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

Joshua D. Gottlieb
University of Chicago
and NBER

Avi Zenilman, R.N.
Yale University

May 14, 2022

Abstract

We study how a market uses temporary workers to accommodate extraordinary demand shocks. When COVID-19 surges, hospitals need additional nurses—especially for specialties central to COVID-19 care. We show that the market for traveling nurses expands dramatically and estimate travel nurse labor supply across space by comparing COVID-relevant and other specialties. 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.

*Gottlieb: jgottlieb@uchicago.edu. Zenilman: avi.zenilman@yale.edu. We are grateful to Health Carousel for providing data, to Vaidehi Parameswaran, Daniel Sonnenstuhl, Scott Loring, and Wanran Zhao for excellent research assistance, and to the Becker-Friedman Institute for support. We thank Bill DeVille, Amie Ewald, Debbie Freund, Stephen Gottlieb, Wes Hamilton, Jeff Hicks, Dmitri Koustas, Brian LeCount, Neale Mahoney, Hugh Shiplett, and Janine Sulavik for helpful comments.

Does temporary staffing help labor markets to address temporary demand shocks (Abraham and Taylor, 1996; Autor, 2003; Katz and Krueger, 2017), or does a fixed stock of qualified workers prevent any such benefits? We use the COVID-19 pandemic to study the short-term labor market for nurses—a context where adequate 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 supply elasticity of temporary nurse labor. We find labor supply to be quite elastic as nurses can choose different locations in response to rapidly fluctuating compensation. We investigate the contribution of workers' mobility across space to illuminate how the labor market accommodates these short-term demand surges. Our results speak to the likely impacts of regulation, such as the price caps that Massachusetts (2020a,b) and Minnesota (2020) impose on hospitals hiring travel nurses and which legislators have proposed elsewhere (Brusie, 2022).

Nursing during COVID-19 is a context in which we might expect little scope for supply adjustments. Entry to nursing requires training and licensure. There are longstanding concerns about insufficient supply (Buerhaus et al., 2000, 2009). COVID-19 led to historic demand shocks (Hawryluk and Bichell, 2020) while immigration bans simultaneously choked off an important part of labor supply (Lind, 2020; Reed and Kreighbaum, 2021).

On the other hand, there are institutions in place to help match supply and demand in this market. Hospitals and other facilities regularly use temporary nurses to fill short-term nursing needs due to seasonal demand spikes, holidays, or idiosyncratic worker absences. Temporary nursing is worth $10 billion annually (Landuis and Starkey, 2020), or approximately 7 percent of the overall nursing labor market (Bureau of Labor Statistics, 2020). Travel nursing—where nurses are hired for multi-week stints, sometimes traveling across the country—comprises the bulk of this market.

Travel nurses are recruited for particular openings, so hospitals must offer terms that attract the needed staff. Nurses choose jobs at fluctuating prices and conditions 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. These intermediaries evaluate match quality, verify nurses' skills (such as critical care or obstetrics experience), and manage regulatory hurdles such

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

as state board licensing.

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 take advantage of these historic demand shocks (Hawryluk and Bichell, 2020) to study supply and worker mobility in this spot labor market. The literature relies on extremely short-term markets for Uber drivers or online tasks to study contingent worker behavior. (Hall et al., 2015; Angrist et al., 2017; Mas and Pallais, 2017; Chen and Sheldon, 2015; Chen et al., 2020; Farrell et al., 2018; Caldwell and Oehlsen, 2018; Koustas, 2019).[2] But contingent work often spans longer than an Uber ride and may have deeper consequences for hospital functioning, patient care, and labor market regulation.

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), is 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, such as ICU and ER nursing, and specialties such as labor & delivery (L&D), which did not experience a demand shock (because the number of near-term pregnant women did not increase exponentially).

Based on the differences in compensation and jobs for COVID-19 specialties and L&D nursing, we use a panel of states over the pandemic to estimate the travel nurse supply curve. We estimate supply elasticities of 2 to 4, suggesting that price signals are an effective way of moving 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, which is especially likely when COVID cases

[2] Autor (2003); Collins et al. (2019); Katz and Krueger (2019a,b) discuss the size and trajectory of the contingency labor workforce. Temporary workers and independent contractors are a blind spot in many labor market datasets (Abraham et al., 2017), and may work simultaneously on multiple platforms (Koustas, 2019). Most of the evidence on the staffing industry comes from employers' perspective (Abraham, 1988; Abraham and Taylor, 1996; Houseman, 2001; Dey et al., 2012).

rise. 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 from low-demand to high-demand regions, 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 to demand and more strongly to compensation when national demand is lower. This suggests that—at least when there is some slack capacity nationally—the supply responses we estimate indeed reallocate workers to where they are needed.

This distinction between state-level and national demand highlights some important qualifications for our results. These elasticities specifically describe the short-term travel nursing markets across space. They cannot be directly applied to the nursing market overall, or an individual hospital's permanent nursing workforce, where supply could behave differently (Staiger et al., 2010; Matsudaira, 2014).

Section 1 discusses the institutional context of travel nursing and introduces our data. The COVID-19 pandemic and recession has many simultaneous shocks, some of which could threaten supply estimation. Section 2 introduces the conceptual and empirical 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. This market has long been the focus of concerns 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 essential structure is similar: the hospital sets a price, working conditions, and contract length (usually 13 weeks). An intermediary, such as a supplemental staffing agency, tries to recruit a registered nurse to match the position. The nurses are generally employees of the intermediary, which provides benefits, liability insurance, and quality check. Hospitals thus outsource recruiting, licensing, and other HR tasks. Nurses that accept these contracts are generally called "travel nurses," even though many live nearby. (Hospitals sometimes hire them full-time after the temporary contract.)

The nurses in this market are licensed like any other registered nurse. They are more likely to have a bachelor's degree, and observational studies have found that, after adjusting for hospital quality, there are no deleterious outcomes associated with their use (Xue et al., 2012a,b). They may take traveling jobs because they are looking for adventure, because they don't have an acceptable job offer in their home location, or because they value the flexibility of temporary work (Mas and Pallais, 2020; He et al., 2021). They may also earn higher hourly pay than a traditional nursing job and may value focusing their labor effort during some times, while taking leisure at other times.

The price the hospital offers for travel nurse labor (the "bill rate" in industry terminology) must cover the nurse's wages and the intermediary's fee, which includes benefits, housing stipends, transportation, and administrative costs.[3] 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. When recruiters text potential recruits, they often include compensation in the initial solicitation. Appendix A shows some examples.

Health Carousel, one of the ten largest healthcare staffing firms in the United States, provided 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 all 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 nationwide average in early 2020. When multiple nurses are requested or hired, we aggregate the total number

[3]Some hospitals have exclusive relationships with staffing agencies that essentially operate their own self-contained marketplace, while others may post to independent vendor management systems for an auction.

of nurses rather than just the number of postings. We convert total counts of both job openings and nurses hired by Health Carousel ("completed jobs") into indices relative to their early-2020 averages.

We measure compensation, job openings, and completed jobs, both nationally and within subsamples by specialty and state. We define six categories of nursing specialties: Emergency Room (ER), Adult Intensive Care (ICU), standard hospital floors (Medical-Surgical or Telemetry), Labor and Delivery (L&D), Operating Room (OR), and Other.[4,5]

For completed jobs, the data report the residential zip code of the nurse who filled the opening. We use this to compute the straight-line travel distance between the nurse's residence and job location. We measure state and national COVID-19 incidence as the number of new cases reported daily or weekly by the Johns Hopkins Coronavirus Resource Center. We use data on staffing shortages that hospitals self-report to the Department of Health and Human Services (2022).

2 Framework

We model log supply of specialty i nurses in location 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 (α^*_j) due to the cost, convenience, or amenities for nurses. Since nurses can choose whether to enter the market, we allow for time-varying national supply shocks α'_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,

[4]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.

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

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

We equate nurse supply to demand and solve for the equilibrium wages and quantity in each market (omitting fixed effects):[6]

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

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

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 (α and γ), and with respect to COVID-19 prevalence (β and δ^i)—and we only have two equations. Understanding the behavior of nursing supply requires further data and assumptions.

We address this by adding a specialty such as L&D, where demand is plausibly independent of COVID-19 cases ($\delta^0 = 0$), alongside others where COVID affects demand ($\delta^i \neq 0$). Assuming the model's remaining parameters are the same across the specialties, we can difference them out and solve for the supply elasticity (α). This approach suggests 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 θ_j and ρ_j are state fixed effects, and ϕ_t and σ_t are time fixed effects. τ and κ estimate the coefficients from (3) and (4) for the specialty unaffected by COVID-19. π_i and μ_i for specialty $i \neq 0$ capture the differences in those coefficients relative to the unaffected specialty. Appendix B shows that the ratio of these parameters yields the supply elasticity: $\alpha = \frac{\mu_i}{\pi_i}$.

The fixed effects in (5) and (6) remove some of the 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 that estimate separate time and/or state fixed effects for each specialty.

These fixed effects ensure that we are identifying the model within state and time. This variation

[6] Appendix B shows the full expressions.

is useful because our goal is understanding short-term reallocation and flexibility in this market. We do not need to understand why baseline compensation is higher in New York than Arizona (unions? living costs? regulations?) in order to understand the within-state variation over time. Nor do we need to know national extensive margin elasticities (due to nurse training in the long run, or short-run entry into travel nursing) in order to understand allocation across space at a point in time.

