

Licensing Barriers to Interstate Mobility: Evidence from Travel Nurses

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Abstract

This paper examines the impact of licensing barriers to interstate mobility on nursing labor markets and health outcomes during the COVID-19 pandemic. Using granular administrative data on US travel nurses with information on individual licenses, I exploit spatial variation from the Nurse Licensure Compact (NLC) and temporal variation from federal emergency waivers to identify the causal effects of licensing barriers. I find a 7% compensating wage differential for unlicensed positions prior to the pandemic, a gap that closed following emergency interventions after a three-month lag. I estimate a structural model of nurse applications to isolate the direct disutility of licensing from hospital wage responses. The results reveal that a lack of licensure reduces application probability by 70% - a deterrent effect more than twice as large as that of geographic distance (30%), despite the presence of a compensating wage premium and emergency measures. Counterfactual estimates reveal that NonNLC states suffered the greatest loss in applications due to licensing barriers. On the outcomes side, NonNLC states experienced 4% higher COVID-19 mortality rates in early 2020, with the gap narrowing in the second half of 2020. Together, the findings highlight that interstate licensing barriers constrained the rapid reallocation of critical health-care labor during the pandemic and that uniform licensing policies like the NLC can enhance labor market responsiveness and improve public health resilience in times of crisis.

1 Introduction

Since 2000, the United States has seen the highest growth rate of 22% in nurses per capita as compared to an average of 12% in the other OECD countries.¹ Despite this, the US has faced persistent nursing shortages since 1998 driven by demographic shifts and educational bottlenecks. While central to the healthcare system, the nursing labor market in the US has received little attention in economic literature. This paper bridges this gap by examining how interstate licensing variations affect the labor market for Registered Nurses (RNs) in the US.

All RNs in the US must be licensed by the state in which they practice, but these licenses may not be valid in other states. This lack of reciprocity can hinder geographic mobility and prevent an efficient labor supply. Such barriers can be especially costly during public health emergencies like COVID-19, when the ability of workers to move across states is vital. Using 2019-2023 administrative data specifically for travel nurses - the most geographically mobile segment of the RN workforce - I quantify how licensing barriers impact nurse wages, willingness to move, and state-level mortality

Travel nurses are RNs hired for temporary hospital assignments, usually lasting 3 to 4 months. During the COVID-19 pandemic, hospitals heavily relied on this flexible workforce to address the surge in healthcare demand.² Their licensing process and policies are the same as that of a regular nurse. A defining feature of licensing policies for RNs is the Nurse Licensure Compact (NLC), an agreement allowing RNs to practice in any member state under a single “multi-state” license. This eliminates the need for relicensure when moving between member states. By 2020, 30 states were members (NLC states), while 20 were not (NonNLC states). Beyond this spatial variation, federal emergency measures adopted during COVID-19 provide temporal variation in licensing barriers throughout my sample period.

The federal emergency (March 2020 - May 2023) temporarily eased mobility barriers by suspending state licensing requirements, enabling RNs to practice nationwide using their existing licenses. However, as the practical impact of these provisions likely unfolded with a delay, NonNLC states initially remained dependent on their local workforces to meet surging demands. Beyond quantifying the effects of licensing barriers on interstate mobility, this paper also evaluates how effectively these emergency measures mitigated these barriers.

¹Peterson-KFF Health System Tracker

²As 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.

The empirical analysis in this paper uses these spatial and temporal differences, alongside detailed administrative data on travel nurse applications from Wanderly between 2019 and 2023.³ Throughout this period, I observe every application submitted by travel nurses through the portal. The data offers detailed insights into each job posting, and most importantly for this paper, it identifies the specific licenses held by each nurse alongside their home state. This allows for a more precise measurement of the regulatory barriers nurses face when choosing between different states unlike previous research that infers license status based on a nurse’s location.

Leveraging all the information, this paper addresses the following research questions: Was there a compensating wage differential (CWD) for obtaining a new license for a Registered Nurse (RN)? If so, how did it change during the emergency period? Was there a difference in COVID-19 mortality reported across NLC and NonNLC states? Finally, did the licensing barrier affect application decision of nurses, beyond any wage effect?

To estimate the effect of licensing barriers on wages, I track individual nurses over time, observing their simultaneous applications to different out-of-state job postings. My identification strategy relies on the fact that these nurses often apply to positions where they hold a license alongside others where they do not. Using a log wage regression with nurse fixed effects, I interact a license-status dummy with half-yearly time indicators to capture how federal emergency measures shifted the relationship between licensure and wages throughout the sample period. The results establish a 7% compensating wage differential (CWD) for positions where the nurse lacks the required state license. This effect persisted through the first half of 2020 but disappeared entirely after that. Following the expiration of the emergency measures in May 2023, the results show a slight uptick in the CWD, suggesting a return of licensing-related wage premiums.

The second part of the analysis examines differences in mortality rates—measured as *deaths per covid case*—between NonNLC and NLC states from 2020 to 2023. Controlling for observable state-level characteristics, I include time interaction terms to assess how these differences evolved throughout the federal emergency. The results suggest that NonNLC states experienced persistently higher mortality than NLC states during 2020, with the gap only closing in 2021. Notably, toward the end of the estimation period—which overlaps with the expiration of federal emergency measures—the mortality gap began to widen again. This pattern mirrors the findings from the CWD analysis. Given that emergency measures were implemented in March 2020, the lag in closing the

³Wanderly is a digital staffing marketplace for travel nurses where they can compare across job postings from multiple agencies and choose where to apply.

mortality gap until 2021 suggests that lingering effects of licensing barriers on nursing supply took time to dissipate.

In the final part of the analysis, I develop and estimate a structural equilibrium model to quantify the effect of licensing barriers to interstate mobility on the distribution of applications across states. I estimate a discrete choice model of nurse applications to quantify how interstate licensing barriers affect nurses' willingness to apply across states, and augment it with a hospital wage-posting response to separate the direct application deterrent from indirect compensating wage premiums. This framework enables counterfactual simulations of application and wage distributions in the absence of licensing barriers. The results show that licensing barriers are the primary constraint on mobility, reducing the probability of a nurse applying by 70%. In contrast, distance decreases the likelihood by only 30%, indicating that regulatory frictions are more than twice as restrictive as geographic ones, despite the presence of a wage premium.

In the model, the licensing barrier is defined by whether a nurse holds a license for a specific state within their choice set. The counterfactual analysis removes this barrier by assuming all nurses are licensed in all states, allowing wages to re-equilibrate. While the model does not explicitly include a control for a state's membership in the Nurse Licensure Compact (NLC), the counterfactual results confirm that the states that would have received the largest influx of applications in the absence of licensing barriers are, indeed, the NonNLC states.

To the best of my knowledge, this is the first paper to provide causal evidence that NonNLC states fared worse than NLC states at the beginning of the pandemic, potentially due to higher licensing barriers for nurses. I demonstrate that while federal emergency measures successfully mitigated wage distortions, the underlying licensing barriers in NonNLC states remained a significant constraint on nursing supply, potentially contributing to the uneven mortality rates observed at the onset of the pandemic. Suspension of varied licensing requirements across states is a commonly adopted measure by a state in the US facing an emergency (wildfire, hurricane, etc.). However, evidence is missing on the consequences of relying on emergency adoption to overcome interstate licensing barriers as opposed to not having them in the first place. The results from this paper show that the catch up of NonNLC states to the NLC states was not immediate in response to the emergency adoption. It took at least three months since the emergency announcement for the catchup, potentially costing in terms of higher mortality.

