

Licensing Barriers to Interstate Mobility in the US: Evidence from Travel Nurses

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Abstract

Occupational licensing is widespread in the United States, yet little is known about how differences in state licensing requirements affect workers' interstate mobility. This paper quantifies the effects of interstate licensing barriers on nursing labor markets during the COVID-19 pandemic. Using novel travel nurse application data from Wanderly, I first exploit variation in Nurse Licensure Compact (NLC) participation and emergency waivers in a difference-in-differences framework. Although non-NLC states saw relative increases in applications during parts of the emergency, they consistently received fewer applications per COVID-19 case than NLC states, indicating lower applicant supply relative to need. To quantify the role of licensing barriers in these trends, I next estimate a model of travel nurse applications and wage posting. The model identifies their effect using differences in nurses' licensing access to the same county and changes in barriers during emergency waivers. The results show that licensing barriers substantially deter applications. Nurses require a compensating wage differential of 67-80% to apply where they lack a license - five to seven times the premium needed to apply twice as far from home. Emergency waivers reduced the licensing penalty only gradually. Counterfactual estimates show that entering the pandemic without these barriers would have halved the non-NLC versus NLC gap in applications per COVID-19 case and redirected travel nurses toward non-NLC states when they faced the greatest COVID-19 burden.

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1 Introduction

Occupational licensing requires workers to obtain state authorization to practice. A key feature of licensing policies in the US is that they vary across states, creating barriers to interstate migration ([Johnson and Kleiner, 2020](#)). In healthcare, the largest licensed sector of the US workforce and one facing persistent staffing shortages, such barriers can affect patient outcomes, especially during emergencies.¹ Yet little is known about how interstate licensing barriers affect the mobility of healthcare workers in the US. This paper bridges this gap by examining how interstate licensing variations shaped the labor market for Registered Nurses (RNs) during COVID-19.

A growing body of evidence links nurse staffing to patient mortality across settings ([Propper and Van Reenen, 2010](#); [Gruber and Kleiner, 2012](#); [Cook et al., 2012](#); [Friedrich and Hackmann, 2021](#)). Notably, [Gruber and Kleiner \(2012\)](#) find that nurse strikes in New York State raised in-hospital mortality by 18%. Public health emergencies can intensify this effect by sharply increasing demand in a hospital system that already reports an average RN vacancy rate of 8%. During COVID-19, hospitals responded to this gap by increasingly relying on travel nurses - RNs hired for temporary assignments - to meet the sudden surge in demand.² ³ Because these assignments often require nurses to cross state lines, state-specific licensing requirements can impede their movement to areas of greatest need. This paper focuses on travel nurses, and their licensing process is the same as that of a regular nurse.

All Registered Nurses (RNs) in the US must hold a license to practice in any state, with licenses not necessarily portable across states. However, for RNs, there exists an agreement - Nurse Licensure Compact (NLC) - that allows them to practice in any member state under a single “multistate” license. This eliminates the need for relicensure when moving between member states. By 2020, 30 states were members (NLC states), while 20 were not (non-NLC states). This could have placed the non-NLC states at a disadvantage when responding to the sudden increase in demand for nurses. However, one other feature of the licensing policies during COVID-19 was the adoption of federal emergency waivers.

During the federal public health emergency, from March 2020 to May 2023, states temporarily eased mobility barriers by suspending interstate licensing requirements. Although

¹“The U.S. health workforce continues to struggle with staffing shortages and maldistribution of health professionals” ([American Hospital Association, 2023](#)).

²[U.S. Government Accountability Office \(2024\)](#).

³As per data from Aya Healthcare, one of the leading healthcare providers in the US, demand for travel nurses jumped by 217% in November 2020 from a year before.

all states adopted waivers in March 2020, state-specific licensing memoranda clarified their implementation only gradually. This uncertainty likely delayed nurses' response, leaving non-NLC states reliant on nurses already licensed there during the initial outbreak.⁴ Non-NLC states entered the pandemic with higher licensing barriers and were also among the states hit earliest by COVID-19, making a rapid inflow of nurses particularly important. Beyond quantifying the effects of licensing barriers on interstate mobility, this setting allows me to evaluate how effectively the emergency measures eased these barriers.

This paper combines novel travel nurse application data from Wanderly for 2019-2023 with the NPPES NPI registry to study how interstate licensing barriers affect the travel nurse labor market. As a digital staffing marketplace, Wanderly allows nurses to compare job postings across agencies and choose where to apply. Because agencies handle the subsequent hiring process, these data capture applications but not the final matches. To bridge this gap, I draw on the NPI registry, which records reported practice locations for approximately 5-7% of RNs. Comparing interstate RN moves in the registry with Wanderly applications across origin-destination state pairs helps inform the application-to-hire conversion rate.

This paper addresses two research questions: First, to what extent do licensing barriers affect nurses' application decisions, beyond any effect operating through wages? Second, to what extent did the federal emergency waivers reduce these effects of interstate licensing barriers?

The empirical analysis proceeds in two steps. First, I exploit cross-state differences in NLC participation and the temporary suspension of licensing requirements during the COVID-19 emergency. Using difference-in-differences and event-study frameworks, I examine how county-level applications and wages changed as interstate licensing barriers eased. Applications to non-NLC states increased relative to NLC states at several points during the emergency, although the response varied over time. Despite these increases, non-NLC states continued to receive fewer applications relative to need, as measured by COVID-19 cases. Periods of higher non-licensed applications to non-NLC states also coincided with increases in their relative wages.

Differences between NLC and non-NLC states, together with other changes during the emergency, make it difficult to attribute the observed patterns solely to licensing barriers. Accordingly, the reduced-form estimates provide suggestive evidence on the effects of licensing barriers and motivate the second part of the analysis of this paper. I next estimate a structural model that uses individual application choices to identify the effect of interstate

⁴Figure A2 in the Appendix provides anecdotal evidence of the delayed response to emergency waivers.

licensing barriers on travel nurse applications and wages using Wanderly data.

I observe every platform application, job-posting characteristics, and each nurse’s home state and license portfolio. Nurses can apply in states where they are not yet licensed and obtain a license after receiving an offer, typically with agency assistance.⁵

Identification comes from three sources of variation. First, for the same county and quarter, I compare applications from nurses who are licensed to practice in the destination state with those who are not. Second, I compare a nurse’s choices across destinations where her licensing status differs. Third, I use changes in licensing barriers over time as emergency waivers took effect and later expired.

I estimate a discrete-choice model of travel-nurse applications, with choice sets comprising counties receiving applications in the same period and specialty. Indirect utility comprises nurse-destination characteristics, county-level mean utility, and an idiosyncratic shock. The model identifies the effect of licensing barriers on application decisions, conditional on distance and county-level mean utility. I allow this effect to vary by half-year to capture changes during emergency waivers. I then decompose mean utility into posted wages and COVID-19 cases, using two-stage least squares with instruments for wages to estimate the wage elasticity of applications. Assuming monopsonistic wage setting and decreasing returns to scale, I recover county-level wage markdowns and use them to estimate the equilibrium wage effects of licensing barriers in the counterfactual.

The results show that licensing barriers substantially deter applications. The estimated barrier reduces the odds of applying to a destination where a nurse lacks a license by about 66%. Holding other factors constant, a nurse requires a wage premium of 67-80% to offset this barrier. By comparison, persuading a nurse to apply twice as far from home requires only one-fifth to one-seventh of this premium. Emergency waivers reduced licensing barriers, although the licensing penalty did not fully disappear until the end of 2021. The wage elasticity of applications is 1.6-2.1, implying that employers of travel nurses have considerable monopsony power, with posted wages roughly 32-38% below the marginal revenue product of labor.

Finally, I simulate applications and wages if all states had joined the NLC before 2020. The largest application gains accrue to non-NLC states.⁶ Removing barriers beforehand would have halved the non-NLC versus NLC gap in applications per COVID-19 case and redirected nurses from NLC to non-NLC states at pandemic onset. This would have increased supply in states hit early by COVID-19, where higher barriers contributed to fewer

⁵For unlicensed applications, the primary remaining cost is the delay in obtaining a new license.

⁶The model defines licensing barriers using nurses’ license portfolios rather than states’ NLC status.

applications per case.

To the best of my knowledge, this is the first paper to quantify the effects of interstate licensing barriers in the US travel nurse labor market. Most existing studies examine licensing as a barrier to occupational entry and its implications for the trade-off between service quality and labor supply (Leland, 1979; Shapiro, 1986; Kleiner and Krueger, 2013; Blair and Chung, 2019; Anderson et al., 2020; Larsen et al., 2020; Kleiner and Soltas, 2023; Atal et al., 2026).

Fewer papers examine licensing as a barrier to mobility across states in the US (Johnson and Kleiner, 2020; Bae and Timmons, 2023), and studies of the NLC find limited effects on nurse supply or migration (DePasquale and Stange, 2016; Shakya et al., 2022). By linking individual licensing records to job applications and posted wages, this paper directly identifies how interstate licensing barriers affect nurses' application decisions and the wages associated with those barriers. Moreover, it focuses on travel nurses, for whom interstate licensing requirements are especially likely to bind.

Second, this paper contributes to the literature estimating employer-specific labor supply and wage-setting power from workers' job choices. Azar et al. (2022) estimate labor supply elasticities using job applications, while Marinescu and Rathelot (2018) document workers' aversion to distant jobs. Hospitals, in particular, have substantial wage-setting power (Staiger et al., 2010; Prager and Schmitt, 2021). I identify interstate licensing as another source of labor market segmentation: by limiting nurses' feasible destinations, licensing barriers make labor supply to counties less elastic. The estimates imply that a nurse requires a 67-80% wage premium to apply where she is not licensed. Embedding the application model in a wage-posting framework, I show that removing these barriers lowers wages through increased labor supply but raises them by reducing wage markdowns. These channels largely offset, resulting in substantial application reallocation but modest wage changes.

Finally, this paper contributes to research on worker reallocation during public health emergencies. While higher pay drew travel nurses toward COVID-19 surge areas (Gottlieb and Zenilman, 2026), evidence on emergency licensing waivers remains largely descriptive (Nguyen et al., 2022). I show that the licensing penalty declined gradually after waivers began and disappeared only by the end of 2021. Had all states joined the NLC before the pandemic, 2.25% of applications - equivalent to roughly 950 nurses, or 3% of reported RN vacancies in non-NLC states - would have shifted toward non-NLC states, narrowing the initial gap in applications per COVID-19 case. These findings highlight the cost of relying on temporary waivers rather than standing reciprocity agreements.

The rest of the paper is structured as follows. Section 2 provides the institutional background. Section 3 describes the data used for the analysis. Empirical strategy and reduced-form evidence are discussed in Section 4. Section 5 discusses in detail the structural equilibrium model. Parameter results and counterfactuals are discussed in Section 6. I conclude in Section 7.

2 Institutional Details

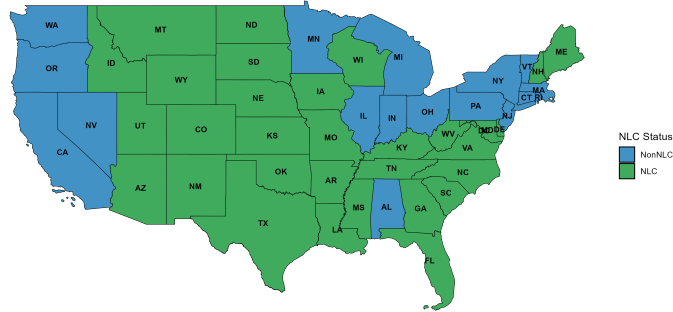
2.1 Registered Nurse Licensure in the US

The US nursing labor market is broadly divided across four professions: Certified Nursing Assistant (CNA), Licensed Practical Nurse (LPN), Registered Nurse (RN), and Advanced Practice Registered Nurse (APRN). This paper focuses on RNs, whose primary responsibilities include assessing patients, making care plans, giving treatments, and coordinating care. All RNs in the US must hold a state-issued license to practice, and they make up about 77% of the licensed nurses in the US. To obtain an initial license, an RN must graduate from an accredited nursing program and pass the national licensing exam (NCLEX-RN), after which they can apply through a state’s board of nursing.

To practice in another state, an RN could be required to obtain the state’s license through “licensure by endorsement”. Under this process, the nurse does not have to take the licensing exam again but still must complete background checks and other administrative requirements. Although these steps are largely bureaucratic, the time needed to obtain a new license ranges from 10 days to 8-12 weeks across states. Renewal requirements also differ considerably across states, including continuing education requirements and how often a license must be renewed. Together, these differences can make it costly for nurses to move or work across state lines. With an aging population and growing RN shortages, these barriers can limit how quickly the RN workforce adjusts to shifts in demand across states. To address this issue, the National Council of State Boards of Nursing (NCSBN) introduced the Nurse Licensure Compact (NLC) in 2000. The NLC allows a nurse to practice in any member state with a single multistate license, removing the licensing barrier to interstate mobility of RNs. Texas, Wisconsin, and Utah were the first three states to pass the NLC into law in 2000, and by the onset of COVID-19 in 2020, 30 states were a part of the compact (*NLC States*) and 20 were not (*non-NLC States*). Figure 1 maps these states and Appendix Figure A1 shows the distribution of the time and fee cost of obtaining a new RN license by the NLC

status of the state.

Figure 1: non-NLC States and NLC States by 2020



Notes: States that were members of the Nurse Licensure Compact (NLC) as of January 2020 are shown in green and non-members in blue. Source: National Council of State Boards of Nursing (NCSBN).

Travel Nurses: Another feature of the RN labor market that has grown with rising shortages is the market for travel nurses, which is also the focus of this paper. Travel nurses are hired by hospitals on short-term (typically 3-month) contracts, and the hiring is mediated through a travel nurse agency. The data for this paper is sourced from Wanderly which is a travel nurse job postings aggregator that lists postings from multiple travel nurse agencies in one place for a nurse to compare and apply to. Aside from contract structure, their licensing process and job responsibilities are the same as those of regular nurses. Because they often work across multiple states, licensing barriers can pose greater mobility constraints for them. Hospitals relied heavily on travel nurses during COVID-19 to meet the sudden surge in demand. Figure A3 plots the yearly unfilled RN vacancies from 2018-2023 against the travel nurse assignments. As the vacancy rate went up during COVID-19, so did the travel nurse assignments.

2.2 Emergency Measures and COVID-19

The US has long used emergency declarations to coordinate disaster responses through the Emergency Management Assistance Compact (EMAC), established in 1996 and adopted by all states by 2020. When a governor declares an emergency, EMAC enables states to share personnel and resources, temporarily waiving licensing restrictions for out-of-state workers.

In response to COVID-19, multiple federal and state emergencies were declared. The first, on January 31, 2020, designated COVID-19 as a Public Health Emergency (PHE), granting governors flexibility to request federal assistance but not removing interstate licensing barriers. By March 13, 2020, 13 NLC and 8 non-NLC states had issued their own licensing waivers, though the measures varied widely. That day, President Trump declared a national emergency under the National Emergencies Act, temporarily suspending interstate licensing variation and allowing healthcare workers with valid state licenses to practice nationwide.

The first confirmed US case of COVID-19 was reported on January 20, 2020, and by March 13, over 30,000 cases had been recorded nationwide. The rapid escalation in infections created an urgent demand for healthcare personnel. NLC states were comparatively better positioned to meet this surge, as they could redeploy nurses across member states under the multistate license. In contrast, non-NLC states were constrained by in-state nurse supply until emergency measures were enacted.

3 Data and Descriptive Evidence

Wanderly is the primary data source for this paper, providing records of their platform’s travel nurse job postings and applications from 2019 to 2023. I supplement these records with National Provider Identifier (NPI) data on registered nurses (RNs) in the US from the National Plan and Provider Enumeration System (NPPES), COVID-19 data from the Centers for Disease Control and Prevention (CDC), and county-level demographic data from the Census Bureau.

Wanderly is an online staffing marketplace that connects travel nurses to short-term hospital contracts through staffing agencies.⁷ Nurses can create an account, compare multiple job postings, and choose where to apply. Once an application is submitted through Wanderly, the staffing agency associated with the posting handles the remaining recruitment process. I therefore observe applications but not final matches or other application outcomes. Nevertheless, these data capture a key margin of nurse decision-making: whether licensing barriers deter nurses from applying to jobs in states where they are not already licensed. Wanderly covers about 4% of US travel RNs each year.

Importantly, Wanderly data includes the set of state licenses held by a travel nurse who submitted an application through the platform. This information allows me to classify the

⁷Wanderly website. Figure A4 provides a snapshot of the website.

licensing barriers faced by each nurse with greater precision. In addition to license holdings, I observe each nurse’s home state and the job posting to which an application was made. For each job posting, I observe the wages, hospital ZIP code, specialty, agency and profession. Wanderly data has information on two professions: Registered Nurses (RNs) and Allied Nurses. Table 1 provides summary statistics of the variables available in the data.

I supplement Wanderly’s application data with NPPES NPI records to relate application patterns to observed interstate moves. NPPES is a public registry of US healthcare providers with a National Provider Identifier (NPI). Monthly records of providers’ locations allow me to track moves across states. Registration is optional for RNs, and the data cover approximately 5-7% of US RNs on average. Although Wanderly does not report NPIs, preventing individual-level linkage, I compare applications and observed RN moves across origin-destination state pairs to estimate the elasticity of applications to actual moves.