Our interpretation requires certain assumptions. First, the parameters aside from δ^i are constant across specialties. While this assumption is strong, its failure would cause errors in a predictable direction. If we incorrectly assume that nurses do not require COVID-19 risk compensation ($\beta = 0$), we would 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 under-states 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 β would be more negative than when we hold β constant. So our framework may underestimate the supply elasticity.

Our second assumption is that the market is segmented between specialties. This may not be perfectly true, but compensation does diverge between specialties, as we would expect from the genuine differences in skills and experience that different specialties require. To the extent nurses can substitute between specialties, this may help explain the high supply elasticities we find.

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.[7] Despite hypothetical concerns, 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 instance, nurses in

[7] Our 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)

economically-disrupted COVID-19 hotspots could lose their jobs and enter the travel nursing workforce, causing a simultaneous nurse supply and demand shocks. Since the workers we conser travel nationally, time fixed effects should control for supply shocks. Nurse preference for shorter travel should bias against the relationship we find between travel distance and pandemic severity.

3 Time-Series Patterns

We begin with descriptive patterns and the time-series relationships in the data. Table 1 displays the descriptive patterns, nationally and in key subsamples.[8] 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 to 156 in late summer and 304 by late fall. The national compensation index was 133 in spring, 103 in early summer, 114 in late 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 spikes in COVID-19 cases. COVID-19 cases began increasing sharply after March 15, 2020, exceeding 30,000 daily by April 2. They gradually declined to 20,000 in early June, before increasing again to 67,000 by July 15. They fell again in late summer, before increasing again to 250,000 in late fall and early winter 2021. The national job openings index fluctuated between 80 and 130 from February 1 through March 15, 2020. The pandemic changed this rapidly. By April 6, the job openings index reached 300. It plummeted to 35 in late May, and stayed low until July, when outbreaks in the southern and southwestern states peaked. It reached 170 by July 27, and 185 by the end of August. After falling slightly, it skyrocketed to 350 in late fall and early winter 2021, before declining back to 150 by the end of our sample.

The graph includes a corresponding trend for New York, which experienced the largest and fastest increase in COVID-19 at the beginning of the pandemic. New York's daily cases (not shown) grew from 300 on March 15 to 10,000 by April 3. The job openings index, stable near its baseline value of 100 until early March, 2020, increased to over 2,500 during the first week of April. (The graph shows the New York index divided by 10.) By April 15, it was 1,100, and

[8] Appendix Table C.1 shows corresponding values for February–August 2020.

ultimately returned to baseline on May 7. The job openings index remained low until late August. It experienced a more modest spike in late fall 2020, which peaked 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, reaching 110 by March 26 and peaking at 125 by April 10. It declined in May, returning to baseline in June. It increased again in the second half of July, reaching 115 by early August and 146 by the end of the sample. New York's compensation index was 105 in February, trended upwards in March, reached 140 by March 24, and then peaked at 165 within days. It remained around 160 through May, and then declined to 100 by the end of 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.[9] Completed jobs more than double from early 2020 to the April peak. Job completions fall in early summer, reaching below the baseline value of 100 in June, before climbing again in late summer, and surging again in early 2021 to nearly the 2020 peak. Compensation follows a similar pattern, increasing during the pandemic's initial phase, falling during the summer, and exceeding the 2020 peak in 2021.

We see additional characteristics for filled jobs: the worker's home location and the location of the job accepted. 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 back to 900 km in the summer and 700 km in fall 2020 and winter 2021. This provides initial evidence that the market accommodated the early surge in demand through workers' willingness to travel longer distances. 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. In contrast, OR and L&D postings don't exhibit COVID-related cylicality, and even decline during the initial wave. Panel 1(e) shows compensation by specialty. Compensation largely follows the pattern of job openings,

[9]For each of these three panels, Appendix Figure C.1 shows an analogous graph incorporating a seasonal adjustment and Figure C.2 shows an analogous graph extending back to September 1, 2018. Panel C.2(a) shows a secular increase in job openings during the pre-pandemic sample, with seasonal increases in December and January.

except at the end of the sample. Compensation for COVID-19 specialties stays high throughout winter 2021, even as job postings decline.

Returning to Table 1(b), the next six rows summarize descriptive patterns by specialty. The first column shows the specialty's share of all 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 late fall, with compensation indices of 131 and 134, respectively. In contrast, the OR job openings index fell to 56 in spring 2020 as many 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 COVID exposure risk or tougher working conditions.

The next three rows summarize New York's, Massachusetts', and Arizona's experiences, and Appendix Table C.2 shows patterns for all states. Despite their 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-day level. The elasticity of job completions with respect to COVID-19 cases of 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, and would generate the correct aggregate elasticity if there were one unified market across all specialties and if COVID cases do not affect labor supply ($\beta = 0$). Under these assumptions, the supply elasticity is 2.7—the ratio of the quantity and compensation

coefficients.

Since nurses might demand risk compensation, the remaining columns implement specifications (5) and (6). Below the estimates, we compute the supply elasticity implied by each pair of regressions. These calculations use our framework from section 2 to solve for α; specifically, they use specialties less affected by COVID-19 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.[10]

In order 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 0.26 and an overall compensation elasticity of 0.035 with respect to local COVID cases. Columns 7 and 8 report separate interactions for each specialty each specialty's separate interaction with COVID cases—π_i and μ_i from equations (5) and (6)—with L&D the omitted category. Both columns show insignificant positive estimates between COVID-19 cases and L&D openings or wages (the omitted specialty). This is consistent with L&D demand being especially insulated from COVID cases.

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 2.2 to 3.7.[11] The coefficients for OR jobs are close to zero and precise. The amorphous "other category" has a significant coefficient of 0.25 for job openings, but a precise zero for compensation.

To interpret the magnitude of these results, consider workers facing two identical job offers,

[10] Appendix Table C.3 shows the robustness of these results to including various fixed effects in the regressions. Appendix Tables C.4 through C.6 show robustness to controlling for lagged COVID case counts. Not surprisingly, given the persistence of cases during a pandemic, the tables with multiple lags exhibit collinearity.

[11] Appendix Table C.7 shows the robustness of these results to including various different fixed effects in the regressions. Tables C.8 through C.11 show robustness to controlling for lagged COVID case counts.

except one pays twice as much as the other. A supply elasticity of 3.7 implies that 13 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.[12] These estimates also suggest that if Massachusetts (2020b) had not increased its nurse price cap by 35 percent during the pandemic, it would have hamstrung its hospitals' ability to hire. Assuming compensation increases by the full amount of the cap, and that this higher amount is the market price, the supply of travel nurses would triple compared with keeping the cap in place.[13]

Figure 2 shows the key relationships between labor market outcomes and COVID-19 cases graphically. Panel A plots the relationship between job postings and COVID-19 cases, and Panel B shows that for compensation. Both panels show binned scatterplots for each specialty, after conditioning on day and state fixed effects. The differences across specialties are apparent in Panel A. L&D and OR job postings are nearly flat with respect to residualized COVID-19 conditions. The slopes for ER, ICU, medical-surgical and miscellaneous other jobs are clearly positive as Table 2 column 7 shows quantitatively. 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 B shows that compensation for all specialties goes up when COVID-19 cases increase. But the slopes for ICU, ER, and medical-surgical jobs are much steeper than for L&D and OR. These differences, combined with the quantity slope differences from Panel A, allow us to compute the supply and demand parameters.

These estimates capture supply elasticities across regions at a given point in time, as in a market with a fixed national supply of workers and labor demand—even within a given 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 it is sensible that they overwhelmingly choose the better-paid opening.

These elasticities are higher than those estimated in many other settings, but the response margins available in those other settings are more limited. Much of the work on Uber/Lyft drivers and other gig economy workers estimates a Frisch labor supply elasticity centered around 0.5 (Chen and Sheldon, 2015; Chen et al., 2020), or an intertemporal labor supply elasticity of 1.2 (Angrist

[12] $2^{3.7} = 13$ and $\frac{13}{1+13} = 0.93$.
[13] $1.35^{3.7} = 3.04$

et al., 2017). But these responses require drivers to change total hours or when they work. Moving 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 chooses to look for rides. But in our context, that simple location choice takes on first-order importance.

In contrast with this literature, 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 drivers' decisions of whether to offer rides on Uber or Lyft, where Caldwell and Oehlsen (2018) estimate elasticities ranging from 2 to 6. In our specifications, workers' outside option is taking a similar job, for the same time period, but in a different state. Given the similarity of the choices—at least 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. Table 2 columns 3 and 4 already showed that our main results hold up in this sample. Figure 3 now explores their location choices in more detail.

Panels 3(a) and 3(b) show the relationship between distance traveled and the local COVID situation. The horizontal axis shows the number of COVID cases by state and week, on a log scale, after partialing out state and specialty fixed effets. 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 also at its peak—and Panel 3(b) for the remaining 75 percent. We see that 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, in Panel 3(b), there is a strong positive relationship between travel distance and COVID.

Panels 3(c) and 3(d) show similar binned scatterplots relating distance traveled to compensation.

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

We interpret this figure as evidence that the travel nursing market is especially effective at reallocating nurses across the country when there is some slack in the national market. We see that travel distances increase in response to local COVID cases and local compensation—which itself resonds to cases. But this relationship weakens when national capacity is at its limits. In this situation, nurses are needed everywhere so local demand may not induce as much movement across space, but instead increases compensation broadly across the country, as we saw in Table 1 and Figure 1.

4.3 Do Nurses Travel to Where They Are Needed?

We conclude by asking if nurses are traveling to locations where they are needed. We use data on "staffing shortages" collected by the Department of Health and Human Services from states and hospitals. We compute the share of hospitals in each state and week reporting a staffing shortage.