This paper further contributes to two key strands of literature. Firstly, this paper adds

to the ever-growing pool of work on occupational licensing by providing causal evidence on the effects of barriers due to variations in interstate licensing requirements. Considering most occupations, Bae and Timmons (2023) find that the adoption of universal recognition of licensing by some US states increased migration to those states and improved labor market efficiency. Focusing on nurses in particular, some papers have studied the labor market effects of NLC. While DePasquale and Stange (2016) do not find any significant impact of NLC on the labor supply of nurses, Shakya et al. (2022) and Johnson and Kleiner (2015) find that NLC does affect the mobility of nurses both within NLC states and from NLC to NonNLC states. However, these studies do not account for potential wage differentials that may arise from licensing mobility barriers. This paper establishes that there is a 7% wage premium in NonNLC States due to higher licensing barriers to mobility and despite the wage premium, the application probability to these states is lower than to the NLC States. This paper further distinguishes itself by utilizing direct information on nurses' existing licenses rather than assuming their status based on residence. By observing the actual licenses held, I can more effectively isolate the deterrent effect of licensing requirements from other state-level characteristics.

Secondly, this paper contributes to the study of the role of nurses in COVID-19. In particular, Gottlieb and Zenilman (2020) study of the market for travel nurses during COVID-19 closely parallels the focus of this paper. They find that a unified national market for travel nurses facilitated their redistribution to high-demand areas during the pandemic. By establishing the relevance of NLC in explaining differences in COVID-19 outcomes of states, I provide evidence that variation in nurse licensure across some states inhibited the integration of this national market for nurses at least in the initial months of the pandemic outbreak.

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 Background

2.1 Occupational Licensing and Nurse Licensure in the US

Occupational licensing refers to the legal requirement of obtaining a state-issued license to practice certain professions such as nursing, teaching, or law. The share of licensed workers in the U.S. has risen sharply, from about 5% in the 1950s to nearly 20% by 2022. This has led to an increase in extensive research on its labor market effects. Proponents argue that licensing corrects information asymmetries (George et al. (1970); Leland (1979); Shapiro (1986)), while critics highlight its potential to restrict labor supply and mobility. Empirical work documents its impacts on service quality (Barrios (2022); Larsen et al. (2020); Farronato et al. (2020)), employment (Blair and Chung (2019)), and wages (Kleiner and Krueger (2013); Gittleman et al. (2018)), with Kleiner and Soltas (2023) finding that licensing reduces employment but raises wages and hours worked. Variation in licensing requirements across states creates interstate barriers with important labor market implications. This paper contributes to this literature by studying the Nurse Licensure Compact (NLC), which introduces uniform licensing for nurses across participating states.

Since the early 1900s, each US state has maintained its own nursing license requirements, restricting nurses to practice only within the state of issuance. In response to growing interstate healthcare needs and the rise of telemedicine, the National Council of State Boards of Nursing (NCSBN)⁴ established a committee in 1995 to explore a unified licensing system. This effort led to the launch of the Nurse Licensure Compact (NLC) in 1999, an interstate agreement that allows nurses in participating states to practice across state lines under a single multistate license.⁵

The compact was formally adopted in 2000 when Texas, Wisconsin, and Utah passed it into law. Subsequently, many states joined the compact, with 30 states being a part of the compact by the beginning of 2020. Figure 7 shows NLC states and NonNLC states on the US map at the onset of the COVID-19 pandemic.⁶ The professions covered under the compact are Registered Nurses and Licensed Practical/ Vocational Nurses. A key feature of the US nurse licensing is that the licensing exam for nurses (NCLEX) is standardized

⁴The NCSBN represents all state nursing boards in the US.

⁵An interstate compact is a formal agreement among states to coordinate on a specific policy issue, here nurse licensing.

⁶While the compact received much support from the states, there were also some criticisms. An enhanced NLC (e-NLC) was adopted in 2017 to address these. Hence, by 2020 the compact that states were a part of was eNLC. For brevity, I do not distinguish between the two compacts and throughout the paper refer to the compact as NLC.

nationally, so nurses need not retake it for a new state license.⁷ Despite this, the time and cost to get a new state license varies substantially across states. (Figure 8)

This paper focuses on travel nurses - the gig workforce of the nursing profession - who are hired by hospitals on short-term (typically 3 month) contracts. Because they often work across multiple states, licensing barriers pose greater mobility constraints for them. Aside from contract structure, their licensing process and job responsibilities are the same as those of regular nurses. The hiring of travel nurses by a hospital is mediated through a travel nurse agency.

2.2 Emergency 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 NonNLC 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, NonNLC states were constrained by in-state nurse supply until emergency measures were enacted.

⁷The exam reports only a pass/fail result, not a numerical score.

3 Data

This paper uses data from three sources: Wanderly data for travel nurses, COVID-19 data from the Centers for Disease Control and Prevention (CDC) and state-level demographics variables from the IPUMS CPS data.

Wanderly is a US travel nurse job aggregator that compiles postings from multiple staffing agencies into one platform. The dataset covers 2019–2023, providing detailed information on nurse applications (including application dates, home states and state licenses held by a nurse) and job postings (such as posting dates, hospital locations, specialties, agencies, and wages). Further, it provides all this information for two sets of professions: Registered Nurses (RN, from hereon) and Allied Nurses (Allied, from hereon). This is crucial for identification of the licensing barrier effects in this paper because only RNs are covered under the Nurse Licensure Compact (NLC). Thus, the Allied group serves as a control group to capture any systematic differences in NLC and NonNLC states other than the licensing barrier.

Table 3 summarizes key variables from the Wanderly data. The applications-to-postings ratio was lower in NonNLC states than in NLC states in 2019, indicating higher mobility barriers. This gap closed in 2020, though the timing of the adjustment warrants closer examination. Further supporting this pattern, NonNLC states received a smaller share of out-of-state applications in 2019, with the gap narrowing in 2020. NonNLC states, on average, offered higher (RPP-adjusted) wages than NLC states in 2019, but this premium declined in 2020. The reduction in wage premium closely parallels the narrowing gaps in mobility-related measures, suggesting that part of the wage premium may have compensated for higher licensing barriers in NonNLC states. Figure 9 shows the trends in these key labor market variables over the months from 2019-2020.

The next part of the empirical analysis uses COVID-19 data from the CDC. Table 4 compares the average COVID-19 statistics across the NLC and NonNLC States. While the NonNLC States reported higher deaths per capits, 11.6 (vs 6.1 in NLC States), they also had a higher COVID-19 case load. To account for this, the preferred measure of comparison used in this paper is *deaths per covid*. As shown in row 3, NonNLC states also reported higher *deaths per covid* in 2020. Figure 10 shows the trends in *deaths per covid* across NLC and NonNLC states through 2020. Notably, the initial divergence between the two sets of states closes in the second half of 2020.