Finally, to control for county-level observable differences I use the COVID-19 data from CDC and county-level demographics data from Census.

Table 1: Wanderly Data Summary Statistics

Panel A: Application Distributions						
	Count	Mean	Min	Max	Std Dev	N
Year	5	12,648	1,835	23,984	8,269	63,239
Nurses	11,087	6	1	147	9	63,239
Specialty	7	9,034	631	19,576	6,134	63,239
Home State	49	1,291	51	10,591	1,966	63,239
Destination State	49	1,291	68	11,444	1,865	63,239
Destination County	1,601	40	1	2,247	107	63,239
Panel B: Compensation and Geographic Proximity						
	Count	Mean	Min	Max	Std Dev	N
Loaded Pay (\$)		92	27	188	24	63,239
Base Pay (\$)		55	12	160	23	63,239
Real Loaded Pay (RPP Adjusted \$)		91	25	212	24	63,239
Real Base Pay (RPP Adjusted \$)		55	13	181	24	63,239
Distance (km)		1,171	0	4,297	1,188	63,239

Notes: RN applications submitted through Wanderly between 2019-2023 (63,239 applications by 11,087 travel nurses). In Panel A, Count is the number of distinct values of each variable and the remaining columns describe the number of applications per value. In Panel B, distance is between the centroids of the nurse’s home state and the destination state. Source: Wanderly.

Variable Construction: The unit of analysis is the county-quarter. The Wanderly data contain 55,241 applications submitted by 9,966 travel nurses from 2019 to 2023.

Wages: The data report two hourly wage measures: basepay and loadedpay. Basepay is

the taxable hourly wage, while loadedpay adds non-taxable stipends, primarily for housing and meals & incidentals, converted to an hourly equivalent using contracted hours. I adjust both measures using Regional Price Parities (RPPs) to account for geographic differences in the cost of living and use RPP-adjusted loadedpay as the wage measure throughout the analysis.

Distance: Using each nurse’s home state and the county in which a job is located, I construct a measure of the distance between the nurse and the job. This measure serves as a proxy for potential travel and relocation costs associated with taking a job farther from home.

License: Each nurse reports the states in which they hold a license, allowing me to identify the licensing barrier they face when applying to a job in a given county. I classify out-of-state applications as “licensed” if the nurse holds a license in the destination state and “non-licensed” otherwise. Applications to jobs in the nurse’s home state are classified separately as “within home state.” Table 2 summarizes the license information from the Wanderly data for the year 2019.

Panel A shows the number of states in which nurses report being licensed and their applications by licensing status. On average, a nurse reported being licensed in 14 states in 2019. Much of this comes from nurses whose home states are NLC members. Since the NLC allows eligible nurses to practice across member states, nurses from NLC home states reported being licensed in 20 states on average, compared with only three for nurses from non-NLC home states. The second section of Panel A shows how nurses’ applications are distributed by licensing status. As expected, out-of-state, non-licensed applications accounted for the lowest share on average in 2019.

Panel B compares licensed and non-licensed applications outside the nurse’s home state. Of the 1,425 applications observed in 2019, 965 were outside the home state. Non-licensed applications tend to be for jobs with slightly higher posted wages and shorter distances than licensed applications. The next section shows the shares of licensed and non-licensed applications across four NLC corridors: NLC to NLC, NLC to non-NLC, non-NLC to NLC, and non-NLC to non-NLC. As expected, licensed applications account for a higher share in all four corridors. For the NLC-to-NLC corridor, 89% of applications are licensed.

Table 2: Licenses and Applications by Licensed Status, 2019

Panel A: Licensure					
	Mean	Min	Max	Std Dev	N
Number of Licenses Held Per Nurse					
Whole Sample	14	1	38	14	610
Home State - NLC	20	1	38	14	377
Home State - non-NLC	3	1	32	6	233
Percent applications by a nurse - by Licensed Status					
Within Home State (%)	39	0	100	47	610
Outside Home State - Licensed (%)	42	0	100	47	610
Outside Home State - Non-Licensed (%)	19	0	100	36	610
Panel B: Out-of-State Applications by Licensed Status					
	Licensed		Non-Licensed		N
Real Loaded Pay (RPP Adjusted \$)	57		59		965
Distance (km)	1,809		1,722		965
Percent applications in each corridor (home to destination)					
NLC to NLC (%)	89		11		371
NLC to non-NLC (%)	62		38		361
non-NLC to NLC (%)	59		41		87
non-NLC to non-NLC (%)	58		42		146

Notes: Notes: The sample comprises 1,425 RN applications submitted by 610 travel nurses through Wanderly in 2019. Panel A reports license holdings by home-state NLC status and application shares by licensing category. Panel B reports average differences between licensed and non-licensed applications and their shares by NLC corridor. For example, 89% of out-of-state applications from NLC to NLC states are licensed.

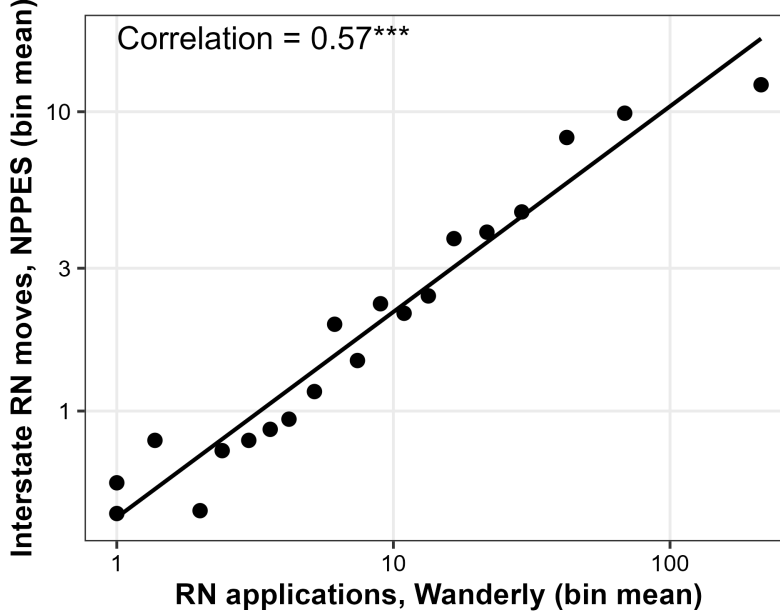
3.1 Descriptive Evidence - NPI Moves and Wanderly Applications

Wanderly records applications but not their final outcomes. To assess how closely these applications reflect actual interstate movement of Registered Nurses (RNs), I compare application patterns across origin-destination state pairs in Wanderly with RN moves observed across the same state pairs in the NPES NPI data. Here, I provide descriptive evidence of that using binned scatter plots, which group origin-destination state pairs into equal-sized bins based on the number of Wanderly applications. Each point plots average interstate RN moves against average applications within a bin, and a fitted line summarizes the relationship between the two variables.

As Figure 2 shows, origin-destination state pairs with more Wanderly applications also tend to have more interstate RN moves recorded in NPES over 2019-2023. The Spearman rank correlation across state pairs is 0.57, statistically significant at the 1% level. This positive relationship suggests that application patterns on Wanderly are informative about

the broader geographic patterns of RN mobility. I provide robustness checks on this measure in Appendix A2 where I further examine this relationship by the potential licensed versus non-licensed corridors.

Figure 2: Interstate RN Moves and Wanderly Applications, 2019-2023



Notes: The figure groups origin-destination state pairs into equal-sized bins by the number of Wanderly applications over 2019-2023. Each point plots the average number of interstate RN moves recorded in the NPES NPI data against the average number of applications within a bin, and the line shows the linear fit. Source: Wanderly and NPES NPI data.

4 Reduced Form Evidence

I first provide reduced-form evidence on the potential effects of interstate licensing barriers in the travel nurse labor market, exploiting two sources of policy variation: cross-state differences in Nurse Licensure Compact (NLC) membership and the temporary suspension of licensing requirements during the COVID-19 emergency. Specifically, I use a difference-in-differences framework to compare changes in travel nurse applications and wages between non-NLC and NLC states. I estimate the following equation for county c in quarter t :

$$\log(y)_{ct} = \sum_{t \neq 2019Q4} \beta_{1t} \mathbf{1}\{Non - NLC\}_{s(c)} \times \mathbf{1}\{Quarter\}_t + \beta_c + \beta_t + \epsilon_{ct} \quad (1)$$

Here, y_{ct} denotes applications per capita, applications per COVID-19 case, or wages (RPP-

adjusted). I estimate the specification separately for each outcome.

The indicator $1\{\text{non-NLC}\}_s$ equals 1 if state s was not an NLC member as of January 2020, and 0 otherwise. The coefficient β_{1t} captures the non-NLC versus NLC gap in $\log(y_{ct})$ in quarter t relative to the baseline gap in 2019Q4. With the COVID-19 outbreak and the March 13, 2020, federal emergency declaration occurring in 2020Q1, 2019Q4 is the last pre-treatment quarter ($t = -1$). I include county and quarter fixed effects, β_c and β_t , respectively, to account for time-invariant differences across counties and changes over time common to all counties.

I estimate Equation 1 for three outcomes. Given the higher pre-emergency licensing barriers in non-NLC states, suspending these barriers should increase applications per capita to non-NLC states relative to NLC states, compared with their pre-emergency differences. This implies a positive β_{1t} during the emergency, potentially returning toward zero as waivers began to expire in early 2023. Figure 3 illustrates the expected pattern in β_{1t} for applications per capita if NLC and non-NLC states differed only in RN licensing barriers and emergency measures only suspended these barriers.

However, because COVID-19 outbreaks differed considerably across states, more applications per capita may not imply enough applications to meet the increased demand for nurses. I therefore also examine applications per COVID-19 case, using cases as a proxy for nursing demand. For this outcome, a negative β_{1t} would indicate a relative decline in applications per case in non-NLC states compared with the baseline gap.⁸ Finally, I estimate Equation 1 for wages. To the extent that higher wages in non-NLC states compensated nurses for licensing barriers, suspending these barriers should narrow the non-NLC-NLC wage gap, implying a negative β_{1t} during the emergency.

Identifying Assumptions for β_{1t} : The federal emergency declaration is the treatment of interest in this analysis.

No Anticipation: The emergency measures were adopted in response to the COVID-19 outbreak in 2020Q1. Nurses and employers were therefore unlikely to anticipate these measures and adjust their application or wage decisions in 2019, supporting the no-anticipation assumption.

Parallel Trends: The parallel-trends assumption requires that, absent the emergency

⁸For this specification, I normalize the COVID-19 cases to 1 in the periods where there was no reporting, i.e., 2019, January and February 2020 and 2023H2.

measures, applications and wages in non-NLC and NLC states would have followed similar trends. The event-study results in subsection 4.1 show no statistically significant pre-emergency difference in trends, consistent with this assumption. However, the assumption that non-NLC and NLC states would have followed the same trend in the absence of emergency waivers is likely violated here.

NLC and non-NLC states differed along other dimensions than just interstate licensing barriers for RNs (Appendix Table A1), and both pandemic severity and emergency policy responses varied considerably across states. State-by-quarter fixed effects could account for these concurrent changes, but would also absorb the treatment variation used for identification. While β_{1t} captures changes in non-NLC and NLC differences following the emergency waivers, it does not necessarily isolate the effects of interstate licensing barriers. These estimates nonetheless offer suggestive evidence of the role of licensing barriers. To disentangle the effects of these barriers I turn to the structural analysis in Section 5, where I exploit variation in individual nurses' license holdings.

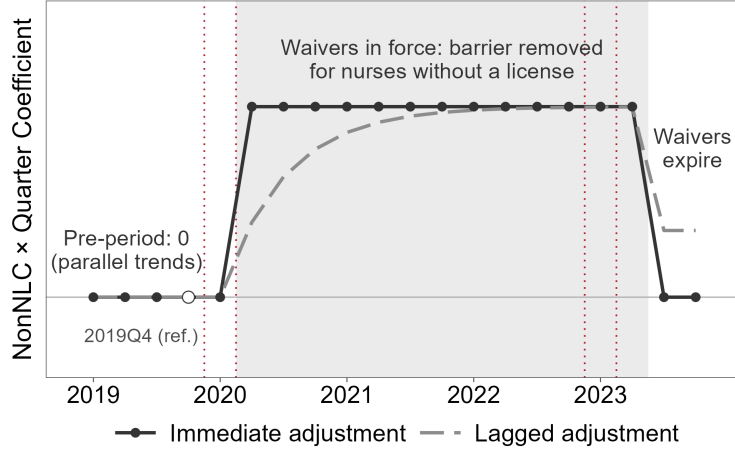
4.1 Reduced Form Results

The estimates of Equation 1 for all four outcomes are presented in Figures 4, 5 and 6, with red dotted lines marking the start (2020Q1) and end (2023Q2) of the emergency period. Overall, applications to non-NLC states increased relative to NLC states during parts of the emergency, but the response varied considerably over time. Figure 4 shows changes in the non-NLC versus NLC gap in applications per capita relative to 2019Q4. The pre-emergency estimate is not statistically different from zero. Applications to non-NLC states rose sharply relative to NLC states in 2020Q2, suggesting an early response to the emergency waivers. However, this relative increase disappeared in 2020Q3 and remained absent through 2021. It reemerged in 2022 before declining again as waivers began to expire in early 2023.⁹

Figure 5 plots the estimated effects on applications per COVID-19 case. Unlike the results for applications per capita, the estimates remain negative throughout the sample period. Together, the results suggest that although non-NLC states received more applications during parts of the emergency, they continued to receive fewer applications relative to need, as measured by COVID-19 cases, than NLC states.

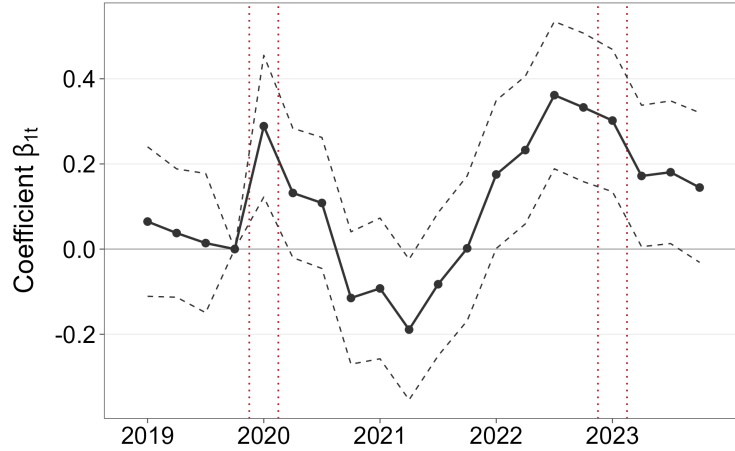
⁹Panels (a) and (b) of Appendix Figure A16 separate non-licensed and licensed applications, respectively.

Figure 3: Effect on applications per capita: With only Interstate Licensing Barrier Variation



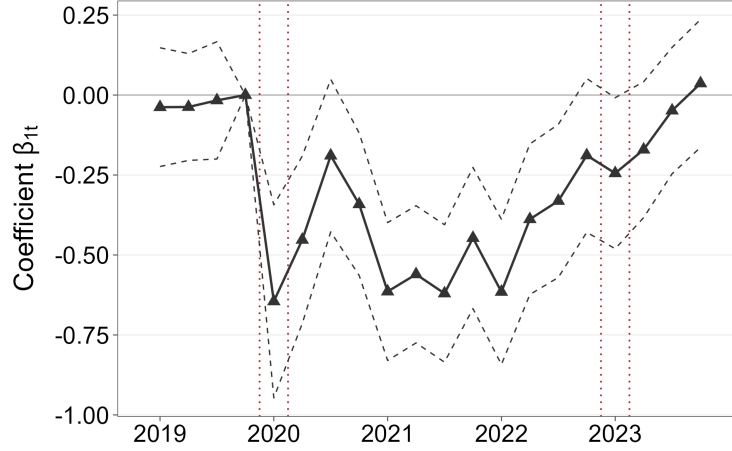
Notes: This illustrative figure shows the expected β_{1t} for applications per capita if NLC and non-NLC states differed only in licensing barriers and emergency measures only suspended these barriers. Applications should rise in non-NLC states relative to NLC states during the waivers ($\beta_{1t} > 0$), then return toward the baseline gap as waivers expire.

Figure 4: Event Study Estimates: RN Applications per Capita



Notes: The figure plots β_{1t} from Equation 1 for **applications per capita**, measuring the quarterly non-NLC-NLC gap relative to 2019Q4. The sample includes 60,635 applications across 806 county-quarter observations. The specification controls for county and quarter fixed effects, with standard errors clustered by county ($R^2 = 0.521$).

