# When Nurses Travel: Labor Supply Responses to Peak Demand for Nurses*

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**Abstract**

We study how a market uses temporary workers to accommodate extraordinary demand shocks. When COVID-19 surges, hospitals need additional nurses—especially in specialties central to COVID-19 care. By comparing markets for COVID-relevant and other specialties, we show that the market for travel nurses expands dramatically and estimate travel nurse labor supply across space. Supply is quite elastic, as workers can choose to travel where they are needed. Workers travel longer distances to temporary jobs when payment increases, suggesting that an integrated national market facilitates reallocation when demand spikes. But when national cases peak, travel distance is less responsive to local demand.

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Does temporary staffing help labor markets address temporary demand shocks (Abraham and Taylor, 1996, Autor, 2003, Katz and Krueger, 2017), or does a fixed stock of qualified workers prevent this? We use the COVID-19 pandemic to study the short-term labor market for nurses—a context where adequate qualified staffing has life-or-death consequences.[1] We examine how labor demand responds to transitory shocks—a rise in local COVID-19 cases—and estimate the local supply elasticity of temporary nurse labor. This supply is quite elastic: nurses choose different locations in response to rapidly fluctuating compensation. We investigate workers' mobility across space to illuminate how the labor market accommodates these short-term demand surges. Our results highlight the likely impacts of regulation, such as price caps that Massachusetts (2020*a*,*b*) and Minnesota (2020) impose on hospitals hiring travel nurses and which legislators elsewhere have proposed (Brusie, 2022).[2]

COVID-19 led to historic nursing demand shocks (Hawryluk and Bichell, 2020), and immigration bans simultaneously choked off an important part of labor supply (Lind, 2020, Reed and Kreighbaum, 2021). Since nursing requires training and licensure, supply adjustment possibilities may be limited. But nursing also has robust institutions that help match supply and demand. While the nursing labor market has gradually adapted to the secular growth in healthcare demand over recent decades (Buerhaus et al., 2000,2009), healthcare facilities regularly use temporary nurses to respond to transitory staffing needs (Baker et al., 2004, Seo and Spetz, 2013). "Travel nurses," hired for multi-week stints, comprise the bulk of the $10 billion temporary nursing market (Landuis and Starkey, 2020), which is approximately 7 percent of the overall nursing labor market (Bureau of Labor Statistics, 2020).

Travel nurses are recruited for specific job openings, and choose jobs in response to fluctuating prices and conditions that they find acceptable. In this specific way, the markets for travel nurses, Uber drivers, and other contingent workers are similar. Unlike ride-sharing, the market for travel nurses is fragmented and intermediated by many different staffing firms and recruiter networks.

[1]The nurse staffing literature (Aiken et al., 2002, Cook et al., 2012, Mark et al., 2013, Needleman et al., 2002, 2011, Sloane et al., 2018, Spetz et al., 2013) includes evidence from staffing ratio mandates at normal times; pandemics likely differ.

[2]Our results are robust to removing these states from the estimation sample.

These intermediaries evaluate match quality, verify nurses' skills (e.g. obstetrics experience), and manage regulatory hurdles such as state licensure.

As COVID-19 surged in different parts of the United States, hospitals in affected regions needed additional nurses to manage the influx of patients. We use these demand shocks to study supply and worker mobility in this spot labor market. The contingent worker behavior literature relies on extremely short-term markets, like Uber drivers or online tasks (Angrist, Caldwell and Hall, 2021, Caldwell and Oehlsen, 2018, Chen et al., 2020, Chen and Sheldon, 2015, Farrell, Greig and Hamoudi, 2018, Hall, Kendrick and Nosko, 2015, Mas and Pallais, 2017).[3] But contingent work often spans longer than an Uber ride and may have deeper consequences for hospital functioning, patient care, and labor market regulation. Travel nursing is one such example.

We find that the number of job openings and compensation level for nursing specialties central to COVID-19 care, such as intensive care unit (ICU) and emergency room (ER), are positively associated with increased state-level COVID-19 case counts, and with reported "staffing shortages." ICU jobs more than tripled in the early months of the pandemic, while compensation increased 50 percent.

We use a simple model of local supply and demand for temporary nurse labor to study these markets. The nursing supply curve may shift in COVID-affected areas because of an altruistic desire to help and because of increased risk when working in a high-COVID location. The model motivates supply estimation based on the differences between specialties whose demand increases in the presence of COVID and specialties such as labor & delivery (L&D), which did not experience a demand shock (because the number of births did not increase exponentially).

[3] Autor (2003), Collins et al. (2019), and Katz and Krueger (2019*a*,*b*) discuss the size and trajectory of the contingent labor workforce. Temporary workers and independent contractors are a blind spot in many labor market datasets (Abraham et al., 2017), and may use multiple platforms (Koustas, 2019). The evidence on the staffing industry mostly comes from employers' perspective (Abraham, 1988, Abraham and Taylor, 1996, Dey, Houseman and Polivka, 2012). The literature on outcomes for temporary employees has primarily focused on low-skill workers and the effects on their wages and long-term employment (Autor and Houseman, 2002, 2005, 2010) and reached little consensus on whether temporary unemployment was a stepping stone to permanent employment (Filomena and Picchio, 2022). But travel nursing is unique compared to the literature's examples of low-skill employment. Travel nurses are highly skilled, highly paid—they make more than their permanent counterparts (Houseman, Kalleberg and Erickcek, 2003)—and their services have life-or-death consequences. This combination of circumstances facilitates the mobility of nurses across labor markets.

The model guides our empirical estimation, intended to understand short-term reallocation and flexibility in this market. We use a panel of states during the pandemic to estimate the travel nurse supply curve across space, exploiting differences in compensation and jobs between COVID-19 specialties and L&D nursing. The model implies an IV estimation, which yields supply elasticities of 2 to 4. This suggests that price signals effectively direct nurses to places with increased staffing needs.

To test this interpretation, we measure the distance between the nurses' home and job locations. We find that they accept positions farther from home when pay is higher. We also see that the market expands when hospitals face a staffing crunch. In an alternative empirical approach, we estimate a multinomial choice model in which nurses directly trade off distance to the potential job against compensation and other job characteristics. The model estimates are consistent with this interpretation: we find a similar supply elasticity, and a distance elasticity close to $-1$. The United States' large size, and nurses' ability to change work locations in response to market signals, appear to be important aspects of how this market adapted to the nursing demand shocks from COVID-19.

This adjustment margin is less valuable when demand spikes simultaneously across many regions. Traveling can reallocate workers, but adding new nurses to the market entirely is harder. We test this by comparing the elasticity of travel distance to COVID-19 cases between times of high and low national demand. We find that travel distance responds more strongly both to demand and compensation when national demand is lower. This suggests that—at least when there is some slack capacity nationally—the supply responses we estimate reallocate workers to where they are needed.

This distinction between state-level and national demand highlights our results' limitations. These elasticities specifically describe the short-term travel nursing markets across space, but cannot be applied to the nursing market overall or an individual hospital's permanent nursing workforce, where supply could behave differently (Matsudaira, 2014, Staiger, Spetz and Phibbs, 2010). We do not need to understand why baseline compensation is higher in New York than Arizona (unions? living costs? regulations?) to understand within-state variation over time. Nor do we need to know national extensive margin elasticities (due to long-run nurse training, or short-run entry into travel nursing) to understand allocation across space at a point in time. Travel nurses are unique in their pay, skill, and responsibilities, so other temporary employees likely exhibit different responses.

Nevertheless, this market fills a similar role as temporary or contingent workers in other industries. The literature on contingent work has studied how these markets buffer firms from permanent worker absence (Houseman, 2001*a*,*b*), or demand shocks (Hosono, Takizawa and Tsuru, 2015), and how temporary work affects job matching (Katz et al., 1999) and productivity (Autor, 2001, Engellandt and Riphahn, 2005, Hirsch and Mueller, 2012). How contingent work fits into workers' broader career trajectories remains contested (Autor and Houseman, 2002, 2005, 2010, de Graaf-Zijl, Van den Berg and Heyma, 2011, Filomena and Picchio, 2022, Jahn and Rosholm, 2014).

Section 1 discusses the institutional context and data. The COVID-19 pandemic and recession brought simultaneous shocks, some of which could threaten supply estimation. Section 2 introduces the framework we use to analyze the data and control for these threats. Section 3 presents descriptive facts and time-series patterns in our data. Section 4.1 presents our labor supply estimates, section 4.2 describes the travel distance patterns, and section 4.3 connects this market to staffing shortages that hospitals report. Section 5 discusses these results and section 6 concludes.

# 1 Setting and Data

Registered nurses are the largest component of hospital labor. In 2019, American hospitals employed over 1.8 million registered nurses, compared to 120,000 physicians.[4] There has long been concern about a mismatch between the nursing workforce needed and the available labor supply (Buerhaus et al. 2000,2009). When a hospital or hospital unit faces an acute nursing staff shortage, it frequently hires temporary nurses. There are multiple ways to access this market, but the nor-

[4]This is a fraction of physicians working, as most are not employed by hospitals (Gottlieb et al., 2023).

mal structure is for the hospital to set a price, working conditions, and contract length (usually 13 weeks). An intermediary, such as a supplemental staffing agency, searches for a registered nurse to match the position. The nurses are generally employees of the intermediary, which provides benefits, liability insurance, and quality checks. Hospitals thus outsource recruiting, licensing, and other HR tasks. The recruited nurses are generally called "travel nurses," though they may live nearby.

Travel nurses are licensed and regulated like other nurses, and observational studies have found that, after adjusting for hospital quality, there are no deleterious outcomes associated with their use (Xue et al., 2012*a*,*b*). Demographically, travelers are more likely to have a bachelor's degree. According to the National Sample Survey of Registered Nurses (NSSRN) (Health Resources and Services Administration, 2018), travel nurses are substantially younger than staff nurses, with over half below age 40 compared to about 30 percent of staff nurses. Travel nurses are much more likely to be male, although nursing remains a female-dominated profession (17% of travelers are male, compared to 10% of staff nurses).[5] Appendix Table E.1 reports these demographic characteristics.

Nurses may take traveling jobs because they are seeking adventure, because there are no acceptable job offers near their home, or because they value flexibility (He, Neumark and Weng, 2021, Mas and Pallais, 2020). They may also earn higher hourly pay than a traditional nursing job.

The price the hospital offers for travel nurse labor (the "bill rate" in industry terminology) covers both wages and the intermediary's fee, which includes benefits, housing stipends, transportation, and administrative costs.[6] If the intermediary subcontracts to a recruiter, it splits its share of the bill rate. Compensation and location are salient to potential nurses; online job listings include them in the headline, along with the specialty and start date. Recruiters text potential recruits, often mentioning compensation in the initial solicitation (see Appendix A). Placements can be extended after the nurse's initial contract; see Appendix B for details.

Health Carousel, one of the largest twenty healthcare staffing firms in the United States, pro-

[5]Travel nurses are less likely to be white or Asian, and more likely to be black, though the differences are not dramatic.

[6]Some hospitals have exclusive relationships with staffing agencies. Others may post to independent vendor management systems for an auction.

vided data on jobs it filled, plus all postings made available to its recruiters, from September 1, 2018 through February 28, 2021. We mainly focus on the COVID-19 era, beginning February 1, 2020. The data include all of the firm's filled jobs and job postings for registered nurses from all fifty states and Washington, D.C.

For each posting, we see the specialty and number of nurses requested, job location and compensation, which we scale as an index relative to the early 2020 nationwide average. We convert total weekly counts of new job openings, and of nurses hired by Health Carousel each week ("completed jobs"), into indices relative to their early-2020 averages.[7] We measure compensation, job openings, and completed jobs, nationally and within subsamples by specialty and state.[8] For completed jobs, we compute the travel distance between nurse residence and job location. Appendix B describes these data and supplementary sources.

# 2 Framework

We model log supply of specialty $i$ nurses in state $j$ at time $t$ as:

$$s^i_{jt}(w^i_{jt}, c_{jt}) = \alpha'_t + \alpha^*_j + \alpha w^i_{jt} + \beta c_{jt} + e^i_{jt}, \tag{1}$$

where $w^i_{jt}$ is log compensation, $c_{jt}$ is log COVID-19 cases, and $e^i_{jt}$ is an orthogonal supply shock. If supply increases in compensation and decreases in COVID-19 risk, $\alpha > 0$ and $\beta < 0$. Supply may differ across locations ($\alpha^*_j$) due to earnings, convenience, or amenities for nurses. Since nurses can choose whether to enter the market, we allow for time-varying national supply shocks $\alpha'_t$.

Log demand is:

$$d^i_{jt}(w^i_{jt}, c_{jt}) = \gamma'_t + \gamma^*_j + \gamma w^i_{jt} + \delta^i c_{jt} + u^i_{jt}, \tag{2}$$

with $u^i_{jt}$ an orthogonal demand shock. If demand decreases with cost, $\gamma < 0$. For some specialties,

[7] These indices are normalized such that the mean from February 1, 2020 through March 14, 2020 is 100.

[8] Appendix E shows that results are similar, though noisier, on a panel of metropolitan statistical areas (MSAs).

such as ICU, we expect COVID prevalence to increase demand ($\delta^i > 0$). For specialties like L&D, $\delta^i = 0$ is plausible. There may be common national demand shocks $\gamma'_t$ and baseline differences in demand across regions, $\gamma^*_j$.

We equate nurse supply to demand and solve for the equilibrium wages and quantity in each market (omitting fixed effects):[9]

$$w^i_{jt} = \frac{-\beta + \delta^i}{\alpha - \gamma} c_{jt} + \frac{u^i_{jt} - e^i_{jt}}{\alpha - \gamma} \tag{3}$$

$$q^i_{jt} = \frac{\alpha\delta^i - \beta\gamma}{\alpha - \gamma} c_{jt} + \frac{\alpha}{\alpha - \gamma} u^i_{jt} - \frac{\gamma}{\alpha - \gamma} e^i_{jt}. \tag{4}$$

The two relationships between wages and quantities, respectively, and the number of cases, are governed by four parameters—the supply and demand elasticities with respect to wages ($\alpha$ and $\gamma$) and COVID-19 prevalence ($\beta$ and $\delta^i$), and we only have two equations. Understanding nurses' supply thus requires further data and assumptions.