4 Empirical Strategy and Identification

4.1 Licensing Barriers and Compensating Wage Differentials

I first test whether interstate licensing barriers are reflected in posted compensation for travel-nurse contracts. Let $s(h)$ denote the state in which hospital h is located, $\tau(t)$ denote the half-year containing week t and let sp denote the specialty of the posting. I estimate:

$$\begin{aligned} \log wage_{ih(sp)t} = & \alpha_0 + \alpha_1 \mathbb{1}\{NonLicensed\}_{is(h)t} + \sum_{\tau(t)} \alpha_{1\tau(t)} \mathbb{1}\{NonLicensed\}_{is(h)t} \times \mathbb{1}\{HalfYear\}_t \\ & + \alpha_2 f(distance)_{iht} + \alpha_3 f(cases)_{ht} + \alpha_4 f(vaccination)_{ht} + \\ & + \Gamma_{i \times \tau(t)} + \Lambda_h + \Theta_{sp \times \tau(t)} + \Pi_{s(h)} \tau(t) + \varepsilon_{ih(sp)t}. \end{aligned} \quad (1)$$

where: (i – nurse; h – hospital; s – state, t – quarter)

The dependent variable is the log of RPP-adjusted hourly compensation posted by hospital h for specialty sp in week t , including the hourly equivalent of the housing stipend. The indicator $\mathbb{1}\{NonLicensed\}_{is(h)t}$ equals one if nurse i reports not holding a license in hospital h 's state, $s(h)$, at time t . To capture changes in licensing barriers during COVID-era emergency waivers, I interact this indicator with half-year indicators. The specification controls flexibly for nurse–hospital distance ($distance_{iht}$), county-level COVID-19 cases per capita ($cases_{c(h)t}$), and county vaccination rates ($vaccination_{c(h)t}$), using up to cubic transformations of each variable. It also includes fixed effects: nurse by half-year ($\Gamma_{i \times \tau(t)}$), hospital ZIPcode (Λ_h), specialty by half-year ($\Theta_{sp \times \tau(t)}$) and state-specific quarterly trends ($\Pi_{s(h)} \tau(t)$).

The parameters of interest are α_1 and $\alpha_{1\tau}$, estimated using travel nurse applications from 2019H2-2023H2. Identification comes from comparing wages across destinations where the same nurse does and does not face a licensing barrier, controlling for local pandemic conditions, distance, destination-specific wage levels, and specialty-specific time shocks. The coefficient α_1 measures the average within-nurse log wage premium associated with being non-licensed in the destination state in the omitted period, 2019H2, while $\alpha_{1\tau}$ captures half-year-specific changes in this gap relative to 2019H2. Thus, $\alpha_1 + \alpha_{1\tau}$ gives the compensating wage differential associated with licensing barriers in half-year τ , and its evolution captures how COVID-era emergency licensing measures affected this premium. If licensing barriers generated compensating wage differentials before the emergency period and were effectively relaxed during it, I expect $\alpha_1 > 0$ and $\alpha_{1\tau} < 0$ during the waiver period, with $\alpha_1 + \alpha_{1\tau}$ moving toward zero.

4.2 Licensing Barriers and Mortality

To identify the effect of interstate licensing barriers on mortality, I exploit two sources of policy variation: cross-state differences in Nurse Licensure Compact (NLC) membership and the temporary suspension of licensing rules during the COVID-19 emergency. Specifically, I estimate the following specification from 2020-2023:

$$\begin{aligned}
 \text{deaths per covid}_{st} = & \beta_0 + \beta_s + \beta_t + \beta_1 \text{ share of other healthcare}_{st} \\
 & + \sum_{t=1}^{14} \beta_{1q} \mathbb{1}\{\text{NonNLC}\}_{st} \times \mathbb{1}\{\text{Quarter}\}_t \\
 & + \beta_3 \text{ inpatient bed util}_{st} + \beta_4 \text{ nurse union}_{st} + \beta_5 X_{st} + \epsilon_{st}
 \end{aligned} \tag{2}$$

where $\text{deaths per covid}_{st}$ for state s in quarter t is the dependent variable. $\mathbb{1}\{\text{NonNLC}\}_{st}$ is an indicator variable that takes value 1 if the state was NOT a part of NLC by January 2020 and 0 otherwise. The coefficients of interest here are β_{1q} which identify the how being a part of NLC before 2020 related to deaths per covid and whether this effect changed over time, under the assumption of exogeneity of $\mathbb{1}\{\text{NonNLC}\}_{st}$. The primary reason for the states to adopt NLC was to meet the increasing demand for in-person and telehealth nursing by reducing friction to the movement of nurses. This, in turn, likely prepared them better to deal with COVID-19. Because this specification is estimated entirely within the emergency period, if the temporary waivers fully eliminated interstate mobility frictions, the coefficients β_{1q} should be statistically indistinguishable from zero across all quarters. Conversely, a non-zero β_{1q} would indicate that residual licensing frictions persisted despite the emergency waivers, potentially driving mortality differentials between NLC and NonNLC states.

There are some endogeneity concerns here, which I address by including controls in the regression. It could be that states that adopted NLC also had other healthcare-related policies. Given all healthcare workers were essential in handling the pandemic, not accounting for them might affect the estimate for β_1 . To address this, I use the state-wise quarterly share of non-nursing healthcare workers ($\text{share other healthcare}_{st}$) as a control in my regression. I control for the state-wise variation in the strain that the COVID-19 outbreak put on hospital infrastructure using $\text{inpatient bed util}_{st}$. Another potential source of endogeneity could be the presence of nursing unions which is also a labor market friction for nurses in addition to licensure. I control for this by including the share of nurses under labor union coverage (nurse union_{st}). I also control for state-level

quarterly demographics in X_{st} : age, race, gender, ethnicity, and any reported difficulty.

My identification assumption for β_{1q} is that after including the controls discussed in the previous paragraph, being a part of the NLC is exogenous to the factors that could affect *deaths per covid*. The sample used for estimating equation 2 is weekly county level data from 2020-2023.

4.3 Reduced-Form Evidence

4.3.1 Licensing Barriers and Compensating Wage Differential

The results from estimation of equation 1 are shown in table 1 and figure 1.

Table 1: Estimates of coefficient α_1 from equation 1

	(1)	(2)	(3)	(4)
$\mathbb{1}\{NonLicensed\}_{is}$	-0.04 (0.03)	0.07 (0.03)	0.07 (0.03)	0.07 (0.03)
$Nurse \times Year$		✓	✓	✓
$f(distance)_{iht}$			✓	✓
$f(cases)_{ht}$				✓
$f(vaccination)_{ht}$				✓
N	54,265	54,265	54,265	54,265
R^2	0.63	0.72	0.72	0.72