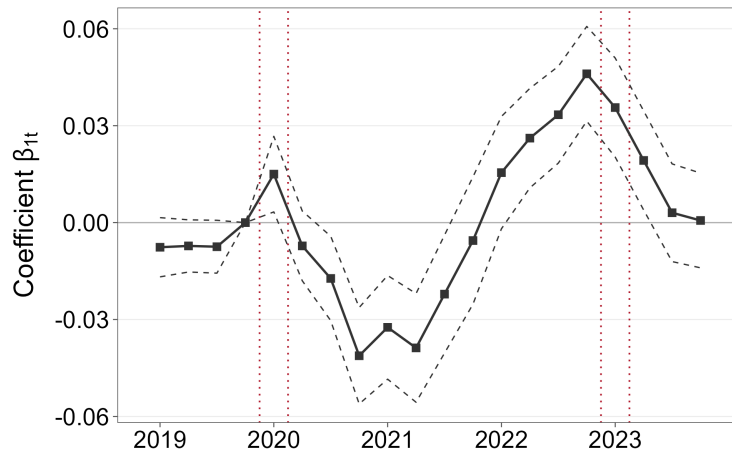
Figure 5: Event Study Estimates: RN Applications per COVID-19 Case



Notes: The figure plots β_{1t} from Equation 1 for **applications per COVID-19 case**, measuring the quarterly non-NLC-NLC gap relative to 2019Q4. The sample includes 60,635 applications across 806 county-quarter observations. The specification controls for county and quarter fixed effects, with standard errors clustered by county ($R^2 = 0.93$). COVID-19 cases are normalized to 1 wherever they were not reported, i.e., in 2019, Jan-Feb 2020 and July-Dec 2023.

Finally, Figure 6 presents the wage estimates. Periods of increased non-licensed applications to non-NLC states also coincide with increases in their wages relative to NLC states. This pattern is consistent with stronger demand raising both wages and applications, suggesting that the observed application response cannot be attributed solely to the easing of licensing barriers.

Figure 6: Event Study Estimates: RN Wages (RPP-adjusted)



Notes: The figure plots β_{1t} from Equation 1 for **wages**, measuring the quarterly non-NLC-NLC gap relative to 2019Q4. The sample includes 60,635 applications across 806 county-quarter observations. The specification controls for county and quarter fixed effects, with standard errors clustered by county ($R^2 = 0.875$).

The reduced-form results provide evidence that licensing barriers potentially contributed to changes in applications and wages. However, nurses may apply to a county because they face lower licensing barriers, receive higher wages, or prefer its location and other characteristics. These factors jointly shape application decisions, making it difficult to separate their effects using aggregate applications alone. In the next section, I use a structural model to separate these factors, drawing on three sources of variation.

First, nurses considering the same county in the same quarter differ in whether they are licensed to practice there. County-quarter fixed effects absorb wages, COVID-19 burden, and other destination characteristics common to these nurses, allowing the model to use differences in their licensing access. Second, the same nurse faces different licensing status across destinations: she is licensed in some states but not others. The model uses this variation across her choices while controlling for distance. Third, licensing access and barriers change over time as emergency waivers temporarily ease restrictions. Allowing the licensing penalty to vary by half-year captures how it changes as these barriers are eased and waivers expire.

5 Travel Nurse Applications: Model and Identification

In this section, I estimate a discrete choice model of travel nurse application decisions to quantify the effect of interstate licensing barriers on a nurse’s willingness to apply. A key feature of the Wanderly data is that they record every state license held by each applicant which allows me to measure the licensing barrier at the nurse level. The licensing effect is identified from different application choices across nurses with different license holdings, for the same destination county in the same specialty. By allowing this effect to vary over time, the model traces how the licensing barrier changed as emergency measures temporarily suspended licensing requirements.

5.1 Supply: Travel Nurse Applications

Each application decision $i = 1, \dots, N$ in market $t = 1, \dots, T$ maximizes utility by choosing county c in the relevant specialty sp . I define the relevant choice set as $\mathcal{C}_{sp,t}$, the set of counties that receive at least one application in specialty sp during market t . The observed application is therefore modeled as a choice among counties active in the same specialty-market. The indirect utility of an application decision i from choosing a county c in market

t is given by:

$$\begin{aligned}
U_{ict} = & \sum_h \sum_k \beta_{1h}^k \mathbf{1}\{\text{NonLicensed}\}_{is(c)t}^k \times \mathbf{1}\{\text{Half-year}\}_{h(t)} \\
& + \underbrace{\beta_2 \log(\text{dist})_{ict} + \beta_3 \mathbf{1}\{\text{State-neighbor}\}_{is(c)t}}_{\mu_{ict}} \\
& + \delta_{ct} + \epsilon_{ict}
\end{aligned} \tag{2}$$

where the licensing category k of $\mathbf{1}\{\text{NonLicensed}\}_{is(c)t}^k$ is defined as

$$k = \begin{cases} 0 & \text{county } c \text{ is in nurse } i\text{'s home state,} \\ 1 & \text{outside home state; licensed through a multistate (NLC) license,} \\ 2 & \text{outside home state; licensed through a single-state license,} \\ 3 & \text{outside home state; not licensed in } s(c). \end{cases} \tag{3}$$

A simple comparison of licensed and unlicensed choices confounds the effect of licensing barriers with nurses' destination preferences, as a nurse may hold a license in a particular state precisely because they prefer to work there. However, a multistate license grants nurses in NLC states access to all compact states, regardless of their preference for any particular state. I take that into account by assigning the counties in an application's choice set into one of the 4 categories as shown in Equation 3. With home state as the omitted baseline, $(\beta_{1h}^3 - \beta_{1h}^1)$ captures the effect of licensing barrier on application decisions and $(\beta_{1h}^2 - \beta_{1h}^1)$ captures the selection effect in every half-year.

Beyond licensing barriers, distance is an important factor affecting an application choice. The term $\log(\text{distance})_{ict}$ controls for geographic distance between nurse i 's home state centroid and county c 's centroid. Together, these terms, denoted μ_{ict} , capture the application specific utility deviation from δ_{ct} , which represents the mean utility of county c in market t . The error term ϵ_{ict} is assumed to be Type I Extreme Value Distributed (EVD). The mean utility δ_{ct} can be further decomposed into observable and unobservable components:

$$\delta_{ct} = \delta_0 + \delta_1 \log(\text{wage})_{ct} + \delta_2 \log(\text{cases})_{ct} + \xi_{ct} \tag{4}$$

where $\log(\text{wage})_{ct}$ is the log of RPP-adjusted hourly compensation posted by county c in week t , including the hourly equivalent of the housing stipend. To account for local COVID-

19 severity in county mean utility, $\log(cases)_{ct}$ controls for COVID-19 cases per capita in county c .

Wage Instrument: A key concern in estimating the wage effect is that posted wages may be endogenous. Some counties may have lower wages because they provide better amenities. To address this concern, I estimate the wage effect using two alternative instruments in separate specifications as a robustness check.

Instrument 1 - Allied IV: Although the model is estimated for RNs, Wanderly also provides posted wages for related allied health occupations, such as respiratory therapists and imaging technicians, whose interstate practice is not governed by the NLC. I use their wages in neighboring counties as an instrument for RN wages. Using different occupations in neighboring counties limits the direct influence of county-specific RN demand on the instrument. The exclusion restriction requires that, conditional on the included controls and fixed effects, neighboring counties' allied wages affect RN applications to county c only through RN wages, rather than through correlated healthcare demand shocks or other determinants of destination attractiveness.

$$\log(wage)_{ct} = \alpha_c + \alpha_t + \alpha_1 \log(wage)_{nct}^{Allied} + \eta_{ct} \quad (5)$$

Instrument 2 - Agency IV: The second is an agency-level Hausman-style instrument. For each agency a posting RN jobs in county c , I calculate its average RN wage in all other counties in quarter t , $\bar{w}_{a,-c,t}$. I then average these wages across agencies, weighting each by its share of RN postings in county c . Common agency costs can generate wage variation across markets; identification assumes that the resulting instrument is uncorrelated with county c 's unobserved attractiveness.

The Allied IV exploits cross-occupation wages in neighboring counties, while the Agency IV exploits agency wages in other markets. Agreement between their estimates supports the robustness of the wage effect.

Together, Equations 2-5 form the model's supply side, describing how nurses allocate applications across counties given licensing barriers, distance, and wages. Licensing barriers affect application decisions through two channels: the direct disutility of applying due to licensing barriers (β_1) and the endogenous wage premiums counties must offer to compensate for them. The latter is captured by the wage coefficient δ_1 , which governs nurses' responsiveness to posted wages, together with the equilibrium wage adjustment implied by

the county-level wage-posting model discussed next.

5.2 Demand: Wage Posting

Hospitals post vacancies and set wages to maximize their profits. Because the supply side is estimated at the county level, I model wage setting at the same level: all hospitals within a county are aggregated into a single representative employer. Following the approach of [Nevo \(2001\)](#), I use the county's monopsonistic wage-setting first order condition to back out the implied wage markdowns.

Let w_{ct} denote the wage posted by county c in market t and L_{ct} the number of travel nurses hired. Assuming decreasing returns to scale, county's profit function is given by:

$$\pi_{ct} = \underbrace{R(L_{ct}(w_{ct}))}_{\text{value-added}} - \underbrace{w_{ct} L_{ct}(w_{ct})}_{\text{wage bill}} \quad (6)$$

$$R(L_{ct}(w_{ct})) = \theta_{ct} (L_{ct}(w_{ct}))^{1-\alpha}, \quad \alpha \in [0, 1) \quad (7)$$

$$L_{ct}(w_{ct}) = \kappa A_{ct}(w_{ct}), \quad A_{ct}(w_{ct}) = N_t s_{ct}(w_{ct}) \quad (8)$$

Since I only observe applications and not the final hires in Wanderly data, I assume applications convert to actual hires L_{ct} at a proportional rate κ . Further, applications to a county can be written as the total applications in market t times the share of applications received by a county in market t - $s_{ct}(w_{ct})$. The wages w_{ct} must satisfy the first order condition:

$$\underbrace{R'(L_{ct})}_{\text{MRPL}} = w_{ct} \left(1 + \frac{1}{\epsilon_{ct}}\right) \Rightarrow \underbrace{w_{ct} = \text{MRPL}_{ct} \cdot \frac{\epsilon_{ct}}{1 + \epsilon_{ct}}}_{\text{Markdown Rule}} \quad (9)$$

where ϵ_{ct} is the elasticity of applications with respect to wages which can be expressed as:

$$\epsilon_{ct} = \frac{\partial \log s_{ct}}{\partial \log w_{ct}} = \delta_1 (1 - \bar{s}_{ct}), \quad \bar{s}_{ct} = \frac{\sum_i s_{ict}^2}{\sum_i s_{ict}} \quad (10)$$

Using estimates from the supply side, I can recover markdown estimates in the baseline with-

out observing actual θ_{ct} . Assuming θ_{ct} does not get affected by licensing barrier, Equation 9 also allows me to recover the wage effect of licensing barrier in the counterfactual with no barrier using baseline MRPL and ϵ_{ct} . Details are discussed in Section 6.

5.3 Identification

Licensing Effect: This is identified by the interaction of $(\beta_{1h}^3 - \beta_{1h}^1)$ with the half-year dummies. With home state as the omitted category, the model estimates 3 coefficients β_{1h}^k (for $k \in \{1,2,3\}$) for each half-year. For the same destination county during the same time period, nurses differ in whether they hold a license for that county’s state. The coefficient is identified from whether nurses with and without a license choose a county at different rates, relative to other counties in their choice set. The model controls for other factors that can confound nurse’s application choice: distance from the destination county and whether the destination county is in a neighboring state. Controlling for county-time fixed effect absorbs any other county specific factors in that time period that affected overall applications to that county. The $(\beta_{1h}^2 - \beta_{1h}^1)$ captures the selection effect of nurses into licenses.

Distinguishing individual licenses from NLC authorization helps account for selection into licensing, but remaining nurse-destination preferences may still affect $\beta_{1h}^3 - \beta_{1h}^1$. Emergency waivers provide additional temporal variation by temporarily easing interstate licensing barriers. Estimating separate licensing coefficients from 2019H2 to 2023H2 allows me to track how the penalty changed during the emergency and as waivers expired. If remaining destination preferences are stable and no other concurrent changes differentially affect the licensing groups after controlling for the included covariates and fixed effects, changes in $\beta_{1h}^3 - \beta_{1h}^1$ relative to the pre-emergency period identify the effect of easing licensing barriers on applications. Under this interpretation, waivers should affect the licensing penalty but leave the selection effect, $\beta_{1h}^2 - \beta_{1h}^1$, relatively unchanged.

Distance: The distance variable measures the distance between the nurse’s home state centroid and the centroid of each destination county in their choice set. Because license holdings may be correlated with geographic proximity, controlling for distance separates the effect of licensing barriers from the costs associated with applying farther from home. The distance coefficient is identified from variation in relative distances across counties within a nurse’s choice set and across nurses from different home states. In particular, counties with the same licensing status for a given nurse may differ in distance, providing variation in geographic proximity while holding licensing access constant. Nurses from different home

states also face different relative distances to the same destination counties. County-time fixed effects absorb differences in destination attractiveness common to all nurses, while the neighboring-state indicator accounts for whether a destination is in a state adjacent to the nurse’s home state. Together, these controls allow the model to distinguish distance from licensing access and common destination characteristics.

Mean Utilities: Mean utility captures the factors that make a county attractive to all nurses, independent of nurse-specific characteristics. Wages and COVID-19 caseloads are the observed factors that may affect a county’s mean utility in a given period. For a given market, the mean utilities are identified from differences in application shares across counties, after removing nurse-specific licensing and distance terms. The wage coefficient (δ_1) is identified from the exogenous change in RN wages over time within a county. Since wages are likely to be endogenous to the other unobserved county characteristics, the model uses two different instruments to identify (δ_1).

5.4 Estimation

I estimate the supply-side model using the two-step approach of [Berry et al. \(1995\)](#). In the first step, I use maximum likelihood estimation (MLE) to estimate the parameters entering the individual-specific utility component, μ_{ict} . Given these estimates, I recover the mean utilities, δ_{ct} , using a contraction mapping algorithm that equates the model-predicted application shares to the observed shares for each ct pair.

The Type 1 extreme value distribution assumption on ϵ_{ict} implies that for a guess of β_1 , β_2 , β_3 and δ_{ct} , the probability that application goes to county c in market t is given by:

$$P_{ict} = \frac{\exp(\mu_{ict} + \delta_{ct})}{\sum_{c' \in \mathcal{C}_{sp,t}} \exp(\mu_{ic't} + \delta_{c't})} \quad (11)$$

The log-likelihood function is given by:

$$\mathcal{L}(\beta, \delta) = \frac{1}{N \times T} \sum_{i=1}^N \sum_{t=1}^T \ln(P_{ic_it}(\beta, \delta)) \quad (12)$$

where c_i denotes the county chosen by application i .

The first stage of estimation maximizes $\mathcal{L}(\beta, \delta)$, for a given starting value of β and δ .

In the current version of the model, the choice set does not include an outside option of not applying in market t . As a result, the mean utilities δ_{ct} are identified only up to a market-specific normalization and are re-centered within each market during estimation.

In the second stage, I use the recovered mean utilities, δ_{ct} , from the first stage to estimate the parameters of the decomposition in Equation 4. Because posted wages may be endogenous, Equation 5 provides an instrument for wages in Equation 4. The second-stage parameters are therefore estimated using two-stage least squares (2SLS) method.

In the final step, I substitute the estimate of δ_1 into Equation 9 to recover implied productivity, v_{ct} , using data on wages w_{ct} and application shares s_{ct} .

Table 3: Estimation Sample

	Pre 2019H2	Emergency 2020H1-2023H1	Post 2023H2	Full 2019H2-2023H2
Panel A: Sample Size				
Applications	1,835	57,384	4,020	63,239
Nurses	747	9,925	1,556	11,087
Destination counties	483	1,554	682	1,601
Markets (quarters)	2	14	2	18
Specialties	7	7	7	7
County $\times$ quarters (stage 2)	594	7,922	913	9,429
Choice set size, mean	97	278	177	266
Choice set size, median	103	267	177	248
Panel B: Licensing Category, % of Choices				
Home state	32.6	28.7	32.4	29.0
Licensed: NLC multistate	16.9	21.3	20.7	21.1
Licensed: single-state	20.6	11.7	14.6	12.1
Not licensed	29.9	38.4	32.3	37.8
Panel C: Covariates				
Log distance	6.58	6.54	6.43	6.54
Neighboring state (%)	12.9	15.0	14.9	14.9
Log RN wage	3.88	4.29	4.16	4.25
Log Allied wage (IV)	3.73	4.00	4.04	3.99
Log cases per capita	0.00	7.15	0.00	6.01

Notes: Sample of Wanderly RN applications used in model estimation, by period.

Panels B and C report averages over the choice sets.

Table 3 summarizes the Wanderly RN application sample used to estimate the model, divided into three periods over 2019H2-2023H2 based on federal emergency measures. The

sample includes 63,239 applications from 11,087 nurses to 1,601 destination counties; second-stage 2SLS estimates use 9,429 county $\times$ quarter observations. The choice set comprises counties receiving at least one application in the sample and expands during the emergency period, alongside the rise in applications.

Panel B reports the average composition of choice sets by licensing status. In 2019H2, 32.6% of counties in an average choice set were in the nurse’s home state. Shares remained broadly stable, although unlicensed options increased during the emergency period, consistent with the waivers. These shares are descriptive: licensing coefficients are identified by variation across nurses within a county and market. Panel C summarizes the remaining covariates, whose stability across periods suggests that licensing changes do not reflect shifts in geography.