Panel 3(e) shows that this share relates strongly to COVID cases, conditional on state and week. Unsurprisingly, states with COVID surges are likely to report an impending staffing shortage. This relationship is extremely strong, with a partial R^2 of 0.77. Panel 3(f) then shows the role of travel nurses in alleviating this shortage. When staffing shortages are widespread, travel nurse jobs increase, in this case with a partial R^2 of 0.56. Together with our earlier evidence on how workers respond to these postings, this suggests that the flexibility this market brings to nursing labor was used as we would expect 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 in different parts of the country—but not with perfect flexibility. Given the nature of this choice, 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 far from infinite. There may also be match-specific reasons that labor supply is not infinitely responsive to price signals. Even within the specialty categories we study, nurses can subspecialize and are not perfect substitutes. When staffing companies consider nurse placements, they evaluate other aspects of nurses' skills, and whether they are a good fit (for example, do they have experience 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.[14] New York, California, and other states temporarily liberalized licensure during the acute phase of the COVID-19 pandemic, perhaps contributing to the large supply elasticity we find.

Workers' ability to travel does make labor supply quite elastic in this context. While our more compelling identification comes from the panel context, and looking across specialties, the time-series patterns 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 offers a great deal of flexibility to accommodate demand shocks. When demand increases in specific geographic areas, nurses' ability to travel can help mitigate a local shortage. When the price signals are effective and there is slack capacity in some regions, they are willing to do so. This suggests that the margin of temporary work can be valuable in increasing the labor supply available in a particular market.

But when numerous different regions experience simultaneous COVID-19 surges, mobility across regions is less relevant. Nurses' 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.

6 Conclusion

We find that labor supply is quite elastic in the traveling nurse market, and this elasticity helps the market accommodate labor demand spikes due to COVID surges. Wages in the travel nurse

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

market adjust to reflect demand, which increases when hospitals report staffing shortages. Nurses' elasticity comes in part from willingness to travel across space to areas with demand spikes, at least when demand does not overwhelm the market's national labor supply. In this clinically significant context, the elastic nature of labor supply helped the labor market accommodates historic demand shifts due to COVID. These results imply that price controls are a risky policy. Hospitals and nursing homes have lobbied state governments—in some cases, successfully—to cap travel nurse compensation. In a market where workers are mobile in response to compensation, this puts a state's travel nurse labor supply at risk.

References

Abraham, Katharine G, "Flexible Staffing Arrangements and Employers' Short-Term Adjustment Strategies," Working Paper 2617, National Bureau of Economic Research June 1988.

_ **and Susan K Taylor**, "Firms' use of outside contractors: Theory and evidence," *Journal of labor economics*, 1996, *14* (3), 394–424.

Abraham, Katharine, John Haltiwanger, Kristin Sandusky, and James Spletzer, "Measuring the gig economy: Current knowledge and open issues," *Measuring and Accounting for Innovation in the 21st Century*, 2017.

Aiken, Linda H, Sean P Clarke, Douglas M Sloane, Julie Sochalski, and Jeffrey H Silber, "Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction," *Jama*, 2002, *288* (16), 1987–1993.

Angrist, Joshua D, Sydnee Caldwell, and Jonathan V Hall, "Uber vs. Taxi: A Driver's Eye View," Working Paper 23891, National Bureau of Economic Research September 2017.

Autor, David H, "Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing," *Journal of labor economics*, 2003, *21* (1), 1–42.

Brusie, Chaunie, "This Legislation Could Cap Travel Nurse Pay, Staffing Agencies Accused of "Price Gouging"," February 3 2022. `https://nurse.org/articles/travel-nurse-pay-caps/` (accessed March 10, 2022).

Buerhaus, Peter I, David I Auerbach, and Douglas O Staiger, "The Recent Surge In Nurse Employment: Causes And Implications: Recession effects that have eased the shortage of hospital nurses must be viewed as temporary, lest they distract policymakers from continuing to address longer-term indicators.," *Health Affairs*, 2009, *28* (Suppl3), w657–w668.

_ **, Douglas O Staiger, and David I Auerbach**, "Implications of an aging registered nurse workforce," *Jama*, 2000, *283* (22), 2948–2954.

Bureau of Labor Statistics, "Registered nurses made up 30 percent of hospital employment in May 2019," 2020. Available online at `https://www.bls.gov/opub/ted/2020/registered-nurses-made-up-30-percent-of-hospital-employment-in-may-2019.htm` (accessed November 17, 2020).

Caldwell, Sydnee and Emily Oehlsen, "Monopsony and the gender wage gap: Experimental evidence from the gig economy," *Massachusetts Institute of Technology Working Paper*, 2018.

Chen, Kuan-Ming, Claire Ding, John A List, and Magne Mogstad, "Reservation Wages and Workers' Valuation of Job Flexibility: Evidence from a Natural Field Experiment," Working Paper 27807, National Bureau of Economic Research September 2020.

Chen, M Keith and Michael Sheldon, "Dynamic pricing in a labor market: Surge pricing and flexible work on the Uber platform," 2015. Mimeo, UCLA Anderson. Available online at `https://www.anderson.ucla.edu/faculty_pages/keith.chen/papers/SurgeAndFlexibleWork_WorkingPaper.pdf`.

Collins, Brett, Andrew Garin, Emilie Jackson, Dmitri Koustas, and Mark Payne, "Is gig work replacing traditional employment? Evidence from two decades of tax returns," *Unpublished paper, IRS SOI Joint Statistical Research Program*, 2019.

Cook, Andrew, Martin Gaynor, Melvin Stephens Jr, and Lowell Taylor, "The effect of a hospital nurse staffing mandate on patient health outcomes: Evidence from California's minimum staffing regulation," *Journal of Health Economics*, 2012, *31* (2), 340–348.

Department of Health and Human Services, "COVID-19 Reported Patient Impact and Hospital Capacity by State Timeseries," May 2022. Available online at `https://healthdata.gov/Hospital/COVID-19-Reported-Patient-Impact-and-Hospital-Capa/g62h-syeh`.

DePasquale, Christina and Kevin Stange, "Labor Supply Effects of Occupational Regulation: Evidence from the Nurse Licensure Compact," Working Paper 22344, National Bureau of Economic Research June 2016.

Dey, Matthew, Susan N Houseman, and Anne E Polivka, "Manufacturers' outsourcing to staffing services," *ILR Review*, 2012, *65* (3), 533–559.

Farrell, Diana, Fiona Greig, and Amar Hamoudi, "The online platform economy in 2018: Drivers, workers, sellers, and lessors," *JPMorgan Chase Institute*, 2018.

Gottlieb, Joshua D. and Avi Zenilman, "When Workers Travel: Nursing Supply During COVID-19 Surges," Working Paper 28240, National Bureau of Economic Research December 2020.

Hall, Jonathan, Cory Kendrick, and Chris Nosko, "The effects of Uber's surge pricing: A case study," *The University of Chicago Booth School of Business*, 2015.

Hawryluk, Markian and Rae Ellen Bichell, "Need a COVID-19 Nurse? That'll Be $8,000 a Week," *Kaiser Health News*, November 24 2020. Available online at `https://khn.org/news/highly-paid-traveling-nurses-fill-staffing-shortages-during-covid-pandemic/`.

He, Haoran, David Neumark, and Qian Weng, "Do workers value flexible jobs? A field experiment," *Journal of Labor Economics*, 2021, *39* (3), 709–738.

Houseman, Susan N, "Why employers use flexible staffing arrangements: Evidence from an establishment survey," *Ilr Review*, 2001, *55* (1), 149–170.

Katz, Lawrence F and Alan B Krueger, "The role of unemployment in the rise in alternative work arrangements," *American Economic Review*, 2017, *107* (5), 388–92.

_ and _ , "The rise and nature of alternative work arrangements in the United States, 1995–2015," *ILR Review*, 2019, *72* (2), 382–416.

_ and _ , "Understanding trends in alternative work arrangements in the United States," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 2019, *5* (5), 132–146.

Koustas, Dmitri K, "What Do Big Data Tell Us about Why People Take Gig Economy Jobs?," in "AEA Papers and Proceedings," Vol. 109 2019, pp. 367–71.

Landuis, Timothy and Curtis Starkey, "Largest Healthcare Staffing Firms in the United States: 2020 Update," 2020. Staffing Industry Analysts.

Lind, Dara, "Hospitals Are Suddenly Short of Young Doctors—Because of Trump's Visa Ban," *ProPublica*, July 17 2020. Available online at `https://www.propublica.org/article/hospitals-are-suddenly-short-of-young-doctors-because-of-trumps-visa-ban`.

Mark, Barbara A, David W Harless, Joanne Spetz, Kristin L Reiter, and George H Pink, "California's minimum nurse staffing legislation: results from a natural experiment," *Health services research*, 2013, *48* (2pt1), 435–454.

Mas, Alexandre and Amanda Pallais, "Valuing alternative work arrangements," *American Economic Review*, 2017, *107* (12), 3722–59.

_ and _ , "Alternative work arrangements," *Annual Review of Economics*, 2020, *12*, 631–658.

Massachusetts, "101 CMR 345.00: Rates for Temporary Nursing Services," Regulation, Executive Office of Health and Human Services August 1 2020. Available online at `https://www.mass.gov/doc/rates-for-temporary-nursing-services-effective-august-1-2020-0/download` (accessed April 10, 2021).

_ , "101 CMR 345.00: Rates for Temporary Nursing Services," Administrative Bulletin 20-39, Executive Office of Health and Human Services May 8 2020. Available online at `https://www.mass.gov/doc/ab-20-39-101-cmr-34500-rates-for-temporary-nursing-services-additional-rate-provision/download` (accessed April 10, 2021).