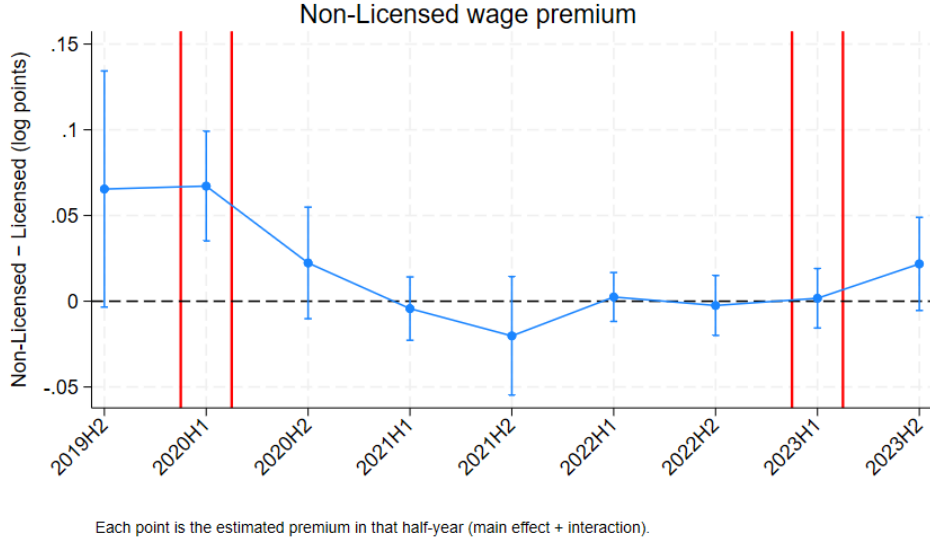
All specifications control for FE: Hospital, Specialty, Specialty $\times$ Half-Year, Quarterly State trend. Standard Errors are clustered at the state level. All the COVID-19 related variables are zero for 2019. Specifications (3) and (4) are placebo tests, where one should not expect any change in the coefficient as these are estimates for 2019H2.

The parameter α_1 identifies the compensating wage differential (CWD) of the licensing barrier in the 2019H2 baseline. Specification (1) demonstrates that failing to control for unobserved worker characteristics yields a counterintuitive 4% wage penalty for applying to a state where the nurse does not currently hold a license. However, including nurse fixed effects in Specification (2) reverses this sign, revealing a true 7% compensating wage premium for crossing the licensing barrier. This stark sign reversal underscores the necessity of controlling for unobserved worker quality and sorting behavior, demonstrating that naive cross-sectional estimates are downward-biased by non-random selection into cross-border job applications.

Given the removal of licensing barriers during the COVID-19 pandemic, I expect this CWD to compress during the emergency period. Figure 1 plots the evolution of the

CWD over time, captured by the baseline and time-varying coefficients (α_1 and $\alpha_{1\tau(t)}$). Consistent with the hypothesis, Figure 1 demonstrates that the baseline premium (α_1) effectively dissipates during the emergency period. However, the premium remains fully intact during 2020H1 despite the March 2020 emergency declaration, suggesting a delayed market equilibrium response. Finally, following the expiration of the federal emergency in May 2023, the estimates exhibit a slight rebound in the wage premium.

Figure 1: CWD over time, ($\alpha_1 + \alpha_{1\tau(t)}$)

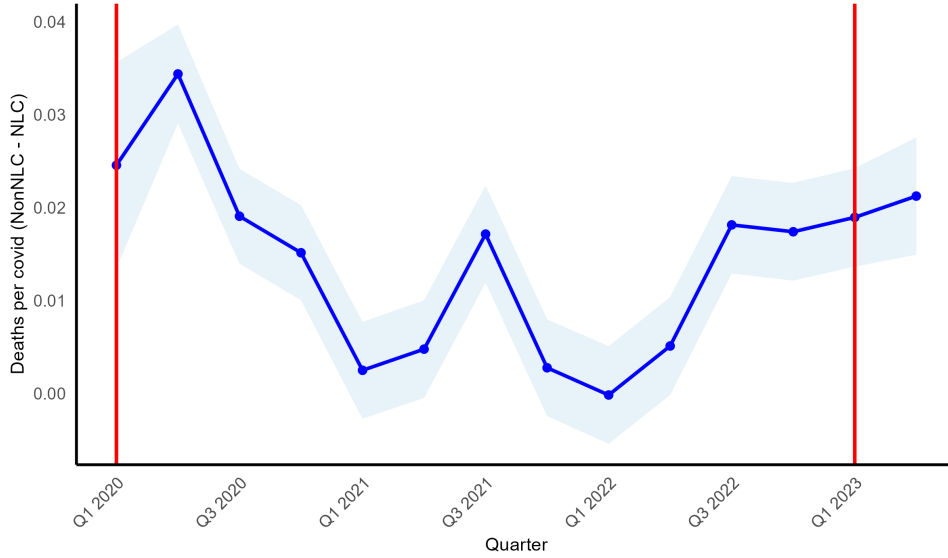


The figure above plots the estimated marginal effect of $\mathbb{1}NonLicensed$ from equation 1. The specification controls for FE: Hospital, Specialty, Specialty $\times$ Half-Year, Quarterly State trend. Controls for COVID-19 cases, vaccination and distance are also included. Standard Errors are clustered at the state level. The red vertical lines indicate the start and end of federal emergency period.

4.3.2 Licensing Barriers and Mortality

Figure 2 plots the quarterly coefficients β_{1q} obtained from the estimation of equation 2. The estimation period for this equation is from 2020-2023. If emergency waivers perfectly eliminated licensing barriers to interstate mobility, we would expect no statistically significant mortality differential between NLC and NonNLC states. However, results show that NonNLC states initially experienced 0.04 units higher mortality. This gap only converged in 2021Q1, suggesting a significant lag in hospitals' ability to utilize the new mobility rules to alleviate staffing shortages. As these emergency policies were phased out toward the end of the estimation period, the mortality gap began to widen once more.

Figure 2: Marginal Effect of $\mathbb{1}\{NonNLC\}$ on *deaths per covid*



The figure above plots the estimated marginal effect of $\mathbb{1}\{NonNLC\}$ from equation 2. The specification controls for State and Quarter Fixed Effects and controls for share of other healthcare workers, inpatient beds utilization and state-level demographics. Standard Errors are clustered at the state level. The red vertical lines indicate the start and end of federal emergency period.

The reduced-form evidence provides evidence of a 7% compensating wage differential for obtaining a new state license, with the closing of this premium during emergency licensing waivers supporting a causal interpretation. The results of the mortality analysis suggest that interstate licensing barriers may have constrained nurse supply during the pandemic, particularly in NonNLC states, contributing to higher initial mortality. These findings point to economically meaningful frictions, but do not directly establish how licensing barriers shaped nurses' mobility decisions. I estimate this margin in the next section.

5 Structural Model of Nurse Applications and Wage Setting

In this section, I describe a two-sided structural equilibrium model used to quantify the effect of interstate licensing barriers on a nurse's willingness to move. Although the Wanderly data do not observe realized hires or matches, they observe the nurse's application decision itself. This application margin provides a key revealed-preference measure of how licensing barriers shape nurses' willingness to pursue jobs across states.

The model consists of two sides: a supply side, in which nurses make discrete choices about where to apply, and a demand side, in which monopsonistic hospitals set wages to maximize expected profits. This framework allows for the simulation of counterfactual scenarios - such as the removal of licensing barriers - by tracking how both nurse application flows and hospital wage offers re-equilibrate.

