many of the years we consider. As a result, it is outside of the convex hull of its donor pool, and a reasonable fit between Nevada and its synthetic cannot be obtained. Even allowing for an intercept does not allow an adequate fit between Nevada and its synthetic when the outcome is licensed NPs.

Synthetic difference-in-differences offers two advantages over synthetic control in the case of Nevada (Arkhangelsky et al., 2021). First, in calculating a set of unit weights to match the pretreatment outcome in Nevada and the average of the donor pool states, SDID includes an intercept. This means that the synthetic control need not match pre-2013 Nevada exactly; it only needs to be parallel. Second, after calculating a set of unit weights, SDID also calculates a set of time weights, such that the pre-treatment time periods predict the post-treatment averages in the controls up to a

TABLE 3 Contributions of donor states when outcome is licensed NPs.

State	New York weight	Nevada weight	Pennsylvania weight
Alabama	0.000	0.112	0.002
Arkansas	0.000	0.118	0.002
California	0.004	0.224	0.008
District of Columbia	0.169	0.000	0.001
Georgia	0.523	0.137	0.004
Iowa	0.000	0.000	0.416
Kansas	0.111	0.000	0.034
Kentucky	0.008	0.000	0.002
Massachusetts	0.173	0.000	0.133
North Carolina	0.008	0.175	0.006
Oregon	0.002	0.177	0.391

Note: Data on licensed NPs come from the NPAALU and is available for the years 1999–2019. Weights for New York and Pennsylvania were calculated using synthetic control, whereas the Nevada weights were calculated using synthetic difference-in-differences.

TABLE 4 Contributions of donor states when outcome is NPs with NPI.

State	New York weight	Nevada weight
Alabama	0.000	0.000
Alaska	0.000	0.084
Arizona	0.000	0.000
Arkansas	0.000	0.034
California	0.000	0.133
District of Columbia	0.224	0.000
Florida	0.000	0.000
Georgia	0.000	0.000
Hawaii	0.000	0.115
Idaho	0.000	0.000
Indiana	0.000	0.000
Iowa	0.000	0.000
Kansas	0.000	0.000
Kentucky	0.000	0.000
Louisiana	0.000	0.000
Maine	0.000	0.000
Massachusetts	0.110	0.000
Michigan	0.000	0.000
Mississippi	0.000	0.000
Montana	0.000	0.068
New Hampshire	0.000	0.000
New Jersey	0.666	0.050
New Mexico	0.000	0.000
North Carolina	0.000	0.000
Ohio	0.000	0.000
Oklahoma	0.000	0.070
Oregon	0.000	0.075
South Carolina	0.000	0.052
Tennessee	0.000	0.000
Texas	0.000	0.044
Washington	0.000	0.085
Wisconsin	0.000	0.000
Wyoming	0.000	0.097

Note: Data on NPs with an NPI come from the AHRF and are available for the years 2010–2019. Weights for New York were calculated using synthetic control, whereas the Nevada weights were calculated using synthetic difference-in-differences.

constant. This is helpful when pretreatment fit is poor even with an intercept, such as the one we see with licensed NPs in Nevada, because it essentially allows us to discard the portion of the pretreatment period with poor fit. Because we are only considering a single state with the SDID method, we use the placebo variance estimation method described in Arkhangelsky et al. (2021), Section 4, to calculate standard errors.

TABLE 5 Contributions of donor states when outcome is employed NPs, average annual wages, and average weekly hours.

State	Employed NPs weight	Wages weight	Weekly hours weight
Alabama	0.000	0.004	0.000
Arizona	0.000	0.204	0.000
Arkansas	0.000	0.002	0.000
California	0.171	0.002	0.162
Florida	0.000	0.004	0.000
Georgia	0.000	0.000	0.000
Idaho	0.000	0.002	0.000
Indiana	0.000	0.002	0.000
Iowa	0.000	0.003	0.000
Kansas	0.000	0.003	0.000
Kentucky	0.000	0.002	0.000
Louisiana	0.336	0.004	0.000
Maine	0.000	0.001	0.000
Massachusetts	0.392	0.430	0.417
Michigan	0.000	0.003	0.000
Mississippi	0.011	0.182	0.303
Montana	0.000	0.001	0.000
New Hampshire	0.000	0.002	0.000
New Jersey	0.091	0.053	0.118
New Mexico	0.000	0.002	0.000
North Carolina	0.000	0.003	0.000
Ohio	0.000	0.003	0.000
Oklahoma	0.000	0.000	0.000
Oregon	0.000	0.002	0.000
South Carolina	0.000	0.002	0.000
Tennessee	0.000	0.002	0.000
Texas	0.000	0.077	0.000
Washington	0.000	0.002	0.000
Wisconsin	0.000	0.002	0.000

Note: Date on these outcomes are all for the state of New York and come from the ACS-PUMS, which is available for the years 2010–2019.

Finally, we use PPSCM to calculate overall ATTs for licensed NPs and NPs with an NPI (Ben-Michael et al., 2022). Partially pooled synthetic control allows us to estimate the ATT for multiple treated units and with staggered treatment timing. For licensed NPs, we combine outcomes from New York, Nevada, and Pennsylvania. Admittedly, Pennsylvania experienced a different policy change than New York and Nevada, and even New York and Nevada's policy change differed slightly, as explained below. We therefore emphasize the results from the individual case studies. Nonetheless, we find these pooled results to be useful overall summaries of the effects of eliminating oversight ratios on NP labor market outcomes. For NPs with an NPI, we combine outcomes from New York and Nevada.

TABLE 6 Predictor weights for synthetic control models.

Predictor	Licensed NPs (NY)	NPs with NPI (NY)	Employed NPs (NY)	Average wages (NY)	Weekly hours (NY)	Licensed NPs (PA)
Pretreatment outcomes						
NPs/Pop (licensed)	0.380					0.623
NPs/Pop (w/NPI)		0.886				
NPs/Pop (employed)			0.611			
Average wages				0.017		
Weekly hours					0.013	
Additional predictors						
Unemployment (%)	0.152	0.004	0.002	0.207	0.000	0.169
Percent in poverty	0.011	0.003	0.302	0.271	0.956	0.207
Real per capita income	0.000	0.000	0.059	0.000	0.003	0.000
Doctors/Pop (hospital)	0.455	0.008	0.002	0.504	0.018	0.000
Doctors/Pop (office)	0.001	0.100	0.025	0.001	0.011	0.000

5 | RESULTS

Here we present the results from our synthetic control estimates. Because of the relatively large number of different estimates involved, we start with a more detailed discussion of New York and then provide a more general overview for Nevada and Pennsylvania. Overall, we find that eliminating oversight ratios has no significant effect on the NP labor market.

5.1 | New York

Following an 8-year lobbying effort, New York passed the Nurse Practitioner Modernization Act (NPMA) in 2014 (Columbia University Irving Medical Center, 2014). Prior to the NPMA, which took effect January 1, 2015, New York required NPs to work under a CPA and maintained an oversight ratio of 1:4. The NPMA eliminated the oversight ratio and the requirement for a written CPA for all NPs with more than 3600 h of clinical practice, which translates to about two years of experience. Instead, NPs with more than 3600 h of experience must have a "collaborative relationship" with at least one physician or hospital and must attest to this relationship by completing a two-page form. This form does not require a physician's signature. Collaborative relationships are the norm for NPs, and this attestation is not seen as restricting NPs' ability to practice. Local NPs interpret the 2015 change in the law as allowing full practice authority (Poghosyan et al., 2020). To be clear, the policy change evaluated here reflects the combination of eliminating the oversight ratio and requirements for collaborate practice agreements.

Notably, the NPMA was originally scheduled to sunset June 30, 2022. A couple months prior to the bill's sunsetting, New York extended and temporarily expanded the NPMA until April 2024. New York again extended the NPMA on March 28, 2024, this time until 2026. From April 1, 2022, to July 1, 2026, NPs with more than 3600 h of practice experience are exempted from the oversight requirement—they will practice with full autonomy and without even a pro forma reporting requirement. Without further legislative action, NP oversight requirements will return to the 2015–22 intermediate regime in July 2026. (2024 McKinney's Session Laws of NY, Ch. 112 (S. 8920)).