Matsudaira, Jordan D, "Monopsony in the low-wage labor market? Evidence from minimum nurse staffing regulations," *Review of Economics and Statistics*, 2014, *96* (1), 92–102.

Minnesota, Department of Health, "SNSA Maximum Charges," December 2020. Available online at `https://nfportal.dhs.state.mn.us/Reports/2021%20SNSA%20Maximum%20Charge.pdf` (accessed January 28, 2022).

Needleman, Jack, Peter Buerhaus, Soeren Mattke, Maureen Stewart, and Katya Zelevinsky, "Nurse-staffing levels and the quality of care in hospitals," *New England Journal of Medicine*, 2002, *346* (22), 1715–1722.

_ , _ , V Shane Pankratz, Cynthia L Leibson, Susanna R Stevens, and Marcelline Harris, "Nurse staffing and inpatient hospital mortality," *New England Journal of Medicine*, 2011, *364* (11), 1037–1045.

Reed, Allie and Andrew Kreighbaum, "Foreign Health-Care Workers Sidelined as Staffing Crisis Surges," *Bloomberg Law*, November 19 2021. Available online at `https://news.bloomberglaw.com/health-law-and-business/foreign-health-care-workers-sidelined-as-staffing-crisis-surges`.

Sloane, Douglas M, Herbert L Smith, Matthew D McHugh, and Linda H Aiken, "Effect of changes in hospital nursing resources on improvements in patient safety and quality of care: a panel study," *Medical care*, 2018, *56* (12), 1001.

Spetz, Joanne, David W Harless, Carolina-Nicole Herrera, and Barbara A Mark, "Using minimum nurse staffing regulations to measure the relationship between nursing and hospital quality of care," *Medical Care Research and Review*, 2013, *70* (4), 380–399.

Staiger, Douglas O, Joanne Spetz, and Ciaran S Phibbs, "Is there monopsony in the labor market? Evidence from a natural experiment," *Journal of Labor Economics*, 2010, *28* (2), 211–236.

Xue, Ying, Joyce Smith, Deborah A Freund, and Linda H Aiken, "Supplemental nurses are just as educated, slightly less experienced, and more diverse compared to permanent nurses," *Health Affairs*, 2012, *31* (11), 2510–2517.

_ **, Linda H Aiken, Deborah A Freund, and Katia Noyes**, "Quality outcomes of hospital supplemental nurse staffing," *The Journal of nursing administration*, 2012, *42* (12), 580.

Table 1: Data Descriptives

(a) Full Sample Summary Statistics

Measure	N	Mean	SD	P10	Median	P90
Job posting index	24284	113.5	294.1	7.8	31.2	264.9
Comp. index (posted jobs)	24284	116	29.8	89.8	107.5	157.5
Filled jobs index	3143	154.6	290.4	41.2	82.4	329.8
Comp. index (filled jobs)	3143	132.4	43.6	87.9	117	198.2
COVID-19 cases (thousands)	41805	1.24	9.52	0	0	1.64
Travel distance (miles)	3143	528.7	623.7	56.8	290.8	1373.5

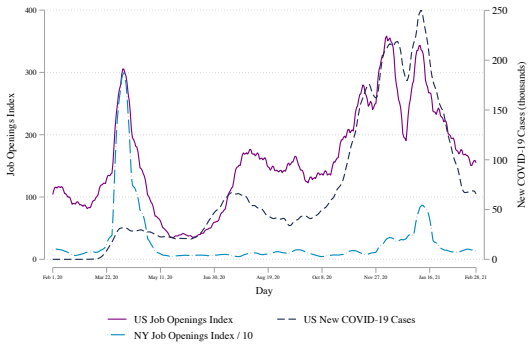
(b) Summary Values During COVID-19

		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

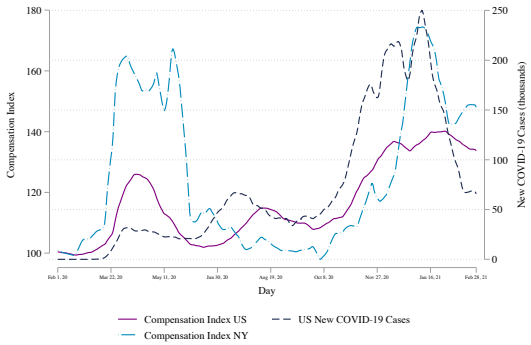
Data are from Health Carousel and are described in detail in the text. The unit of observation in Panel 1(a) is the state-by-day. The compensation index is normalized to national daily average from February 1–March 14, 2020 for all subsets, weighted by number of job postings. The job posting index is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

Figure 1: Time-Series Patterns

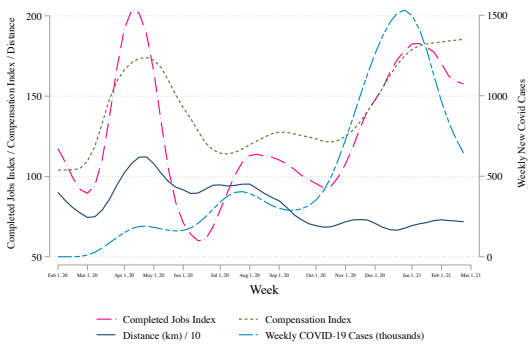
(a) Job Openings



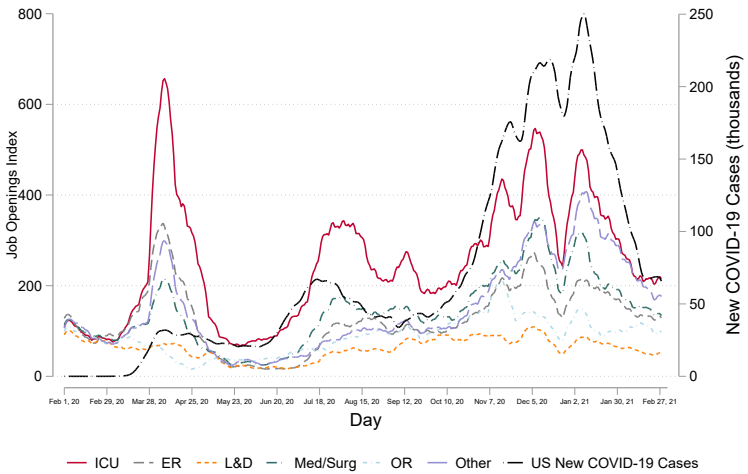
(b) Compensation Offered



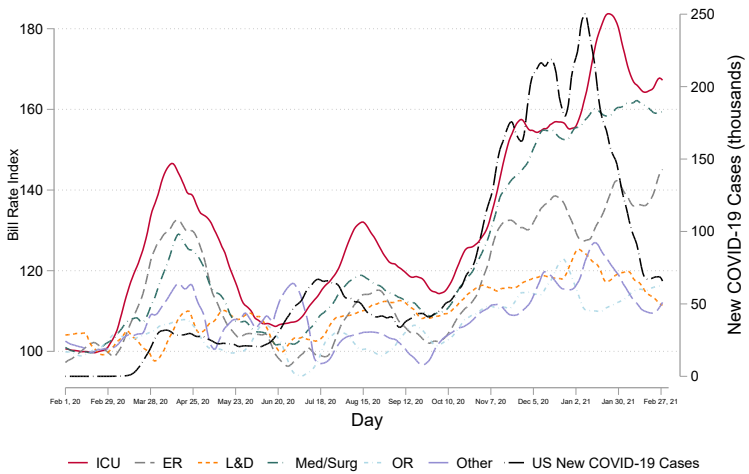
(c) Completed Jobs



(d) Job Openings by Specialty



(e) Compensation by Specialty



Panel (a) shows job postings in the United States and in New York state from February 1, 2020 through February 28, 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. Panels (c), (d), and (e) show smoothed time series of job postings and compensation from February 1, 2020 through February 28, 2021. 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.