5.5 Estimation Results

5.5.1 Licensing Penalty over Time

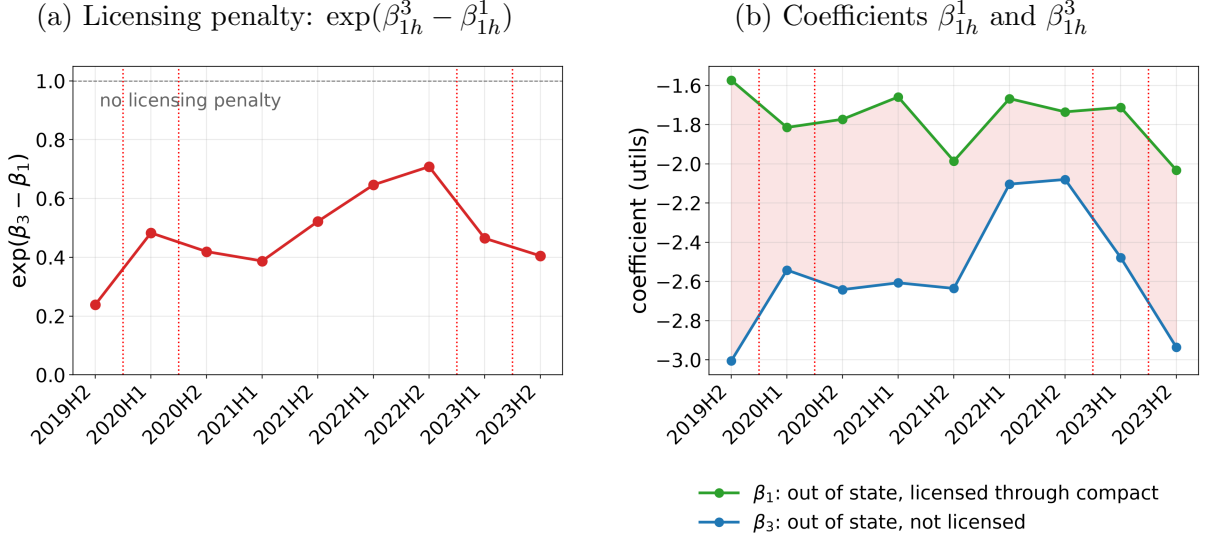
The estimates of β_{1h}^3 and β_{1h}^1 are plotted in Figure 7. Their difference, $\beta_{1h}^3 - \beta_{1h}^1$, captures the licensing penalty in application decisions over time. Panel (a) plots the exponentiated difference, which should be below one if lacking a license deters applications. The estimates remain below one throughout the sample. However, the penalty declined after emergency measures were introduced in 2020H1 and began increasing again when they expired in 2023H1. Notably, there was a slow adjustment to the emergency measures with the penalty declining the most in 2022 before starting to return to pre-emergency levels again. Panel (b) shows that this pattern is driven primarily by changes in β_{1h}^3 , while β_{1h}^1 remains relatively stable. This supports interpreting the change as the effect of emergency licensing waivers, which directly altered the application choices captured by β_{1h}^3 .

I estimate the effect of licensing penalty on application decisions as:

$$\Delta^L = (\beta_{1,\text{pre}}^3 - \beta_{1,\text{pre}}^1) - \max_{h \in \mathcal{E}} (\beta_{1h}^3 - \beta_{1h}^1) \quad (13)$$

where pre denotes the pre-emergency half-year (2019H2) and $\mathcal{E} = \{2020H1, \dots, 2022H2\}$ the emergency half-years.

Figure 7: Licensing Penalty over Time: $\exp(\beta_{1h}^3 - \beta_{1h}^1)$ and Individual Coefficients



$$\begin{aligned}
 \Delta^L &= (\beta_{1,2019H2}^3 - \beta_{1,2019H2}^1) - (\beta_{1,2022H2}^3 - \beta_{1,2022H2}^1) \\
 &= (-3.005 - (-1.573)) - (-2.080 - (-1.735)) \\
 &= -1.432 - (-0.345) = -1.087
 \end{aligned}$$

The licensing barrier cuts the odds of applying to the unlicensed county by about 66%. I quantify the Willingness to Accept (WTA) for this barrier in Section 5.5.4.

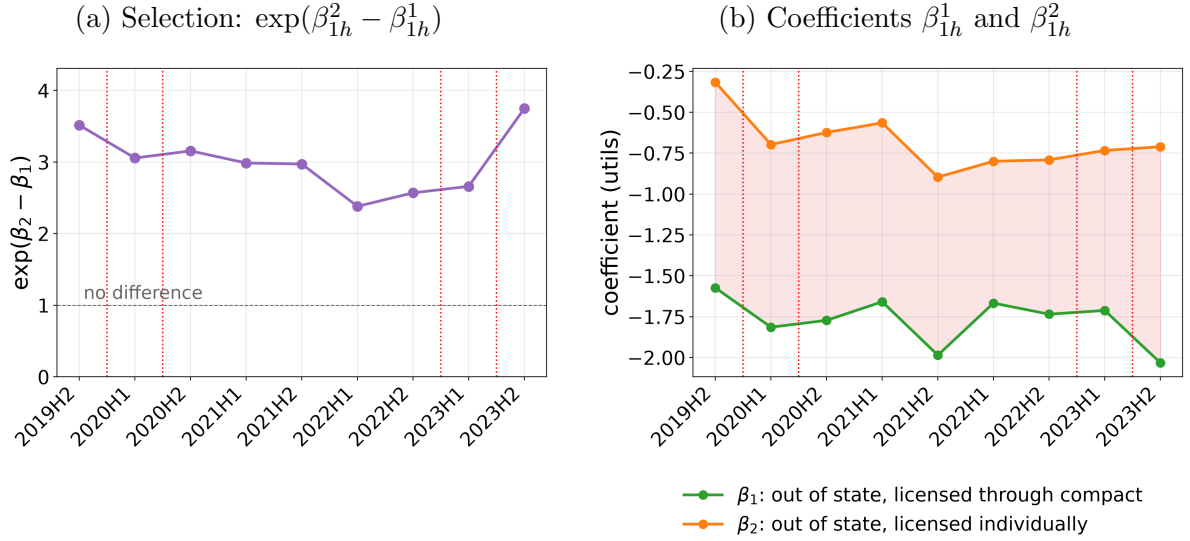
5.5.2 Selection into Licensing over Time

The difference $\beta_{1h}^2 - \beta_{1h}^1$ captures selection into destination-specific licensing in each half-year. Both coefficients correspond to counties where the nurse is authorized to practice. However, β_{1h}^1 represents authorization through an NLC multistate license, which does not require obtaining a separate license for the destination state, whereas β_{1h}^2 represents authorization through an individually acquired state license. Nurses may obtain individual licenses precisely because they prefer to work in those states, making license holdings non-random. Distinguishing these two forms of authorization allows the model to account for destination preferences associated with acquiring a license. Panel (a) of Figure 8 plots $\exp(\beta_{1h}^2 - \beta_{1h}^1)$,

while Panel (b) plots the individual coefficients.

As expected, the selection effect is positive throughout the sample: nurses are more likely to apply to destinations for which they acquired an individual state license than to those where they are authorized through the NLC. The effect also remains relatively stable over time, consistent with the expectation that emergency waivers primarily affect the licensing penalty while leaving nurses' destination preferences unchanged.

Figure 8: Selection over Time: $\exp(\beta_{1h}^2 - \beta_{1h}^1)$ and Individual Coefficients



Notes: Panel (a): $\exp(\beta_{1h}^2 - \beta_{1h}^1)$ by half-year, where a value of one means no difference between individually held and compact licenses. Panel (b): β_{1h}^1 (licensed through the compact) and β_{1h}^2 (licensed individually), relative to the home state; vertical dotted lines mark the start and end of the emergency period.

5.5.3 Distance and Neighboring State

In line with expectations, the model estimates a deterrent effect of distance on probability of applications while a positive effect of being a neighboring state on probability of applications. Doubling the distance cuts the odds of applying by 18%, suggesting frictions such as relocation costs, travel and distance from family, matter even on 13-week contracts. On the other hand, for the same distance and licensing status, a county in a state bordering the nurse's home state is about 1.9 times as likely to be chosen as a county in a non-bordering state. This likely reflects familiarity with the regional labor market, professional networks, being able to return home between shifts, and cross-border metro areas.

5.5.4 Wage Instruments and Elasticity of Applications

Table 4 presents the 2SLS estimates from Equations 4-5 using two alternative instruments for RN wages. With either instrument, the estimate of δ_1 is larger than its OLS counterpart. This is consistent with downward bias in OLS: counties with better amenities may attract applications while offering lower wages. The 2SLS estimates are similar across the two instruments, and the coefficient on log cases remains stable across specifications. Together, these results support the robustness of the estimates. The wage coefficients imply that a 1% increase in wages raises applications by approximately 1.6%-2.1%.

Table 4: Mean utility on log wage and cases, Equations 4-5

Instrument	Allied IV	Agency IV
log(wage), OLS	1.1177	1.1071
log(wage), 2SLS (δ_1)	2.1146	1.5889
$f(\text{cases})$, OLS	0.0600	0.0588
$f(\text{cases})$, 2SLS	0.0347	0.0478
<i>First stage</i>		
Coefficient on instrument	0.1625	0.5955
Partial R^2	0.0296	0.0615
F-stat	132.61	81.22
Observations	9,429	10,091
County clusters	1,446	1,531

Notes: Estimates of Equation 4 with county and quarter fixed effects; the 2SLS rows instrument the log RN wage with the Allied IV or the Agency IV (Equation 5). The F-statistic is from the first stage, with standard errors clustered by county; observations are county-quarters.

The estimates for δ_1 and β_1 can be used to get the Willingness to Accept (WTA) for the licensing barrier for nurses using:

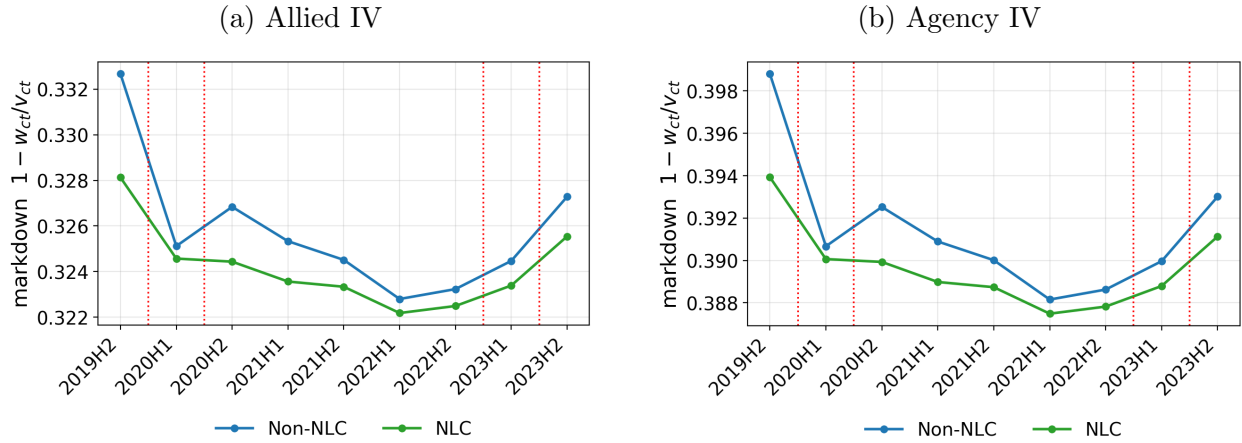
$$\text{WTA} = -\frac{\Delta^L}{\delta_1} \quad (14)$$

The estimated willingness to accept (WTA) for the licensing barrier is 67-80%: holding other factors constant, a nurse requires this wage premium to be equally likely to apply to an unlicensed destination as to a licensed one.

5.5.5 Markdowns

Using estimates from the supply side of travel nurse applications, I recover the marginal revenue product of labor (MRPL) from the markdown condition in Equation 9. Figure 9 plots the implied markdowns by the NLC status of the destination county. Higher licensing barriers make labor supply less elastic, allowing hospitals to impose larger markdowns. Thus, binding barriers should generate higher markdowns in non-NLC states, while emergency licensing measures should reduce them. Figure 9 shows both patterns. Markdown estimates are higher in non-NLC states throughout the sample, but decline in both groups after emergency measures are introduced in 2020H1 and begin rising again when the measures expire in 2023H1.

Figure 9: Wage Markdowns by NLC Status of the Destination State



Notes: Average markdown $1 - w_{ct}/v_{ct}$ by half-year for destination counties in non-NLC and NLC states, using δ_1 from the Allied IV in panel (a) and the Agency IV in panel (b). Vertical dotted lines mark the start and end of the emergency period.

6 Counterfactual

6.1 Counterfactual Estimation

The counterfactual of interest is the distribution of applications across locations in the absence of interstate licensing barriers. To construct this counterfactual, I remove the licensing penalty Δ^L from the utility of out-of-state counties in which the nurse is not licensed. Specifically, I remove $(\Delta^L$ from $\beta_{3h} - \beta_{1h})$ for each half-year. Keeping everything else unchanged,

this increases applications to hospitals in states with above-average exposure to licensing barriers and reduces applications to hospitals in states with below-average exposure. However, removing licensing barriers changes the supply of applicants available to hospitals and therefore their wage-setting incentives. The counterfactual must therefore allow wages to adjust endogenously rather than holding them fixed at their observed levels. I utilize Equation 9 to incorporate this. Equation 9 can be re-written as:

$$w_{ct} = \underbrace{v_{ct} \left(\frac{s_{ct}}{s_{ct}^0} \right)^{-\alpha}}_{\text{MRPL}_{ct}} \cdot \frac{\epsilon_{ct}}{1 + \epsilon_{ct}}, \quad \epsilon_{ct} = \delta_1 (1 - \bar{s}_{ct}) \quad (15)$$

Given estimates of v_{ct} and δ_1 , Equation 15 determines the equilibrium wages and application shares in the absence of licensing barriers. These barriers affect application supply through two channels: scarcity and elasticity. First, licensing barriers reduce the number of applications a county receives. Removing them therefore increases application supply and, through decreasing returns to scale, lowers wages - the scarcity channel. Second, licensing barriers restrict nurses' feasible choices, making application supply less elastic and increasing hospitals' wage-setting power. Removing them makes supply more elastic, reduces wage markdowns, and raises wages - the elasticity channel. I decompose the counterfactual wage change into these two opposing forces:

$$\underbrace{\Delta \log w_{ct}}_{\text{total}} = \underbrace{-\alpha \Delta \log s_{ct}}_{\text{(i) compensating differential}} + \underbrace{\Delta \log \frac{\epsilon_{ct}}{1 + \epsilon_{ct}}}_{\text{(ii) supply elasticity}}$$

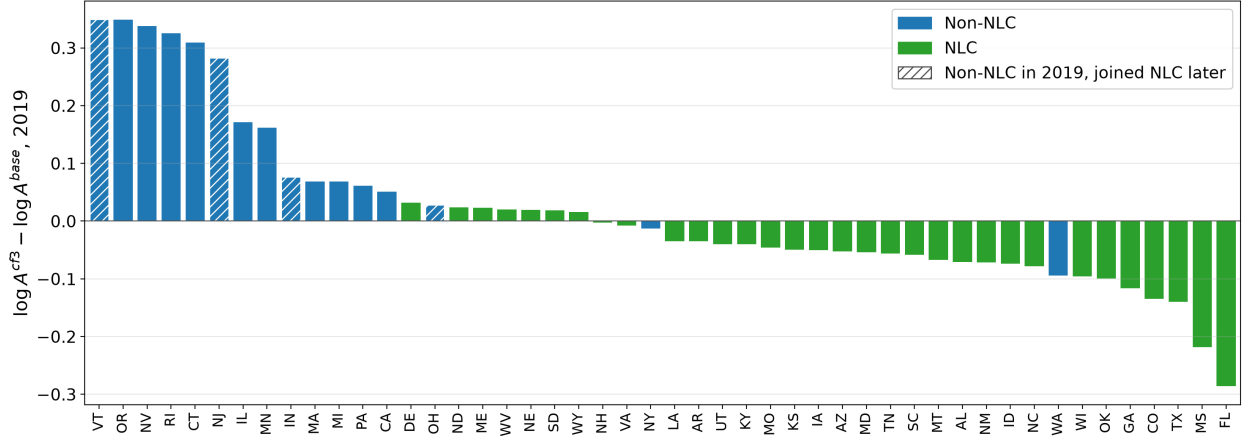
After simulating the removal of the licensing barrier, I apply a dampened fixed-point iteration algorithm, iteratively updating nurse choice probabilities and optimal hospital wage responses until market shares and wages converge to a new steady state.

6.2 Counterfactual Results

In the counterfactual analysis, I shut down the licensing barrier for nurses by allowing all of them to hold the license for every state. The hospitals then re-equilibrate in response to supply changes. Figures 10, 11, and 12 show the results from counterfactual estimation.

Figure 10 ranks states by the average county-level percentage change in applications between the counterfactual and baseline for 2019. Although exposure to licensing barriers varies

Figure 10: Change in applications across states in the absence of licensing barriers, 2019



Notes: The figure plots, for each state, the log difference between counterfactual applications with the licensing barrier removed and wages re-equilibrated, and baseline applications in 2019. Non-NLC states are in blue and NLC states in green; hatched bars are states that were not in the NLC in 2019 but joined later.

considerably across states, non-NLC states experience the largest application gains when the barriers are removed. Because licensing barriers in the model are defined using nurses' reported licenses rather than the NLC status of destination states, this pattern confirms that non-NLC states were, in practice, the most exposed to these barriers.