Beginning with licensed NPs—the measure of NP labor supply from the NPAALU data set—the donor pool and each donor's contribution to synthetic New York is reported in the first column of Table 3. Table 3 shows that our synthetic New York is composed of 52.3% Georgia, 17.3% Massachusetts, 16.9% District of Columbia, 11.1% Kansas, and less than 3% of the remaining states in the donor pool. The first panel of Table 7 shows that our synthetic New York's predictors are close to those of true New York. In particular, synthetic New York is closer to true New York in its

TABLE 7 Summary statistics for predictor variables, New York (All outcomes).

	Treated	Synthetic	Sample mean
Licensed NPs			
NPs per 100,000 pop.	68.485	68.498	55.612
Unemployment (%)	6.254	6.252	6.294
Poverty (%)	14.506	14.528	14.570
Real per capita income ($1000s)	21.934	19.974	18.379
GP physicians per 100,000 pop. (Hospital)	1.405	1.404	1.583
GP physicians per 100,000 pop. (Office)	14.910	21.062	26.194
NPs with an NPI			
NPs per 100,000 pop.	54.562	54.535	49.144
Unemployment (%)	7.853	8.529	7.626
Poverty (%)	15.800	12.661	15.982
Real per capita income ($1000s)	23.365	25.773	18.452
GP physicians per 100,000 pop. (Hospital)	1.310	1.186	2.117
GP physicians per 100,000 pop. (Office)	14.897	15.820	27.789
Employed NPs			
NPs per 100,000 pop.	42.899	43.006	38.344
Unemployment (%)	7.853	7.688	7.731
Poverty (%)	15.800	15.298	16.377
Real per capita income ($1000s)	23.365	21.300	17.698
GP physicians per 100,000 pop. (Hospital)	1.310	1.527	2.003
GP physicians per 100,000 pop. (Office)	14.897	20.988	27.340
Wages			
Average annual wages (2024 $)	107,069.878	107,108.458	105,284.105
Unemployment (%)	7.853	7.855	7.731
Poverty (%)	15.800	15.797	16.377
Real per capita income ($1000s)	23.365	20.016	17.698
GP physicians per 100,000 pop. (Hospital)	1.310	1.310	2.003
GP physicians per 100,000 pop. (Office)	14.897	19.758	27.340
Hours worked			
Average weekly hours	38.068	38.399	38.752
Unemployment (%)	7.853	8.430	7.731
Poverty (%)	15.800	15.779	16.377
Real per capita income ($1000s)	23.365	20.726	17.698
GP physicians per 100,000 pop. (Hospital)	1.310	1.422	2.003
GP physicians per 100,000 pop. (Office)	14.897	19.675	27.340

Note: For the outcome Licensed NPs, data on the predictors are from the years 1999–2014. For NPs with an NPI, employed NPs, average annual wages, and average weekly hours, the data are from the years 2010–2014.

TABLE 8 Summary statistics for predictor varialbes, Pennsylvania (licensed NPs).

	Treated	Synthetic	Sample mean
NPs per 100,000 pop.	46.037	46.078	48.145
Unemployment (%)	5.227	5.224	5.525
Poverty (%)	11.036	11.056	13.612
Real per capita income ($1000s)	18.309	17.608	18.003
GP physicians per 100,000 pop. (Hospital)	1.852	1.624	1.486
GP physicians per 100,000 pop. (Office)	23.155	28.673	26.060

Note: For the outcome Licensed NPs, data on the predictors are from the years 1999–2009. Because Pennsylvania enacted its policy in 2010, there is no pretreatment data available on the other outcomes, so the summary statistics on predictor variables for those outcomes are omitted.

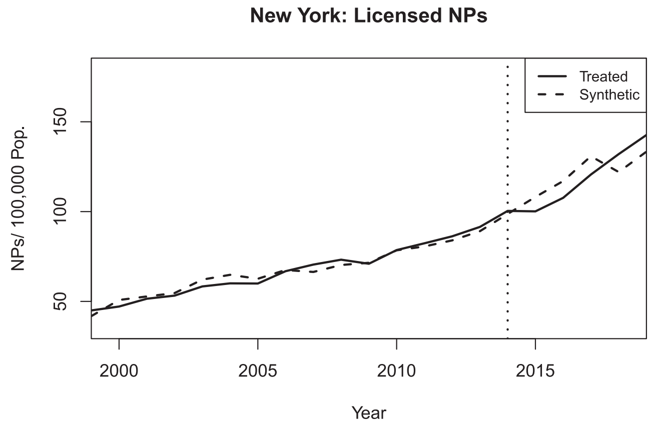

FIGURE 6 Path plot for New York Licensed NPs synthetic control study.

number of hospital- and office-based general practitioner physicians per 100,000 people in the population, which is especially relevant in this context.

Figure 6 presents the evolution of licensed NPs in New York, as well as its synthetic control. The dashed line indicates the last year of the pretreatment period—here, 2014. We can see that both New York and its synthetic increase steadily over the course of the sample period. Judged by the standard of how well the synthetic unit matches New York during the pretreatment period, this case study seems to do quite well.

As for the effect of eliminating oversight ratios and CPAs on NP labor supply in New York, this study indicates that the policy change initially had little, if any effect. In the first three years after the policy change, New York had 8.03, 9.33, and 10.17 fewer NPs per 100,000 residents than its synthetic control. In the fourth and fifth years afterward, however, New York had 9.98 and 9.27, respectively, more NPs per 100,000 residents than the synthetic. On average, New York had 1.66 fewer NPs per 100,000 residents than its synthetic during the post-treatment period. This is a difference of less than 2% of the New York post-treatment average.

The 9.98 and 9.27 per 100,000 residents increase over the synthetic in the fourth and fifth years after the NPMA may represent a lagged effect. After all, RNs motivated by the change in the law to become NPs would need to apply to and complete the advanced NP training curriculum, a process that takes about 3 years. However, looking at Figure 6, it appears that this increase over the synthetic is driven less by an uptick in NPs in New York and more by a drop in NPs in the synthetic; though it could be that New York's expansion of SOP insulated its NP market from a downturn it otherwise would have experienced. Unfortunately, while this ambiguity might have otherwise been resolved in the fullness of time, the disruptions of the COVID-19 pandemic undermine the validity of any potential conclusions beyond 2019.

Figure 7 shows the path of the New York placebos. The placebos plot is generated by applying the synthetic control algorithm to each state in the donor pool and plotting the gap between each state and its synthetic. Since the donor pool is explicitly constructed to omit any states that experienced a similar policy change to New York, Figure 5 compares New York's experience to those of states that did not eliminate oversight ratios or transition to FPA during the sample period. Figure 5 therefore provides useful context for the results in Figure 4. We can see in Figure 5 that in terms of

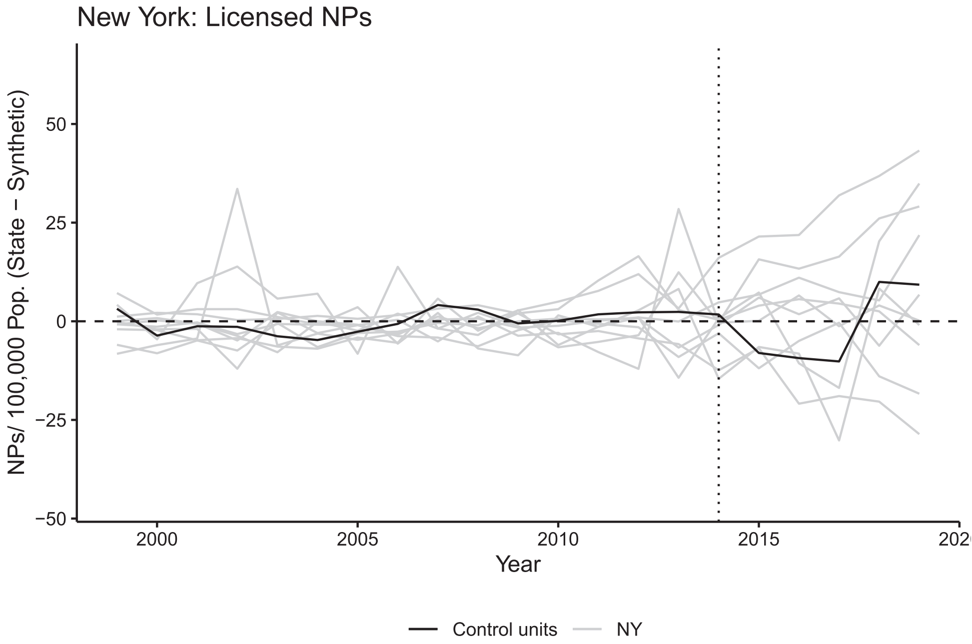

FIGURE 7 Placebos plot for New York NPs synthetic control study.

difference from the post-treatment synthetic, New York is in the middle of the pack, which supports the conclusion that eliminating oversight ratios and transitioning to FPA did not have a sizable effect.