We address this by adding a specialty such as L&D, indexed by $i = 0$, where demand is plausibly independent of COVID-19 cases (so $\delta^0 = 0$), alongside specialties where COVID affects demand ($\delta^i \neq 0$). Assuming the model's remaining parameters are the same across specialties, we can difference them out and solve for the supply elasticity ($\alpha$). These assumptions imply the following estimating equations:

$$w_{ijt} = \tau c_{jt} + \pi_i \mathbb{1}_i c_{jt} + \theta_j + \phi_t + \varepsilon_{ijt} \tag{5}$$

$$q_{ijt} = \kappa c_{jt} + \mu_i \mathbb{1}_i c_{jt} + \rho_j + \sigma_t + \nu_{ijt} \tag{6}$$

where $\theta_j$ and $\rho_j$ are state fixed effects, and $\phi_t$ and $\sigma_t$ are time fixed effects. $\tau$ and $\kappa$ estimate the coefficients from (3) and (4) for the non-COVID-19 specialty. For each specialty $i \neq 0$, $\pi_i$ and $\mu_i$ capture the differences in those coefficients relative to the non-COVID-19 specialty. Appendix C shows that the ratio of these parameters yields the supply elasticity: $\alpha = \dfrac{\mu_i}{\pi_i}$.

[9] Appendix C shows the full expressions.

Equations (5) and (6) thus serve as the first stage and reduced form, respectively, of an IV estimation of $\alpha$ in which the COVID cases-specialty interaction serves as the instrument. We estimate this system using GMM[10] and report estimates of $\hat{\alpha}_i$.

The fixed effects in (5) and (6) remove some residual variation from the equilibrium equations, increasing the plausibility of the identifying assumption: $\{\varepsilon_{ijt}, \nu_{ijt}\} \perp c_{jt}|j, t$. We also consider specifications with separate time and/or state fixed effects for each specialty, and check robustness to controls for local economic trends and state COVID policies. The fixed effects ensure that we are identifying the model within state and time. This variation is useful because our goal is understanding short-term reallocation and flexibility in this market.

Our interpretation requires certain assumptions. First, parameters aside from $\delta^i$ are constant across specialties. This implies ICU and ER nurses require the same risk compensation as L&D nurses, though their units treat sicker, COVID-positive patients. While this assumption is strong, its failure would cause errors in a predictable direction. If ICU and ER nurses demand extra risk compensation, their $\beta$ would be more negative than when we hold $\beta$ constant. So our framework may underestimate the supply elasticity, $\alpha$. Appendix C and Appendix Figure C.1 illustrate this.

Our second assumption is that the market is segmented between specialties. This may not be perfectly true, but compensation does diverge between specialties. Third, we assume demand for non-COVID specialties is invariant to COVID-19 conditions. This assumption is most plausible for L&D, where the lag inherent in pregnancy justifies it.[11] L&D job postings do not vary substantially with respect to COVID-19 cases, conditional on our fixed effects.

Finally, nursing supply shocks could covary with demand shocks. For example, nurses in economically-disrupted COVID-19 hotspots could lose their jobs and enter the travel nursing workforce, causing simultaneous supply and demand shocks. Since the workers we consider travel nationally, time fixed effects should control for supply shocks. Nurse preference for shorter travel should bias against the observed relationship between travel distance and pandemic severity.

[10]The interaction with $c_{jt}$ in equations (5) and (6) lend this system to estimation by GMM rather than 2SLS.

[11]Results are similar when estimated on a limited sample that ends less than nine months after COVID-19 arrived in the U.S. (Gottlieb and Zenilman, 2020).

An alternative estimation framework is to focus on each nurse's decision and estimate the parameters of a multinomial choice model. This approach directly accounts for changes in nurses' choice sets as COVID conditions change, but requires explicit specification of a choice set that is not directly observed. We implement a multinomial choice model in Appendix D and estimate a similar labor supply elasticity.

# 3 Time-Series Patterns

Table 1 displays the descriptive patterns in our data, nationally and in key subsamples.[12] The baseline national indices for both job openings and compensation are normalized to 100. The first row in Panel 1(b) shows that the national job openings index increased to 165 in spring 2020, fell to 47 in early summer, and increased again in late summer, reaching 304 by late fall. The national compensation index was 133 in spring, 103 in early summer, and 141 by late fall.

Figure 1(a) shows a smoothed time series of the national job openings index, overlaid with the time series of new COVID-19 cases. Job openings closely track COVID-19 case spikes. COVID-19 cases began increasing sharply after March 15, 2020, exceeding 200,000 weekly by April 8. They gradually declined to 152,000 by June, before increasing to 443,000 by July 15. They fell again in late summer, before increasing again to over 1,630,000 in late fall and early winter 2021.

The national job openings index fluctuated between 80 and 130 from February 1 through March 15, 2020. This quickly changed. By April 1, the job openings index reached 320. It plummeted to 38 in late June, and stayed low until July, when outbreaks in southern states peaked. It reached 172 by July 29, and only fell slightly by late September. It skyrocketed in late fall and early winter 2021, before declining back to 174 by the end of our sample.

The graph includes a corresponding trend for New York, which experienced the sharpest increase in COVID-19 at the beginning of the pandemic. New York's weekly cases (not shown) grew from 10,000 the week of March 11 to 60,000 by April 1. The job openings index increased to over

[12] Appendix Table E.3 shows corresponding values for February–August 2020.

3,400 during the first week of April. (The graph divides the New York value by 10.) By April 15, it was below 1,000, and ultimately returned to baseline by May 6. It experienced a more modest spike in late fall 2020, peaking at less than one-third of its early demand.

Panel 1(b) shows the compensation index. Average compensation nationally was stable until early March 2020. It then increased significantly, peaking at 139 by April 8. It declined in May, returning to baseline in June. It increased again in the second half of July, reaching 116 by early August and 148 by the end of the sample. New York's compensation index was 105 in February but spiked in mid-March, peaking at 175 by April. It remained around 150 through May, and then declined to 100 by late July. It again increased dramatically in fall 2020, exceeding its spring 2020 peak—even though Panel 1(a) showed that New York's own job openings were restrained.

Panel 1(c) shows the time-series patterns for filled jobs, using smoothed weekly data.[13] Completed jobs more than doubled from early 2020 to the April peak. Job completions fell in early summer, reaching below baseline in June, before climbing in late summer, and surging again in early 2021 to nearly the peak. Compensation follows a similar pattern, increasing during the pandemic's initial phase, falling in summer, and exceeding the 2020 peak in 2021.

We see additional characteristics for filled jobs: the worker's home and job locations. We plot the average distance between these two points (in tens of kilometers) in Panel 1(c). The average distance increased from 800 to 1,200 km when the pandemic began, before falling to 900 km in the summer and lower by winter 2021. This provides initial evidence that the market accommodated the early surge in demand through workers' willingness to travel farther. But as compensation and job completions escalated in winter 2020–21, travel distance did not recover.

Panel 1(d) splits job postings by specialty. The pandemic is associated with dramatic increases in postings for COVID-19-related jobs: ICU, ER, and medical-surgical, while OR and L&D postings do not exhibit COVID-related cylicality—they even declined during the initial wave. Panel 1(e) shows compensation by specialty. Compensation largely follows the pattern of job open-

[13]For each of these three panels, Appendix Figure E.2 shows both an analogous graph incorporating a seasonal adjustment and one extending the sample back to Sept 3, 2018. Panel E.2(d) shows a secular increase in job openings during the pre-pandemic sample, with seasonal increases in December and January.

ings, until winter 2021, when job postings for COVID-19 specialties declined but compensation stayed high.

Returning to Table 1(b), the next six rows summarize descriptive patterns by specialty. The first column shows the specialty's share of job postings. The baseline openings index for each specialty is scaled to 100, while the baseline compensation index is scaled relative to the national mean. ICU, ED, L&D, and OR nurse postings had compensation indices above 100 in February, and medical-surgical was 95. In spring, the ICU job openings index more-than-tripled to 339, while the compensation index rose to 157. In late fall, ICU job openings reached 470 and compensation 164. The ER job openings index increased to 189 in spring and 220 in fall, with compensation indices of 131 and 134, respectively. In contrast, the OR job openings index fell to 56 in spring 2020 as elective surgeries were canceled.

L&D is especially instructive. In the spring, openings declined to 78 and compensation rose from 110 at baseline to 115. The quantity decline and compensation increase cannot be driven only by increased demand. There must be a negative supply shock, which we interpret as nurses demanding compensating differentials for riskier working conditions.

The next three rows summarize New York's, Massachusetts', and Arizona's experiences. Despite different patterns early in the pandemic and through early fall 2020, all three states experienced spikes in late fall, with job opening indices above 300 and compensation from 133 to 168.

# 4 Travel Nurse Labor Supply

## 4.1 Labor Supply Estimates

Table 2 shows our main labor supply estimates. Columns 1 and 2 regress log completed jobs and log compensation, respectively, against log cases at the state-by-week level. The elasticity of job completions with respect to COVID-19 cases is 0.20, and that of compensation is 0.077. We cluster standard errors by state, and both estimates are easily distinguishable from zero. These columns do not distinguish among specialties, so yield the correct aggregate elasticity if there is one unified market across specialties and COVID cases do not affect labor supply ($\beta = 0$). Under these assumptions, the supply elasticity is 2.7.

Since nurses might demand risk compensation, columns 3 and 4 implement the IV setup in (6) and (5). Below the estimates, we compute the supply elasticity estimated by GMM. These columns use non-COVID specialties like L&D to control for supply and demand shifters. The "COVID-19" variable indicates observations comprising medical-surgical, ER, and ICU jobs, and its interaction with log cases allows us to infer the differential supply response for these specialties compared with others. The coefficients on log cases alone shows the relationship for non-COVID specialties. These coefficients fall relative to those in columns 1 and 2, and become indistinguishable from zero. The coefficients on the interactions imply substantial quantity and compensation response to local COVID cases. The ratio of the jobs interaction and the compensation interaction implies a supply elasticity of 4.3.[14]

To exploit more granularity in timing and specialty, the remaining columns use data on posted jobs rather than completed jobs. Columns 5 and 6 show an overall job-posting elasticity of 0.34 and an overall compensation elasticity of 0.045 with respect to local COVID cases. Columns 7 and 8 report separate interactions for each specialty's separate interaction with COVID cases—$\pi_i$ and $\mu_i$ from equations (5) and (6)—with L&D the omitted category. Both columns show small positive estimates between COVID-19 cases and L&D openings or wages. This is consistent with L&D demand being somewhat insulated from COVID cases.[15]

The interactions with other specialties capture the incremental relationships between COVID cases and other specialties' labor demand and compensation offered. We estimate positive and significant wage and job posting relationships for ICU, ER, and medical-surgical postings, with implied supply elasticities from 2.0 to 3.8. The coefficients for OR jobs are close to zero and precise. This supply elasticity remains stable under alternative specifications, presented in Ap-

[14]In Appendix D we develop a choice model at the nurse-by-opening level to make the supply elasticity concept more precise. We estimate the resulting job choice elasticity using a multinomial logit, and find similar results to our baseline IV estimation.

[15]Nurses can get sick, which could lead hospitals to need temporary workers across all specialties when local COVID case counts increase.

pendix E.

The coefficients for ER are lower and less precise than for ICU and medical-surgical nurses. The imprecision likely reflects the much smaller number of ER jobs in our data compared to ICU or medical/surgical positions (Table 1). The lower coefficient likely indicates that COVID had a larger proportional impact on hospital admissions than ER visits. This could reflect crowding out of other ER visits, whether because patients were afraid to visit the ER during COVID waves or because COVID (or COVID precautions) reduced other infectious diseases and injuries. This crowding-out effect is likely weaker for ICU and medical-surgical admissions. COVID may be a more serious disease than the sources of ED visits that were crowded out, leading to a larger proportional impact on ICU and medical-surgical staffing needs than ER needs.

To interpret the magnitude of these results, consider workers facing two identical job offers, except one pays twice as much as the other. A supply elasticity of 3.8 implies that 14 times as many workers choose the higher-paid job; 93 percent of workers would choose the job paying double, while 7 percent would choose the job paying half (see Appendix E). These estimates have implications for regulatory price caps, such as Massachusetts (2020*b*), which increased its nurse price cap by 35 percent during the pandemic. With such a large supply elasticity, price caps below the market bill rate hamstring local hospitals' ability to hire.

Figure 2 graphically displays the key relationships between labor market outcomes—job postings and compensation—and COVID-19 cases. The panels show binned scatterplots for each specialty, conditional on week and state fixed effects. The differences across specialties are apparent. L&D and OR job postings are nearly flat with respect to COVID-19 conditions. The slopes for ER, ICU, medical-surgical and miscellaneous other jobs are clearly positive. This is consistent with our assumption that demand for some specialties does not respond to local COVID-19 cases, while demand for others does.

Panel 2(b) shows that compensation for all COVID-related specialties goes up when COVID-19 cases increase, while the slopes for L&D and OR are indistinguishable from zero. These differences, combined with the quantity slope differences from Panel 2(a), allow us to compute the supply elasticity.

These estimates capture supply elasticities across regions at a point in time, in a market with a fixed national supply of workers and labor demand, even within a specialty. Thus, a worker can only choose location. In this context, a large supply elasticity makes sense. From workers' perspective, temporary job markets are supposed to maximize short-term earnings, so they overwhelmingly choose the better-paid opening.

These elasticities are higher than those estimated in many other settings, but the response margins in other settings are limited. Work on Uber/Lyft drivers and other gig economy workers estimates a Frisch labor supply elasticity centered around 0.5 (Chen et al., 2020, Chen and Sheldon, 2015), or an intertemporal labor supply elasticity of 1.2 (Angrist, Caldwell and Hall, 2021). But these responses require drivers to change total hours or when they work. Beyond ride-sharing, Mas and Pallais (2017) find similar estimates for temporary remote work, and show that workers have a meaningful, decreasing valuation of non-work time. These elasticities do not measure decisions about which work to accept, conditional on taking a job—for instance, which neighborhood an Uber driver prefers. But in our context, that simple location choice takes on first-order importance.

In contrast, our estimates do not require workers to substitute between working at different times, or away from home production. This choice may be more comparable to deciding between Uber or Lyft, where Caldwell and Oehlsen (2018) estimate elasticities ranging from 2 to 6. In our specifications, the outside option is taking a similar job, likely for the same time period, but in a different state. Given the similarity of the choices once we have adjusted for the COVID-19 risk compensation differential, it makes sense they are close substitutes. This setting implies that the temporary staffing market rapidly overcomes job search frictions. We next investigate one aspect of how it does so.

## 4.2 Travel Distance

We use data on completed jobs to test our interpretation that workers' mobility is an important part of this response. Figures 3(a) and 3(b) show the relationship between distance traveled and the local COVID situation among workers in our completed jobs data. The horizontal axis shows the number of COVID cases by state and week, on a log scale, conditional on state and specialty fixed effects. The vertical axis shows the log distance traveled for each completed job. We then aggregate observations into 20 bins based on the horizontal axis and each panel shows a binned scatterplot.

Panel 3(a) shows the data for the 25 percent of weeks with the highest *national* COVID counts—when travel nursing demand was at its peak—and Panel 3(b) for the remaining 75 percent. During the periods of high national demand, there is a negative (and marginally significant) relationship between travel distance and the local COVID situation. In contrast, there is a strong positive relationship between travel distance and COVID cases at other times (Panel 3(b)).