Figure 11 plots the counterfactual changes across three periods: pre-emergency, during the emergency, and post-emergency. The effects are highest in 2019, decrease during the emergency, and pick up again in 2023 as emergency measures expire.

The scarcity channel captures how higher licensing barriers reduce overall applications to a county. Removing these barriers increases applications and lowers wages in states with higher baseline barriers, while reducing applications and raising wages in states with lower baseline barriers. The signs of wage changes across non-NLC and NLC states confirm this pattern. The elasticity channel, on the other hand, captures how nurses now have more "feasible" destinations, making applications more responsive to wages. Through this channel, wages increase in both groups, with a slightly smaller increase in NLC states. Overall, the wage effects are much smaller than the application effects.

The results suggest that non-NLC states lose substantially more applications - and hence potential nurse supply - because of licensing barriers, while the corresponding wage premium is relatively modest. Finally, in Figure 12, I present the counterfactual effects on applications by half-year and compare applications per COVID-19 case in the absence of licensing barriers with the baseline.

Figure 11: Change in wages and applications in the absence of licensing barriers, by period

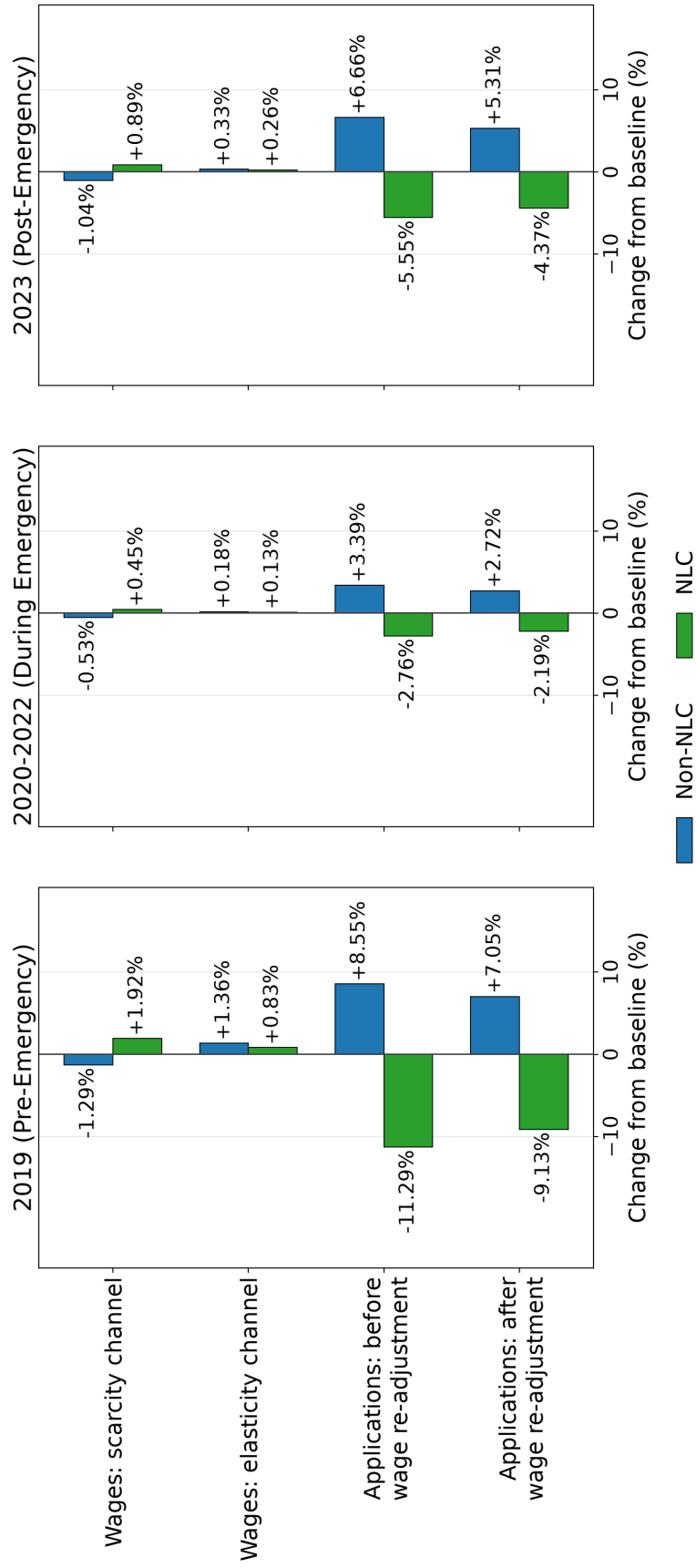
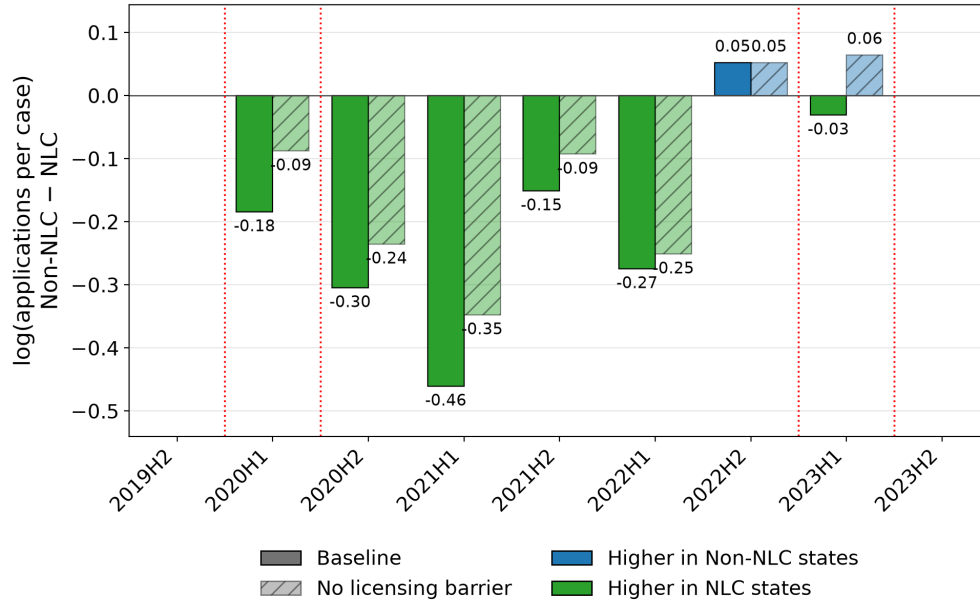


Figure 12: Difference in applications per COVID-19 case, non-NLC vs NLC states



Notes: The figure plots, by half-year, the difference in log applications per COVID-19 case between non-NLC and NLC states. Solid bars are the baseline; hatched bars remove the licensing barrier and allow wages to re-equilibrate. Vertical lines mark the start and end of the emergency period.

As Figure 12 shows, the gap in applications per COVID-19 case between non-NLC and NLC states would have narrowed by approximately 0.09 log points at the beginning of the COVID-19 outbreak if all states had been a part of the NLC. This translates to 2.25% of applications moving from NLC to non-NLC states, which is roughly 125 more applications on the Wanderly platform. Scaling it to the overall travel-nurse market gives around 4,000 more applications to non-NLC states. At an application-to-move elasticity of 0.7, this translates to around 950 travel nurses relocating to non-NLC states from NLC states.

7 Conclusion

This paper quantifies the effect of interstate licensing barriers for nurses and provides evidence that interstate variation in nurse licensing requirements constrained reallocation of travel nurses during the COVID-19 outbreak. The states that were a part of the Nurse Licensure Compact (NLC) before 2020 reported higher applications per COVID-19 case throughout the sample period. Notably, the results from this paper show 50% of that gap can be explained by the differences in interstate licensing barriers between non-NLC and NLC states. While emergency measures did help in reducing the effect of licensing barriers, the adjustment was slow and gradual.

On average, a nurse required a 67-80% wage premium to be indifferent between applying to a county whose state she does not hold the license to versus the one for which she holds a license, keeping everything else unchanged. By comparison, a nurse needs only one-fifth to one-seventh of this wage premium to be willing to apply twice as far from home.

The results from this paper establish that interstate licensing barriers did affect the application decisions of travel nurses. While emergency waivers eased these barriers, it was with a lag and during a public health emergency such as COVID-19, such constraints could have mortality consequences.

The evidence also highlights the broader policy implications of uniform licensing frameworks like the Nurse Licensure Compact (NLC). States that had already adopted the NLC were better positioned to mobilize nurses during the initial surge of COVID-19, reflected in faster labor market adjustment. Given the expanding scope of occupational licensing in the US, these results underscore that licensing mobility barriers can have serious consequences across professions, with particularly severe implications during emergencies when timely labor reallocation is essential.

References

- American Hospital Association (2023). Supporting the health care workforce: Lessons following the covid-19 pandemic. Technical report, American Hospital Association.
- Anderson, D. M., R. Brown, K. K. Charles, and D. I. Rees (2020). Occupational licensing and maternal health: Evidence from early midwifery laws. *Journal of Political Economy* 128(11), 4337–4383.

- Atal, J. P., T. Larroucau, P. Muñoz, and C. Otero (2026). Physicians’ occupational licensing and the quantity-quality trade-off. Working paper.
- Azar, J., S. Berry, and I. Marinescu (2022). Estimating labor market power. Working Paper 30365, National Bureau of Economic Research.
- Bae, K. and E. Timmons (2023). Now you can take it with you: Effects of occupational credential recognition on labor market outcomes. *Available at SSRN 4389898*.
- Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica* 63(4), 841–890.
- Blair, P. Q. and B. W. Chung (2019). How much of barrier to entry is occupational licensing? *British Journal of Industrial Relations* 57(4), 919–943.
- Cook, A., M. Gaynor, M. Stephens Jr., and L. Taylor (2012). The effect of a hospital nurse staffing mandate on patient health outcomes: Evidence from california’s minimum staffing regulation. *Journal of Health Economics* 31(2), 340–348.
- DePasquale, C. and K. Stange (2016). Labor supply effects of occupational regulation: Evidence from the nurse licensure compact. Technical report, National Bureau of Economic Research.
- Friedrich, B. U. and M. B. Hackmann (2021). The returns to nursing: Evidence from a parental-leave program. *Review of Economic Studies* 88(5), 2308–2343.
- Gottlieb, J. D. and A. Zenilman (2026, September (forthcoming)). When nurses travel: Labor supply responses to peak demand for nurses. *The Review of Economics and Statistics*.
- Gruber, J. and S. A. Kleiner (2012). Do strikes kill? evidence from new york state. *American Economic Journal: Economic Policy* 4(1), 127–157.
- Johnson, J. E. and M. M. Kleiner (2020). Is occupational licensing a barrier to interstate migration? *American Economic Journal: Economic Policy* 12(3), 347–373.
- Kleiner, M. M. and A. B. Krueger (2013). Analyzing the extent and influence of occupational licensing on the labor market. *Journal of Labor Economics* 31(S1), S173–S202.
- Kleiner, M. M. and E. J. Soltas (2023). A welfare analysis of occupational licensing in US states. *Review of Economic Studies* 90(5), 2481–2516.
- Larsen, B., Z. Ju, A. Kapor, and C. Yu (2020). The effect of occupational licensing stringency on the teacher quality distribution. Technical report, National Bureau of Economic

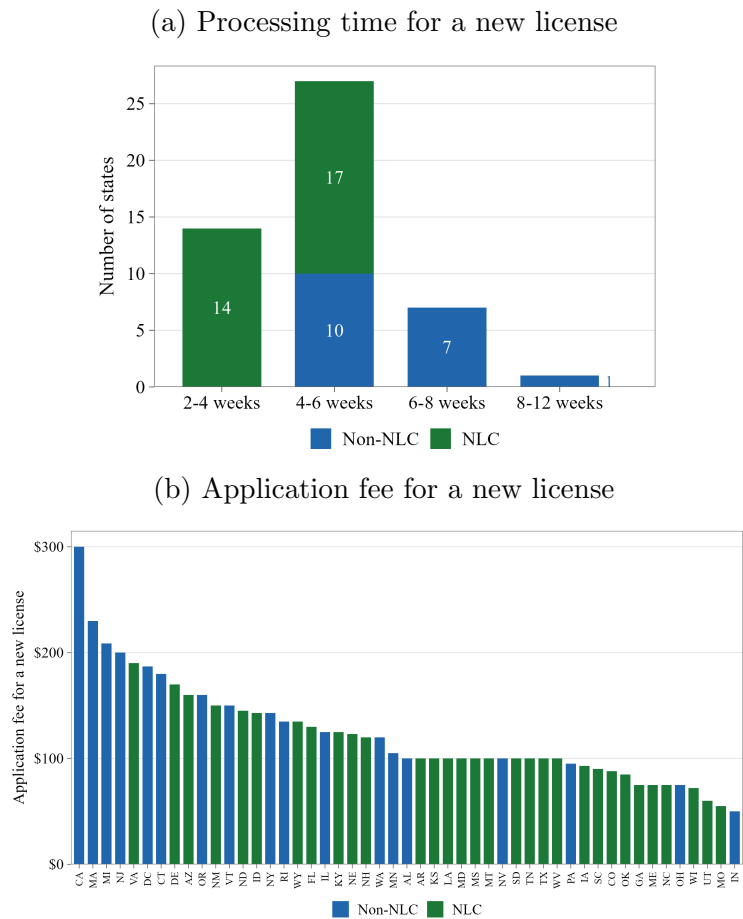
Research.

- Leland, H. E. (1979). Quacks, lemons, and licensing: A theory of minimum quality standards. *Journal of political economy* 87(6), 1328–1346.
- Marinescu, I. and R. Rathelot (2018). Mismatch unemployment and the geography of job search. *American Economic Journal: Macroeconomics* 10(3), 42–70.
- Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica* 69(2), 307–342.
- Nguyen, A. M., M. Schaler-Haynes, J. Chou, M. Wetzel, M. Koller, M. J. Yedidia, and J. C. Cantor (2022). Impact of the New Jersey COVID-19 temporary emergency reciprocity licensure program on health care workforce supply. *Health Affairs* 41(8), 1125–1132.
- Prager, E. and M. Schmitt (2021). Employer consolidation and wages: Evidence from hospitals. *American Economic Review* 111(2), 397–427.
- Propper, C. and J. Van Reenen (2010). Can pay regulation kill? panel data evidence on the effect of labor markets on hospital performance. *Journal of Political Economy* 118(2), 222–273.
- Shakya, S., S. Ghosh, and C. Norris (2022). Nurse licensure compact and mobility. *Journal of Labor Research* 43(2), 260–274.
- Shapiro, C. (1986). Investment, moral hazard, and occupational licensing. *The Review of Economic Studies* 53(5), 843–862.
- Staiger, D. O., J. Spetz, and C. S. Phibbs (2010). Is there monopsony in the labor market? evidence from a natural experiment. *Journal of Labor Economics* 28(2), 211–236.
- U.S. Government Accountability Office (2024). Hospitals: Expanded use of supplemental nurses during the covid-19 pandemic. Technical Report GAO-24-106447, U.S. Government Accountability Office.

A1: Institutional Details

Licensure by Endorsement: Every Registered Nurse (RN) in the United States must hold a license to practice, but state-specific requirements limit license portability. The Nurse Licensure Compact (NLC) allows eligible nurses residing in member states to practice across the compact with a multistate license. Beyond this, nurses must obtain separate licenses for each state where they practice through “licensure by endorsement.” This generally does not require retaking the licensing exam, but applicants must meet destination-state requirements, which may include background checks and license verification. These requirements can impose substantial delays: Figure A1 shows processing times ranging from 2-4 weeks to 8-12 weeks across states. Application fees also vary considerably. Beyond these, the renewal requirements also vary substantially across states making it tedious to maintain the licenses.