The post/pre MSPE ratio histogram in Figure 8 further confirms the lack of an effect in New York. This histogram is generated as described in Section 4 above. The dark shaded block here corresponds to New York, and all other states from the donor pool are shaded gray. Two things stand out in Figure 8. First, since New York has the third highest MPSE ratio out of the 12 states (the 11 control units plus New York), its *p*-value is 0.25. Second, even though there are few enough units here to limit the importance of the *p*-value on its own, we can see that New York is relatively close to a grouping of states and the two states with higher MPSE ratios are more distant from the pack.

The other measures of NP labor supply tell a similar story in New York. The first columns of Tables 4 and 5 show the weights attached to the donor states for synthetic New York when the outcome is NPs with an NPI and employed NPs, respectively. These weights differ from those when the outcome is licensed NPs because they cover different years and have more states available to them. Despite these different weights, the predictors in the synthetic New Yorks are quite similar to those of real New York, as can be seen in panels two and three of Table 7. Figure 9 shows the same plots as Figures 6–8, but for NPs with an NPI. As noted above, NPs are included as a separate taxonomy field in the NPPES data starting in 2010, whereas data on licensed NPs comes from state licensing agencies and state nursing associations.

Again, we observe a close fit between New York and its synthetic counterpart during the pretreatment period, which is reassuring. These results show a very small, if somewhat negative effect on NP labor supply from eliminating the oversight ratios and transitioning to FPA. Even though the number of NPs measured by the AHRF is growing during the post-treatment period, New York has on average 1.63 fewer NPs per 100,000 residents than its synthetic counterpart. The small size of the effect is even more apparent when compared to the placebos in the second panel of Figure 9. The permutation test results in the third panel of Figure 9 further indicate that this effect was not significant. Here, New York's post/pre MSPE ratio is ranked 26 out of 34 (33 control units plus New York), which gives it a *p*-value of 0.76.

Figure 10 shows the paths of NPs who report being employed on the ACS-PUMS survey along with the placebo paths and permutation testing. While the data from the ACS- PUMS is clearly more volatile than either the NPAALU or AHRF (NPPES), we still observe a fairly tight fit between New York and its synthetic in the pretreatment period. In the first post-treatment year, New York has 8.09 more employed NPs per 100,000 people in the population than its synthetic. Thereafter, synthetic New York has more employed NPs per capita, and this gap fluctuates considerably.

The placebo plot in Panel 2 of Figure 10 is probably the most helpful figure to determine whether the gap is significant. Compared with the placebo states from its donor pool, New York is very average, even with the more extreme states excluded. Admittedly, New York has the second highest post-to pre-treatment MSPE ratio and its *p*-value is 0.067.

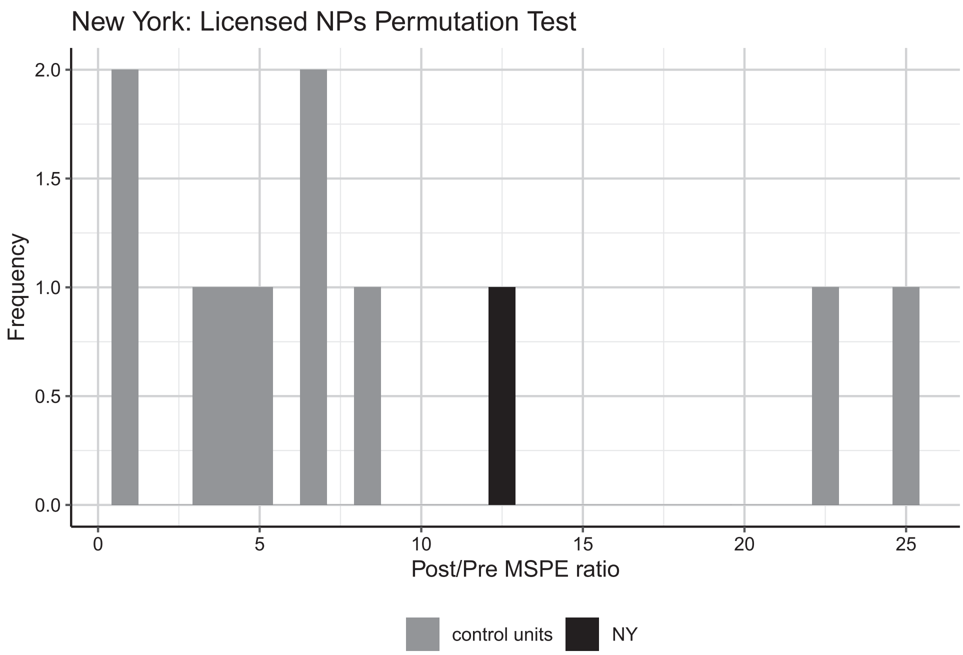

FIGURE 8 Permutation test for New York Licensed NPs synthetic control study.

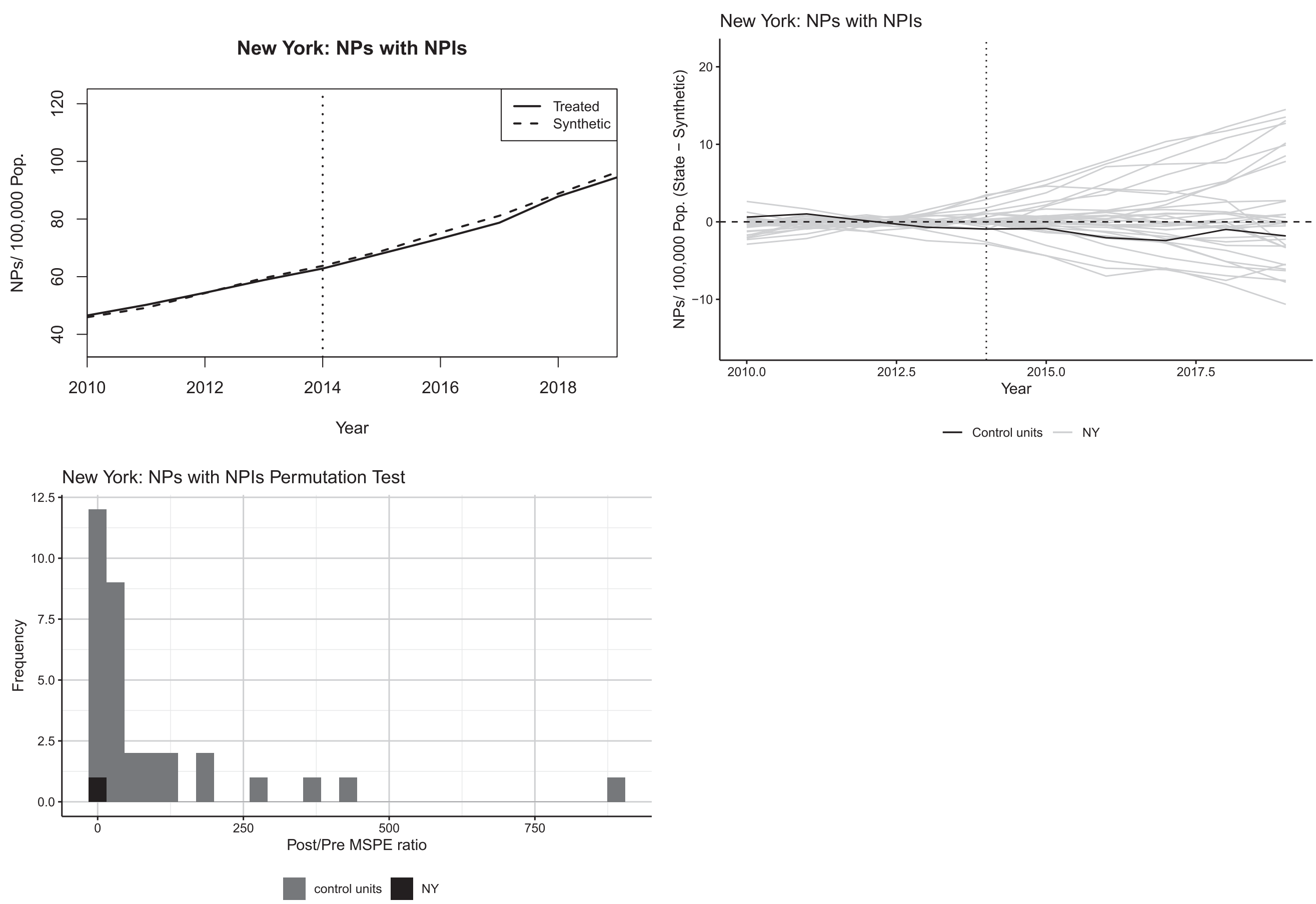

FIGURE 9 Synthetic Control Results for NPs with an NPI in NY. The first panel plots the evolution of NP labor supply over time. The second panel plots the gap between the observed data and the synthetic control for New York and the placebo states. The third panel is a histogram of the ratio of the post-to pretreatment MSPE.