5.1 Supply Side: Nurse Application Decision

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

$$U_{iht} = \underbrace{\beta_1 \mathbf{1}\{NonLicensed\}_{is(h)t} + \beta_2 f(distance)_{iht}}_{\mu_{iht}} + \delta_{ht} + \epsilon_{iht} \quad (3)$$

where

$$\mathbf{1}\{NonLicensed\}_{is(h)t} = \begin{cases} 0, & \text{if hospital } h \text{ is in nurse } i\text{'s home state,} \\ 1, & \text{if hospital } h \text{ is outside nurse } i\text{'s home state and nurse } i \text{ is licensed in } s(h), \\ 2, & \text{if hospital } h \text{ is outside nurse } i\text{'s home state and nurse } i \text{ is not licensed in } s(h). \end{cases}$$

The difference $(\beta_{12} - \beta_{11})$ will capture the effect of licensing barrier on application decisions. The term $f(distance)_{iht}$ flexibly controls for geographic distance between nurse i 's home state and hospital h 's ZIP code, allowing application decisions to vary nonlinearly with distance. Together, these two terms, denoted μ_{iht} , capture the application specific utility deviation from δ_{ht} , which represents the mean utility of hospital h in market t .

The error term ϵ_{iht} is assumed to be Type I Extreme Value Distributed (EVD). The mean utility δ_{ht} can be further decomposed into observable and unobservable components:

$$\delta_{ht} = \delta_0 + \delta_1 \log(wage)_{ht} + \delta_2 f(cases)_{c(h)t} + \xi_{ht} \quad (4)$$

where $\log(wage)_{ht}$ is the log of RPP-adjusted hourly compensation posted by hospital h for specialty sp in week t , including the hourly equivalent of the housing stipend. To account for local COVID-19 severity in hospital mean utility, $f(cases)_{c(h)t}$ flexibly controls for COVID-19 cases per capita in hospital h 's county.

A key concern in estimating the wage effect is that posted wages may be endogenous. Hospitals may raise wages in response to unobserved demand shocks that also affect nurses' application decisions. To address this concern, I instrument for Registered Nurse wages using wages posted for Allied positions in neighboring counties, with the following first-stage regression:

$$\log(wage)_{ht} = \alpha_0 + \alpha_h + \alpha_t + \alpha_1 \log(wage)_{nc(h)t}^{Allied} + \eta_{ht} \quad (5)$$

In this framework, licensing barriers affect the application decision through two primary channels: the direct disutility of applying due to legal or geographic barriers (β_1), and the endogenous wage premiums hospitals must offer to compensate for these barriers. The latter channel is captured by the wage coefficient δ_1 , which governs nurses' responsiveness to posted wages, together with the equilibrium wage adjustment implied by the hospital wage-posting model discussed next.

5.2 Demand Side: Hospital Wage Setting

Hospitals post vacancies and set wages to maximize their profits. Let v_{ht} denote the marginal revenue product of labor (MRPL) for hospital h in quarter t , w_{ht} the wage, and L_{ht} the number of nurses hired. The profit function is given by:

$$\pi_{ht} = (v_{ht} - w_{ht})L_{ht} \quad (6)$$

Because the final match between nurse and hospital is unobserved in the data, I assume the number of hires is proportional to the number of applications received, such that $L_{ht} = \mu \times A_{ht}$. Thus, the profit function can be rewritten in terms of applications:

$$\pi_{ht} = (v_{ht} - w_{ht})\mu \times A_{ht} \quad (7)$$

Assuming hospitals have some monopsony power and face an upward-sloping labor supply curve, the first-order condition (FOC) with respect to the wage w_{ht} is:

$$v_{ht} - w_{ht} = \frac{s_{ht}(w)}{\frac{\partial s_{ht}}{\partial w_{ht}}} \quad (8)$$

where $s_{ht}(w)$ is the hospital's share of total applications. From the logit supply-side estimation, the derivative of the market share with respect to the wage is given by:

$$\frac{\partial s_{ht}}{\partial w_{ht}} = s_{ht}(1 - s_{ht}) \frac{\delta_1}{w_{ht}} \quad (9)$$

Substituting this derivative back into the first-order condition yields the hospital's optimal wage-setting rule:

$$v_{ht} = w_{ht} \left(1 + \frac{1}{(1 - s_{ht})\delta_1} \right) \quad (10)$$

This equilibrium condition is critical as it allows to back out the unobserved marginal value of a nurse (v_{ht}) for each hospital based on observed wages and estimated application shares. Recovering this parameter is crucial for the counterfactual analysis, which requires endogenous wage adjustments in the absence of the licensing barrier.

5.3 Estimation

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

The Type 1 extreme value distribution assumption on ϵ_{iht} implies that for a guess of β_1, β_2 and δ_{ht} , the probability that application goes to hospital h in market t is given by:

$$P_{iht} = \frac{\exp(\mu_{iht} + \delta_{ht})}{\sum_{h' \in \mathcal{H}_{sp,t}} \exp(\mu_{ih't} + \delta_{h't})} \quad (11)$$

The log-likelihood function is given by:

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

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_{ht} 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_{ht} , from the first stage to estimate the parameters of the decomposition equation in (3). Because posted wages may be endogenous, equation (4) provides an instrument for wages in (3). The second-stage parameters are therefore estimated using two-stage least squares (2SLS) method.

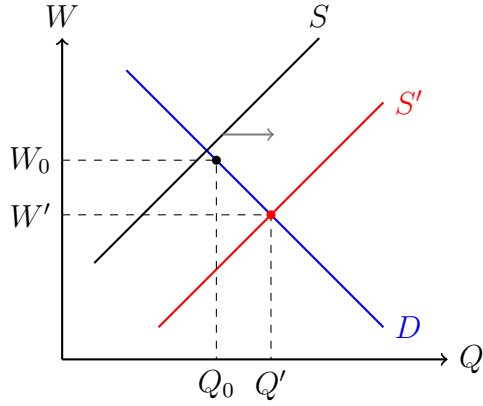
In the final step, I substitute the estimate of δ_1 from (9) to recover implied productivity, v_{ht} , using data on wages w_{ht} and application shares s_{ht} .

5.4 Counterfactual Estimation

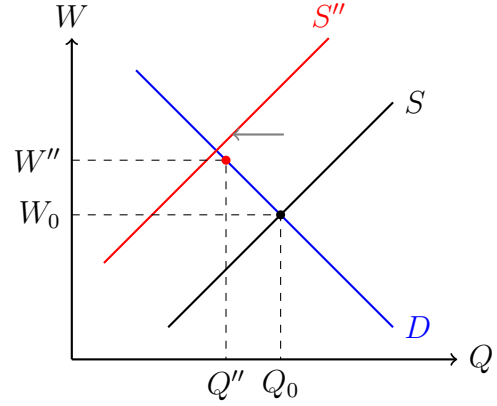
The counterfactual of interest is the distribution of applications across locations in the absence of interstate licensing barriers. To construct this counterfactual, I eliminate the licensing disadvantage in utility by setting $\mathbb{1}\{NonLicensed\} = 1$ for all out-of-state hospitals in the choice set. 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, the reduced-form evidence indicates that licensing barriers also generated a compensating wage differential. Accordingly, the counterfactual application distribution in the absence of licensing barriers must also shut down this wage premium. I utilize equation (9) to incorporate this. Equation (9) can be re-written as:

$$w_{ht} = \frac{v_{ht}}{1 + \frac{1}{(1-s_{ht})\delta_1}} \quad (13)$$

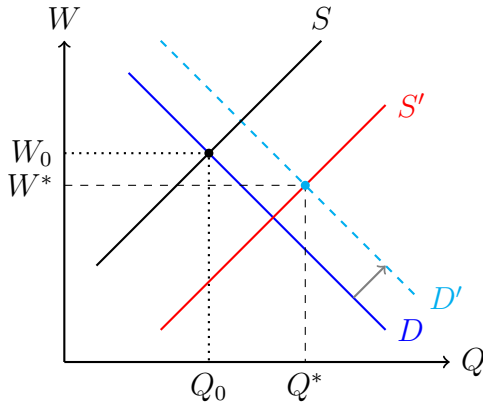
For given estimates of δ_{ht} and δ_1 , equation (12) can be used to estimate the new equilibrium wage and shares in the absence of licensing barriers. After simulating the removal of the licensing barrier, I apply a dampened fixed-point iteration algorithm, iteratively updating nurse choice probabilities and optimal hospital wage responses until market shares and wages converge to a new steady state. Figure 1 summarizes the adjustment mechanisms under each counterfactual scenario.