Panels 3(c) and 3(d) show similar scatterplots relating distance traveled to compensation. We again split the panels based on national COVID counts, as a proxy for periods of high national travel nursing demand. In these panels, both relationships are significant and positive, but the one in Panel 3(d) (during lower national demand) is stronger. Compensation induces nurses to travel farther when national demand is not extreme.

This is evidence that the travel nursing market is especially effective at reallocating nurses across the country when there is slack in the national market. Travel distances increase in response to local COVID cases and local compensation—which itself responds to cases. But this relationship weakens when national capacity approaches its limits and nurses are needed everywhere. In this case, local demand doesn't induce as much movement across space, but instead increases compensation broadly across the country (see Table 1 and Figure 1).

## 4.3 Do Nurses Travel to Where They Are Needed?

We conclude by asking if nurses travel to where they are needed, using data on "staffing shortages" collected by the Department of Health and Human Services.[16] We compute the share of hospitals in each state and week reporting a staffing shortage.

[16]See Appendix B for data details.

Panel 3(e) shows an extremely strong relationship between state-level COVID cases and reports of impending staffing-shortage, with a partial $R^2$ of 0.77. Panel 3(f) shows how travel nurses alleviate this shortage. When staffing shortages are widespread, travel nurse jobs increase, with a partial $R^2$ of 0.57. These results, along with the earlier evidence on worker response to job postings, suggest that this nursing labor market was used to address COVID staffing challenges.

# 5 Discussion

The national labor market for short-term nurse staffing appears to have very elastic supply. Workers respond to price signals and choose jobs all over the country—but not with perfect flexibility. Why is supply not perfectly elastic with respect to wages?

Even for short-term travel work, workers appear to value proximity to home. The elasticities of distance traveled, and of leaving one's home state, with respect to compensation are positive but not infinite. The choice model in Appendix D estimates a distance elasticity around $-1$. There may be match-specific reasons that labor supply is not infinitely responsive to price signals; even within specialty categories, nurses can subspecialize so are not perfect substitutes. When staffing companies consider nurse placements, they evaluate other aspects of nurses' skills and fit for the job (for example, are they familiar with the hospital's electronic health record software?). The labor supply elasticity may also be depressed by regulatory hurdles, such as state-specific licensure requirements, which can cause delays.[17] New York, California, and other states temporarily liberalized licensure in early 2020, perhaps contributing to the large supply elasticity we find.

Workers' ability to travel makes labor supply quite elastic. While our more compelling identification comes from the panel context, and looking across specialties, the time series remain illustrative: compensation only increased by 55 percent in the early phase of the pandemic, when job filling tripled. Looking across states, we see that a national staffing market can accommodate demand shocks. When demand increases in specific geographic areas, nurses' travel ability can

[17] The Nurse Licensure Compact eliminates these requirements among most states, though DePasquale and Stange (2016) find no effect on labor supply.

help mitigate a local shortage. When prices signal acute shortages in specific places, nurses' travel ability can help. This suggests that the margin of temporary work can be valuable in increasing the labor supply available in a particular market.

But when multiple regions experience simultaneous COVID-19 surges, mobility across regions is less relevant. The ability to relocate cannot increase the total number of workers to address a simultaneous national shortage. In this case, aggregate national supply would have to expand through longer work hours, hiring nurses who normally work outside the hospital, or increased labor force participation. Since we rely on cross-state variation, our empirical strategy does not incorporate these extensive margin responses.

# 6 Conclusion

We find that labor supply is quite elastic in the travel nursing market, which helps the market accommodate labor demand spikes from COVID surges. Travel nurse costs adjust to reflect demand, which increases when hospitals report staffing shortages. Nurses' elasticity is partially due to their willingness to travel to areas with demand spikes, at least when demand does not overwhelm the national labor supply. This elastic labor supply helped the market accommodate historic demand shifts. These results imply that price controls are a risky policy. Hospitals and nursing homes have lobbied state governments to cap travel nurse compensation. In a market with mobile workers, this puts a state's travel nurse supply at risk.

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## Table 1: Data Descriptives

### (a) Full Sample Summary Statistics

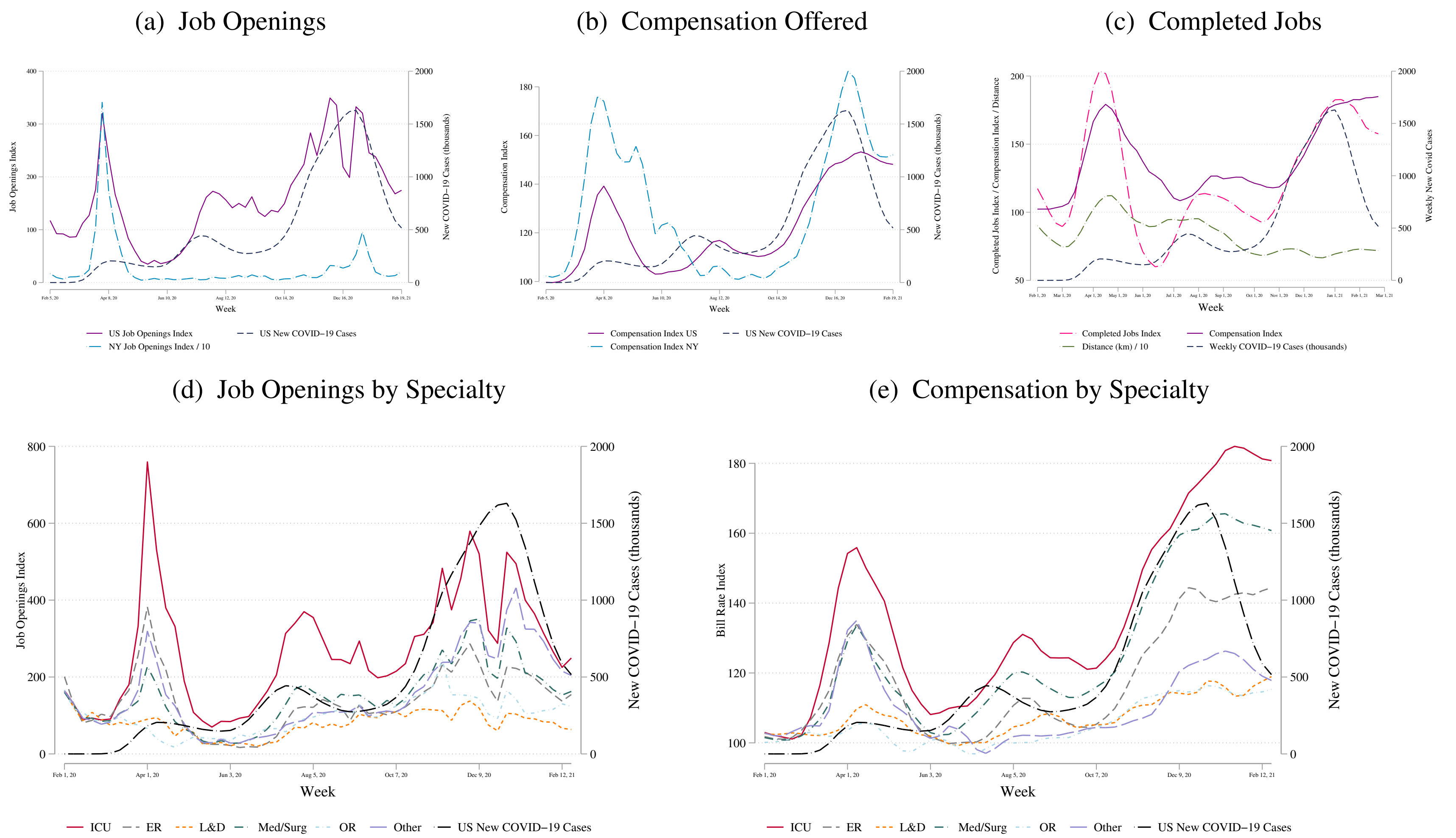
| Measure | N | Mean | SD | P10 | Median | P90 |
|---|---|---|---|---|---|---|
| Job posting index | 6443 | 100.8 | 140.1 | 15.5 | 63.5 | 212.3 |
| Comp. index (posted jobs) | 6436 | 111.6 | 23.2 | 89.9 | 103.7 | 146.9 |
| Filled jobs index | 2491 | 145.9 | 219.8 | 41.2 | 82.4 | 329.8 |
| Comp. index (filled jobs) | 2491 | 126.2 | 40.8 | 87.2 | 111.4 | 187.9 |
| COVID-19 cases (thousands) | 6443 | 4.4 | 14.77 | 0 | 0 | 11.3 |
| Travel distance (miles) | 2491 | 552.1 | 645.4 | 58.9 | 308.5 | 1472.6 |

### (b) Summary Values During COVID-19

| | | Feb 1–Mar 14 | | Mar 15–May 16 | | May 17–Jul 18 | | Jul 19–Sep 12 | | Sep 13–Nov 14 | | Nov 15–Jan 16 | | Jan 17–Feb 28 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample | Share | Job index | Comp index | Job index | Comp index | Job index | Comp index | Job index | Comp index | Job index | Comp index | Job index | Comp index | Job index | Comp index |
| National | 100 | 100 | 100 | 165 | 133 | 47 | 103 | 156 | 114 | 170 | 115 | 304 | 141 | 215 | 146 |
| ICU | 25 | 100 | 105 | 339 | 157 | 104 | 110 | 300 | 126 | 266 | 129 | 470 | 164 | 315 | 183 |
| ER | 8 | 100 | 103 | 189 | 131 | 22 | 102 | 111 | 110 | 129 | 112 | 220 | 134 | 175 | 144 |
| LD | 2 | 100 | 110 | 78 | 115 | 27 | 107 | 68 | 113 | 112 | 114 | 109 | 123 | 85 | 121 |
| Med/Surg | 41 | 100 | 95 | 130 | 119 | 39 | 97 | 159 | 110 | 167 | 112 | 300 | 146 | 192 | 151 |
| OR | 5 | 100 | 108 | 56 | 108 | 50 | 104 | 95 | 106 | 138 | 111 | 162 | 121 | 124 | 121 |
| Other | 18 | 100 | 100 | 162 | 125 | 37 | 99 | 101 | 100 | 148 | 103 | 337 | 110 | 286 | 112 |
| NY | 6 | 100 | 106 | 863 | 185 | 49 | 125 | 76 | 107 | 75 | 108 | 316 | 168 | 177 | 159 |
| MA | 3 | 100 | 106 | 174 | 131 | 94 | 106 | 65 | 103 | 137 | 111 | 338 | 133 | 169 | 120 |
| AZ | 2 | 100 | 93 | 145 | 113 | 75 | 104 | 228 | 126 | 116 | 104 | 416 | 139 | 271 | 155 |
| Completed | 100 | 100 | 104 | 325 | 162 | 94 | 121 | 245 | 127 | 153 | 125 | 326 | 174 | 291 | 191 |

Data are from Health Carousel and are described in detail in the text. The unit of observation in Panel (a) is the state-by-week. The compensation index is normalized to national daily average from February 1–March 14, 2020 for all subsets, weighted by number of job postings. The job posting index is normalized average daily postings for February 1–March 14, 2020 for each subsample.

**Figure 1: Time-Series Patterns**




Panel (a) shows job postings in the United States and in New York state from February 5, 2020 through February 25, 2021. Data are smoothed using an Epanechnikov kernel. The panel also shows (smoothed) national new COVID-19 cases. Panel (b) shows compensation trends, also nationally and for New York state, along with national COVID-19 cases. Panel (c) shows jobs filled by the recruiting agency, and adds the nurse's travel distance from home to the job location in addition to compensation and the count. Panels (d) and (e) consider six specialty categories: intensive care (ICU), emergency room (ER), labor and delivery (L&D), standard hospital floors (Med/Surg), operating room (OR), and other. All indices are normalized to a mean of 100 in February 2020.

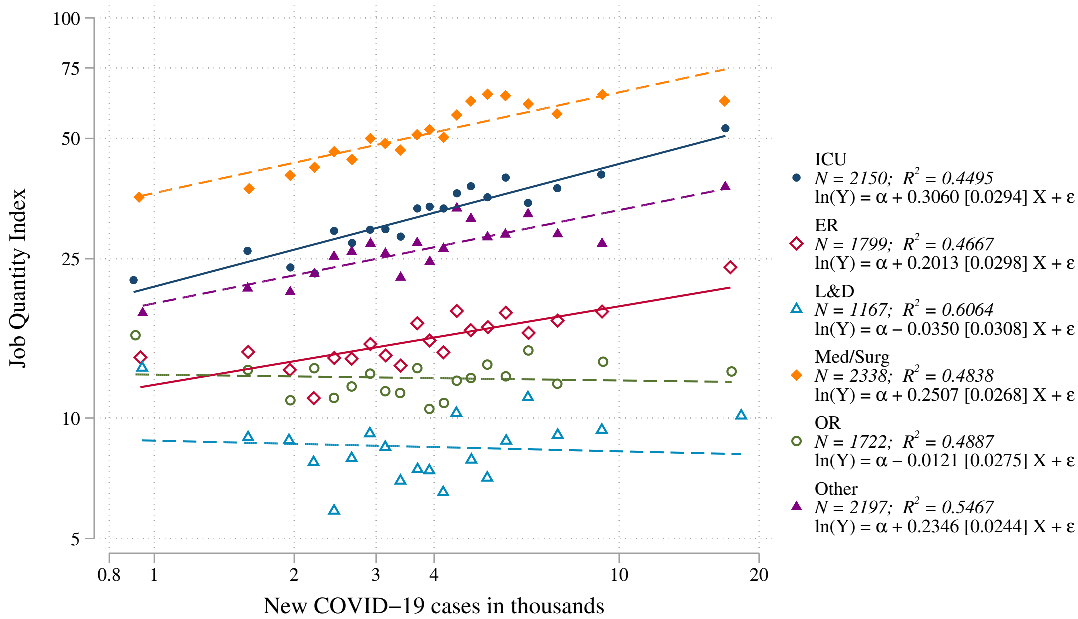
## Table 2: Regression Estimates

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Jobs | Comp. | Jobs | Comp. | Jobs | Comp. | Jobs | Comp. |
| ln(cases) | 0.20*** | 0.077*** | 0.062 | 0.025* | 0.34*** | 0.045*** | 0.14** | 0.0021 |
| | (0.053) | (0.0098) | (0.045) | (0.012) | (0.062) | (0.012) | (0.055) | (0.012) |
| COVID-19 × ln(cases) | | | 0.23* | 0.053*** | | | | |
| | | | (0.093) | (0.016) | | | | |
| ICU × ln(cases) | | | | | | | 0.19*** | 0.063*** |
| | | | | | | | (0.032) | (0.0078) |
| ER × ln(cases) | | | | | | | 0.076 | 0.038*** |
| | | | | | | | (0.042) | (0.0079) |
| Med/Surg × ln(cases) | | | | | | | 0.22*** | 0.058*** |
| | | | | | | | (0.028) | (0.0060) |
| OR × ln(cases) | | | | | | | 0.040 | 0.010 |
| | | | | | | | (0.027) | (0.0081) |
| Other × ln(cases) | | | | | | | 0.23*** | 0.0080 |
| | | | | | | | (0.027) | (0.0083) |
| $\alpha$ (overall or ICU) | | 2.7*** | | 4.3* | | 7.5*** | | 3.1*** |
| | | (0.67) | | (1.69) | | (1.12) | | (0.41) |
| $\alpha$ (ER) | | | | | | | | 2.0* |
| | | | | | | | | (0.87) |
| $\alpha$ (Med/Surg) | | | | | | | | 3.8*** |
| | | | | | | | | (0.38) |
| Observations | 1582 | 1582 | 1079 | 1079 | 11373 | 11373 | 11373 | 11373 |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ |
| Week-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | | |

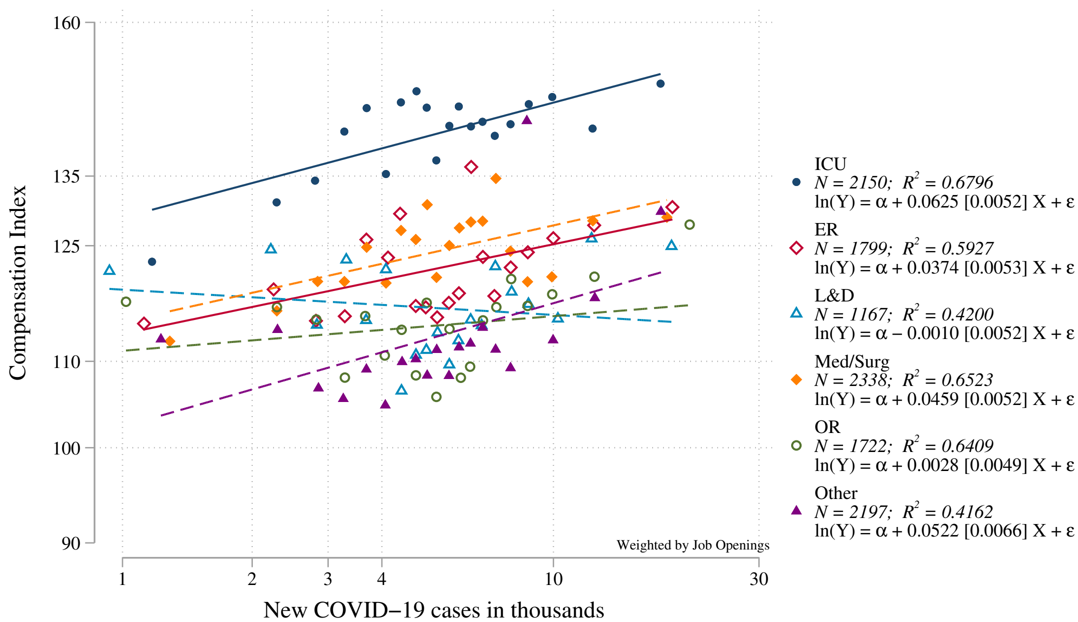
This table reports estimates of equations (6) and (5) on Health Carousel data on travel nursing job postings from February 2020–February 2021. Parameters are estimated using GMM. The dependent variable in cols. 1 and 3 is the log number of filled nursing jobs by state-week-specialty and the log number of job postings by state-week-specialty in cols. 5 and 7. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. Filled jobs are a subset of all posted jobs, which explains the large difference in sample size between cols. 1–4 and 5–8. Cols. 1–2 do not distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta = 0$). Cols. 3–6 combine ICU, ER, and Med-Surg together into "COVID-19 specialties," and combine OR with L&D into the omitted category; the "Other" specialty is dropped, resulting in a smaller sample size compared to cols. 1–2. In cols. 7–8, the omitted nursing specialty is labor and delivery. All specifications include state and specialty fixed effects. Cols. 1–4 are weighted by number of filled jobs and cols. 5–8 are weighted by number of job postings. Standard errors, in parentheses, are clustered by state. ${}^{*}p < 0.05$, ${}^{**}p < 0.01$, ${}^{***}p < 0.001$.

**Figure 2: Graphical Supply Estimates by Specialty**

(a) Job Postings vs. COVID-19 Cases | Fixed Effects



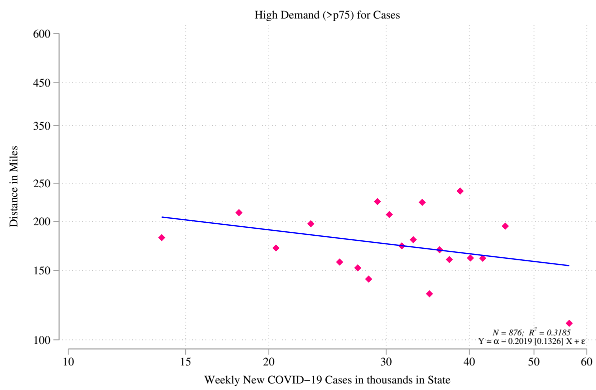

(b) Compensation vs. COVID-19 Cases | Fixed Effects



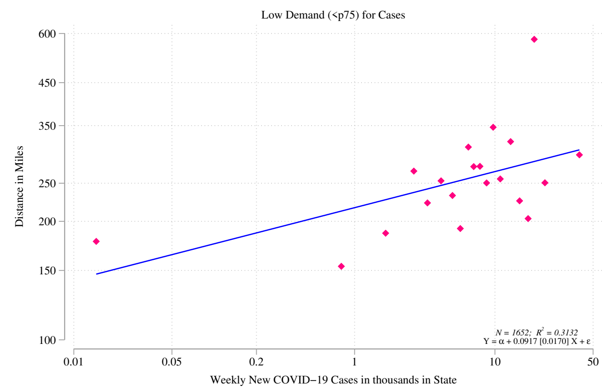

Panel (a) shows six binned scatterplots of job postings against COVID-19 cases by state/week, after conditioning on state and week fixed effects. We show separate scatterplots and corresponding log-linear fits for six specialty categories: intensive care (ICU), emergency room (ER), labor and delivery (L&D), standard hospital floors (Med-Surg), operating room (OR), and other. Panel (b) is analogous, but shows the mean compensation for the corresponding jobs rather than the quantity.

## Figure 3: Travel, Staffing Needs, and COVID-19 Cases

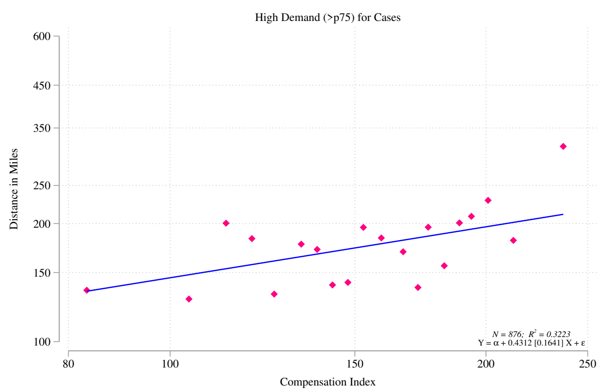
**(a)** Distance and COVID-19 Cases: High Demand



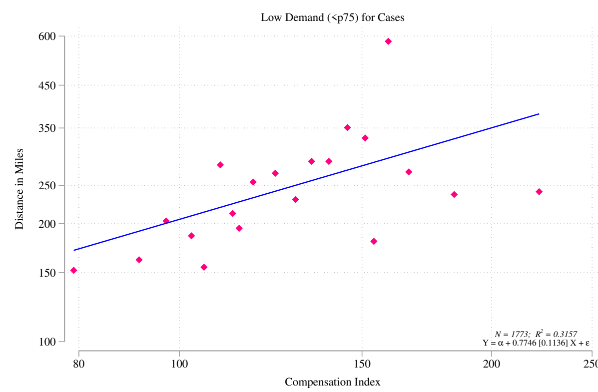

**(b)** Distance and COVID-19 Cases: Normal Demand



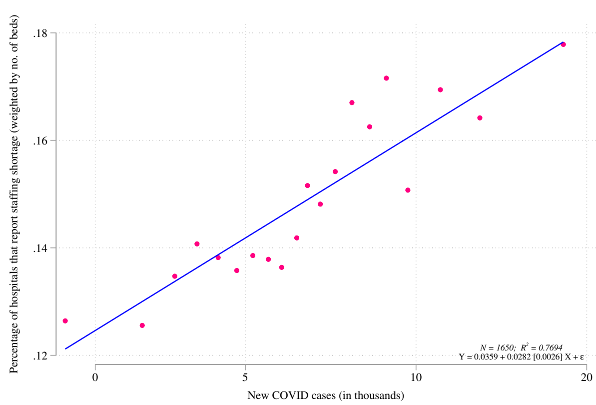

**(c)** Distance and Compensation: High Demand



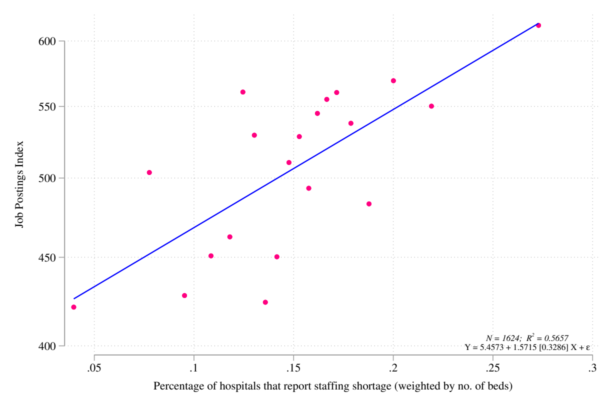

**(d)** Distance and Compensation: Normal Demand




**(e)** Staffing Shortages vs. COVID Prevalence




**(f)** Travel Nursing vs. Staffing Shortages

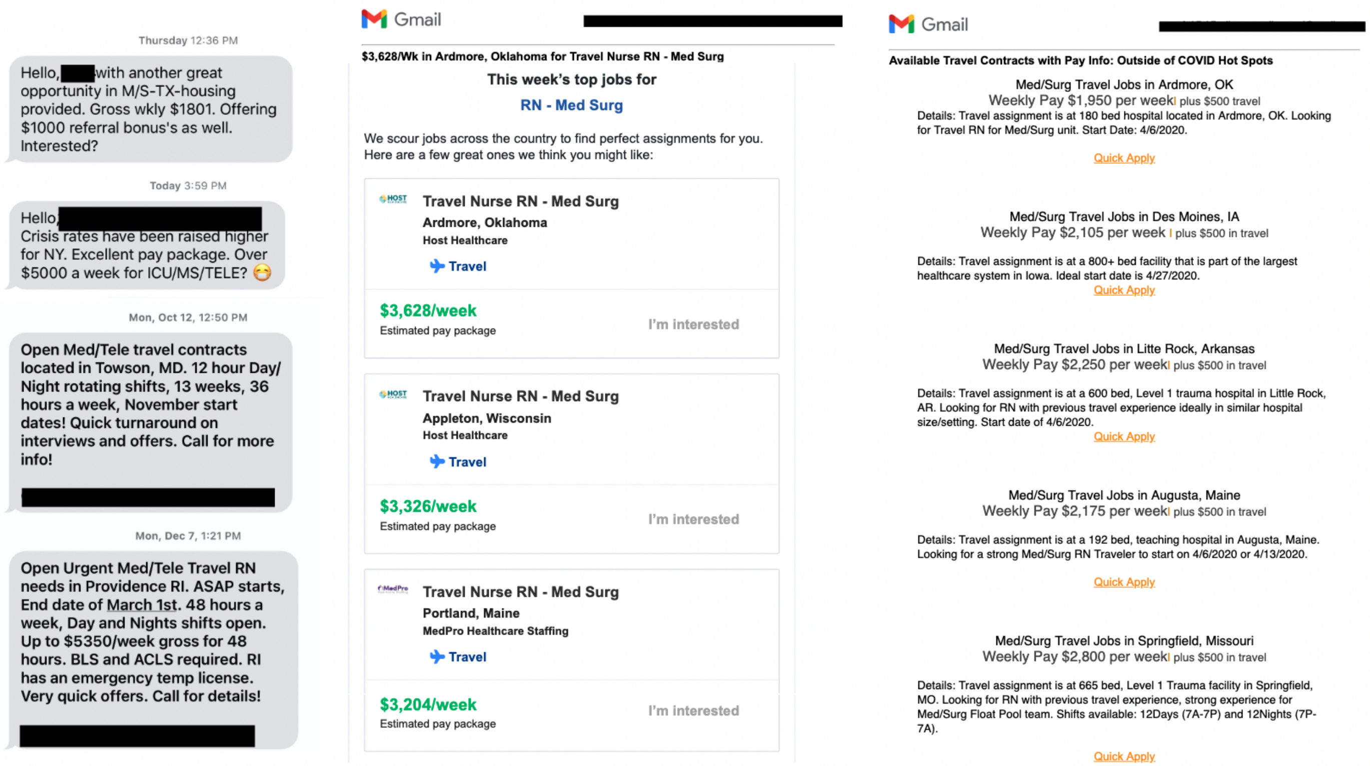



This figure shows show binned scatterplots of the relationship between travel distance against the job location's weekly COVID-19 new case count (Panels (a) and (b)) or the job's own compensation (Panels (c) and (d)) using a sample split based on the weekly caseload. High demand weeks are defined as weeks with new cases greater than the 75$^{\text{th}}$ percentile of national weekly cases. Panels (a) and (c) restrict the sample to high demand periods while Panels (b) and (d) restrict the sample to the low demand periods. The binned scatterplots are all conditional on state and specialty fixed effects. Panels (e) and (f) use data on staffing shortages to describe the relationship between COVID-19 and staffing shortages faced by hospitals at the state-week level. Panel (e) plots the percentage of hospitals that report staffing shortage against new COVID cases. Panel (f) describes the relationship between the number of job openings and hospitals with staffing shortages. The binned scatterplots are conditional on state and week fixed effects.

# Online Appendices

## A Recruitment Examples

**Figure A.1: Example Travel Nurse Recruitment by Text and Email**




This figure shows four examples of text message solicitations from nurse recruiters and two examples of email solicitations from a travel nursing agency. All examples are anonymized and excerpted.

# B Data Appendix

## B.1 Travel Nursing Data Description

The staffing firm provides us with data from two separate sources: job postings made available to its recruiters and completed job assignments.