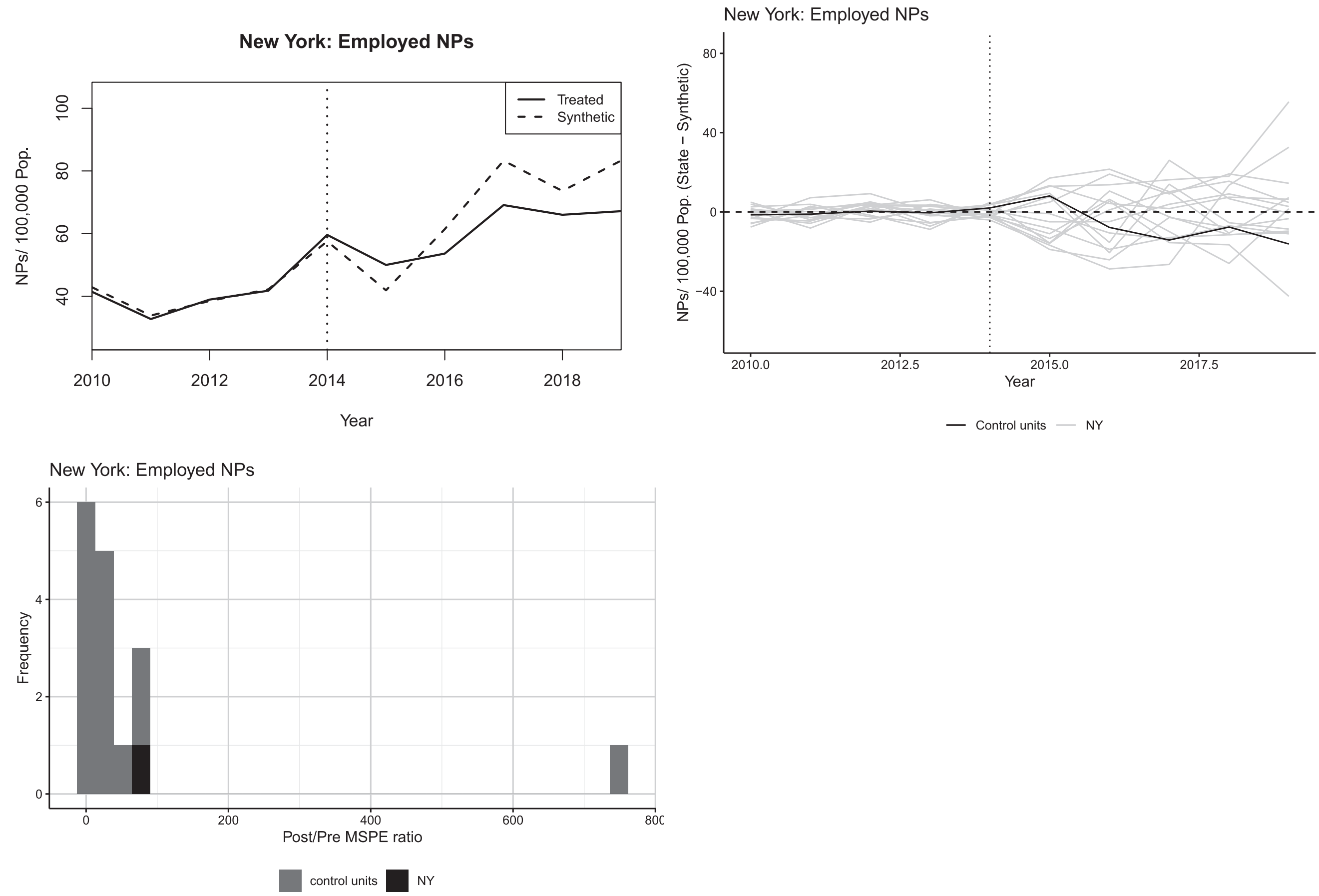

FIGURE 10 Paths Plot (Panel 1), Placebos Plot (Panel 2), and Permutation Testing (Panel3) for employed NPs in New York.

However, Panel 3 of Figure 9 shows that its ratio is much closer to the rest of the donor pool states than the state with the highest ratio. In addition, while it is the size of the first year's difference and the subsequent gaps that contribute to New York's high MSPE ratio, the fact that these gaps have opposing signs suggests that the difference between New York and its synthetic is most likely driven by the volatility of the ACS-PUMS data. Overall, we conclude that the NPMA did not have a significant impact on the number of employed NPs in New York.

Wages also appear to have been unaffected by New York's elimination of oversight ratios and CPAs. Figure 11 presents our results on wages in New York. Because data on wages come from the ACS-PUMS survey, they are similarly noisy as the employment data. Nonetheless, as can be seen in Panel 1, pretreatment fit between New York and its synthetic is not terrible. In the post-treatment period, New York and its synthetic remain close, especially when compared to the placebo states. The *p*-value from permutation testing for NP wages in New York is 0.6.

The same conclusion also seems to hold for hours worked per week. Pretreatment fit between New York and its synthetic—seen in Figure 12, Panel 1—is not particularly tight, but is likely serviceable. The synthetic is, if anything, closer to New York following treatment, and this partly explains why the post-to pre-treatment MSPE ratio is so low in Panel 3. But comparing the difference between New York and its synthetic to the placebo states that New York is very much in the middle of the pack. Therefore, the NPMA most likely did not affect NP labor supplied on the intensive margin as well as the extensive margin.

The results for New York indicate very small average effects of eliminating the legislated oversight ratios on the three different measures of NP labor supply. One possible reason for the overall lack of an effect could be the sunsetting provision in the 2014 legislative change (and every change since). Recall that it takes 3 years for an existing registered nurse to get the necessary further education and another two to get the necessary practical experience to qualify for the more autonomous practice environment in New York. So, an RN in 2014 would not have been able to look forward to enjoying very many years of more autonomous practice under the NPMA, to say nothing of a person without a nursing background. If the sunsetting provision is, in fact, what limited the influx of new NPs into the New York market, then it is possible that the 2022 amendments may actually attract more workers to NP practice. Unlike in 2014, a person