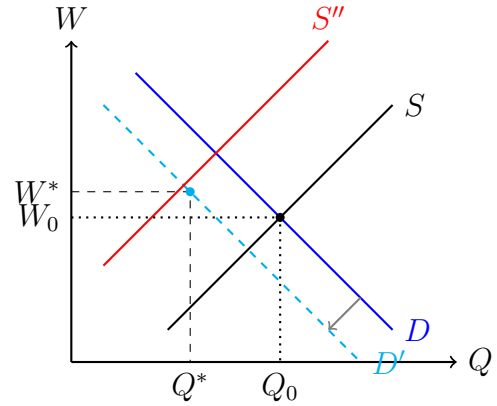
(a) High-Barrier State: Supply Increases



(b) Low-Barrier State: Supply Decreases



(c) High-Barrier State: Demand Adjusts



(d) Low-Barrier: Demand Adjusts

Figure 3: General Equilibrium Effects of Removing Licensing Barriers. The top panels show the partial equilibrium supply shock. The bottom panels show the new general equilibrium as hospitals re-optimize labor demand (D'). The vertical gap between the supply curves represents the compensating wage differential associated with the licensing barrier.

6 Results

6.1 Willingness to Pay (WTP) for the Licensing Barrier

To provide a meaningful economic interpretation of the structural parameters, I translate the abstract utility coefficients into a Willingness to Pay (WTP) framework. Using estimates from the system of equations 3 - 5, WTP can be calculated as:

$$WTP = \frac{\beta_{12} - \beta_{11}}{\delta_1} = \frac{-3.0244 - (-1.4571)}{1.5644} = -1.00$$

The negative coefficients for both β_{11} and β_{12} indicate that nurses are significantly less likely to apply to out-of-state positions relative to the home-state baseline. Crucially, the finding that $|\beta_{12}| > |\beta_{11}|$ confirms that the licensing barrier is indeed a deterrent to a nurse's probability of applying. By benchmarking these utility parameters against the wage coefficient (δ_1), I quantify the compensating wage differential required to induce a nurse to cross this barrier. The results imply that a nurse requires approximately a 100% wage increase ($e^{1.0018} - 1$) to be indifferent between applying to a state where they hold a license versus one where they do not. This substantial magnitude underscores the licensing barrier as a formidable friction in the labor market for nurses.

6.2 Wage Instrument Regression

To address potential wage endogeneity, I implement an instrumental variables (IV) strategy, instrumenting for Registered Nurse (RN) wages using the wages of allied health professionals in neighboring counties. Table 2 presents the first-stage estimates from Equation 5. The positive and statistically significant coefficients across all specifications provide strong evidence for the instrument's relevance. To satisfy the exclusion restriction, specifically, to account for unobserved local shocks that might simultaneously influence both allied health wages and RN application decisions, I include hospital zipcode and quarter fixed effects. This specification allows to isolate variation in RN wages that is exogenous to a nurse's application decision.

Table 2: Coefficient α_1 from first stage estimation of equation 5

	(1)	(2)	(3)	(4)
$logwage_{(nc)t}^{Allied}$	0.67 (0.01)	0.23 (0.02)	0.17 (0.02)	0.18 (0.02)
Quarter FE		✓	✓	✓
County FE			✓	
Hospzip FE				✓
N	16,629	16,629	16,629	16,629
F-stat	2215	144	118	110

6.3 Wage Elasticity of Supply

Using a 2SLS estimation strategy that instruments for RN wages using allied health wages, I find that the coefficient for log wage (δ_1) in the mean utility decomposition increases from 0.99 to 1.56. This upward shift suggests that the instrumental variable approach successfully addresses the endogeneity of wages, correcting for the downward bias present in a standard OLS estimation. The wage elasticity of supply can be calculated as:

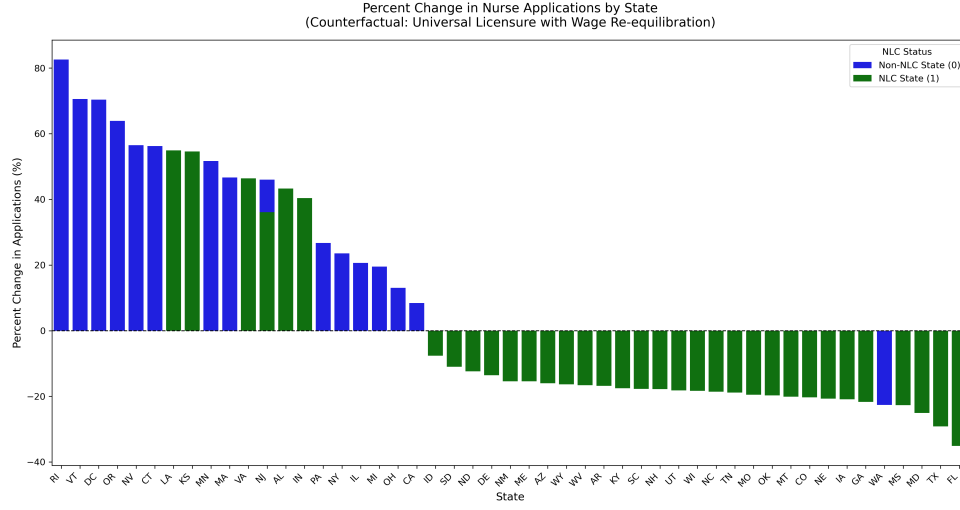
$$\epsilon_{ht} = \frac{\partial \ln s_{ht}}{\partial \ln w_{ht}} = \delta_1 (1 - s_{ht})$$

This yields an average own-wage elasticity of 1.52, indicating that a 1% increase in the offered wage leads to a 1.52% increase in the probability of a nurse applying to that position. This suggests that travel nurse supply is relatively elastic, meaning nurses are highly responsive to wage changes when choosing between assignments.