For each posted job, main variables include: a job identifier, number of positions available, bill rate, specialty, working hours per week and per day, type of shift, assignment length, job location (city, state, and ZIP code), type of employer, estimated start date and end date. For completed jobs, the data include: an assignment identifier, the job identifier (linking postings with completed jobs), specialty, the nurse's home location (city, state, and ZIP code), and some variables from the postings data (e.g., job characteristics). Computation of key variables are described further below.

**Calculation of the number of job postings.** Our dataset has three types of job assignments: initial, extension, and replacement. Our main analyses use only initial assignment postings. We aggregate the total number of nurses requested or hired rather than counting the number of postings to capture the actual number of nurses demanded (some job postings request multiple nurses).

**Aggregation of specialties.** We use six nursing specialties: Emergency Room (ER), Adult Intensive Care (ICU), standard hospital floors (Med/Surg), Labor and Delivery (L&D), Operating Room (OR), and Other. ER, L&D, and OR are provided in the original data. Other categories are defined by aggregating as follows (aggregated specialty followed by its raw components):

- ICU: ICU, CVICU (Cardiovascular Intensive Care Unit), PACU (Post-Anesthesia Care Unit);
- Med/Surg: MS (Medical-Surgical), TELE (Telemetry);
- Other: all postings whose specialties are not specified.[18]

**Data cleaning and index construction for main variables.** For the number of positions of each job posting, we drop outliers and replace missing counts with 1 to indicate at least one position being offered. We also drop observations with zero compensation for being obviously erroneous.

As explained in section 1, we scale the count of job postings and of completed jobs, as well as compensation, as indices relative to their national average in February 2020. (We calculate the mean of each variable in February 2020 and normalize it to 100.) The index construction process is slightly different for the MSA-level analysis in Appendix E in two ways:

1. For the state-level analysis, we first collapse and normalize at the day level and then collapse the normalized dataset to the week level. At the MSA level, we first collapse to the week level to ensure sufficient sample size and then normalize. This choice has virtually no impact.
2. For the state-level analysis, we normalize based on the mean of each variable in February 2020. For the MSA-level datasets, we normalize based on the mean of each variable over the entire sample period; of course this has no impact on the results.

When plotting the time series graphs of these indices, we use an Epanechnikov kernel to smooth the data. The bandwidths for each variable (in weeks) are in parentheses: COVID cases (1), job openings (0.5), completed jobs (2), bill rate (1), travel distance (2), length of spells (2).

[18] The "Other" category includes a broad range of specialties, including psychiatry, cardiac catheterization, pediatrics, administration, and ambulatory care. Some of these may be relevant to COVID-19 care; others are less so.

**Computation of travel distance.** We compute the distance between a nurse's home (residential ZIP code) and working location (ZIP code of the job opening) as the geographical distance (i.e., shortest path along the earth's surface) between the two points using Stata package `geodist`.

**Counting renewed jobs.** We count how often a nurse's job is renewed for a subsequent contract. We define a "spell" as a group of stints where: (1) the same nurse gets hired by the same hospital, and (2) one stint starts within 30 days after the previous ends.[19] Appendix E presents data on spells.

## B.2 Additional Data Sources

**National COVID-19 cases.** We measure COVID incidence using the number of daily new cases from the Johns Hopkins Coronavirus Resource Center.[20] We also use county-level daily COVID cases reported by the New York Times for our MSA-level analysis in Appendix E.[21]

**Hospital staffing shortages.** Hospitals' staffing shortages are self-reported by hospitals to the Department of Health and Human Services (HHS).[22] We use the number of hospitals that anticipate a critical staffing shortage in each week in that state, obtained from the HHS dataset.

**Unemployment rate.** State-level monthly unemployment rate data are published by the Bureau of Labor Statistics. We retrieve these data from Federal Reserve Economic Data (FRED).[23]

**House prices.** House prices data are also obtained from FRED.[24] We use the state-level quarterly all-transactions House Price Index (published by the Federal Housing Finance Agency), a general measure of single-family house prices based on repeat mortgage transactions of these properties.

**COVID-19 policies.** The Oxford COVID-19 Government Response Tracker (OxCGRT) collects information on COVID-related government policies.[25] It covers five categories (containment & closure, economic, health system, vaccination, and miscellaneous) and provides daily measures of the stringency of tens of policies in each U.S. state. We use the four policy indices (government response, containment & health, stringency, and economic support)— weighted averages of more granular measures—for our robustness analysis.[26] Average of these (highly correlated) indices are used as an aggregate policy index for our robustness checks. Principal component analysis (PCA) of the four indices results in a first component that accounts for 88% of the variation. Using this first component as an aggregate policy index yields very similar estimates (not shown).

**COVID vaccination data.** County-level COVID vaccination data from the CDC report the share of population at each stage of the vaccination sequence.[27] We aggregate the data to the state level and use the share of population with a full sequence of vaccination for our robustness checks.

[19] Results are robust to alternative definitions of spells, including using smaller intervals between stints and relying on a variable in the raw data that identifies contract extensions.

[20] See https://coronavirus.jhu.edu/.

[21] See https://github.com/nytimes/covid-19-data.

[22] See https://healthdata.gov/Hospital/COVID-19-Reported-Patient-Impact-and-Hospital-Capa/g62h-syeh.

[23] See https://fred.stlouisfed.org/tags/series?t=monthly%3Bstate%3Bunemployment.

[24] See https://fred.stlouisfed.org/searchresults?st=housing%20price&t=housing%3Bquarterly%3Bstate.

[25] See https://github.com/OxCGRT/covid-policy-tracker.

[26] See a detailed definition of these indices at https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md.

[27] See https://data.cdc.gov/resource/8xkx-amqh.csv.

# C Model Appendix

**Equilibrium.** The full expressions for equilibrium wages and quantities are:

$$w^i_{jt} = \frac{-\beta + \delta^i}{\alpha - \gamma} c_{jt} + \psi_{jt} + \frac{u^i_{jt} - e^i_{jt}}{\alpha - \gamma} \tag{7}$$

$$q^i_{jt} = \frac{\alpha\delta^i - \beta\gamma}{\alpha - \gamma} c_{jt} + \bar{\gamma}_{jt} + \gamma\psi_{jt} + \frac{\alpha}{\alpha - \gamma} u^i_{jt} - \frac{\gamma}{\alpha - \gamma} e^i_{jt} \tag{8}$$

where $q^i_{jt} = s^i(w^i_{jt}, c_{jt}) = d^i(w^i_{jt}, c_{jt})$ is the equilibrium number of jobs and $\bar{\alpha}_{jt} = \alpha'_t + \tilde{\alpha}_j$, $\bar{\gamma}_{jt} = \gamma'_t + \tilde{\gamma}_j$, and $\psi_{jt} = \frac{\bar{\gamma}_{jt} - \bar{\alpha}_{jt}}{\alpha - \gamma}$ collect parameters. Note that $\psi_{jt}$ is additively separable in components that depend on $t$ and those that depend on $j$, so it can be represented empirically through location and time fixed effects.

**Solving for Parameters from Coefficients.** To back out the model's parameters from our estimates, we sequentially use the coefficients $\pi_i$ and $\mu_i$ for each COVID-19-related specialty $i \in \{\text{ICU}, \text{ER}, \text{Med-Surg}\}$, along with the $\tau$ and $\kappa$ coefficients for L&D. (That is, $\tau$ and $\kappa$ remain the same as we move across specialties $i$.) Setting the empirical coefficients in (5) and (6) equal to the appropriate model-implied coefficients from (3) and (4) yields:

$$\mu_i + \kappa = \frac{\alpha\delta^i - \beta\gamma}{\alpha - \gamma} \tag{9}$$

$$\kappa = \frac{\alpha\delta^0 - \beta\gamma}{\alpha - \gamma} = -\frac{\beta\gamma}{\alpha - \gamma}, \text{ and } \mu_i = \frac{\alpha\delta^i}{\alpha - \gamma} \tag{10}$$

$$\pi_i + \tau = \frac{-\beta + \delta^i}{\alpha - \gamma} \tag{11}$$

$$\tau = \frac{-\beta + \delta^0}{\alpha - \gamma} = -\frac{\beta}{\alpha - \gamma}, \text{ and } \pi_i = \frac{\delta^i}{\alpha - \gamma} \tag{12}$$

$$\frac{\mu_i}{\pi_i} = \alpha \tag{13}$$

Table 2 reports the of $\hat{\alpha}$ at the bottom of each pair of regressions.

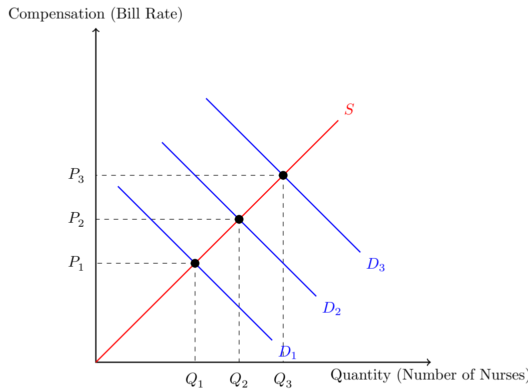
**Limitations and Potential Bias.** Suppose we were to compute the supply elasticity by simply taking the ratio of the coefficients on $c_{jt}$ between equations (4) and (3), without using a control specialty like L&D. But if the true $\beta \neq 0$, the estimate would actually yield

$$\frac{\delta^i\alpha - \gamma\beta}{\delta^i - \beta} < \alpha.$$

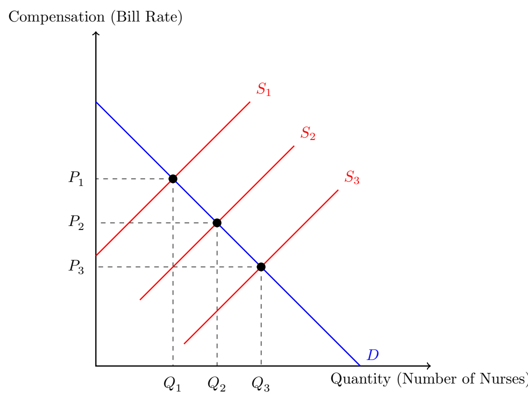
With the mistaken $\beta = 0$ assumption, we would incorrectly believe we computed the supply elasticity, although the estimate actually understates it. We also assume ICU and ER nurses require the same risk compensation as L&D nurses, though their units treat sicker, COVID-positive patients. If they demand extra, their $\beta$ would be more negative than when we hold $\beta$ constant. So our framework may underestimate the supply elasticity.

**Figure C.1: Identifying Supply Elasticity Using Demand Shifters**

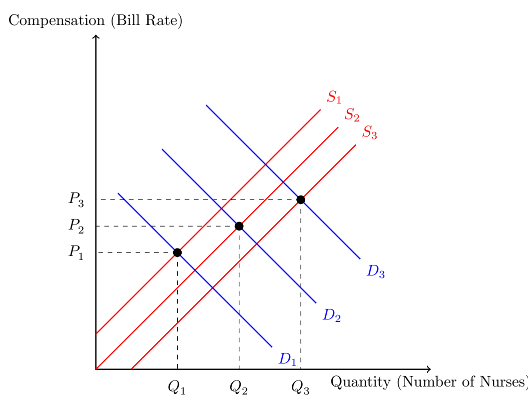
(a) Demand Shifts on a Supply Curve




(b) Supply Shifts on a Demand Curve




(c) Demand and Supply Both Shift




This figure illustrates our main empirical strategy. Panel (a) shows that we can identify the supply curve ($S$) when demand ($D$) shifts exogenously. Panel (b) shows analogously that we can identify the demand curve when supply shifts exogenously. Panel (c) shows how supply estimation would be biased if both curves shift simultaneously; the equilibrium observations (black dots) in Panel (c) do not lie on the same supply curve, so an empirical analysis based on those observations would yield an incorrect estimate of the supply elasticity. Our empirical strategy addresses this bias by measuring compensation ($P$) and quantity ($Q$) relative to a "control" specialty, and using COVID case variation as a demand shifter. The comparision with an unaffected specialty should difference out shifts in the labor supply curve, making the *relative* values we observe close to the situation in Panel (a). Demand curves shift across specialties and states due to COVID case variation over time, enabling us to identify the supply elasticity.

# D Multinomial Choice Model

As an alternative to the baseline model, we implement a multinomial choice model in which nurses choose one job from a specified choice set of jobs available to them. This choice set is defined as all jobs that meet the following two criteria:

- The job is posted in the same week as the job the nurse ultimately accepted. (We can also broaden the choice set to jobs posted over two weeks, or shrink it; results are similar.)
- The job matches the nurse's specialty. Here we focus on five aggregated specialties used throughout the paper: ICU, ER, L&D, Med-Surg, and OR (the "Other" category is dropped here because it consists of sub-specialties that are not necessarily related).

This approximates the true choice set, as we do not actually know the jobs filled by the time a nurse applies, whether she was rejected from a particular job, or other details of the choice set.

Given these assumptions, we construct a dataset of nurse-posting pairs where each nurse is paired with all job postings in her choice set, and each nurse-posting pair is assigned a binary indicator for whether the nurse ultimately filled that position.

**First stage: control function estimation.** As in our baseline estimation, we use state-week log COVID case counts as an instrument for log bill rate. We implement this instrument using a control function approach (Petrin and Train, 2010) to address potential endogeneity concerns in bill rate (e.g., unobserved job characteristics that affect both job choice and the bill rate). Specifically, we run an initial linear regression that relates the state-week bill rate index to the number of new COVID cases in that state and week:

$$w_{ijt} = \tau c_{jt} + \sum_{i=1}^{4} \pi_i \mathbb{1}_i c_{jt} + \theta_{ij} + \phi_t + \eta_{ijt}$$

where:

- $w_{ijt}$ is the log bill rate for specialty $i$ in state $j$ in week $t$
- $\tau$ is the coefficient for our reference specialty expected to be unaffected by COVID: L&D.
- $\sum_{i=1}^{4} \pi_i$ are a set of coefficients for each non-L&D specialty interacted with COVID cases (specialty $i = 0$ represents L&D).
- $\theta_{ij}$ are state-specialty fixed effects
- $\phi_t$ are week fixed effects
- $\eta_{ijt}$ is the residual term at the state-week-specialty level.

The estimates are reported in column (1) of Table E.11. We then control for a polynomial of this regression's residual $\hat{\eta}_{ijt}$ in the second stage choice model to account for endogeneity.

The correlation of COVID cases between states could bias our estimates of the labor supply elasticity, specifically by causing our exclusion restriction to fail. To account for such geographical spillovers, we estimate a second version of this control function in which we add neighboring states' COVID cases as well as their interactions with specialty effects in the first-stage regression. Specifically, we control for the average COVID cases across all neighboring states of a state in the first stage, and retrieve the residuals to implement the second stage. These estimates are reported in column (2) of Table E.11.