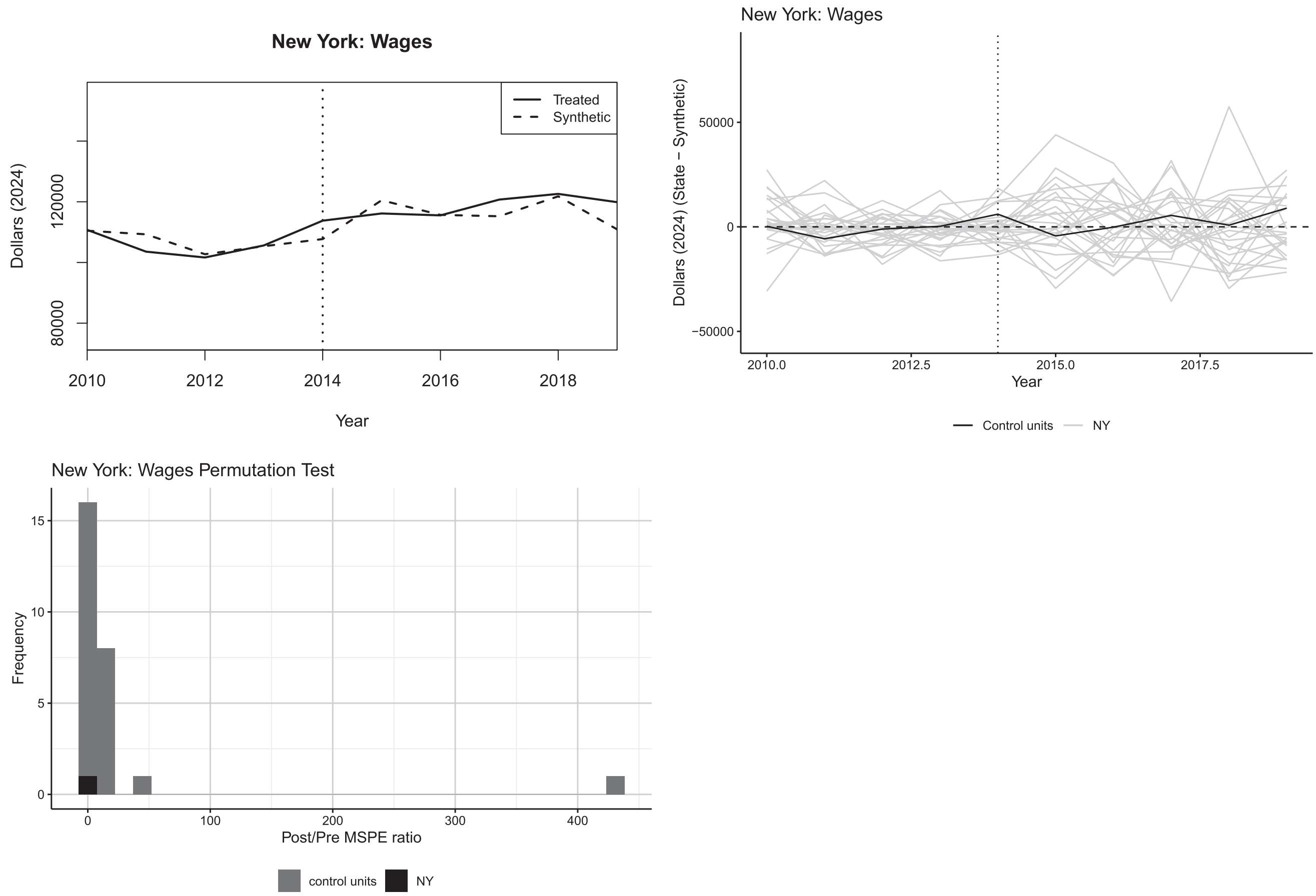

FIGURE 11 Paths Plot (Panel 1), Placebos Plot (Panel 2), and Permutation Testing (Panel3) for NP wages in New York.

considering the NP career field starting in 2022 could look forward to eventually practicing with at least 2015–22 levels of autonomy not too distantly in the future.

Similarly, while the NPMA did afford considerably more autonomy to NPs with more than 3600 h of experience, it still required NPs to comply with some documentation mandates and stipulated that physicians could overrule NPs on matters of patient care. It could be that this was not enough autonomy to draw new entrants into the NP career field. Given the findings of Poghosyan et al. (2020) discussed above, this seems like a less likely explanation for the lack of an effect. Nonetheless, the 2022 amendments to the NPMA, as extended in 2024, may provide an opportunity to test this hypothesis in a few years.

5.2 | Nevada

Nevada transitioned to full practice authority by eliminating its collaborative practice agreements and oversight ratios in June 2013 following the enactment of AB 170. Prior to AB 170's enactment, Nevada maintained an oversight ratio of 1:3. AB 170 marked a significant change in the legal treatment of NPs in Nevada. In addition to transitioning to FPA, AB 170 transitioned Nevada from a certification to a licensing regime, created a malpractice insurance requirement for NPs, and, in exchange for FPA, required supervision for NPs with fewer than 2000 h of practice experience to prescribe schedule II drugs. In this later case—NPs with fewer than 2000 h of experience who wish to prescribe schedule II drugs—the 1:3 oversight ratio is still in effect. (Nev. Admin. Code §630.495 (2020)).

As discussed in Section 4, above, synthetic control is not a viable empirical strategy for Nevada because we cannot obtain reasonable pretreatment fit between Nevada and its synthetic for any outcome. Instead, we use SDID.

The weights of our donor pool states for Nevada are reported in the second column of Tables 3 and 4 for licensed NPs and NPI-holding NPs, respectively. For both outcomes, California contributes the most to Nevada's synthetic control; it is 22.4% of Nevada's synthetic when the outcome is licensed NPs and 13.3% when the outcome is NPs with an

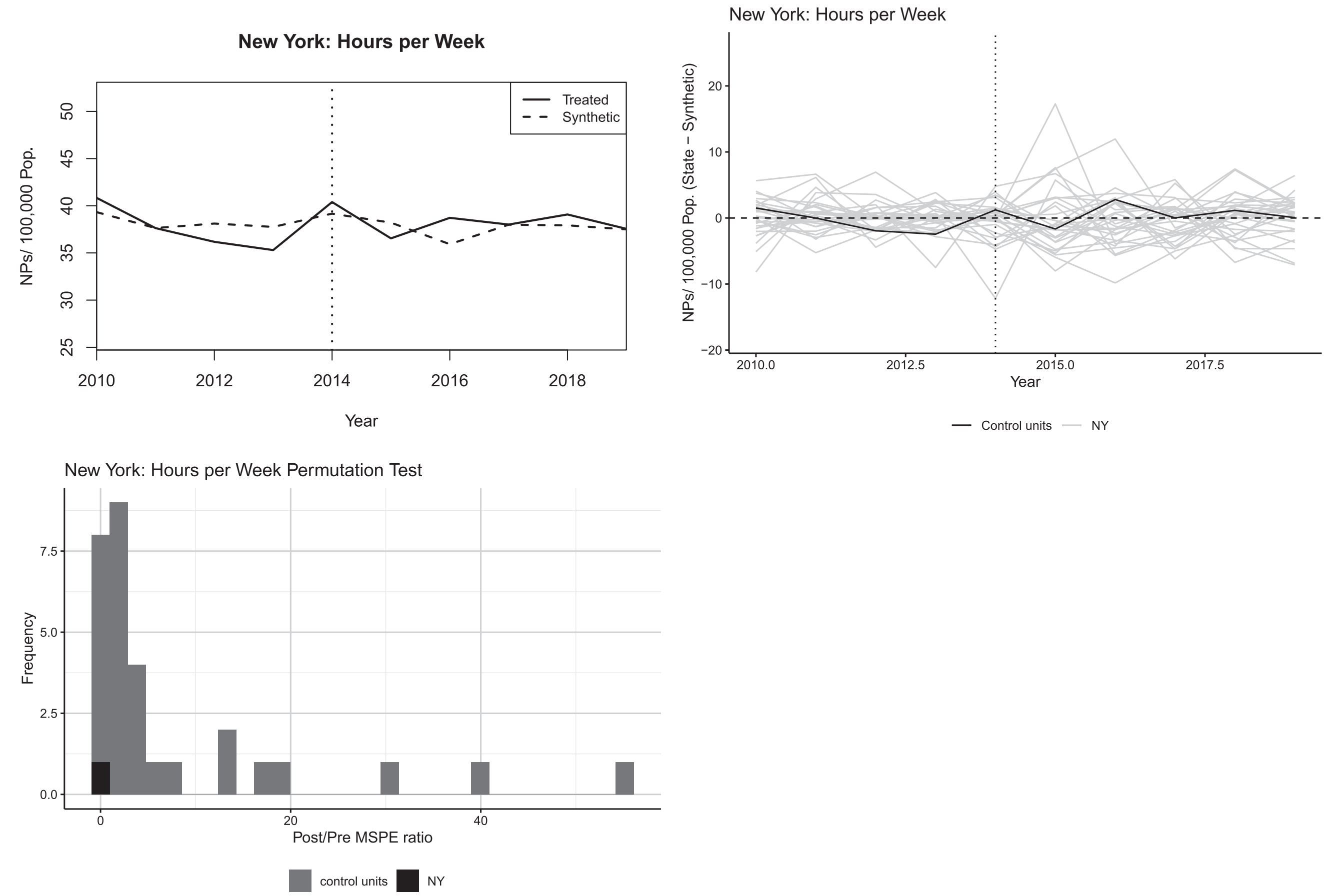

FIGURE 12 Paths Plot (Panel 1), Placebos Plot (Panel 2), and Permutation Testing (Panel3) for NP hours worked per week in New York.