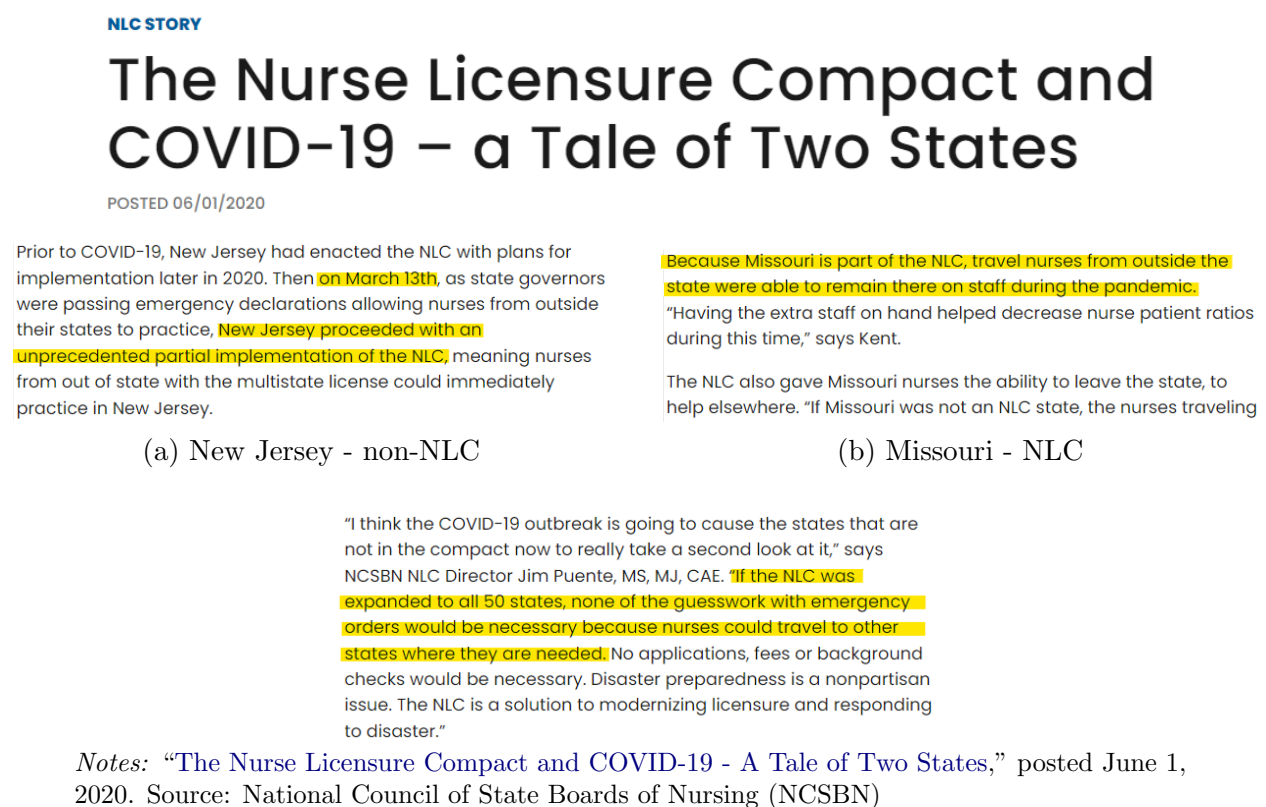
Figure A1: Time and Cost of Obtaining a New RN License by NLC Status



Notes: Panel (a): number of states by the processing time for a new RN license by endorsement. Panel (b): application fee for a new RN license by state.

Nurse Licensure Compact (NLC) and Emergency Measures: During the federal public health emergency, states temporarily waived interstate licensing requirements for nurses. However, the scope of these waivers varied, and unclear communication may have created uncertainty and delayed nurses' responses. Figure A2 provides anecdotal evidence from a June 2020 article published by the National Council of State Boards of Nursing (NCSBN). The article documents confusion surrounding emergency waivers and suggests that NLC states were better positioned than non-NLC states to meet nursing demand at the onset of the pandemic.

Figure A2: The Nurse Licensure Compact and Emergency Measures during COVID-19

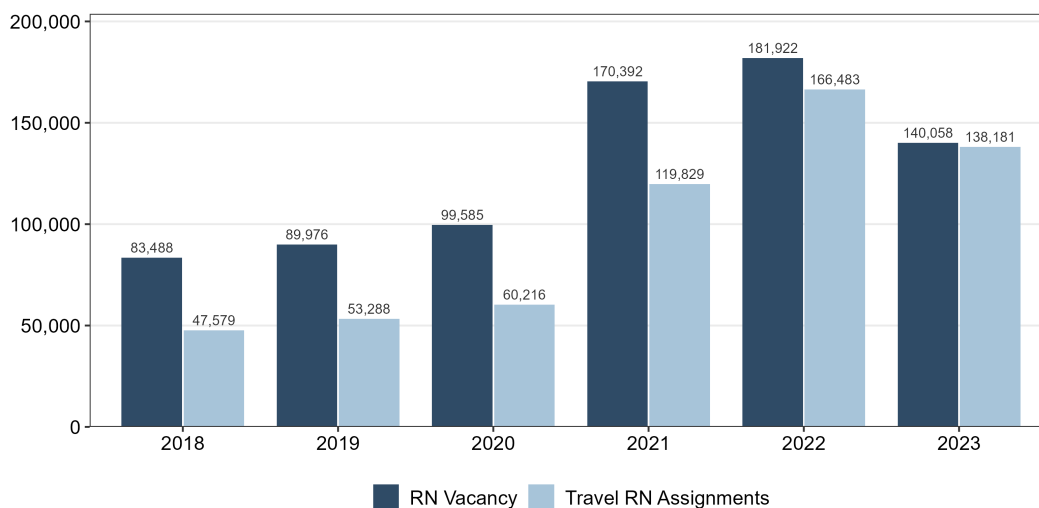


Travel Nurses in the US

Hospitals hire travel nurses for short-term assignments, usually lasting 13 weeks. Growing RN vacancies have increased demand for travel nurses, particularly during COVID-19, when surging patient demand strained hospital staffing. Figure A3 compares annual RN vacancy measures from the Area Health Resources Files (AHRF) with National Association of Travel Healthcare Organizations (NATHO) estimates of travel nurses on assignment for

2018-2024. Travel nurse activity closely tracks RN vacancy trends, consistent with hospitals using temporary staffing to address shortages.

Figure A3: RN Vacancies and Travel RN Assignments, 2018-2023

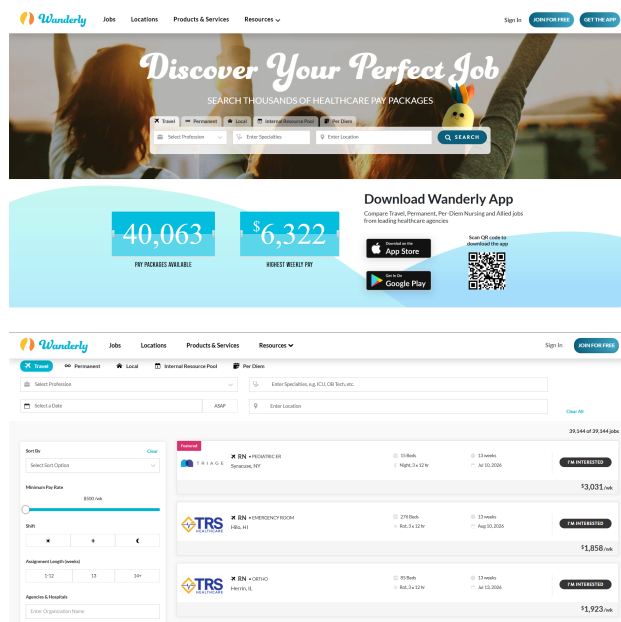


Notes: RN vacancies are vacant hospital RN positions reported in the AHRF; travel RN assignments are the number of travel RNs on assignment nationally. Sources: AHRF; SIA/NATHO.

Wanderly Data

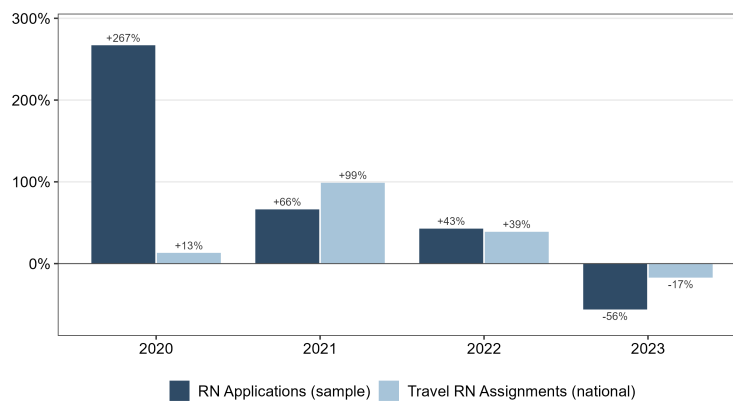
Wanderly is a travel nurse job aggregator listing postings from approximately 80-100 U.S. staffing agencies. Nurses can create an account, compare postings, and choose where to apply. Figure A4 shows a snapshot of the website. Figure A5 compares annual growth in Wanderly applications with growth in national travel nurse assignments reported by SIA/NATHO. Wanderly applications rose substantially faster in 2020, likely reflecting the platform's smaller initial sample in 2019. In subsequent years, application growth closely tracks national assignment growth, suggesting that the Wanderly sample captures broader trends in travel nursing. Figure A6 shows the geographic distribution of the Wanderly applications for every year from 2019 to 2023.

Figure A4: Snapshot of Wanderly Website



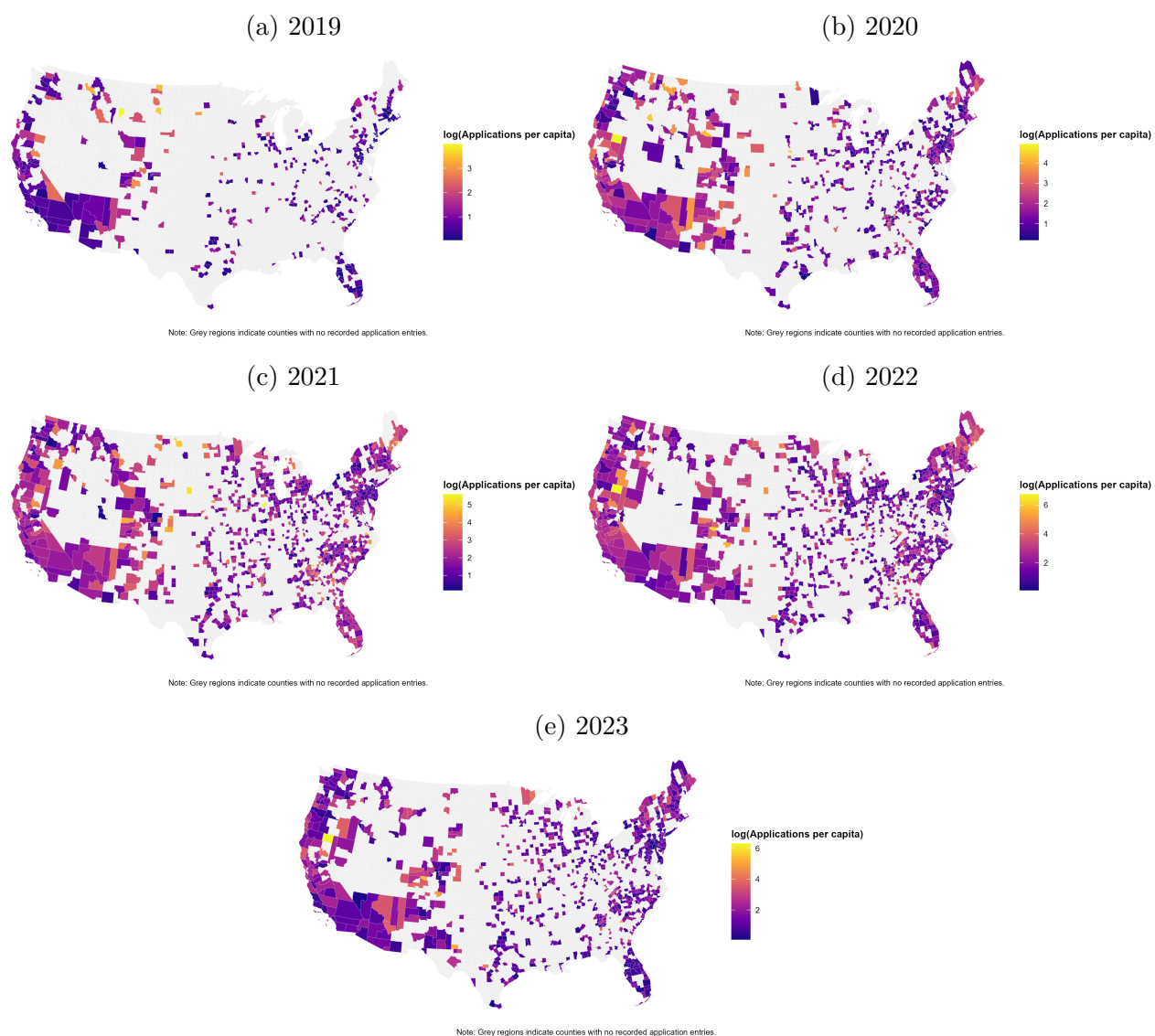
Notes: The figure above shows snapshots from the Wanderly website and illustrates what a travel nurse sees when choosing where to apply.

Figure A5: Growth in Wanderly RN Applications vs National Travel RN Assignments



Notes: Year-over-year percent change in RN applications in the Wanderly sample and in national travel RN assignments. Sources: Wanderly; SIA/NATHO.

Figure A6: Distribution of Wanderly RN Applications per Capita by County, 2019-2023



Notes: Counties are shaded by log RN applications per capita received through Wanderly in each year; gray counties received no applications. Source: Wanderly.

A2: NPI Moves and Wanderly Applications

To assess how closely Wanderly applications reflect actual RN mobility, this section compares application patterns with moves observed in NPI data, extending the discussion from section 3.1. Here, I examine this relationship by the potential licensed versus non-licensed corridors. I classify origin-destination state pairs into four NLC corridors: NLC to NLC, NLC to non-NLC, non-NLC to NLC, and non-NLC to non-NLC. NLC-to-NLC pairs are expected to have a higher share of licensed applications than the other corridors. I therefore compare the correlation between applications and observed RN moves for NLC-to-NLC pairs with that for all other pairs. I also examine this relationship separately for 2019 (pre-emergency), 2020-2022 (during the emergency), and 2023 (when waivers began to expire), to assess whether it changed as emergency measures eased licensing barriers and subsequently expired.

As Figure A7 shows, the correlation between applications and RN moves was higher for NLC-to-NLC pairs than for other pairs in 2019. The correlations became similar during 2020-2022, but the difference reemerged in 2023, when emergency measures expired. These patterns suggest that Wanderly applications reflect broader RN mobility and that their relationship with observed moves may vary with the licensing environment.

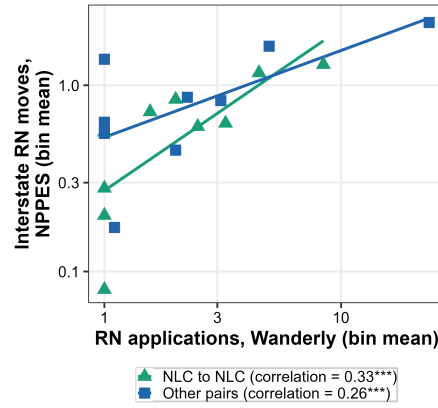
To quantify this relationship, I aggregate moves and out-of-state applications to origin $\times$ destination $\times$ half-year cells and estimate, by Poisson pseudo-maximum likelihood (PPML),

$$E[M_{odt}] = \exp(\eta \log A_{odt} + \gamma_{ot} + \gamma_{dt}), \quad (16)$$

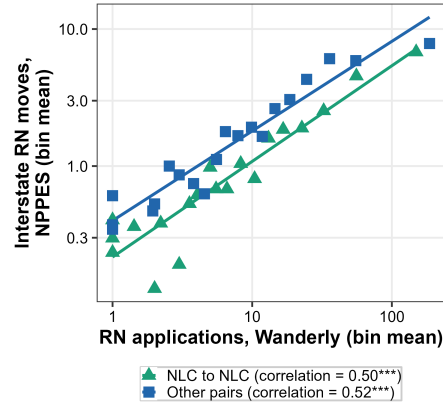
where M_{odt} and A_{odt} are NPES moves and Wanderly applications from state o to state d in half-year t . Origin $\times$ half-year and destination $\times$ half-year fixed effects absorb differences in NPES and Wanderly coverage and destination demand, and standard errors are clustered by state pair. The sample includes the 8,619 cells with at least one application, 2,461 of which record a move. The estimated elasticity is $\hat{\eta} = 0.71$ (s.e. 0.046): moves increase with applications, but less than proportionally. Interacting $\log A_{odt}$ with NLC-to-NLC and emergency-period indicators gives elasticities of 0.49 for other pairs and 0.75 for NLC-to-NLC pairs outside the emergency, and 0.69 and 0.79 during it. Consistent with Figure A7, applications convert into moves less readily when the license is not portable, and this gap nearly closes while licensing requirements were waived.

Figure A7: Interstate RN Moves and Wanderly Applications by NLC Corridor

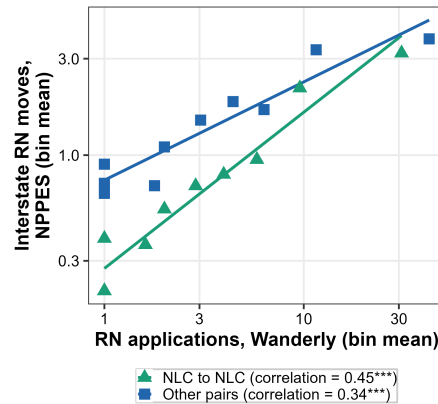
(a) 2019 (Pre-emergency)



(b) 2020-2022 (During emergency)



(c) 2023 (Post-emergency)



Notes: Binned scatter plots of interstate RN moves (NPPES) against Wanderly applications across origin-destination state pairs, shown separately for NLC-to-NLC pairs and all other pairs. Pairs are grouped into equal-sized bins by applications (10 bins in 2019 and 2023, 20 in 2020-2022); both axes are on a log scale. Source: Wanderly and NPPES NPI data.