**Second stage: multinomial logit estimation.** In the second stage, we estimate a multinomial logit model where the outcome is a dummy variable indicating whether a nurse actually chose the job. Assume each nurse's utility function takes the following form:

$$U_{(ijt)_{np}} = \lambda w_{(ijt)_p} + \varrho c_{jt} + \varphi_1 \xi^1_{(ijt)_p} + \varphi_2 \xi^2_{(ijt)_p} + \psi \chi_{(ijt)_{np}} + \vartheta_j + \upsilon_t + \epsilon_{(ijt)_{np}} \tag{14}$$

which is a function of log bill rate, $w_{(ijt)_p}$, log COVID case count (alternatively, log average COVID case count in neighboring states), $c_{jt}$, two job characteristics (length of assignment, $\xi^1_{(ijt)_p}$, and working hours per week, $\xi^2_{(ijt)_p}$), travel distance between nurse $n$ and job $p$, $\chi_{(ijt)_{np}}$, state fixed effects, $\vartheta_j$, and week fixed effects, $\upsilon_t$. As discussed above, we implement this choice model by additionally controlling for a polynomial $g(\cdot)$ of the control function residuals $\hat{\eta}_{ijt}$ obtained from the first stage. The key assumption is that the new error term, $\tilde{\epsilon}_{(ijt)_{np}}$, is independent of $w_{(ijt)_p}$, having conditioned out the dependence of $w_{(ijt)_p}$ on $\epsilon_{(ijt)_{np}}$ through including $g(\hat{\eta}_{ijt})$. We specifically assume $\epsilon_{(ijt)_{np}}$ is an IID draw from a type 1 extreme value distribution. This implies the following choice probabilities:

$$\Pr\{y_{(ijt)_{np}} = 1\} = \frac{\exp\left(\tilde{\lambda} w_{(ijt)_p} + \tilde{\varrho} c_{jt} + \tilde{\varphi}_1 \xi^1_{(ijt)_p} + \tilde{\varphi}_2 \xi^2_{(ijt)_p} + \tilde{\psi} \chi_{(ijt)_{np}} + \tilde{\vartheta}_j + g(\hat{\eta}_{ijt})\right)}{1 + \sum_{p'} \exp\left(\tilde{\lambda} w_{(ijt)_p} + \tilde{\varrho} c_{jt} + \tilde{\varphi}_1 \xi^1_{(ijt)_p} + \tilde{\varphi}_2 \xi^2_{(ijt)_p} + \tilde{\psi} \chi_{(ijt)_{np}} + \tilde{\vartheta}_j + g(\hat{\eta}_{ijt})\right)} \tag{15}$$

where the tildes ($\sim$) distinguish the coefficients from those in the utility function (14). Time fixed effects are omitted from the model because each choice set is constructed to have only jobs from the same week, which implicitly accounts for those fixed effects.

Table E.12 reports estimates of (15) with varying sets of controls. Different estimates control for additional job characteristics (assignment length and work hours), distance between the nurse's home and the job location, or both; a third-order orthogonal polynomial of the control function residuals is included in even-numbered columns. Results are similar across models, and robust to controlling for log distance squared or changing the choice set (not shown).

**Elasticity calculation.** For each specification of the choice model, we compute nurse $n$'s labor supply elasticity for job (posting) $p$ as:

$$\alpha_{np} = (1 - s_{np})\tilde{\lambda}$$

where $s_{np}$ is nurse $n$'s predicted probability of choosing position $p$ from the second stage, and $\tilde{\lambda}$ is the coefficient on log bill rate from the second stage. We compute the average of $\alpha_{np}$ and report this average labor supply elasticity $\alpha$, along with its standard error obtained using the delta method, in Table E.12.

# E Additional Results

## Table of Contents

**Appendix Table E.1** shows the percentage of travel and non-travel nurses in the National Sample Survey of Registered Nurses (NSSRN) data by sex and race.

**Appendix Figure E.1** shows the time series patterns of the length of a spell, i.e., a nurse working for the same employer for a number of consecutive stints.

**Appendix Table E.2** shows the distribution of the number of stints within a spell.

**Appendix Table E.3** shows summary statistics of main variables during the COVID pandemic.

**Appendix Figure E.2** shows time-series patterns of job posting, compensation, and completed job indices, after seasonal adjustment or across an extended time window.

**Appendix Table E.4** shows robustness of our results to including various different fixed effects in the regressions.

**Appendix Table E.5** controls for lagged COVID cases in the estimation based on posted jobs.

**Appendix Table E.6** controls for lagged COVID cases in the estimation based on completed jobs.[28]

**Appendix Table E.7** add controls for local economic conditions (unemployment, housing market) and for states' COVID policies, such as lockdown orders.

**Appendix Table E.8** uses metropolitan statistical area (MSA) as the geographic level of analysis because some states are quite large and may have sub-regions with different COVID conditions and labor market conditions at any point in time. We find similar (though less precise) results.

**Appendix Table E.9** shows robustness to dropping states with travel nurse wage caps (MA and MN).

**Appendix Table E.10** shows that our results are stable under estimation that accounts for serial correlation in the data.

**Appendix Table E.11 and E.12** show the multinomial choice model results outlined in Appendix D. Table E.11 shows the first-stage control function estimations, and Table E.12 shows the labor supply elasticity estimated using the baseline choice set described in Appendix D.

**Quantifying Supply Elasticity** The paper states:

> To interpret the magnitude of these results, consider workers facing two identical job offers, except one pays twice as much as the other. A supply elasticity of 3.8 implies that 14 times as many workers choose the higher-paid job; 93 percent of workers would choose the job paying double, while 7 percent would choose the job paying half.

This calculation is based on the following calculation: $2^{3.8} \approx 14$ and $\frac{14}{1+14} \approx 0.93$.

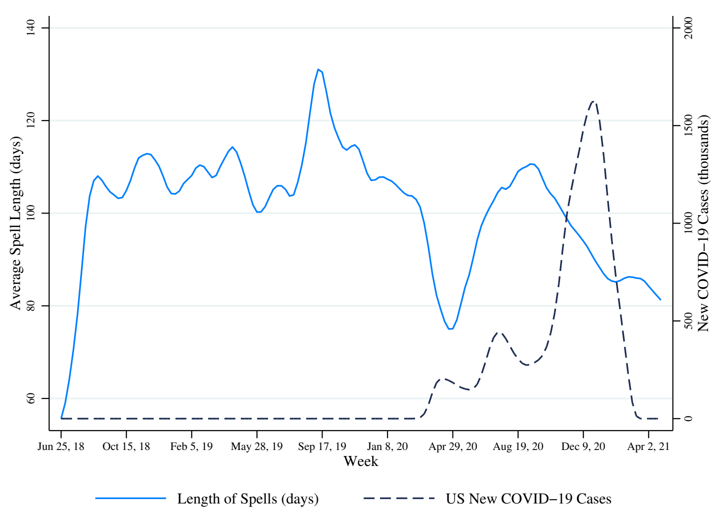
[28]Not surprisingly, given the persistence of cases during a pandemic, the tables with multiple lags suffer from near-collinearity.

**Table E.1: Percentage of Nurses by Sex and Race (from NSSRN Data)**

| | (1) NSSRN - All | (2) NSSRN - Non-Travel | (3) NSSRN - Travel |
|---|---|---|---|
| **Panel A: Sex** | | | |
| Male | 9.61 | 9.54 | 17.09 |
| Female | 90.39 | 90.46 | 82.91 |
| **Panel B: Race** | | | |
| American Indian/Alaska Native | 0.45 | 0.45 | 0.19 |
| Asian | 5.32 | 5.35 | 2.71 |
| Black | 8.06 | 7.96 | 18.87 |
| Native Hawaiian/Pi | 0.67 | 0.66 | 1.50 |
| White | 80.67 | 80.73 | 73.13 |
| Some Other Race | 2.57 | 2.57 | 2.39 |
| Multiracial | 2.26 | 2.27 | 1.20 |
| $N$ | 50273 | 49832 | 441 |

Data are from the 2018 National Sample Survey of Registered Nurses (NSSRN). Col. 1 includes all nurses appearing in the NSSRN dataset. Col. 2 includes only non-travel nurses. Col. 3 includes only travel nurses.

**Figure E.1: Time Series Patterns of Spell Length**




This figure shows the time trends of the length of a "spell", using the full sample of 2018-2021. A spell is defined as the same nurse employed by the same hospital for a number of consecutive stints (see Appendix B for more details). Spells are plotted by week based on their start date, along with national new COVID-19 cases in that week. Data are smoothed using an Epanechnikov kernel.

**Table E.2: Distribution of the Number of Stints within a Spell**

| Period | One stint (%) | Two stints (%) | Three stints (%) | Four or more stints (%) | Overall mean |
|---|---|---|---|---|---|
| Full sample | 87.1 | 8.2 | 2.7 | 2.1 | 1.22 |
| Pre COVID (start date) | 85.7 | 8.1 | 2.7 | 3.5 | 1.28 |
| During COVID (start date) | 89.7 | 7.3 | 1.9 | 1.1 | 1.15 |
| COVID peaks (start date) | 88.3 | 8.2 | 2.7 | .8 | 1.16 |
| Pre COVID (end date) | 85.4 | 8.7 | 3.2 | 2.7 | 1.26 |
| During COVID (end date) | 87.5 | 8.1 | 2 | 2.5 | 1.22 |
| COVID peaks (end date) | 86.3 | 8.6 | 2.8 | 2.3 | 1.24 |

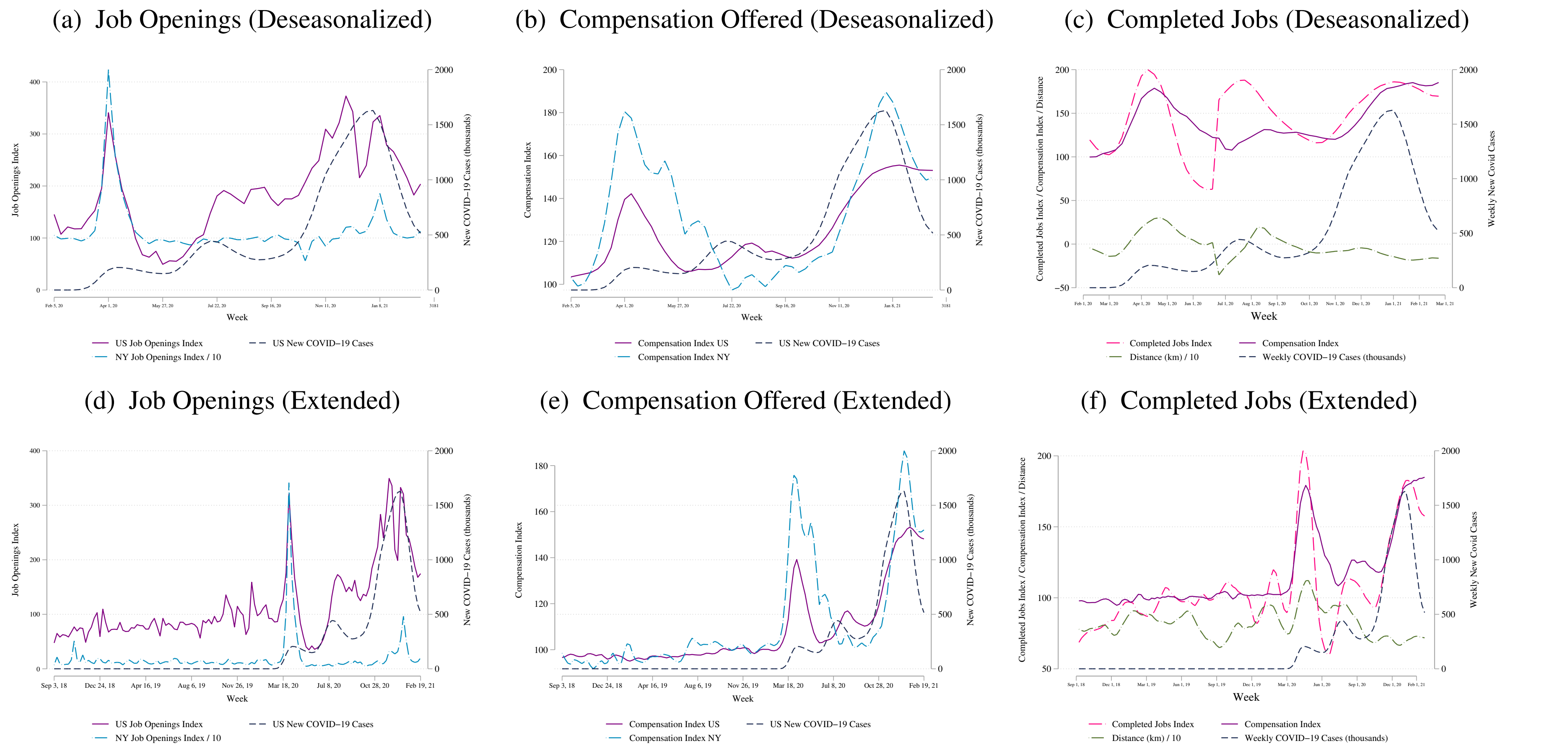
This table shows the share of spells that contain 1, 2, 3, or $\geq 4$ stints, as well as the mean number of stints, for different sample specifications. For each specification (except for the full sample), we use two ways to define the time attribute of a spell, either using its start date or end date (indicated in parenthesis in each row). "COVID peaks" is defined as the 25 percent of weeks with the highest national COVID case counts.

**Table E.3: Summary Statistics During COVID-19 Pandemic**

| Measure | N | Mean | SD | P10 | Median | P90 |
|---|---|---|---|---|---|---|
| Job posting index | 2786 | 129.9 | 171.8 | 19.4 | 81.3 | 283.3 |
| Comp. index (posted jobs) | 2781 | 123.3 | 24.3 | 95.8 | 119.1 | 158.7 |
| Filled jobs index | 1110 | 193.3 | 288.7 | 41.2 | 82.4 | 445.2 |
| Comp. index (filled jobs) | 1110 | 145.9 | 41.7 | 96.6 | 138.4 | 201.3 |
| COVID-19 cases (thousands) | 2786 | 10.17 | 21.11 | .02 | 3.7 | 25.54 |
| Travel distance (miles) | 1110 | 543.1 | 627.1 | 58.5 | 318.3 | 1380.6 |

Data are from Health Carousel and are described in detail in the text. The unit of observation is the state-by-week. The compensation index is normalized relative to the national daily average from February 1–March 14, 2020, weighted by number of job postings. The job posting index is normalized average daily postings, relative to each subsample's average from February 1–March 14, 2020.