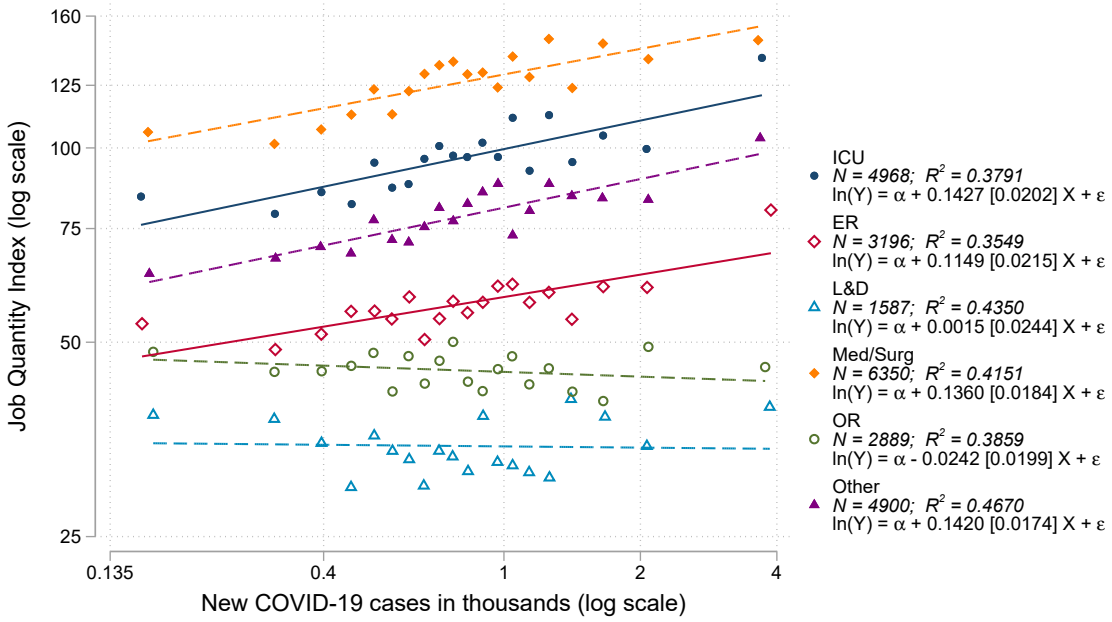
Table 2: Regression Estimates

	(1) Jobs	(2) Comp.	(3) Jobs	(4) Comp.	(5) Jobs	(6) Comp.	(7) Jobs	(8) Comp.
ln(cases)	0.20***	0.077***	0.062	0.025	0.26***	0.035***	0.079	0.000037
	(0.026)	(0.0082)	(0.045)	(0.013)	(0.0088)	(0.0021)	(0.055)	(0.011)
COVID-19 × ln(cases)			0.23*	0.053**				
			(0.094)	(0.016)				
ICU × ln(cases)							0.17***	0.054***
							(0.042)	(0.0067)
ER × ln(cases)							0.070*	0.032***
							(0.031)	(0.0061)
Med/Surg × ln(cases)							0.18***	0.050***
							(0.027)	(0.0054)
OR × ln(cases)							0.000015	-0.0031
							(0.028)	(0.0041)
Other × ln(cases)							0.25***	-0.014
							(0.026)	(0.0078)
N	1582	1582	1079	1079	23890	23890	23890	23890
R^2	0.73	0.76	0.67	0.71	0.54	0.43	0.58	0.47
α (overall or ICU)		2.7		4.3		7.4		3.1
α (ER)								2.2
α (Med/Surg)								3.7
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Date Fixed Effects					✓	✓	✓	✓
Specialty Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects	✓	✓	✓	✓				
State-Specialty FE	✓	✓	✓	✓			✓	✓
Date-Specialty FE								
Week-Specialty FE	✓	✓	✓	✓				

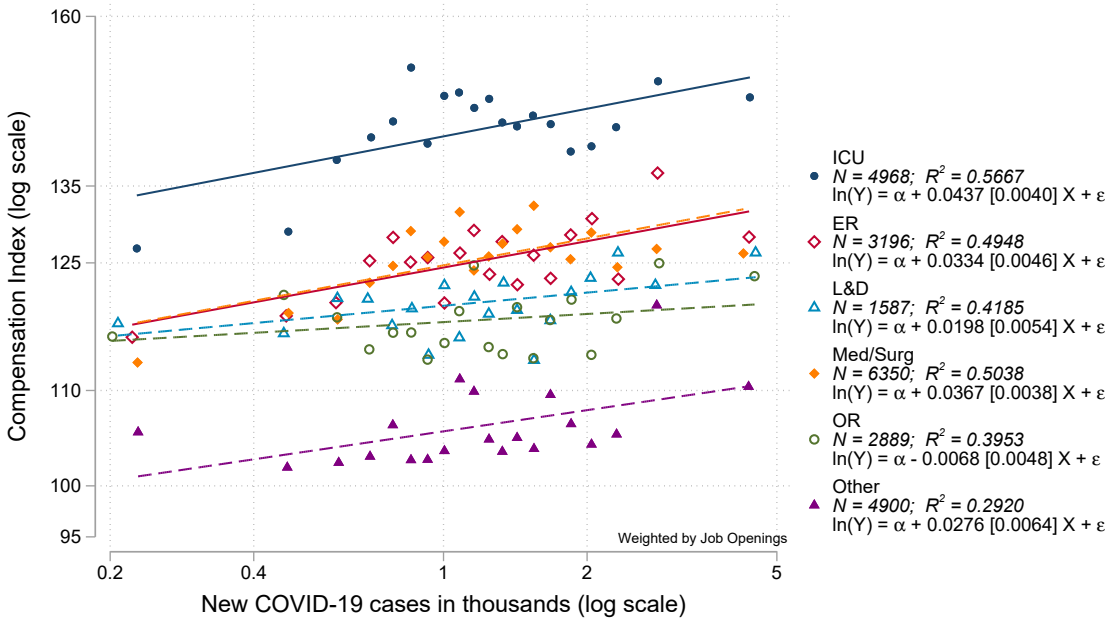
This table reports estimates of equations (6) and (5) on Health Carousel data on travel nursing job postings from February 2020–February 2021. The dependent variable in cols. 1 and 3 is the log number of filled nursing jobs by state-week-specialty and the log number of job postings by state-day-specialty 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 don't 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 parenthesis, 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



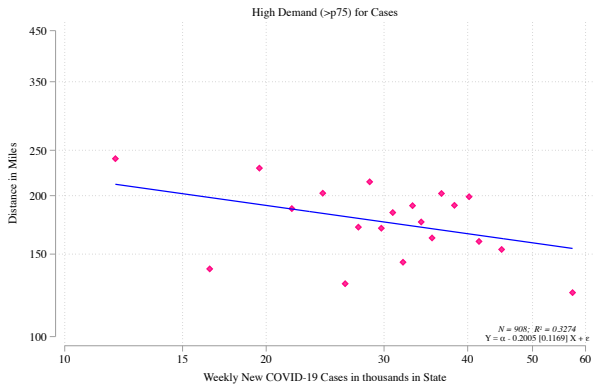
(b) Compensation vs. COVID-19 Cases | Fixed Effects



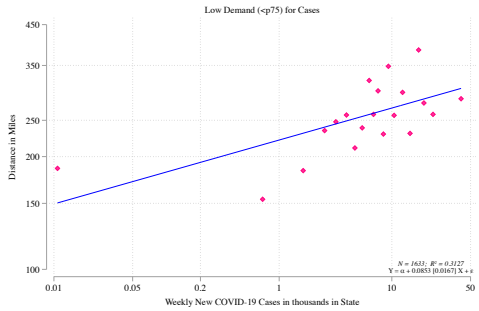
Panel (a) shows six binned scatterplots of job postings against COVID-19 cases by state/day, after conditioning on state and day fixed effects. We show separate scatterplots and corresponding log-linear fits for six specialty categories: intensive care (ICU), emergency room (ER), labor and delivery (L&D), 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

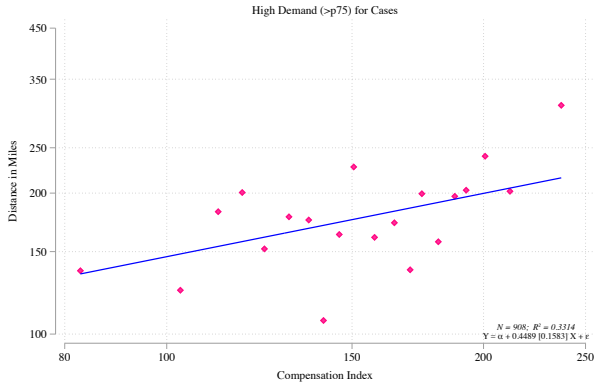
(a) Distance and COVID-19 Cases: High Demand



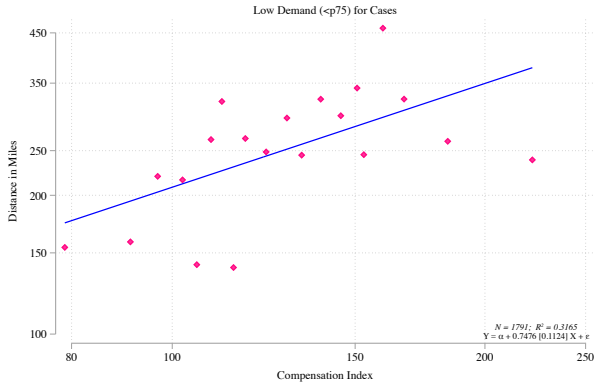
(b) Distance and COVID-19 Cases: Normal Demand



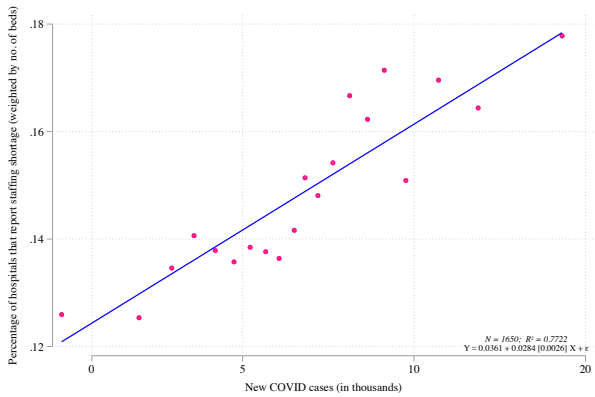
(c) Distance and Compensation: High Demand



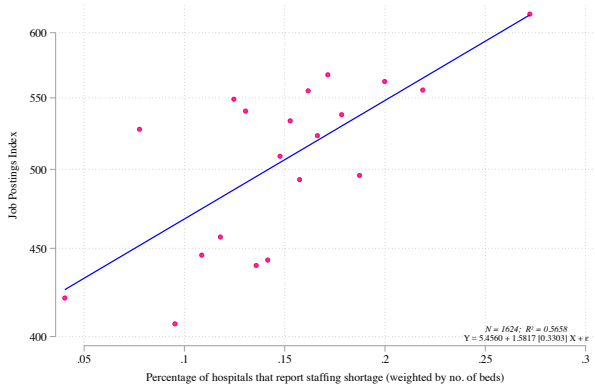
(d) Distance and Compensation: Normal Demand