NPI. Given the geographic proximity between the two states, this makes sense intuitively. The remainder of the synthetic is quite different between the two outcomes, though this is not surprising either. The outcomes come from two different data sources—with different missing observations leading to different donor pools—that span two different time periods. The weights for both of these outcomes are less sparse than the states where we use synthetic control because of SDID's regularization and use of an intercept.

For Nevada, eliminating oversight ratios and transitioning to FPA did not have any significant effect on the rate of licensed NPs or NPs with an NPI in the population. Figure 13 presents the time series plot of Nevada and its synthetic as well as the parallelogram plot for the SDID estimate. The SDID estimate for the effect of Nevada's policy change on licensed NPs is −2.97 NPs per 100,000 people in the population. We obtain similarly small results for the effect of Nevada's legal change on the rate of NPs with an NPI. The point estimate for that outcome is 0.69. The time series and parallelogram plot for NPs with an NPI is presented in Figure 14. Our standard errors for both outcomes are fairly large —13.77 for licensed NPs and 3.74 for NPs with an NPI. The confidence intervals that these standard errors generate are represented by the gray, wavy bars in Figures 13 and 14. Nonetheless, given the consistency of the size and statistical insignificance of effects across both outcomes and across other states (discussed above and below), we are fairly confident that these represent null effects.

As discussed in Section 3, above, we do not consider the outcomes employed NPs, average hours per week, or average wages for NPs in Nevada.

5.3 | Pennsylvania

Pennsylvania transitioned from a supervisory to a collaborative regulatory regime for NPs in 2002 (Act of Dec. 9, 2002, P.L. 1567, No. 206). However, Pennsylvania's oversight ratio remained in place until December 12, 2009,

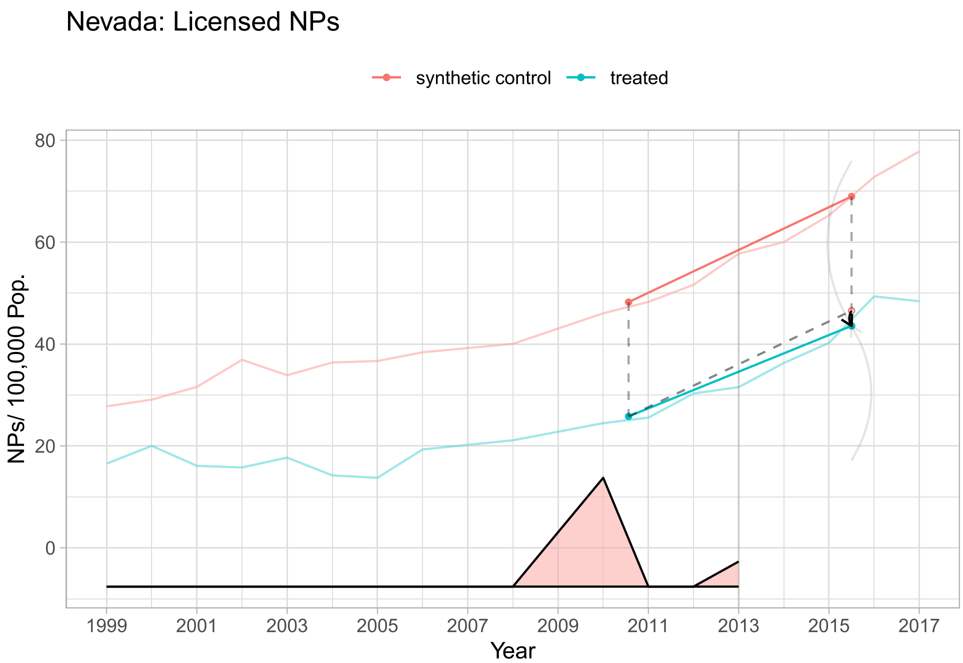

FIGURE 13 Synthetic DiD Plot for Licensed NPs in Nevada. The shaded region above the x-axis indicates how much weight is placed on which years.

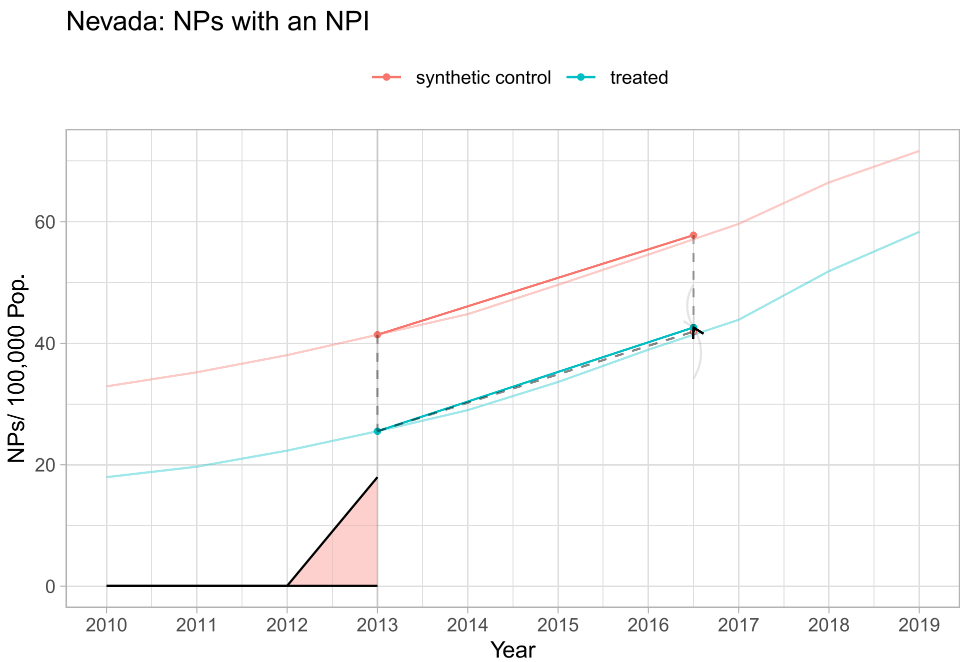

FIGURE 14 Synthetic DiD Plot for NPs with an NPI in Nevada. The shaded region above the x-axis indicates how much weight is placed on which years.

when the Pennsylvania Board of Nursing (BON) finalized administrative rulemaking in response to legislative amendments to the 2002 Act (Act of July 20, 2007, P.L. 318, No. 48; Certified Registered Nurse Practitioners; General Revisions, 39 Penn. Bulletin 6994–7005). The BON eliminated the oversight ratio of 1:4 over the objections of the Pennsylvania House Professional Licensing Committee and Pennsylvania Medical Society. In addition to removing the oversight ratio, the BON simultaneously expanded the length of time for which Pennsylvania NPs can prescribe schedule II, III, and IV drugs. But note that Pennsylvania retained its CPA requirement, so incentives are different for NPs in Pennsylvania as compared to New York and Nevada. The results for Pennsylvania can be considered as the "cleanest" test of eliminating the oversight ratio since NPs still must find a physician collaborator in order to practice.

Table 3, Column 3, shows the weights of each donor state in Pennsylvania's donor pool for licensed NPs. Pennsylvania's synthetic is more evenly weighted between its contributors than New York's, but less balanced compared to Nevada. For Pennsylvania's synthetic, 41.6% comes from Iowa, 39.1% from Oregon, 13.3% from Massachusetts, 3.4% from Kansas, and less than 4% comes from the remaining states. Table 8 reports the sample averages of the predictor variables for Pennsylvania and its synthetic compared to the overall donor pool.

Because Pennsylvania eliminated its oversight ratios in 2010, the same year that NPs were first reported in the AHRF and ACS-PUMS, there are no pretreatment years to use to evaluate the impact of the policy change on the employment status of NPs in this state. We therefore limit our analysis of Pennsylvania's policy change to licensed NPs as discussed above.