**Figure E.2: Deseasonalized and Extended Time-Series Patterns**




Panels (a) through (c) show time-series patterns after seasonal adjustment, and Panels (d) through (f) show time-series patterns across a longer time window. Panel (a) shows job postings in the United States and in New York state from February 5, 2020 through February 25, 2021 minus the value at the corresponding time of the pre-pandemic baseline year September 2018 to August 2019. Data are smoothed using an Epanechnikov kernel. The panel also shows (smoothed) national new COVID-19 cases. Panel (b) shows compensation trends that have been similarly deseasonalized, nationally and for New York state, along with national COVID-19 cases. Panel (c) shows smoothed time series of jobs filled by the recruiting agency, and adds the nurse's travel distance from home to the job location in addition to compensation and the count. Panel (d) shows job postings in the United States and in New York state from September 3, 2018 through February 25, 2021. Data are smoothed using an Epanechnikov kernel. The panel also shows (smoothed) national new COVID-19 cases. Panel (e) shows compensation trends, also nationally and for New York state, along with national COVID-19 cases. Panel (f) shows time series of completed jobs and compensation, average distance traveled from a nurse's home to the job location, and COVID-19 cases over the same time period. All indices are normalized to a mean of 100 in February 2020.

## Table E.4: Labor Supply Estimates with Alternative Fixed Effects

| | (1) Jobs | (2) Comp. | (3) Jobs | (4) Comp. | (5) Jobs | (6) Comp. | (7) Jobs | (8) Comp. | (9) Jobs | (10) Comp. |
|---|---|---|---|---|---|---|---|---|---|---|
| ln(cases) | 0.22*** | 0.075*** | 0.22*** | 0.018 | 0.22*** | 0.040*** | 0.12* | 0.011 | 0.014 | -0.0010 |
| | (0.051) | (0.011) | (0.056) | (0.0096) | (0.047) | (0.012) | (0.058) | (0.011) | (0.033) | (0.010) |
| COVID × ln(cases) | | | 0.071*** | 0.027*** | 0.064** | 0.037*** | | | | |
| | | | (0.021) | (0.0049) | (0.022) | (0.0050) | | | | |
| ICU × ln(cases) | | | | | | | 0.29*** | 0.046*** | 0.37*** | 0.064*** |
| | | | | | | | (0.047) | (0.0065) | (0.086) | (0.016) |
| ER × ln(cases) | | | | | | | 0.12*** | 0.029*** | 0.18* | 0.038* |
| | | | | | | | (0.026) | (0.0049) | (0.075) | (0.017) |
| Med/Surg × ln(cases) | | | | | | | 0.27*** | 0.050*** | 0.36*** | 0.047** |
| | | | | | | | (0.039) | (0.0059) | (0.069) | (0.014) |
| OR × ln(cases) | | | | | | | 0.080 | 0.0038 | -0.034 | 0.0038 |
| | | | | | | | (0.048) | (0.0051) | (0.053) | (0.012) |
| Other × ln(cases) | | | | | | | 0.23*** | 0.013 | 0.33*** | 0.053** |
| | | | | | | | (0.031) | (0.0075) | (0.074) | (0.020) |
| $\alpha$ (overall or ICU) | | 2.9*** | | 2.6*** | | 1.8*** | | 6.3*** | | 5.8*** |
| | | (0.55) | | (0.93) | | (0.53) | | (0.76) | | (1.54) |
| $\alpha$ (ER) | | | | | | | | 4.1*** | | 4.7* |
| | | | | | | | | (0.90) | | (1.96) |
| $\alpha$ (MS/Surg) | | | | | | | | 5.3*** | | 7.6*** |
| | | | | | | | | (0.44) | | (1.77) |
| Observations | 1582 | 1582 | 1078 | 1078 | 1079 | 1079 | 11373 | 11373 | 11373 | 11373 |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Specialty FE | ✓ | ✓ | | | ✓ | ✓ | | | ✓ | ✓ |
| Week-Specialty FE | | | | | | | | | ✓ | ✓ |

This table reports estimates of equations (6) and (5) on Health Carousel data on travel nursing job postings from February 2020–February 2021. Parameters are estimated using GMM. The dependent variable in cols. 1, 3 and 5 is the log number of filled nursing jobs by state-week-specialty and the log number of job postings by state-week-specialty in cols. 7 and 9. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. Filled jobs are a subset of all posted jobs, which explains the large difference in sample size between cols. 1–6 and 7–10. Cols. 1–2 do not distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta = 0$). Cols. 3–6 combine ICU, ER, and Med-Surg together into "COVID-19 specialties," and combine OR with L&D into the omitted category; the "Other" specialty is dropped, resulting in a smaller sample size compared to cols. 1–2. All specifications include week, state, and specialty fixed effects. Cols. 1–2, 5–6 and 9–10 introduce state-specialty interacted fixed effects, and cols. 9–10 additionally introduce week-specialty interacted fixed effects. All columns are weighted by number of filled jobs. Standard errors, in parentheses, are clustered by state. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

## Table E.5: Regression Estimates with Lags of COVID-19 Cases: Posted Jobs

| | (1) Jobs | (2) Comp. | (3) Jobs | (4) Comp. | (5) Jobs | (6) Comp. | (7) Jobs | (8) Comp. | (9) Jobs | (10) Comp. |
|---|---|---|---|---|---|---|---|---|---|---|
| ln(cases) | 0.063 | -0.016 | -0.18 | 0.015 | -0.19* | -0.047** | -0.15 | -0.068*** | -0.19* | -0.056** |
| | (0.098) | (0.016) | (0.13) | (0.036) | (0.078) | (0.015) | (0.085) | (0.015) | (0.076) | (0.017) |
| COVID × ln(cases) | | | 0.13* | 0.030*** | | | | | | |
| | | | (0.052) | (0.0087) | | | | | | |
| ICU × ln(cases) | | | | | 0.37*** | 0.054*** | 0.26*** | 0.092*** | 0.38*** | 0.069*** |
| | | | | | (0.060) | (0.0092) | (0.058) | (0.013) | (0.078) | (0.017) |
| ER × ln(cases) | | | | | 0.17*** | 0.036*** | 0.11 | 0.057*** | 0.20** | 0.042* |
| | | | | | (0.033) | (0.0066) | (0.074) | (0.012) | (0.072) | (0.020) |
| Med/Surg × ln(cases) | | | | | 0.36*** | 0.063*** | 0.34*** | 0.089*** | 0.39*** | 0.050** |
| | | | | | (0.053) | (0.0090) | (0.052) | (0.011) | (0.062) | (0.016) |
| OR × ln(cases) | | | | | 0.091 | 0.0072 | 0.034 | 0.020 | -0.066 | 0.0024 |
| | | | | | (0.070) | (0.0087) | (0.051) | (0.015) | (0.051) | (0.016) |
| Other × ln(cases) | | | | | 0.32*** | 0.019 | 0.37*** | 0.015 | 0.36*** | 0.060* |
| | | | | | (0.044) | (0.011) | (0.051) | (0.015) | (0.070) | (0.024) |
| 1 Week Lag | -0.20 | -0.024 | 0.18 | -0.14* | -0.095 | -0.0096 | -0.11 | -0.013 | -0.15 | -0.014 |
| | (0.12) | (0.022) | (0.20) | (0.057) | (0.11) | (0.021) | (0.11) | (0.022) | (0.100) | (0.021) |
| 2 Week Lag | 0.52*** | 0.10*** | 0.023 | 0.074 | 0.40*** | 0.059* | 0.35*** | 0.059* | 0.37*** | 0.062** |
| | (0.10) | (0.024) | (0.14) | (0.045) | (0.10) | (0.023) | (0.10) | (0.024) | (0.097) | (0.023) |
| 3 Week Lag | 0.029 | -0.0036 | 0.20 | 0.073* | -0.017 | 0.0089 | 0.033 | 0.012 | 0.022 | 0.012 |
| | (0.075) | (0.014) | (0.11) | (0.030) | (0.075) | (0.015) | (0.073) | (0.014) | (0.055) | (0.013) |
| Observations | 2380 | 2380 | 1008 | 1008 | 10694 | 10694 | 10694 | 10694 | 10694 | 10694 |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Specialty FE | | | | | | | ✓ | ✓ | ✓ | ✓ |
| Week-Specialty FE | | | | | | | | | ✓ | ✓ |
| Calendar Week Lags | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 |

This table reports estimates of equations (6) and (5) and includes lagged number of cases as a robustness check. Parameters are estimated using GMM. The dependent variable in cols. 1, 5, 7, and 9 is the log number of job postings while it is log number of filled nursing jobs in column 3. The dependent variable in odd columns is the log compensation for jobs included in the preceding column. Cols. 1–2 are at the state-week level, cols. 3–4 are at the state-week-specialty level, and cols. 5–10 are at the state-week-specialty level. Cols. 3–4 combine ICU, ER, and Med/Surg together into "COVID-19 specialties," and OR and L&D form the omitted category. All specifications include state and specialty fixed effects. Cols. 1-2 and 5-10 are weighted by number of job postings. Cols. 3-4 are weighted by number of filled jobs. All columns include 3 lagged variables that represent number of cases (in log scale) in each of the 3 previous weeks. Standard errors, in parentheses, are clustered by state. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

**Table E.6: Regression Estimates with Lags of COVID-19 Cases: Completed Jobs**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Jobs | Comp. | Jobs | Comp. | Jobs | Comp. | Jobs | Comp. |
| ln(cases) | -0.024 | -0.011 | -0.039 | -0.024 | $0.17^{***}$ | $0.046^{***}$ | 0.038 | $0.030^{*}$ |
| | (0.11) | (0.028) | (0.12) | (0.034) | (0.041) | (0.010) | (0.045) | (0.014) |
| COVID-19 $\times$ ln(cases) | | | | | $0.065^{***}$ | $0.037^{***}$ | $0.21^{***}$ | $0.056^{***}$ |
| | | | | | (0.020) | (0.0060) | (0.060) | (0.017) |
| 1 Week Lag | 0.15 | -0.017 | 0.11 | -0.023 | 0.0055 | 0.000037 | 0.0056 | 0.000032 |
| | (0.16) | (0.038) | (0.17) | (0.043) | (0.0040) | (0.00098) | (0.0042) | (0.0010) |
| 2 Weeks Lag | -0.056 | $0.080^{*}$ | 0.051 | $0.11^{**}$ | 0.0053 | -0.00049 | 0.0056 | -0.00036 |
| | (0.13) | (0.032) | (0.12) | (0.035) | (0.0051) | (0.0013) | (0.0053) | (0.0014) |
| 3 Weeks Lag | $0.20^{*}$ | 0.031 | 0.13 | 0.022 | $-0.010^{**}$ | -0.00041 | $-0.010^{**}$ | -0.00056 |
| | (0.100) | (0.022) | (0.087) | (0.025) | (0.0032) | (0.00085) | (0.0034) | (0.00087) |
| Observations | 1492 | 1492 | 1492 | 1492 | 1079 | 1079 | 1079 | 1079 |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Specialty FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week-Specialty FE | | | ✓ | ✓ | | | ✓ | ✓ |

This table reports estimates of equations (6) and (5) and includes lagged number of cases as a robustness check. Parameters are estimated using GMM. The dependent variable in the odd-numbered columns is the log number of filled nursing jobs by state-week-specialty. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. All columns include 3 lagged variables that represent number of cases (in log scale) in each of the 3 previous weeks. Cols. 1–4 do not distinguish among specialties. Cols. 5–8 combine ICU, ER, and Med-Surg together into "COVID-19 specialties," and combine OR with L&D into the omitted category. Cols. 3–4 and 7–8 introduce week-specialty fixed effects. All specifications include week, state, specialty, and state-specialty interacted fixed effects, and are weighted by the number of filled jobs. Standard errors, in parentheses, are clustered by state. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

**Table E.7: Labor Supply Estimates Controlling for Unemployment, House Prices, and COVID-19 Policy**

| | (1) Jobs | (2) Comp. | (3) Jobs | (4) Comp. | (5) Jobs | (6) Comp. | (7) Jobs | (8) Comp. |
|---|---|---|---|---|---|---|---|---|
| ln(cases) | 0.20*** | 0.078*** | 0.075 | 0.018 | 0.33*** | 0.045*** | 0.11* | 0.0019 |
| | (0.048) | (0.0085) | (0.052) | (0.013) | (0.058) | (0.012) | (0.051) | (0.015) |
| COVID-19 × ln(cases) | | | 0.21* | 0.061*** | | | | |
| | | | (0.095) | (0.018) | | | | |
| ICU × ln(cases) | | | | | | | 0.25*** | 0.056*** |
| | | | | | | | (0.047) | (0.015) |
| ER × ln(cases) | | | | | | | 0.12* | 0.042** |
| | | | | | | | (0.062) | (0.014) |
| Med/Surg × ln(cases) | | | | | | | 0.27*** | 0.055*** |
| | | | | | | | (0.038) | (0.0100) |
| OR × ln(cases) | | | | | | | 0.023 | 0.020 |
| | | | | | | | (0.042) | (0.011) |
| Other × ln(cases) | | | | | | | 0.22*** | 0.029 |
| | | | | | | | (0.040) | (0.016) |
| $\alpha$ (overall or ICU) | | 2.5*** | | 3.4* | | 7.4*** | | 4.5*** |
| | | (0.63) | | (1.51) | | (1.15) | | (0.94) |
| $\alpha$ (ER) | | | | | | | | 2.9*** |
| | | | | | | | | (0.97) |
| $\alpha$ (Med/Surg) | | | | | | | | 4.9*** |
| | | | | | | | | (0.62) |
| Observations | 1582 | 1582 | 1079 | 1079 | 11373 | 11373 | 11373 | 11373 |
| Economic control(s) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Economic control(s) × COVID specialties | | | ✓ | ✓ | | | | |
| Economic control(s) × all specialties | | | | | | | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ |
| Week-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | | |

This table reports estimates of equations (6) and (5) on Health Carousel data on travel nursing job postings from February 2020–February 2021. State-month level unemployment rate, state-quarter level House Price Index and state-week level COVID policy index are included as control variables in all columns. Parameters are estimated using GMM. The dependent variable in cols. 1 and 3 is the log number of filled nursing jobs by state-week-specialty and the log number of job postings by state-week-specialty in cols. 5 and 7. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. Cols. 1–2 and 5–6 do not distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta = 0$). Cols. 3–4 combine ICU, ER, and Med-Surg together into "COVID-19 specialties," and combine OR with L&D into the omitted category; these columns also control for the interaction between each economic control and "COVID-19 specialties." In cols. 7–8, the omitted nursing specialty is labor and delivery; these columns also control for the interaction between each economic control and each specialty except for L&D. All specifications include state and specialty fixed effects. Cols. 1–4 are weighted by number of filled jobs and cols. 5–8 are weighted by number of job postings. Standard errors, in parentheses, are clustered by state. $^{*}p < 0.05$,$^{**}p < 0.01$,$^{***}p < 0.001$.