(e) Staffing Shortages vs. COVID Prevalence



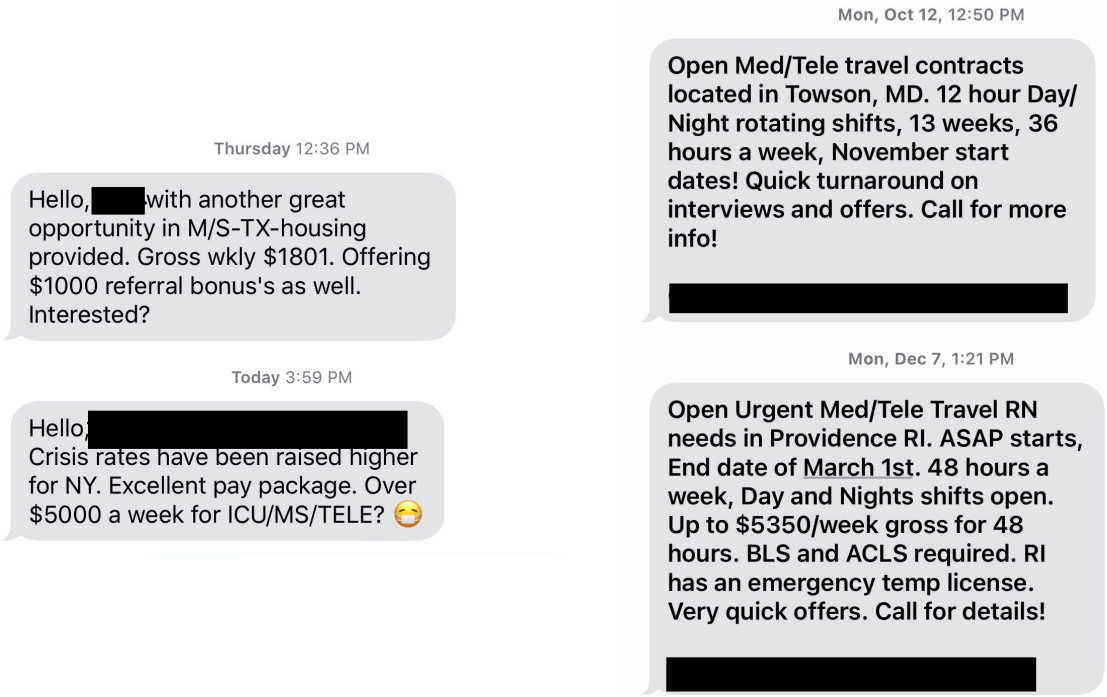
(f) Travel Nursing vs. Staffing Shortages



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 daily caseload. High demand days are defined as days with daily new cases greater than the 75th percentile of national daily 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.

A Recruitment Examples

Figure A.1: Example Travel Nurse Recruitment by Text Message



This figure shows four examples of text messages solicitations from nurse recruiters.

Figure A.2: Example Travel Nurse Recruitment by Email

Gmail [redacted]

$3,628/Wk in Ardmore, Oklahoma for Travel Nurse RN - Med Surg

This week's top jobs for

RN - Med Surg

We scour jobs across the country to find perfect assignments for you. Here are a few great ones we think you might like:

HOST HEALTHCARE

Travel Nurse RN - Med Surg

Ardmore, Oklahoma

Host Healthcare

Travel

$3,628/week

Estimated pay package

I'm interested

HOST HEALTHCARE

Travel Nurse RN - Med Surg

Appleton, Wisconsin

Host Healthcare

Travel

$3,326/week

Estimated pay package

I'm interested

MedPro Healthcare Staffing

Travel Nurse RN - Med Surg

Portland, Maine

MedPro Healthcare Staffing

Travel

$3,204/week

Estimated pay package

I'm interested

This figure shows an (anonymized, excerpted) example email solicitation from a travel nursing agency.

Figure A.3: Example Travel Nurse Recruitment by Email

Gmail [redacted]

Available Travel Contracts with Pay Info: Outside of COVID Hot Spots

Med/Surg Travel Jobs in Ardmore, OK
Weekly Pay $1,950 per week | plus $500 travel
Details: Travel assignment is at 180 bed hospital located in Ardmore, OK. Looking for Travel RN for Med/Surg unit. Start Date: 4/6/2020.

Quick Apply

Med/Surg Travel Jobs in Des Moines, IA
Weekly Pay $2,105 per week | plus $500 in travel

Details: Travel assignment is at a 800+ bed facility that is part of the largest healthcare system in Iowa. Ideal start date is 4/27/2020.
Quick Apply

Med/Surg Travel Jobs in Litte Rock, Arkansas
Weekly Pay $2,250 per week | plus $500 in travel

Details: Travel assignment is at a 600 bed, Level 1 trauma hospital in Little Rock, AR. Looking for RN with previous travel experience ideally in similar hospital size/setting. Start date of 4/6/2020.
Quick Apply

Med/Surg Travel Jobs in Augusta, Maine
Weekly Pay $2,175 per week | plus $500 in travel

Details: Travel assignment is at a 192 bed, teaching hospital in Augusta, Maine. Looking for a strong Med/Surg RN Traveler to start on 4/6/2020 or 4/13/2020.

Quick Apply

Med/Surg Travel Jobs in Springfield, Missouri
Weekly Pay $2,800 per week | plus $500 in travel

Details: Travel assignment is at 665 bed, Level 1 Trauma facility in Springfield, MO. Looking for RN with previous travel experience, strong experience for Med/Surg Float Pool team. Shifts available: 12Days (7A-7P) and 12Nights (7P-7A).

Quick Apply

This figure shows an (anonymized, excerpted) example email solicitation from a travel nursing agency.

B Model Solution

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 ψ_{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 π_i and μ_i for each COVID-19-related specialty $i \in \{ICU, ER, \text{Med-Surg}\}$, along with the τ and κ coefficients for L&D. (That is, τ and κ 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:

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

$$\kappa = \frac{\alpha\delta^0 - \beta\gamma}{\alpha - \gamma} = -\frac{\beta\gamma}{\alpha - \gamma} \tag{10}$$

$$\mu_i = \frac{\alpha\delta^i}{\alpha - \gamma} \tag{11}$$

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

$$\tau = \frac{-\beta + \delta^0}{\alpha - \gamma} = -\frac{\beta}{\alpha - \gamma} \tag{13}$$

$$\pi_i = \frac{\delta^i}{\alpha - \gamma} \tag{14}$$

$$\frac{\mu_i}{\pi_i} = \alpha \tag{15}$$

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

C Additional Results

Table C.1: Summary Statistics During COVID-19 Pandemic

Measure	N	Mean	SD	P10	Median	P90
Job posting index	10449	154.7	385.5	7.8	46.7	381.8
Comp. index (posted jobs)	10449	128.6	32	95.2	122.3	173.7
Filled jobs index	1432	207.9	392.8	41.2	82.4	494.7
Comp. index (filled jobs)	1432	152.4	43.3	98	147.6	214.7
COVID-19 cases (thousands)	18122	2.85	14.3	0	.47	4.4
Travel distance (miles)	1432	528.6	606.3	57.6	296	1310.9

Data are from Health Carousel and are described in detail in the text. The unit of observation is the state-by-day. 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.

Table C.2: State Summary

		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
AL	.82	100	88	62	90	66	84	163	107	44	103	113	137	89	145
AK	.62	100	104	88	95	49	106	81	101	179	120	231	127	211	115
AZ	2.36	100	93	145	113	75	104	228	126	116	104	416	139	271	155
AR	1.55	100	100	86	101	40	96	296	111	234	123	356	143	465	159
CA	12.66	100	116	131	137	32	118	147	131	151	128	243	128	157	152
CO	.93	100	97	96	100	38	89	76	89	205	102	382	119	222	124
CT	.76	100	115	173	133	58	123	67	119	124	139	272	164	296	141
DE	.19	100	100	341	126	33	123	101	101	196	113	303	141	183	159
FL	5.22	100	91	140	117	17	90	322	114	151	100	373	135	267	130
GA	3.28	100	95	116	109	40	93	190	127	175	115	360	140	416	160
HI	.29	100	105	165	126	17	101	146	145	228	131	265	123	364	158
ID	.27	100	102	37	88	17	84	126	102	200	124	343	148	111	112
IL	3.05	100	93	203	117	65	96	118	120	200	116	342	146	161	132
IN	2.12	100	94	74	99	41	98	70	113	107	114	296	135	110	147
IA	1.19	100	102	104	101	66	99	112	113	182	118	271	150	193	154
KS	.35	100	100	52	95	19	87	96	104	193	101	126	134	70	129
KY	1.81	100	96	128	105	37	96	155	109	198	112	299	134	216	136
LA	.96	100	92	220	104	47	92	279	105	463	113	451	126	249	145
ME	.65	100	93	137	97	69	92	101	94	191	103	319	135	330	106
MD	4.35	100	93	208	105	119	107	135	110	216	120	567	158	362	160
MA	2.9	100	106	174	131	94	106	65	103	137	111	338	133	169	120
MI	2.07	100	110	243	137	32	90	49	88	181	102	527	151	238	138
MN	.47	100	96	106	95	48	124	65	101	115	113	341	164	109	131
MS	.34	100	65	242	100	77	83	1087	106	604	94	793	112	1277	147
MO	3.14	100	98	112	105	30	94	177	105	221	114	317	155	176	160