Figure 15 shows the time series of licensed NPs in Pennsylvania compared to its synthetic. Note the close fit between Pennsylvania and its synthetic during the pretreatment period. Ignoring the synthetic, Pennsylvania appears to steadily increase its rate of NPs in the population over the sample period—if anything, accelerating after the implementation of its policy change in 2010. But Pennsylvania just slightly *under* performed its synthetic in the growth of its NP labor supply. Whether this underperformance represents a decrease or no change relative to the counterfactual is not immediately obvious. The permutation test in Figure 16 shows that Pennsylvania's post-to pretreatment MSPE ratio is the third highest among its comparator states, which means its p-value is 0.25. More importantly, Pennsylvania's MSPE ratio is fairly close to the majority of placebo states, particularly compared to the top state, Georgia, which is a clear outlier. In addition, Pennsylvania's distance from its synthetic appears quite average compared to the placebos in Figure 17, which suggests that its high post-to pre-MSPE ratio is likely driven by its very tight fit in the pretreatment period relative to the placebo states. Moreover, when we exclude the states that have never had an oversight regime from our donor pool in the online Appendix, we see the same basic pattern, but with Pennsylvania's post-to pre-MSPE ratio much lower. Overall, we conclude that eliminating oversight ratios in Pennsylvania did not have any effect on its NP labor supply.

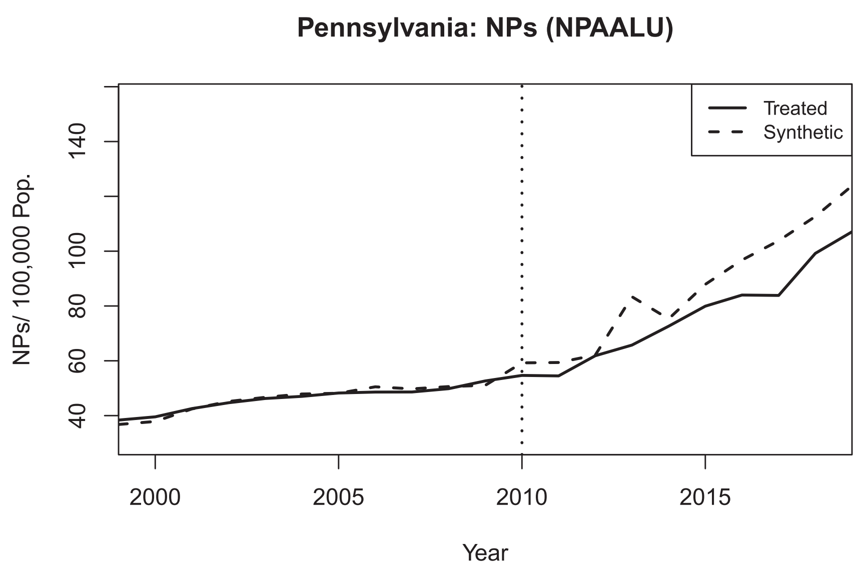

FIGURE 15 Path plot for Pennsylvania licensed NPs synthetic control study.

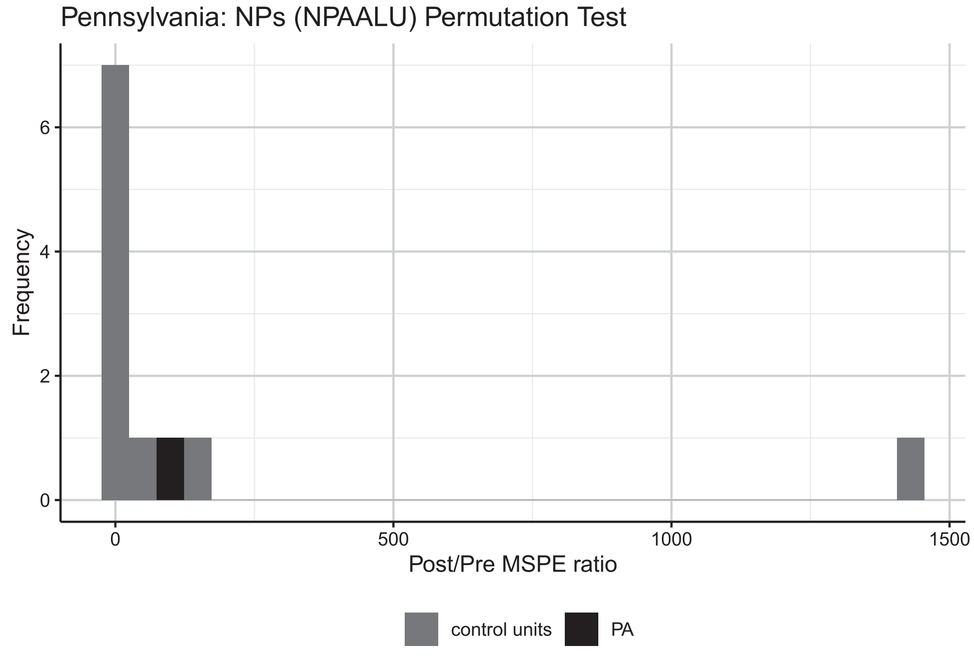

FIGURE 16 Permutation test for licensed NPs in Pennsylvania.

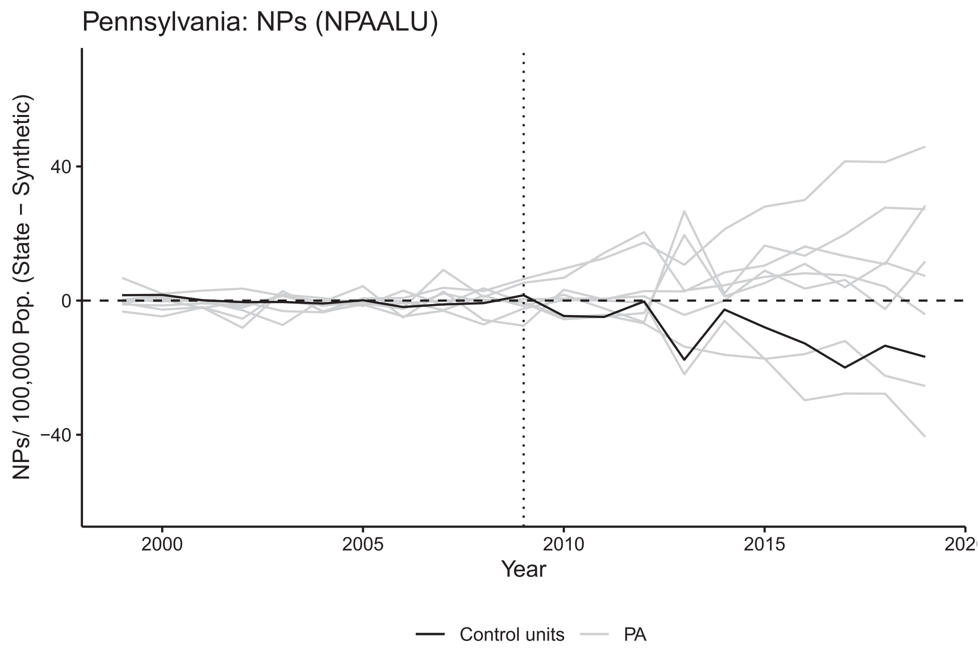

FIGURE 17 Placebo plot for licensed NPs in Pennsylvania.

5.4 | Overall average treatment effects

In addition to the individual state-level outcomes discussed above, we also take advantage of PPSCM to report overall ATTs for certain outcomes. It only makes sense to estimate PPSCM models for outcomes with more than one treated unit. In this study those outcomes are licensed NPs—New York, Nevada, and Pennsylvania—and NPs with an NPI—

New York and Nevada. The overall ATT on the rate of licensed NPs across the treated states is −5.577 NPs per 100,000 people in the population. The standard error for this point estimate is 11.292. For NPs with an NPI, our point estimate and standard error are both smaller, at 1.041 and 7.502, respectively. Both point estimates are economically and statistically insignificant, which is consistent with our findings for individual states. These results are presented graphically in Figures 18 and 19.