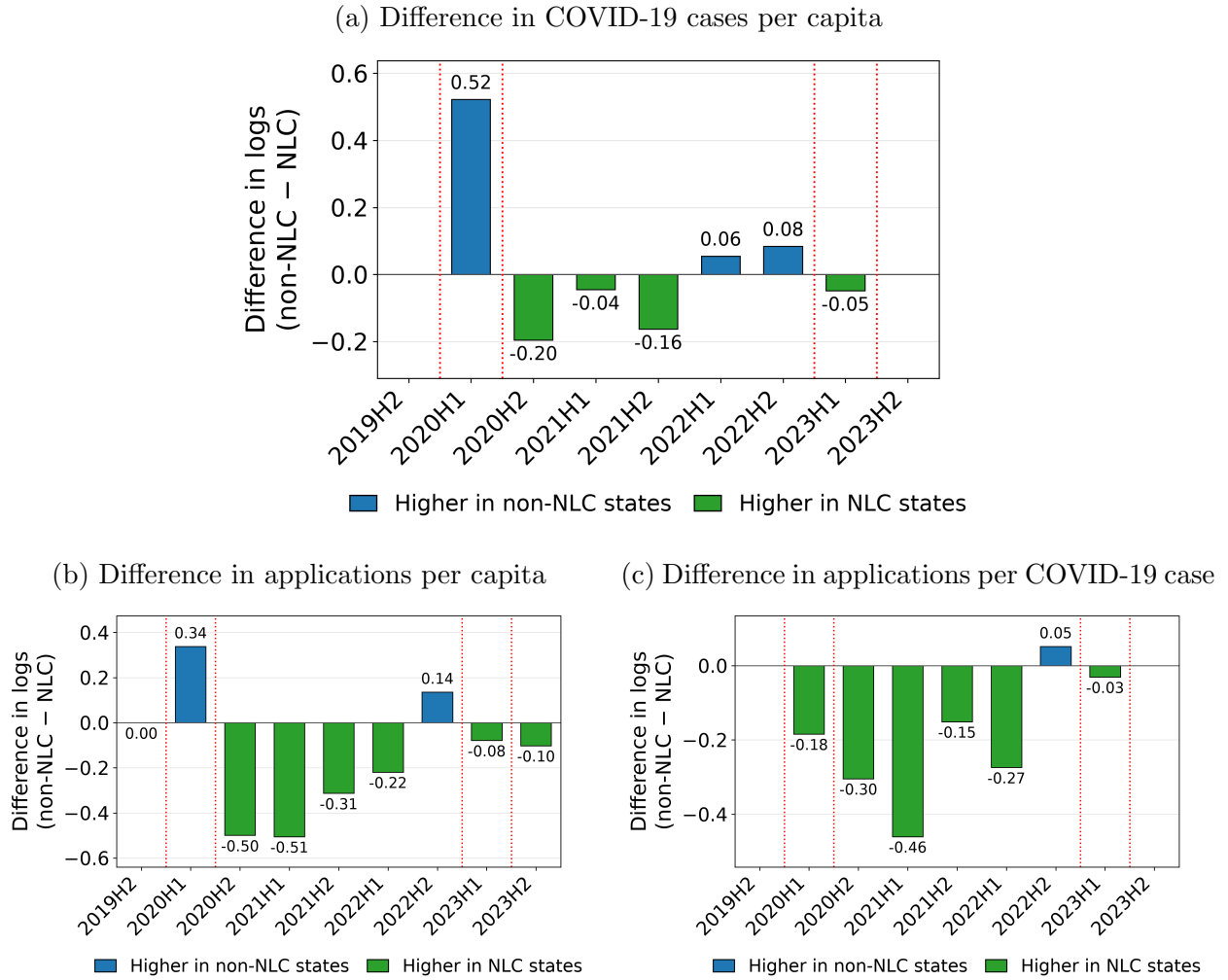
A3: Descriptive Evidence

This appendix documents the differences in non-NLC and NLC states over time across multiple patterns. As Panel (a) of Figure A8 shows not only did non-NLC states have a higher interstate licensing barrier to movement of nurses, they were also hit with the COVID-19 wave first. They reported 50% higher COVID-19 cases per capita in the first half of COVID-19. At such a time, the restrictions to movement can have even bigger consequences by preventing the nurses from being reallocated to their place of need.

Panels (b) and (c) of Figure A8 show the differences between non-NLC and NLC states in applications per capita and applications per COVID-19 case, respectively. The latter measures application activity relative to local COVID-19 burden, a proxy for pandemic-related healthcare demand. In Panel (b), the difference in applications per capita broadly tracks the corresponding difference in COVID-19 cases per capita. This pattern is consistent with emergency waivers easing licensing barriers and facilitating an initial application response to the greater caseload in non-NLC states.

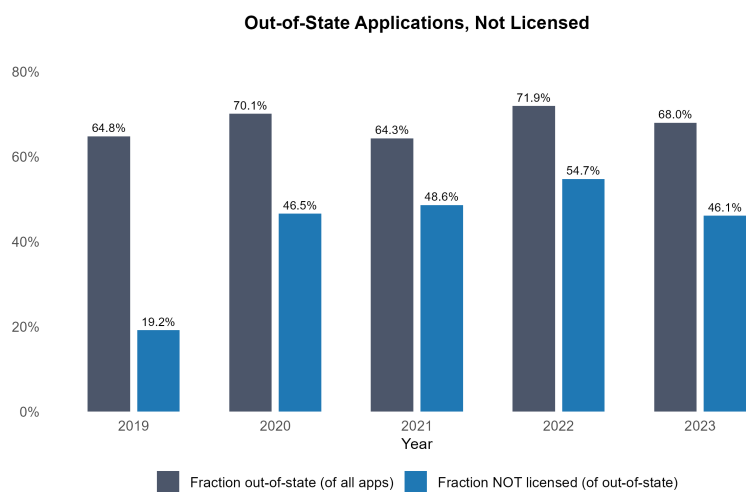
Panel (c) shows that applications per COVID-19 case remained lower in non-NLC states in most half-years, with the exception of a small positive gap in 2022H2. Thus, the initial increase in applications per capita did not translate into more applications relative to COVID-19 burden. These patterns suggest that applicant supply relative to pandemic-related demand remained generally lower in non-NLC states, although this comparison alone cannot determine how much of the difference reflects remaining licensing barriers.

Figure A8: COVID-19 Cases and Applications, non-NLC vs NLC States



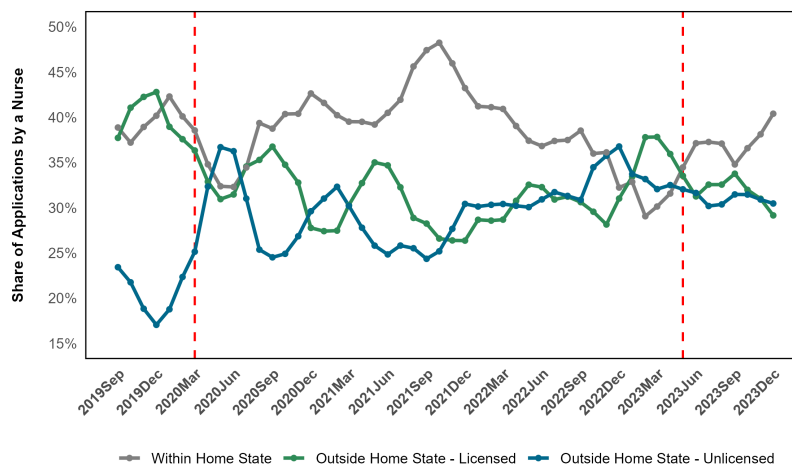
Notes: Panel (a) plots, by half-year, the difference in log COVID-19 cases per capita between non-NLC and NLC states. Cases are summed over each group's destination counties and divided by their population. Vertical lines mark the start and end of the emergency period.

Figure A9: Out-of-State and Unlicensed Applications by Year



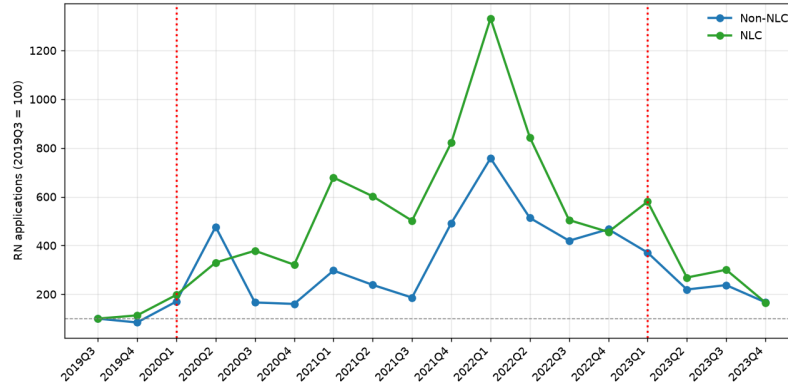
Notes: Dark bars show the share of all travel nurse applications made to jobs outside the nurse's home state. Blue bars show the share of these out-of-state applications made to jobs in states where the nurse does not hold a license. Source: Wanderly.

Figure A10: Share of licensed applications by a travel nurse



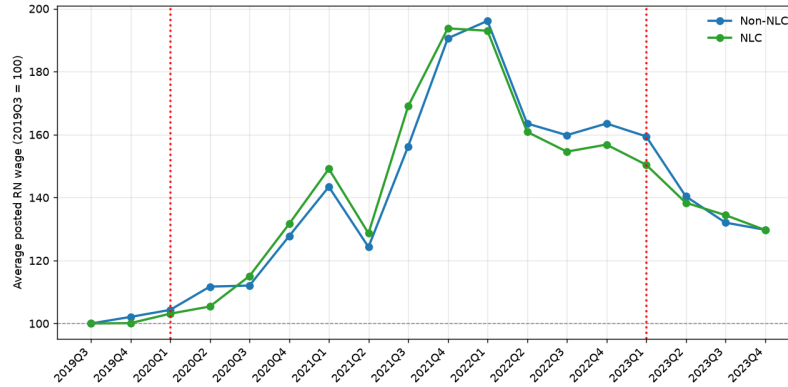
Notes: Monthly shares of travel nurse applications to jobs in the nurse's home state, to out-of-state jobs where the nurse holds a license, and to out-of-state jobs where the nurse does not. Vertical dashed lines mark the start and end of the emergency period. Source: Wanderly.

Figure A11: RN Applications to non-NLC and NLC States, 2019Q3-2023Q4



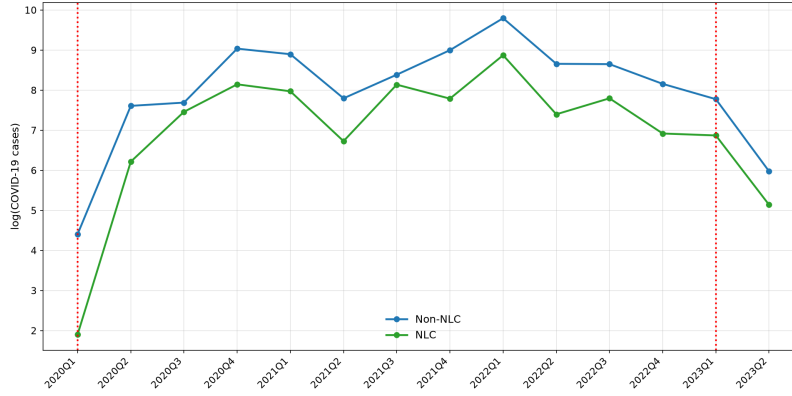
Notes: Number of RN applications to jobs in non-NLC and NLC states by quarter, indexed to 2019Q3 = 100; states are classified by NLC status as of January 2020. Red dotted lines mark 2020Q1 and 2023Q1. Source: Wanderly.

Figure A12: Average Posted RN Wage in non-NLC and NLC States, 2019Q3-2023Q4



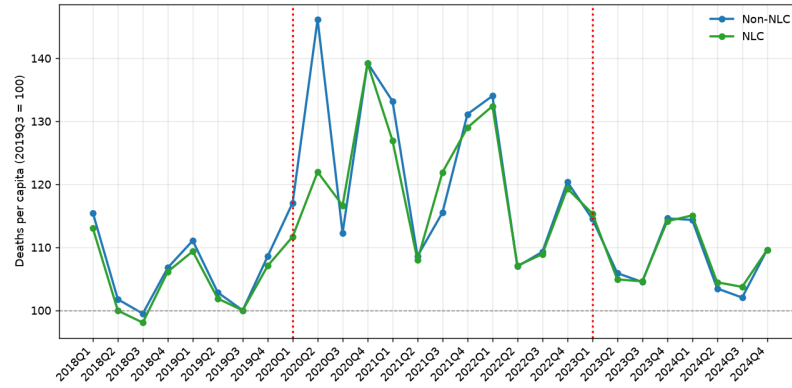
Notes: Average RPP-adjusted hourly loaded pay of RN job postings in non-NLC and NLC states by quarter, indexed to 2019Q3 = 100; states are classified by NLC status as of January 2020. Red dotted lines mark 2020Q1 and 2023Q1. Source: Wanderly.

Figure A13: COVID-19 Cases in non-NLC and NLC Counties, 2020Q1-2023Q2



Notes: Log of average COVID-19 cases per county by quarter and NLC status as of January 2020, for all counties. Red dotted lines mark 2020Q1 and 2023Q1. Source: CDC.

Figure A14: Deaths per Capita in non-NLC and NLC Counties, 2018Q1-2024Q4



Notes: All-cause deaths per capita by quarter and NLC status as of January 2020, indexed to 2019Q3 = 100, for counties on either side of borders between NLC and non-NLC states. Red dotted lines mark 2020Q1 and 2023Q1. Source: CDC.

Table A1: Mortality Data Summary Statistics by NLC Status

Panel A: Demographic Distribution			
	non-NLC	NLC	Difference (non-NLC – NLC)
Population	226,026	100,397	125,629***
Urban Population Percentage (%)	51.1	40.9	10.2***
Age Share: 0 to 44 (%)	53.8	55.0	-1.2***
Age Share: 45 to 64 (%)	26.1	25.6	0.5***
Age Share: 65 to 74 (%)	11.8	11.4	0.3***
Age Share: 75+ (%)	8.3	8.0	0.3***
Share: Non-Hispanic White (%)	80.4	73.1	7.3***
Share: Non-Hispanic Black (%)	4.5	12.1	-7.6***
Share: Non-Hispanic Asian (%)	2.6	1.4	1.2***
Share: Hispanic (%)	9.4	9.9	-0.5***
Share: Bachelor's Degree or Higher (%)	27.1	23.7	3.4***
Unemployment Rate (%)	5.1	4.2	0.8***
Median Household Income (\$)	70,264	61,750	8,513***
Panel B: Mortality and Health Indicators			
	non-NLC	NLC	Difference (non-NLC – NLC)
Total Deaths	170.6	81.7	88.9***
Deaths Per 100k Population	96.6	107.4	-10.8***
COVID-19 Deaths	15.7	7.0	8.7***
COVID-19 Deaths Per 100k	7.9	9.8	-2.0***
COVID-19 Confirmed Cases	1,505.4	640.3	865.1***
COVID-19 Cases Per 100k	647.9	683.3	-35.4***
Vaccine: Received At Least 1 Dose (%)	32.6	28.3	4.3***
Vaccine: Completed Primary Series (%)	57.0	52.7	4.3***
Vaccine: Received Up-to-Date Series (%)	29.2	24.6	4.6***
County-months, 2018-2024	52,538	154,610	
County-months, 2020-2023 (COVID-19 rows)	28,476	91,284	

Notes: Means over county-months, 2018-2024; COVID-19 and vaccination variables cover 2020-2023. NLC status is the state's status in the year of the observation. Difference is the non-NLC mean minus the NLC mean; stars from a two-sample Welch t -test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A4: Reduced Form Evidence by Licensed Status

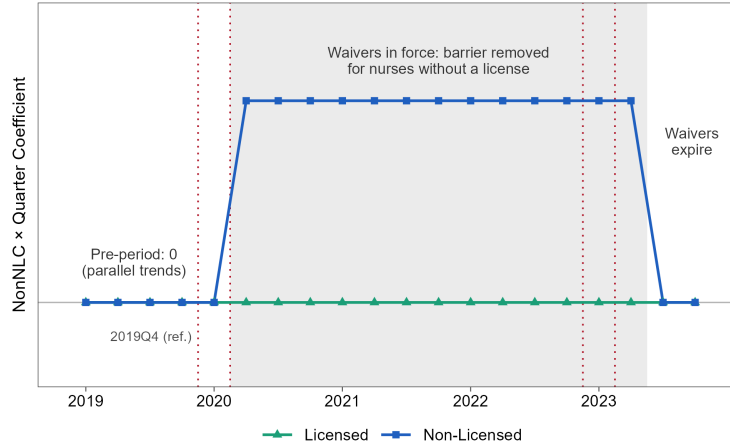
Section 4 presents suggestive reduced-form evidence based on differences in RN applications per capita between non-NLC and NLC states over time. Here, I further separate applications by licensing status. Using nurses' reported license holdings in Wanderly, I classify an application as licensed if the nurse holds a license for the destination state and unlicensed otherwise. I then aggregate applications in each category by county and quarter and estimate Equation 1 separately for licensed and unlicensed applications.

$$\log(y^k)_{ct} = \sum_{t \neq 2019Q4} \beta_{1t}^k \mathbf{1}\{Non - NLC\}_{s(c)} \times \mathbf{1}\{Quarter\}_t + \beta_c^k + \beta_t^k + \epsilon_{ct}^k, \quad k \in \{NL, L\} \quad (17)$$

As Figure A15 shows, if only the interstate licensing barriers differed across non-NLC and NLC states and emergency waivers only removed these barriers, one would expect the effect to only show up for non-licensed applications and the gap in licensed applications should be relatively flat.