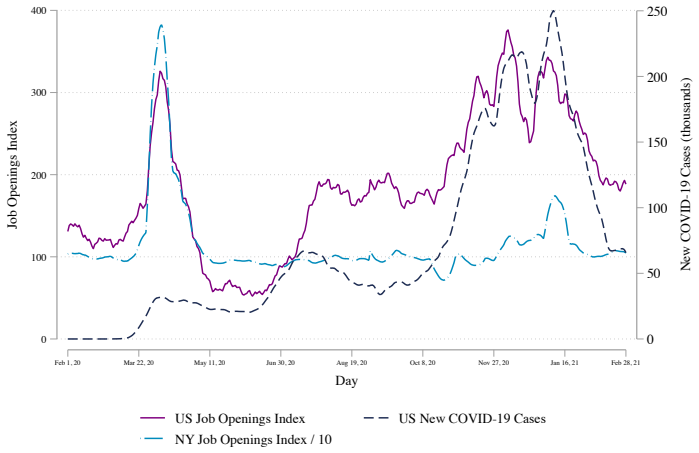
State Summary (Continued)

		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
MT	.8	100	103	78	101	65	96	115	98	220	112	203	136	130	123
NE	.74	100	100	72	102	38	85	86	102	208	124	268	150	274	143
NV	1.92	100	100	168	114	14	96	258	129	177	123	633	164	140	164
NH	.6	100	100	108	104	55	99	129	102	157	103	192	106	164	105
NJ	1.55	100	120	513	182	34	117	64	115	73	127	211	179	148	177
NM	1.33	100	90	107	96	44	103	53	111	125	141	155	166	121	167
NY	6.03	100	106	863	185	49	125	76	107	75	108	316	168	177	159
NC	3.61	100	92	119	94	36	90	193	104	185	104	270	132	335	138
ND	.67	100	105	73	106	20	108	54	114	208	124	323	152	373	184
OH	2.21	100	92	135	112	62	98	179	100	211	107	366	131	248	137
OK	1.35	100	97	54	95	14	93	113	120	200	123	248	154	137	165
OR	1.64	100	106	150	111	37	100	129	106	189	109	309	122	174	121
PA	2.92	100	97	145	109	75	96	145	102	239	111	354	137	222	146
RI	.35	100	110	679	115	242	114	187	115	374	118	826	188	326	154
SC	2.24	100	92	106	93	31	93	343	113	174	106	297	134	262	177
SD	.54	100	98	121	100	103	97	148	98	249	124	272	138	207	160
TN	2.15	100	77	111	96	48	98	182	101	248	106	309	125	176	118
TX	5.78	100	96	53	97	63	101	492	116	336	108	558	135	643	158
UT	.12	100	101	247	89	250	172	264	79	793	101	401	110	113	127
VT	.73	100	99	98	101	31	97	120	107	107	105	144	106	151	99
VA	3.73	100	95	113	97	56	97	141	104	138	106	160	123	178	127
WA	2.78	100	105	152	128	23	106	68	110	105	123	169	132	112	140
WV	1.16	100	88	90	88	74	91	203	94	181	104	212	125	175	128
WI	1.71	100	92	178	120	22	99	56	100	148	118	316	155	155	145
WY	.24	100	88	64	88	48	83	59	99	167	97	199	156	114	114

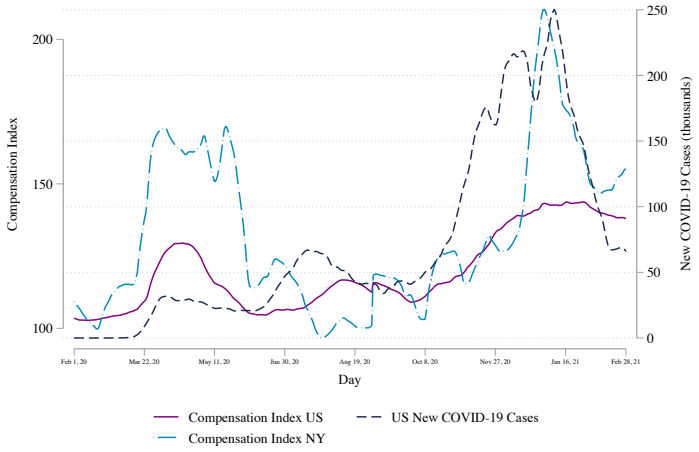
Data are from Health Carousel and are described in detail in the text. The unit of observation is the state-by-day. The compensation index is normalized relative to the national daily average from February 1–March 14, 2020, weighted by number of job postings. The job posting index is average daily postings,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

Figure C.1: Time-Series Patterns After Seasonal Adjustment

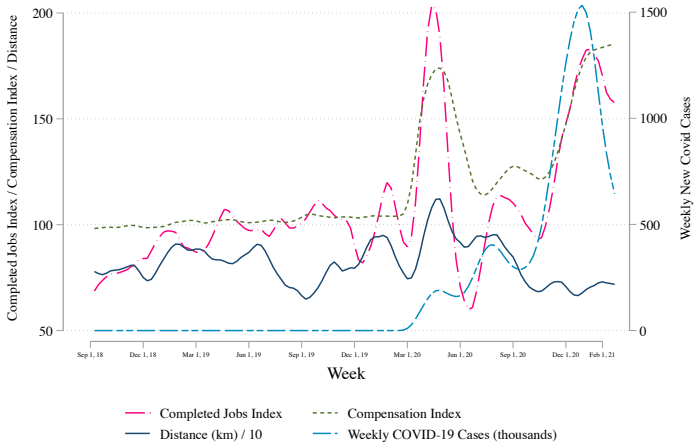
(a) Job Openings



(b) Compensation Offered



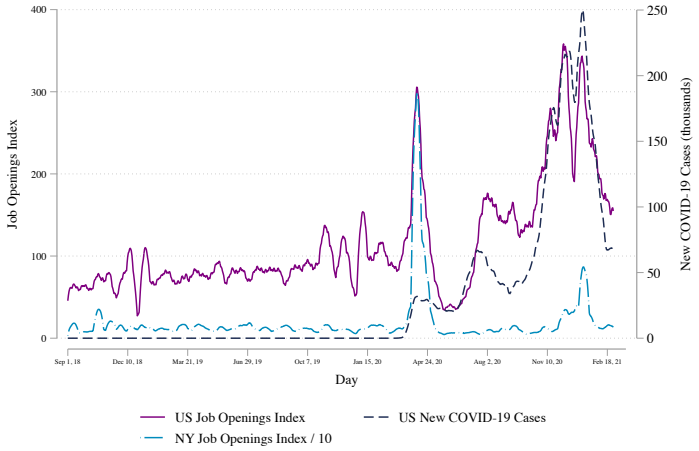
(c) Completed Jobs



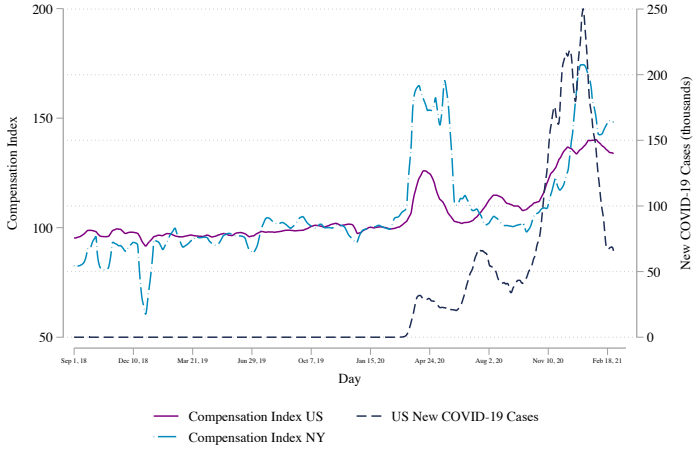
Panel (a) shows job postings in the United States and in New York state from February 1, 2020 through February 28, 2021 minus the value at the corresponding time of the pre-pandemic baseline year September 2018 - August 2019. Data are smoothed using an Epanechnikov kernel. The panel also shows (smoothed) 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. All indices are normalized to a mean of 100 in Feburary 2020.

Figure C.2: Extended Time-Series Patterns

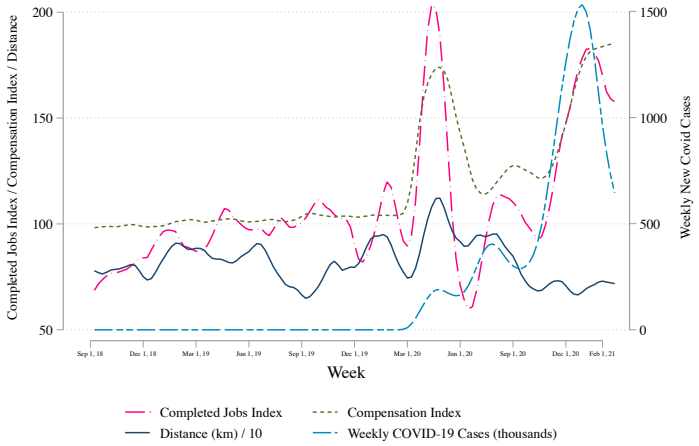
(a) Job Openings



(b) Compensation Offered



(c) Completed Jobs



Panel (a) shows job postings in the United States and in New York state from September 1, 2018 through February 28, 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 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 Feburary 2020