6.4 Counterfactual

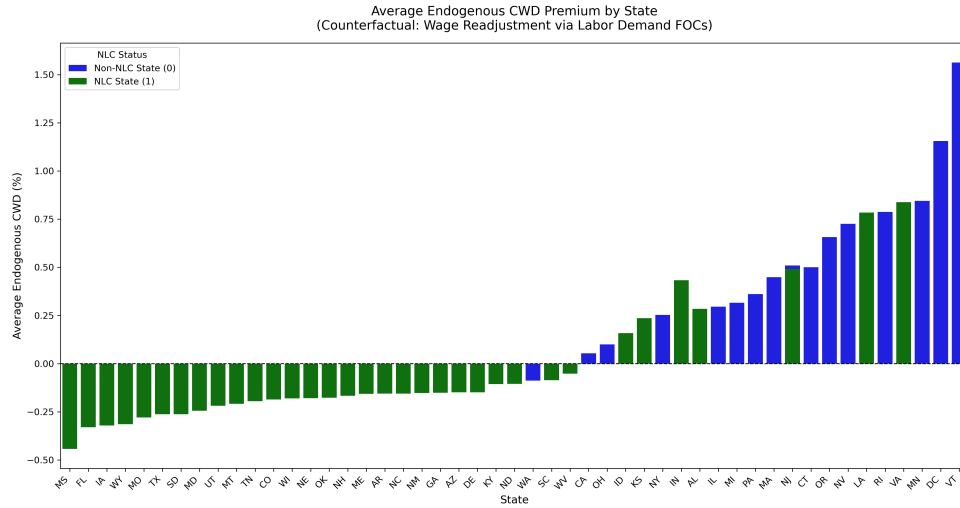
In the counterfactual analysis, I shut down the licensing barrier for nurses by allowing all of them to hold the license for every state. The hospitals then re-equilibriate in response to supply changes. Figures 4, 5 and 6 show the results from counterfactual estimation.

Figure 4: Percent change in applications across States in the absence of licensing barriers



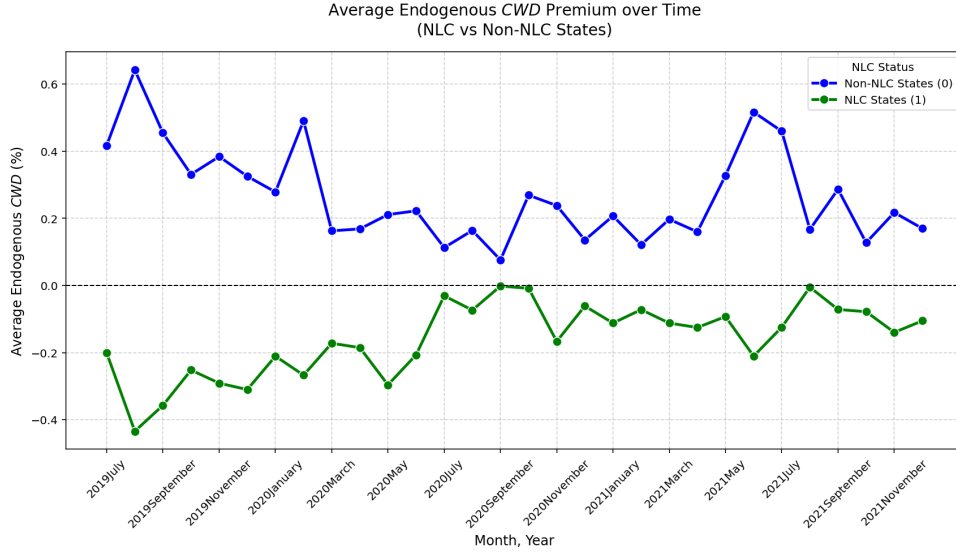
The figure above plots the state-wise heterogeneity in the percent applications they would have received in the absence of interstate licensing barrier. Notably, the states that would have benefited the most are the NonNLC States (blue).

Figure 5: Compensating Wage Differential (CWD) across States



The figure above plots the state-wise heterogeneity in the CWD that was present across states due to licensing barrier. This is calculated using the re-equilibrated wages. Notably, the states that had a positive CWD were the NonNLC States (blue).

Figure 6: Compensating Wage Differential (CWD) over time



The figure above plots the trend in CWD calculated through the model. This is calculated using the re-equilibrated wages. Showing some lagged effects of emergency measures, the difference in CWD between NonNLC and NLC states started to fall by mid-2020 and pretty much remained closed until the end of 2021.

7 Conclusion

This paper provides causal evidence that interstate variation in nurse licensing requirements constrained labor mobility and worsened early COVID-19 outcomes. Before the pandemic, NonNLC states paid a 7% wage premium to attract nurses, yet applications to these states were 18% lower than to NLC states, underscoring the effect of licensing barrier to mobility of nurses. Despite emergency waivers temporarily removing interstate licensing restrictions, the response in nurse mobility and wages was delayed, indicating that information frictions and institutional inertia slowed the adjustment. The findings demonstrate that fragmented licensing systems can significantly impede the efficient allocation of healthcare labor when rapid response is most critical.

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 lower early mortality rates and faster labor market adjustment. Given the expanding scope of occupational licensing in the U.S., 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.

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Appendix: Figures and Tables

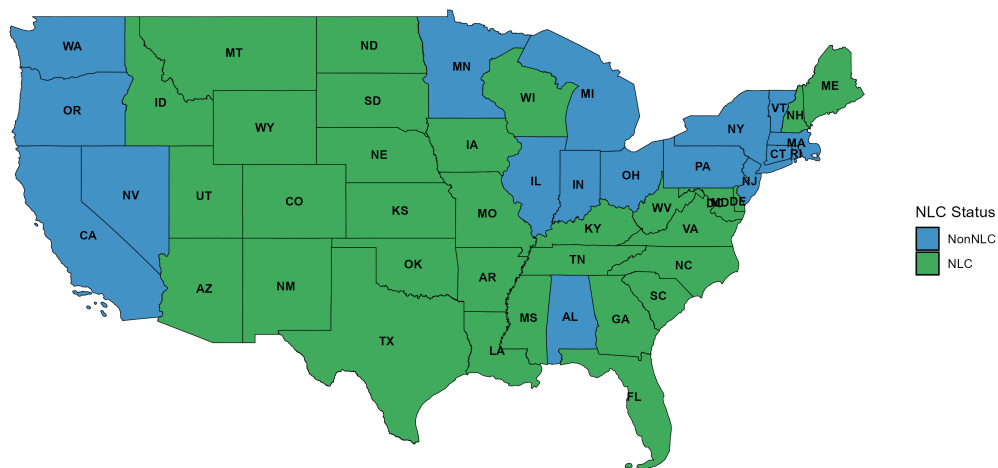


Figure 7: NonNLC States and NLC States by 2020. Source: National Council of State Boards of Nursing (NCSBN)