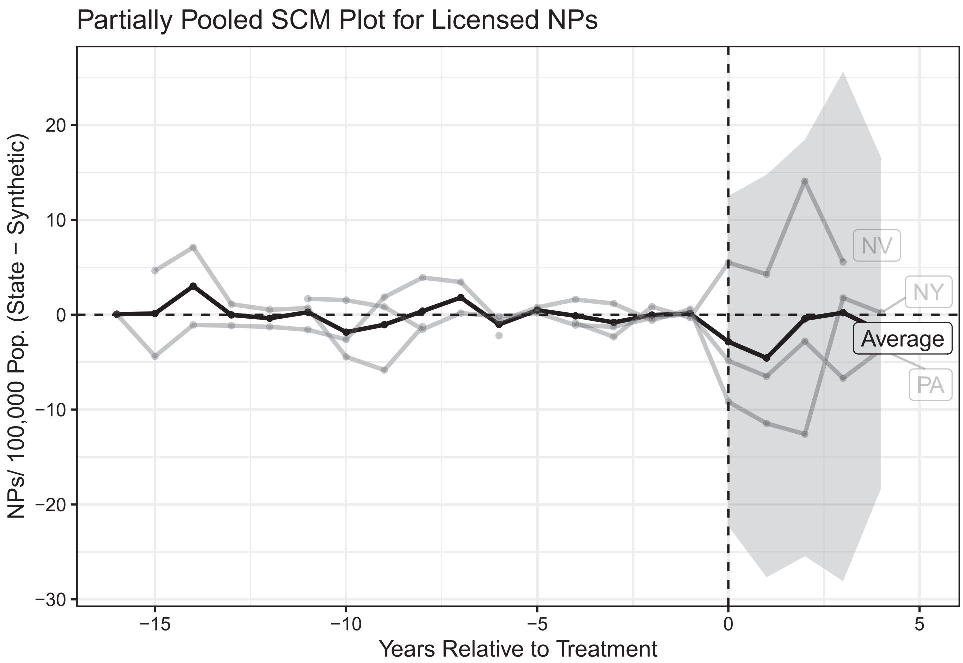

FIGURE 18 Partially pooled synthetic control plot for Licensed NPs in New York, Nevada, and Pennsylvania. The bold time series represents the partially pooled average across the states, and the shaded region represents the 95 percent confidence interval.

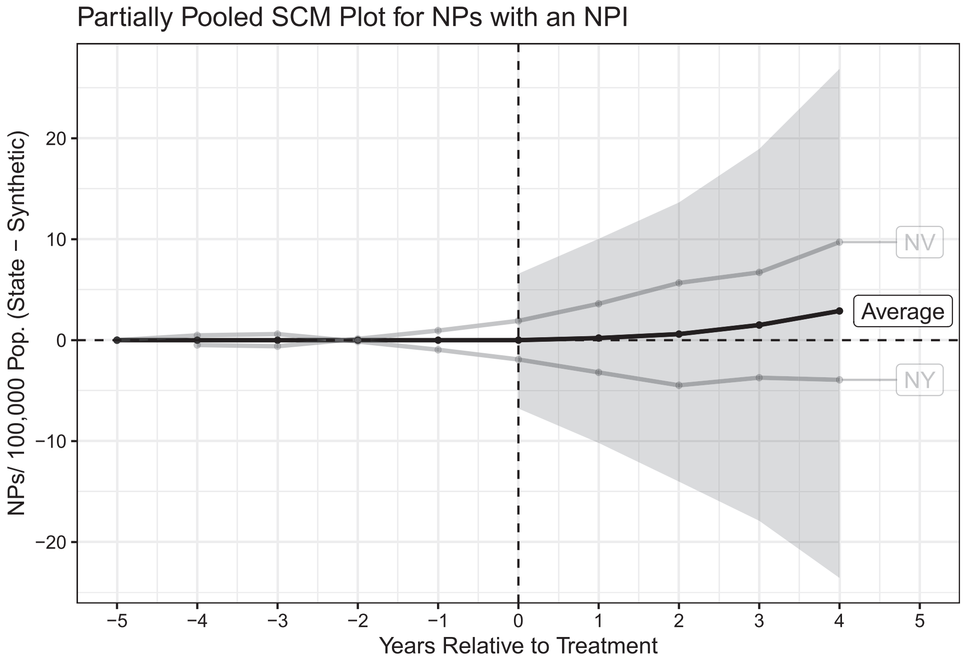

FIGURE 19 Partially pooled synthetic control plot for NPs with an NPI in New York and Nevada. The bold time series represents the partially pooled average across the states, and the shaded region represents the 95 percent confidence interval.

6 | CONCLUSION

In this paper, we analyze the effect of oversight ratios on NP labor market outcomes. We leverage the progressive elimination of these oversight ratios by states and compare the outcomes before and after elimination with states that experienced no policy change. Specifically, we consider what happens to the rate of licensed, NPI-holding, and employed NPs per capita following the repeal of oversight ratios in New York, Nevada, and Pennsylvania. We also consider the average annual wages and average weekly hours for NPs in New York.

The weight of the evidence supports the conclusion that eliminating NP oversight ratios has little effect on the labor supply—as measured by the rate of licensed and NPI- holding NPs per population—or the number or NPs employed at equilibrium. Wages and hours are similarly unaffected. These conclusions hold regardless of whether collaborative practice agreements are eliminated or maintained at the same time. Given the data limitations, the estimates from any one particular outcome variable may not establish this null result conclusively. However, the results from the various different outcome measures all point in the same direction: eliminating oversight ratios does not increase the rate of NPs in a state.

These results are surprising because, intuitively, capping the number of NPs with whom a physician may enter into a CPA should restrain the number of NPs in a jurisdiction for the reasons discussed above. Removing the caps should lower search costs and encourage more people to enter the NP career field.

There are, however, several possible reasons for why we observe no effect of eliminating oversight ratios on the outcome measures we studied. Of course, it could be the case that oversight ratios and their elimination have no impact on NP labor market decisions one way or another. Another explanation is that the ratios are not limiting, and there are sufficient numbers of physicians willing to oversee the NP labor force. Given that physicians may charge the NPs substantial fees to enter into CPAs, price mechanisms may serve to eliminate any supervisor supply shortages. Another possibility is that the NP training pipeline is sufficiently long that the increase in NPs in states that have eliminated their oversight ratios just has not yet been realized. While Nevada and Pennsylvania eliminated their oversight ratios long enough ago that we should have seen any delayed effects by now, this explanation very well could account for why New York did not see an increase in NPs following its repeal of oversight ratios. Alternatively, the schools that train NPs may simply lack the capacity to accommodate the increased number of NP hopefuls generated by the lifting of oversight ratios. Future research should look at enrollment rates and class sizes at APRN programs.

In New York, at least, the absence of an effect could stem from the particulars of policy design. As discussed above, either the sunsetting provision or the continued formal reporting requirement could have frustrated New York's attempt to boost its supply of NPs. Future researchers should evaluate the effects of New York's 2022 and 2024 legislative changes.

Policy makers should take the absence of meaningful effects of eliminating oversight ratios into consideration when debating how to expand access to care and whether to change SOP for NPs. However, an important limitation of this research is that we do not address potential effects on quality of care, nor other aspects of access such as waiting times and time spent with patients. Labor market effects are only one aspect of the debate surrounding SOP, and policy makers need to consider the totality of effects of eliminating physician oversight of nurse practitioners.

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DATA AVAILABILITY STATEMENT

The Data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] Similarly, while it would be interesting to study the effect of loosening the oversight ratios without eliminating them entirely, only two states have enacted such a policy—Virginia in 2012 and Missouri in 2018. Unfortunately, the timing of Missouri's change leaves it with only one post-treatment year. Virginia's timing leaves it with only two pretreatment years for most of our outcomes, which is not sufficient for any of our methods. For the remaining outcome, the data source stops reporting the number of NPs in Virginia 2 years after the state modified its oversight ratios, meaning it has too few post-treatment years.

[2] We end our data series in 2019 specifically to avoid the pandemic years. During the public health emergency, most states temporarily waived or suspended practice agreement requirements to address the immediate healthcare worker shortage (AANP, 2021). This would affect the composition of the control group, as states that in other times have no full practice authority temporarily became treated states. Future work could evaluate the effects of the temporary changes to SOP during pandemic years on the nurse labor force.

[3] This includes half or more of the years of data for Connecticut, Hawaii, Indiana, New Jersey and Wisconsin.

[4] Note that the NPAALU and the AHRF/NPPES distinguish among the different types of APRNs, which allows us to isolate the experience of NPs in these data sources.

[5] This pattern is not affected when we include states that are neither treated nor in the donor pool.

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