**Table E.8: Labor Supply Estimates at MSA Level**

| | (1) Jobs | (2) Comp. | (3) Jobs | (4) Comp. | (5) Jobs | (6) Comp. | (7) Jobs | (8) Comp. |
|---|---|---|---|---|---|---|---|---|
| ln(cases) | 0.18* | 0.054*** | 0.056 | 0.012 | 0.26*** | 0.034*** | 0.11 | 0.0014 |
| | (0.088) | (0.014) | (0.032) | (0.019) | (0.077) | (0.0099) | (0.063) | (0.0082) |
| COVID × ln(cases) | | | 0.17 | 0.040 | | | | |
| | | | (0.098) | (0.023) | | | | |
| ICU × ln(cases) | | | | | | | 0.14*** | 0.048*** |
| | | | | | | | (0.040) | (0.0049) |
| ER × ln(cases) | | | | | | | 0.082*** | 0.029*** |
| | | | | | | | (0.021) | (0.0045) |
| Med/Surg × ln(cases) | | | | | | | 0.16*** | 0.043*** |
| | | | | | | | (0.026) | (0.0042) |
| OR × ln(cases) | | | | | | | 0.021 | 0.00032 |
| | | | | | | | (0.022) | (0.0031) |
| Other × ln(cases) | | | | | | | 0.17*** | 0.00027 |
| | | | | | | | (0.026) | (0.0061) |
| $\alpha$ (overall or ICU) | | 3.3** | | 4.3 | | 7.5*** | | 3.0*** |
| | | (1.23) | | (2.34) | | (0.69) | | (0.70) |
| $\alpha$ (ER) | | | | | | | | 2.8*** |
| | | | | | | | | (0.65) |
| $\alpha$ (Med/Surg) | | | | | | | | 3.8*** |
| | | | | | | | | (0.48) |
| Observations | 1336 | 1336 | 1248 | 1248 | 32158 | 32158 | 31691 | 31691 |
| MSA FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| MSA-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ |
| Week-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | | |

This table reports estimates of equations (6) and (5) on Health Carousel data on travel nursing job postings from February 2020–February 2021. Parameters are estimated using GMM. The dependent variable in cols. 1 and 3 is the log number of filled nursing jobs by MSA-week-specialty and the log number of job postings by MSA-week-specialty in cols. 5 and 7. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. Cols. 1–2 and 5–6 do not distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta = 0$). Cols. 3–4 combine ICU, ER, and Med-Surg together into "COVID-19 specialties," and combine OR with L&D into the omitted category. In cols. 7–8, the omitted nursing specialty is labor and delivery. All specifications include MSA and specialty fixed effects. Cols. 1–4 are weighted by number of filled jobs and cols. 5–8 are weighted by number of job postings. Standard errors, in parentheses, are clustered by MSA. $^{*}p < 0.05$,$^{**}p < 0.01$,$^{***}p < 0.001$.

## Table E.9: Labor Supply Estimates Excluding States with Travel Nurse Wage Caps

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Jobs | Comp. | Jobs | Comp. | Jobs | Comp. | Jobs | Comp. |
| ln(cases) | 0.21*** | 0.076*** | 0.061 | 0.024* | 0.35*** | 0.044*** | 0.15** | 0.00090 |
| | (0.053) | (0.0099) | (0.045) | (0.012) | (0.064) | (0.013) | (0.057) | (0.013) |
| COVID × ln(cases) | | | 0.24* | 0.055*** | | | | |
| | | | (0.094) | (0.016) | | | | |
| ICU × ln(cases) | | | | | | | 0.20*** | 0.063*** |
| | | | | | | | (0.034) | (0.0081) |
| ER × ln(cases) | | | | | | | 0.078 | 0.038*** |
| | | | | | | | (0.043) | (0.0082) |
| Med/Surg × ln(cases) | | | | | | | 0.22*** | 0.058*** |
| | | | | | | | (0.030) | (0.0063) |
| OR × ln(cases) | | | | | | | 0.039 | 0.011 |
| | | | | | | | (0.028) | (0.0085) |
| Other × ln(cases) | | | | | | | 0.22*** | 0.0072 |
| | | | | | | | (0.029) | (0.0087) |
| $\alpha$ (overall or ICU) | | 2.7*** | | 4.3** | | 7.9*** | | 3.1*** |
| | | (0.67) | | (1.63) | | (1.27) | | (0.43) |
| $\alpha$ (ER) | | | | | | | | 2.1* |
| | | | | | | | | (0.88) |
| $\alpha$ (Med/Surg) | | | | | | | | 3.8*** |
| | | | | | | | | (0.40) |
| Observations | 1538 | 1538 | 1050 | 1050 | 10892 | 10892 | 10892 | 10892 |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| State-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | ✓ | ✓ |
| Week-Specialty FE | ✓ | ✓ | ✓ | ✓ | | | | |

This table reports estimates of equations (6) and (5) on Health Carousel data on travel nursing job postings from February 2020–February 2021. States with travel nurse wage caps (MA and MN) are excluded. Parameters are estimated using GMM. The dependent variable in cols. 1 and 3 is the log number of filled nursing jobs by state-week-specialty and the log number of job postings by state-week-specialty in cols. 5 and 7. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. Cols. 1–2 and 5–6 do not distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta = 0$). Cols. 3–4 combine ICU, ER, and Med-Surg together into "COVID-19 specialties," and combine OR with L&D into the omitted category. In cols. 7–8, the omitted nursing specialty is labor and delivery. All specifications include state and specialty fixed effects. Cols. 1–4 are weighted by number of filled jobs and cols. 5–8 are weighted by number of job postings. Standard errors, in parentheses, are clustered by state. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

**Table E.10: Labor Supply Estimates with Autocorrelation Adjustment: Cochrane-Orcutt Method**

| | (1) Jobs | (2) Comp. | (3) Jobs | (4) Comp. |
|---|---|---|---|---|
| ln(cases) | $0.45^{***}$ | $0.054^{***}$ | $0.31^{***}$ | 0.013 |
| | (0.036) | (0.0070) | (0.034) | (0.0089) |
| ICU $\times$ ln(cases) | | | $0.12^{***}$ | $0.055^{***}$ |
| | | | (0.030) | (0.0088) |
| ER $\times$ ln(cases) | | | 0.041 | $0.031^{***}$ |
| | | | (0.029) | (0.0085) |
| Med/Surg $\times$ ln(cases) | | | $0.14^{***}$ | $0.054^{***}$ |
| | | | (0.026) | (0.0080) |
| OR $\times$ ln(cases) | | | -0.0070 | 0.0028 |
| | | | (0.029) | (0.0088) |
| Other $\times$ ln(cases) | | | $0.17^{***}$ | 0.0015 |
| | | | (0.030) | (0.0083) |
| $\alpha$ (overall or ICU) | | 8.4*** | | 2.2*** |
| | | (1.06) | | (0.45) |
| $\alpha$ (ER) | | | | 1.3 |
| | | | | (0.79) |
| $\alpha$ (Med/Surg) | | | | 2.6*** |
| | | | | (0.39) |
| Observations | 9391 | 9391 | 9391 | 9391 |
| $\rho$ | 0.17 | 0.32 | 0.11 | 0.24 |
| State FE | ✓ | ✓ | ✓ | ✓ |
| Week FE | ✓ | ✓ | ✓ | ✓ |
| Specialty FE | ✓ | ✓ | ✓ | ✓ |
| State-Specialty FE | | | ✓ | ✓ |

This table re-runs cols. 5–8 of the main table using the Cochrane-Orcutt method of accommodating autocorrelation. In this table, one autocorrelation parameter, $\rho$, is estimated for the entire dataset. The estimates in this table were generated by manually implementing the Cochrane-Orcutt method. This table reports estimates of equations (6) and (5) on Health Carousel data on travel nursing job postings from February 2020-February 2021. The dependent variable in cols. 1 and 3 is the log number of job postings by state-week-specialty. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. Cols. 1–2 do not distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta$ = 0). In cols. 3–4, the omitted nursing specialty is labor and delivery. Cols. 1–4 are weighted by number of job postings. Standard errors, in parentheses, are heteroskedasticity and autocorrelation robust and employ a bartlett kernel with a lag of 2. $^{*}p < 0.05$,$^{**}p < 0.01$,$^{***}p < 0.001$.

**Table E.11: Multinomial Choice Model: First Stage**

| Dependent variable: | ln(bill rate) | |
|---|---|---|
| | (1) | (2) |
| ln(cases) | -0.0043 | -0.025** |
| | (0.0065) | (0.0090) |
| ICU × ln(cases) | 0.046*** | 0.054*** |
| | (0.0037) | (0.011) |
| ER × ln(cases) | 0.024*** | 0.037** |
| | (0.0031) | (0.013) |
| Med/Surg × ln(cases) | 0.032*** | 0.047*** |
| | (0.0031) | (0.0089) |
| OR × ln(cases) | 0.0068* | 0.026* |
| | (0.0029) | (0.012) |
| ln(avg neighbors' cases) | | 0.026* |
| | | (0.011) |
| ICU × ln(avg neighbors' cases) | | -0.0056 |
| | | (0.011) |
| ER × ln(avg neighbors' cases) | | -0.011 |
| | | (0.012) |
| Med/Surg × ln(avg neighbors' cases) | | -0.013 |
| | | (0.0094) |
| OR × ln(avg neighbors' cases) | | -0.019 |
| | | (0.012) |
| $N$ | 8315 | 8286 |
| adj. $R^2$ | .54 | .54 |
| ln(cases) × specialty joint $F$-stat | 50.14 | 37.84 |
| $p$ value for joint $F$-stat | $< 0.01$ | $< 0.01$ |
| Instrument contains neighbors' COVID cases | | ✓ |
| State FE | ✓ | ✓ |
| Week FE | ✓ | ✓ |
| State-specialty FE | ✓ | ✓ |
| Specialty FE | ✓ | ✓ |

This table reports estimates of the control function to be used in estimating the multinomial logit job choice model. This estimation uses state-week-specialty-level data. The dependent variable in both columns is the average log compensation. The common regressors in both columns are the log number of weekly new COVID cases in a given state and its interactions with all specialties other than "L & D," and in col. 2 the regressors also include the log number of average weekly new COVID cases across all of the state's neighboring states and its interactions with specialties. All specifications include state and specialty fixed effects. Standard errors, in parentheses, are clustered by state. $^{*}p < 0.05$,$^{**}p < 0.01$,$^{***}p < 0.001$.

**Table E.12: Estimates of Multinomial Choice Model**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Labor supply elasticity ($\alpha$) | $2.80^{***}$ | $2.79^{***}$ | $2.91^{***}$ | $2.74^{***}$ | $2.83^{***}$ | $2.83^{***}$ | $2.93^{***}$ | $2.79^{***}$ |
| | (0.11) | (0.11) | (0.12) | (0.12) | (0.11) | (0.11) | (0.12) | (0.12) |
| ln(cases) ($\tilde{\varrho}_1$) | $-0.12^{***}$ | $-0.19^{***}$ | $-0.13^{***}$ | $-0.20^{***}$ | $-0.19^{***}$ | $-0.10^{*}$ | $-0.12^{***}$ | $-0.11^{*}$ |
| | (0.011) | (0.016) | (0.015) | (0.018) | (0.014) | (0.049) | (0.022) | (0.054) |
| ln(avg neighbors' cases) ($\tilde{\varrho}_2$) | | | | | $0.16^{***}$ | $-0.12^{*}$ | -0.040 | $-0.12^{*}$ |
| | | | | | (0.020) | (0.053) | (0.028) | (0.057) |
| Control function residuals—linear | $-0.42^{*}$ | $-0.15^{***}$ | -0.31 | $-0.075^{*}$ | $-0.56^{**}$ | $-0.16^{***}$ | -0.31 | $-0.085^{*}$ |
| | (0.21) | (0.031) | (0.25) | (0.034) | (0.21) | (0.031) | (0.25) | (0.034) |
| Control function residuals—quadratic | | $0.073^{**}$ | | $0.11^{***}$ | | $0.074^{**}$ | | $0.11^{***}$ |
| | | (0.027) | | (0.026) | | (0.027) | | (0.026) |
| Control function residuals—cubic | | $-0.078^{***}$ | | $-0.070^{**}$ | | $-0.076^{***}$ | | $-0.068^{**}$ |
| | | (0.022) | | (0.023) | | (0.022) | | (0.023) |
| Assignment length ($\tilde{\varphi}_1$) | | 0.021 | | $0.029^{*}$ | | 0.021 | | $0.029^{*}$ |
| | | (0.011) | | (0.011) | | (0.011) | | (0.011) |
| Hours per week ($\tilde{\varphi}_2$) | | $0.071^{***}$ | | $0.063^{***}$ | | $0.070^{***}$ | | $0.062^{***}$ |
| | | (0.0045) | | (0.0053) | | (0.0045) | | (0.0053) |
| ln(distance) ($\tilde{\psi}$) | | | $-1.12^{***}$ | $-1.13^{***}$ | | | $-1.12^{***}$ | $-1.13^{***}$ |
| | | | (0.024) | (0.025) | | | (0.024) | (0.025) |
| $N$ | 1937440 | 1928966 | 1622220 | 1615147 | 1932356 | 1923898 | 1618169 | 1611100 |
| Neighbors' COVID in first stage | | | | | ✓ | ✓ | ✓ | ✓ |
| State FE | | ✓ | | ✓ | | ✓ | | ✓ |

This table reports second-stage results from estimating a multinomial logit model with a control function. Each observation in the regressions is a nurse-posting pair. Cols. 1–4 use control function residuals obtained from the first-stage regression in which we only control for a state's own COVID cases, and thus a state's own log COVID case count is included in the regressions; cols. 5–8 use control function residuals obtained from the first-stage regression in which we control for a state's own COVID cases as well as its neighboring states' COVID cases, and thus we control for a state's own log COVID cases and COVID cases of its neighboring states. The dependent variable in all columns is an binary indicator variable for whether the nurse accepted that position. In cols. 1 and 5, the regressors include log bill rate and the control function residuals from the first-stage regression. Cols. 2 and 6 additionally control for job posting characteristics (i.e., length of assignment and working hours per week). Cols. 3–4 and 7–8 are analogous to cols. 1–2 and 5–6, respectively, additionally controlling for log distance between the nurse and the working location. State fixed effects and a third-order orthogonal polynomial of the control function residuals are included in even-numbered columns. For simplicity, we omit the coefficients on log bill rate and directly report the computed labor supply elasticities ($\alpha$) instead. The standard error of $\hat{\alpha}$ is computed by the delta method, and all standard errors are robust to heteroskedasticity. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.