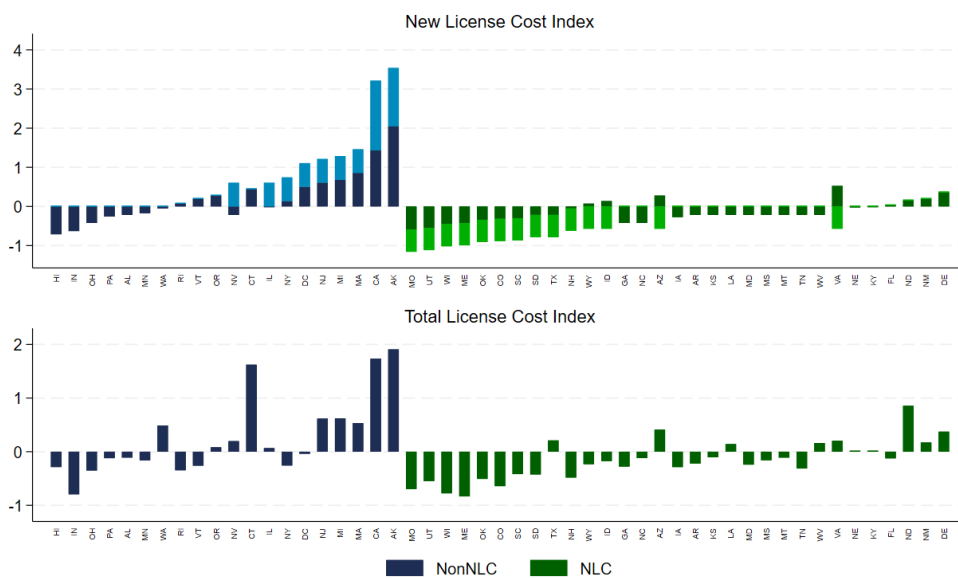


Figure 8: Index for cost of getting a new license in a state as well as maintaining the license in that state.

Travel Nurse Data

Table 3: Summary Statistics - Travel Nurses

	2019			2020		
	NLC	NonNLC	Diff	NLC	NonNLC	Diff
Applications/Postings	0.44	0.37	-0.07	0.37	0.39	0.02
Average hourly wages	46.5	47.6	1.08	50.7	51.1	0.46
Observations	2,231	1,515		3,318	3,448	
% apps out of home state	72	43	-29	73	58	-15
Observations	3,388	2,541		12,132	7,440	

Source: Wanderly Data. Diff = NonNLC - NLC. Differences in black are statistically significant; red ones are not.

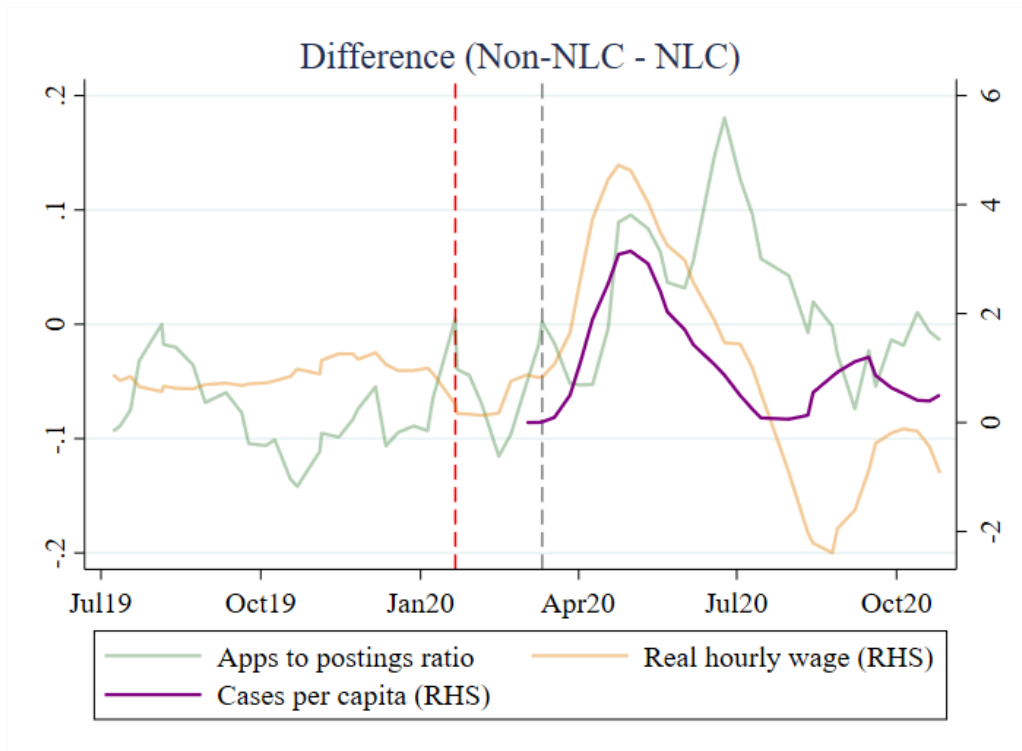


Figure 9: Source: Wanderly Data.
Travel Nurse Labor Market Difference across NLC and NonNLC States.

COVID-19 Data

Table 4: Summary Statistics - COVID-19

	NLC	NonNLC	Diff
Deaths per 100,000	6.1	11.6	5.5
Cases per 100,000	279.9	352.2	72.3
Deaths per covid (%)	2.2	3.3	1.1
Inpatient bed utilization (%)	60.8	63.7	3.7
Observations	336	200	

Source: CDC. (Diff = NonNLC - NLC. Differences are statistically significant)

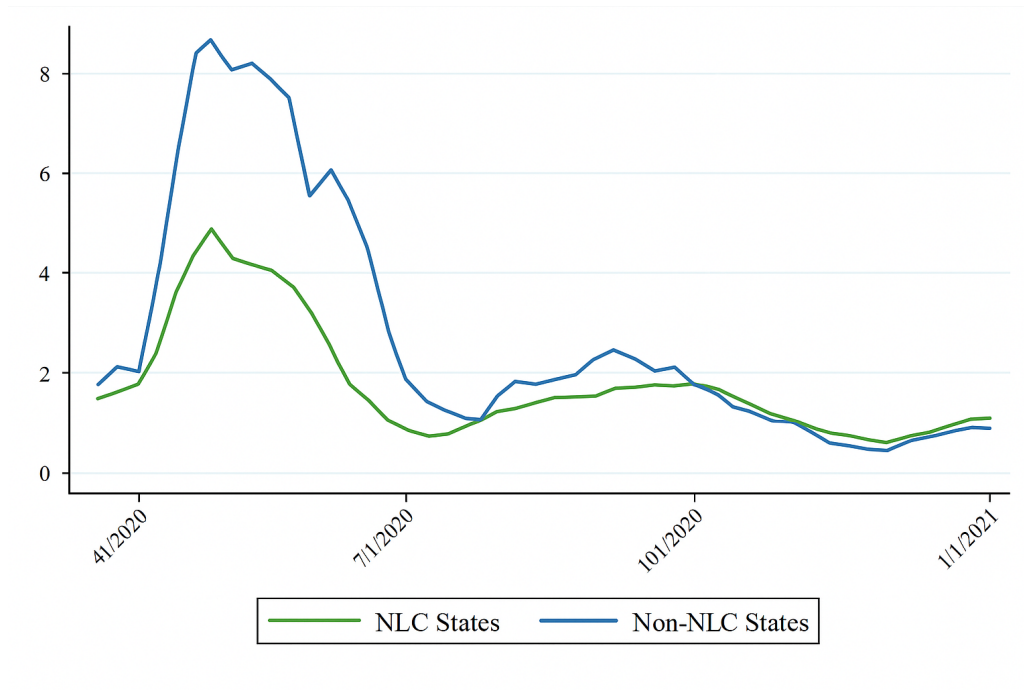


Figure 10: Source: Wanderly Data.
deaths per covid Difference across NLC and NonNLC States.