Here, y_{ct}^{NL} and y_{ct}^L denote non-licensed and licensed RN applications per capita to county c in quarter t , respectively. I estimate the specification separately for each outcome.

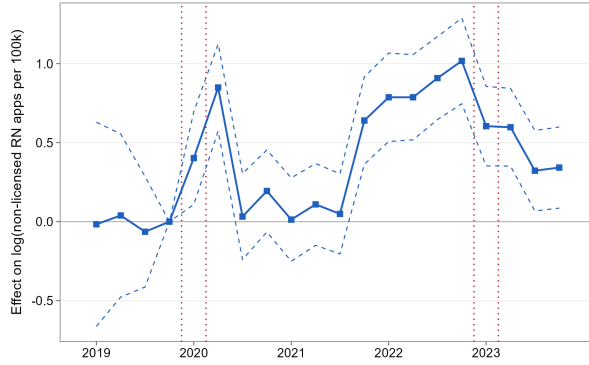
Figure A15: Licensed vs Non-Licensed RN Applications: only interstate licensing barrier variation



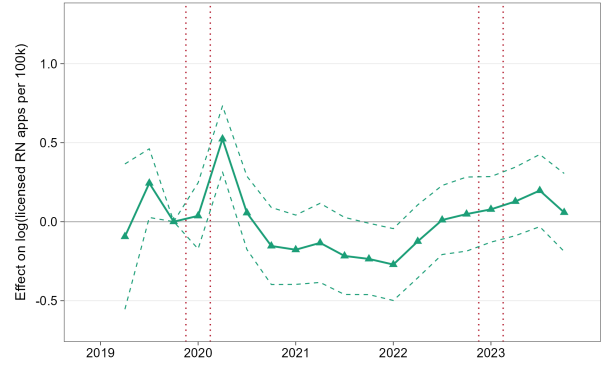
Notes: This illustrative figure shows the expected β_{1t}^k from Equation 17 if NLC and non-NLC states differed only in licensing barriers and emergency measures only suspended these barriers. Non-licensed applications should rise in non-NLC states relative to NLC states during the waivers, while the gap in licensed applications should remain flat.

Figure A16: Event Study Estimates: Non-NLC vs NLC States

(a) Non-Licensed RN Applications per Capita



(b) Licensed RN Applications per Capita



Notes: The figure plots β_{1t}^k from Equation 17, measuring the quarterly non-NLC-NLC gap relative to 2019Q4, with 90% confidence intervals. Panel (a): non-licensed applications, 4,494 county-quarter observations across 639 counties ($R^2 = 0.610$). Panel (b): licensed applications, 4,754 county-quarter observations across 622 counties ($R^2 = 0.631$). Both specifications include county and quarter fixed effects, with standard errors clustered by county.

Figure A16 confirms the pattern suggested by Figure A15. Changes in the application-per-capita gap between non-NLC and NLC states largely reflect movements in unlicensed applications (Panel (a)), while the gap in licensed applications remains relatively flat (Panel (b)). Two features, however, complicate the interpretation. First, both categories show an initial jump in 2020H1, making it difficult to determine how much of the increase in unlicensed applications reflects the emergency waivers. Second, the pattern in unlicensed applications in Panel (a) closely tracks the wage patterns in Figure 6. If the federal emergency waivers eliminated licensing barriers, unlicensed applications could have increased without a corresponding wage increase. The observed comovement therefore makes it difficult to separate the effects of lower licensing barriers from responses to higher wages. Although the contrasting patterns for licensed and unlicensed applications suggest a role for interstate licensing barriers, these estimates cannot isolate their effects.

A5: Model Derivations

A5.1: Markdown First Order Condition

Each county c chooses its wage w_{ct} to maximize profits in Equation 6, taking the wages of all other counties as given:

$$\max_{w_{ct}} \pi_{ct} = R(L_{ct}(w_{ct})) - w_{ct} L_{ct}(w_{ct}).$$

Differentiating with respect to w_{ct} ,

$$\frac{\partial \pi_{ct}}{\partial w_{ct}} = R'(L_{ct}) \frac{\partial L_{ct}}{\partial w_{ct}} - L_{ct} - w_{ct} \frac{\partial L_{ct}}{\partial w_{ct}} = 0.$$

Rearranging,

$$R'(L_{ct}) = w_{ct} + L_{ct} \left(\frac{\partial L_{ct}}{\partial w_{ct}} \right)^{-1} = w_{ct} \left(1 + \frac{L_{ct}}{w_{ct}} \frac{\partial w_{ct}}{\partial L_{ct}} \right).$$

Since $L_{ct} = \kappa N_t s_{ct}(w_{ct})$, and neither the conversion rate κ nor the total number of applications N_t depends on w_{ct} (the choice set has no outside option),

$$\frac{w_{ct}}{L_{ct}} \frac{\partial L_{ct}}{\partial w_{ct}} = \frac{\partial \log L_{ct}}{\partial \log w_{ct}} = \frac{\partial \log s_{ct}}{\partial \log w_{ct}} \equiv \epsilon_{ct}.$$

Substituting into the rearranged condition above gives the first order condition in Equation 9:

$$\underbrace{R'(L_{ct})}_{\text{MRPL}_{ct}} = w_{ct} \left(1 + \frac{1}{\epsilon_{ct}} \right) \implies w_{ct} = \text{MRPL}_{ct} \cdot \frac{\epsilon_{ct}}{1 + \epsilon_{ct}}.$$

The county's share of applications in market t is the average of the individual choice probabilities,

$$s_{ct} = \frac{1}{N_t} \sum_i s_{ict}, \quad s_{ict} = \frac{\exp(\mu_{ict} + \delta_{ct})}{\sum_{c' \in \mathcal{C}_{sp,t}} \exp(\mu_{ic't} + \delta_{c't})}.$$

From Equation 4, $\partial \delta_{ct} / \partial \log w_{ct} = \delta_1$, and the logit form implies $\partial s_{ict} / \partial \delta_{ct} = s_{ict}(1 - s_{ict})$. Therefore,

$$\frac{\partial s_{ct}}{\partial \log w_{ct}} = \frac{1}{N_t} \sum_i \frac{\partial s_{ict}}{\partial \delta_{ct}} \frac{\partial \delta_{ct}}{\partial \log w_{ct}} = \frac{\delta_1}{N_t} \sum_i s_{ict}(1 - s_{ict}).$$

Dividing by $s_{ct} = \frac{1}{N_t} \sum_i s_{ict}$,

$$\epsilon_{ct} = \frac{\partial \log s_{ct}}{\partial \log w_{ct}} = \delta_1 \frac{\sum_i s_{ict}(1 - s_{ict})}{\sum_i s_{ict}} = \delta_1 \left(1 - \frac{\sum_i s_{ict}^2}{\sum_i s_{ict}} \right) = \delta_1 (1 - \bar{s}_{ct}).$$

Defining the markdown as the share of the marginal revenue product that is not paid to nurses,

$$1 - \frac{w_{ct}}{\text{MRPL}_{ct}} = 1 - \frac{\epsilon_{ct}}{1 + \epsilon_{ct}} = \frac{1}{1 + \epsilon_{ct}}.$$

Given the estimate of δ_1 and the observed wages and shares, the baseline MRPL is recovered as $v_{ct} = w_{ct}(1 + \epsilon_{ct})/\epsilon_{ct}$. The markdown falls as application supply becomes more elastic.

A5.2: Decomposition of the Counterfactual Change in Log Wages

With $R(L_{ct}) = \theta_{ct} L_{ct}^{1-\alpha}$,

$$R'(L_{ct}) = (1 - \alpha) \theta_{ct} L_{ct}^{-\alpha}.$$

Let superscript 0 denote the baseline equilibrium, so that $v_{ct} = R'(L_{ct}^0)$. Since $L_{ct} = \kappa N_t s_{ct}$, and θ_{ct} , κ and N_t are unchanged in the counterfactual,

$$\frac{R'(L_{ct})}{R'(L_{ct}^0)} = \left(\frac{L_{ct}}{L_{ct}^0} \right)^{-\alpha} = \left(\frac{\kappa N_t s_{ct}}{\kappa N_t s_{ct}^0} \right)^{-\alpha} = \left(\frac{s_{ct}}{s_{ct}^0} \right)^{-\alpha} \implies \text{MRPL}_{ct} = v_{ct} \left(\frac{s_{ct}}{s_{ct}^0} \right)^{-\alpha}.$$

Substituting into the markdown rule gives Equation 15:

$$w_{ct} = v_{ct} \left(\frac{s_{ct}}{s_{ct}^0} \right)^{-\alpha} \cdot \frac{\epsilon_{ct}}{1 + \epsilon_{ct}}.$$

Taking logs,

$$\log w_{ct} = \log v_{ct} - \alpha (\log s_{ct} - \log s_{ct}^0) + \log \frac{\epsilon_{ct}}{1 + \epsilon_{ct}}.$$

In the baseline, $s_{ct} = s_{ct}^0$, so

$$\log w_{ct}^0 = \log v_{ct} + \log \frac{\epsilon_{ct}^0}{1 + \epsilon_{ct}^0}.$$

Let superscript *cf* denote the counterfactual equilibrium without licensing barriers and

$\Delta x_{ct} = x_{ct}^{cf} - x_{ct}^0$. Subtracting the baseline from the counterfactual, $\log v_{ct}$ cancels:

$$\underbrace{\Delta \log w_{ct}}_{\text{total}} = \underbrace{-\alpha \Delta \log s_{ct}}_{\text{(i) compensating differential}} + \underbrace{\Delta \log \frac{\epsilon_{ct}}{1 + \epsilon_{ct}}}_{\text{(ii) supply elasticity}}, \quad \Delta \log s_{ct} = \log s_{ct}^{cf} - \log s_{ct}^0.$$

The decomposition is exact rather than a first-order approximation, because log wages are additively separable in the two terms. Both terms are evaluated at the counterfactual equilibrium, where s_{ct}^{cf} and $\epsilon_{ct}^{cf} = \delta_1(1 - \bar{s}_{ct}^{cf})$ solve the fixed point jointly with w_{ct}^{cf} .

Removing licensing barriers raises applications to the most exposed counties, $\Delta \log s_{ct} > 0$, so term (i) is negative: more applicants lower the MRPL under decreasing returns to scale, and wages fall. To the extent that removing barriers spreads a county's applications across more nurses, it lowers the share-weighted average $\bar{s}_{ct}$ and raises ϵ_{ct} . Since $\epsilon/(1 + \epsilon)$ is increasing in ϵ , term (ii) is positive: the markdown shrinks and wages rise. The sign of the total wage change depends on which channel dominates.

A6: Additional Counterfactual Results

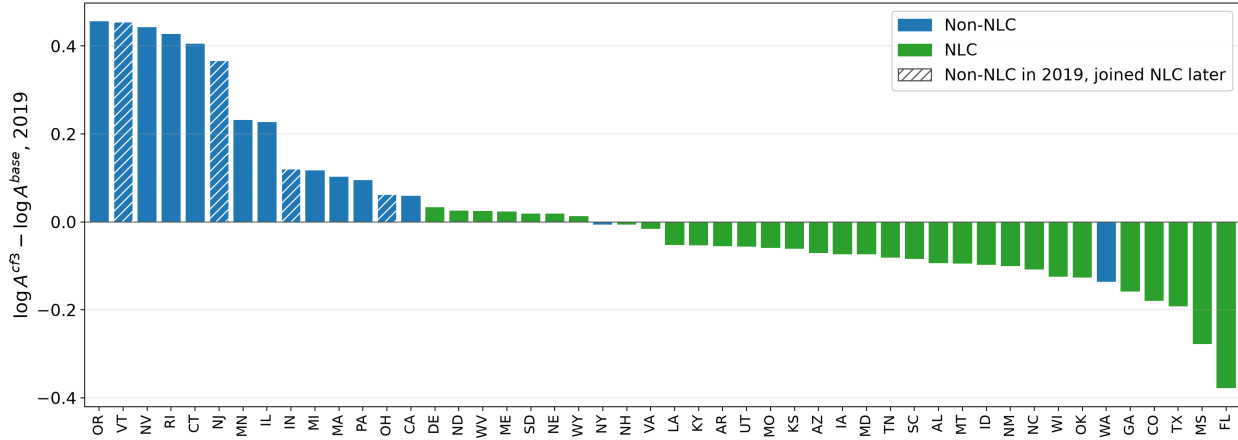
A6.1: Willingness to Accept by Period

Table A2: Willingness to Accept for the Licensing Barrier (Allied IV)

Period	$\beta_{1h}^3 - \beta_{1h}^1$	WTA (log points)	WTA (%)
Pre-emergency (2019H2)	-1.43	0.68	97
During emergency (2020H1-2023H1)	-0.68	0.32	38
Post-emergency (2023H2)	-0.90	0.43	53

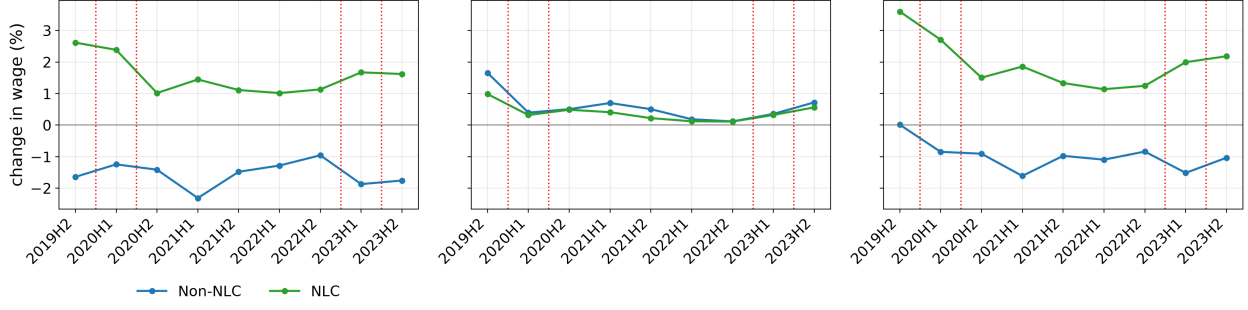
Notes: $WTA_h = -(\beta_{1h}^3 - \beta_{1h}^1)/\delta_1$ with $\delta_1 = 2.11$ (Allied IV). The emergency period reports the average over its half-years. $WTA (\%) = \exp(WTA) - 1$.

Figure A17: Change in applications across states in the absence of licensing barriers, 2019



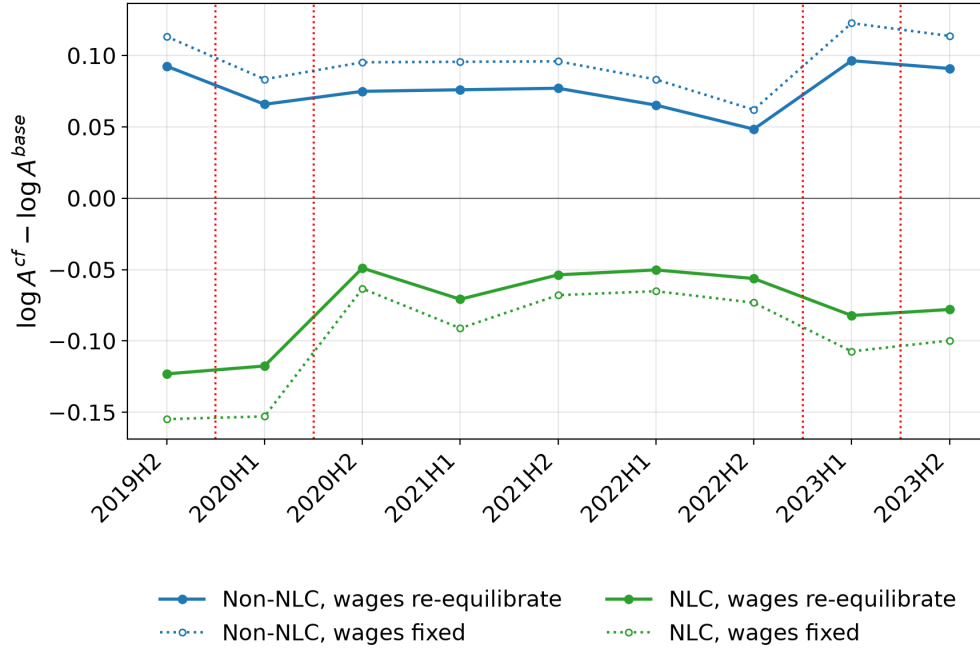
Notes: The figure plots, for each state, the log difference between counterfactual applications with the licensing barrier removed and wages re-equilibrated, and baseline applications in 2019. Non-NLC states are in blue and NLC states in green; hatched bars are states that were not in the NLC in 2019 but joined later.

Figure A18: Wage re-adjustment in the absence of licensing barriers, non-NLC vs NLC states



Notes: The figure plots the percent change in wages by half-year, separately for non-NLC and NLC states. Left panel: (i) compensating differential, $-\alpha \Delta \log s_{ct}$. Middle panel: (ii) supply elasticity, $\Delta \log[\epsilon_{ct}/(1 + \epsilon_{ct})]$. Right panel: total wage change, (i) + (ii).

Figure A19: Change in applications over time, non-NLC vs NLC states



Notes: The figure plots the log difference between counterfactual and baseline applications by half-year, separately for non-NLC and NLC states. Solid lines allow wages to re-equilibrate; dotted lines hold wages at their observed levels. Vertical lines mark the start and end of the emergency period.