Table C.3: Robustness of Regression Estimates: Completed Jobs

	(1) Jobs	(2) Comp.	(3) Jobs	(4) Comp.	(5) Jobs	(6) Comp.	(7) Jobs	(8) Comp.
ln(cases)	0.22^{***}	0.075^{***}	0.20^{***}	0.077^{***}	0.22^{***}	0.040^{**}	0.062	0.025
	(0.025)	(0.0078)	(0.026)	(0.0082)	(0.047)	(0.012)	(0.045)	(0.013)
COVID-19 × ln(cases)					0.064^{**}	0.037^{***}	0.23^{*}	0.053^{**}
					(0.023)	(0.0051)	(0.094)	(0.016)
N	1582	1582	1582	1582	1079	1079	1079	1079
R^2	0.65	0.69	0.73	0.76	0.67	0.69	0.67	0.71
α (overall or ICU)		2.9		2.7		1.8		4.3
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week-Specialty FE			✓	✓			✓	✓
State-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. 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. Cols. 1–4 don't distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta = 0$). 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. All columns are weighted by number of filled jobs. Standard errors, in parenthesis, are clustered by state. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Table C.4: Regression Estimates with Lagged COVID-19 Cases: Completed Jobs

	(1) Jobs	(2) Comp.	(3) Jobs	(4) Comp.	(5) Jobs	(6) Comp.	(7) Jobs	(8) Comp.
ln(cases)	-0.039	0.0099	-0.073	-0.0089	0.19***	0.049**	0.043	0.032*
	(0.071)	(0.022)	(0.077)	(0.025)	(0.048)	(0.014)	(0.046)	(0.013)
COVID-19 × ln(cases)					0.063**	0.037***	0.22*	0.056**
					(0.023)	(0.0053)	(0.094)	(0.017)
1 Week Lag	0.27***	0.070**	0.29***	0.091***	0.0021	-0.00082*	0.0023	-0.00082*
	(0.068)	(0.022)	(0.074)	(0.024)	(0.0022)	(0.00033)	(0.0022)	(0.00032)
N	1554	1554	1554	1554	1079	1079	1079	1079
R^2	0.65	0.69	0.73	0.76	0.67	0.70	0.67	0.71
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week-Specialty FE			✓	✓			✓	✓
State-Specialty FE	✓	✓	✓	✓	✓	✓	✓	✓
Calendar Week Lags	1	1	1	1	1	1	1	1

This table reports estimates of equations (5) and (6) and includes lagged number of cases as a robustness check. 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 a lagged variable that represents number of cases (in log scale) in the previous week. Cols. 1–4 don't 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 parenthesis, are clustered by state. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Table C.5: Regression Estimates with Lagged COVID-19 Cases: Completed Jobs

	(1) Jobs	(2) Comp.	(3) Jobs	(4) Comp.	(5) Jobs	(6) Comp.	(7) Jobs	(8) Comp.
ln(cases)	-0.050	-0.015	-0.051	-0.031	0.18***	0.047**	0.029	0.030*
	(0.087)	(0.027)	(0.094)	(0.030)	(0.048)	(0.014)	(0.049)	(0.014)
COVID-19 × ln(cases)					0.063**	0.037***	0.22*	0.056**
					(0.023)	(0.0054)	(0.093)	(0.017)
1 Week Lag	0.083	0.029	0.048	0.041	0.0087	0.00017	0.0090	0.00021
	(0.11)	(0.034)	(0.12)	(0.037)	(0.0051)	(0.0013)	(0.0054)	(0.0013)
2 Weeks Lag	0.21**	0.069***	0.24***	0.075***	-0.0065	-0.00097	-0.0065	-0.0010
	(0.065)	(0.020)	(0.068)	(0.022)	(0.0034)	(0.0012)	(0.0036)	(0.0013)
N	1522	1522	1522	1522	1079	1079	1079	1079
R^2	0.66	0.70	0.74	0.76	0.67	0.70	0.68	0.71
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week-Specialty FE			✓	✓			✓	✓
State-Specialty FE	✓	✓	✓	✓	✓	✓	✓	✓
Calendar Week Lags	2	2	2	2	2	2	2	2

This table reports estimates of equations (5) and (6) and includes lagged number of cases as a robustness check. 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 2 lagged variables that represents number of cases (in log scale) in the each of the 2 previous weeks. Cols. 1–4 don't 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 parenthesis, are clustered by state. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Table C.6: Regression Estimates with Lagged COVID-19 Cases: Completed Jobs

	(1) Jobs	(2) Comp.	(3) Jobs	(4) Comp.	(5) Jobs	(6) Comp.	(7) Jobs	(8) Comp.
ln(cases)	-0.024	-0.011	-0.039	-0.024	0.17***	0.046**	0.038	0.030*
	(0.093)	(0.029)	(0.10)	(0.032)	(0.048)	(0.014)	(0.051)	(0.013)
COVID-19 × ln(cases)					0.065**	0.037***	0.21*	0.056**
					(0.022)	(0.0054)	(0.093)	(0.017)
1 Week Lag	0.15	-0.017	0.11	-0.023	0.0055	0.000037	0.0056	0.000032
	(0.13)	(0.041)	(0.14)	(0.044)	(0.0039)	(0.0012)	(0.0042)	(0.0012)
2 Weeks Lag	-0.056	0.080*	0.051	0.11**	0.0053	-0.00049	0.0056	-0.00036
	(0.11)	(0.034)	(0.11)	(0.035)	(0.0050)	(0.0019)	(0.0050)	(0.0019)
3 Weeks Lag	0.20**	0.031	0.13	0.022	-0.010	-0.00041	-0.010	-0.00056
	(0.070)	(0.022)	(0.072)	(0.023)	(0.0057)	(0.0013)	(0.0059)	(0.0014)
N	1492	1492	1492	1492	1079	1079	1079	1079
R^2	0.67	0.70	0.74	0.76	0.68	0.70	0.68	0.71
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Week-Specialty FE			✓	✓			✓	✓
State-Specialty FE	✓	✓	✓	✓	✓	✓	✓	✓
Calendar Week Lags	3	3	3	3	3	3	3	3

This table reports estimates of equations (5) and (6) and includes lagged number of cases as a robustness check. 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 represents number of cases (in log scale) in the each of the 3 previous weeks. Cols. 1–4 don't 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 parenthesis, are clustered by state. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$.

Table C.7: Robustness of Regression Estimates: Posted Jobs

	(1) Jobs	(2) Comp.	(3) Jobs	(4) Comp.	(5) Jobs	(6) Comp.	(7) Jobs	(8) Comp.	(9) Jobs	(10) Comp.
ln(cases)	0.26***	0.035***	0.22***	0.031	0.050	0.0094	0.079	0.000037	0.023	0.020*
	(0.0088)	(0.0021)	(0.055)	(0.018)	(0.065)	(0.012)	(0.055)	(0.011)	(0.027)	(0.0076)
COVID-19 × ln(cases)			0.071**	0.034***						
			(0.021)	(0.0040)						
ICU × ln(cases)					0.26***	0.035**	0.17***	0.054***	0.26**	0.024
					(0.056)	(0.011)	(0.042)	(0.0067)	(0.091)	(0.021)
ER × ln(cases)					0.13***	0.024*	0.070*	0.032***	0.13	0.014
					(0.033)	(0.0093)	(0.031)	(0.0061)	(0.067)	(0.022)
Med/Surg × ln(cases)					0.23***	0.036***	0.18***	0.050***	0.22**	0.017
					(0.040)	(0.010)	(0.027)	(0.0054)	(0.071)	(0.018)
OR × ln(cases)					0.00093	-0.0062	0.000015	-0.0031	-0.11	-0.027**
					(0.036)	(0.0057)	(0.028)	(0.0041)	(0.056)	(0.0096)
Other × ln(cases)					0.24***	0.0032	0.25***	-0.014	0.27***	0.0078
					(0.040)	(0.012)	(0.026)	(0.0078)	(0.052)	(0.022)
N	23890	23890	1077	1077	23890	23890	23890	23890	23890	23890
R^2	0.54	0.43	0.65	0.58	0.55	0.43	0.58	0.47	0.63	0.53
α (overall or ICU)		7.4		2.1		7.4		3.1		10.9
α (ER)						5.6		2.2		9.9
α (Med/Surg)						6.3		3.7		13.1
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects			✓	✓						
Date Fixed Effects	✓	✓			✓	✓	✓	✓	✓	✓
Date-Specialty FE									✓	✓
State-Specialty FE							✓	✓	✓	✓

This table reports estimates of equations (5) and (6) on Health Carousel data on travel nursing job postings from February 2020–February 2021. The dependent variable in cols. 1–2 and 5–10 is the log number of job postings by state-specialty-day and log number of filled jobs by state-specialty-week in column 3. The dependent variable in the even-numbered columns is the average log compensation for the jobs included in the prior column. Cols. 1–2 don't distinguish among specialties, and the supply calculations assume that local supply is unaffected by local COVID-19 conditions ($\beta = 0$). In cols. 5–10, the omitted nursing specialty is labor and delivery. Cols. 3–4 combine ICU, ER, and Med/Surg together into "COVID-19 specialties", and OR and L&D form the omitted category. Cols. 1-2 and 5-10 are weighted by number of job postings and cols. 3-4 are weighted by number of filled jobs. Standard errors, in parenthesis, are clustered by state. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table C.8: Regression Estimates with Lagged 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)	0.023	0.00021	0.60**	0.024	-0.12	-0.016	-0.077	-0.025*	-0.14*	-0.0068
	(0.020)	(0.0041)	(0.21)	(0.048)	(0.071)	(0.013)	(0.058)	(0.0097)	(0.057)	(0.016)
COVID-19 × ln(cases)			0.11***	0.040***						
			(0.030)	(0.0058)						
ICU × ln(cases)					0.26***	0.034**	0.17***	0.054***	0.27**	0.025
					(0.056)	(0.011)	(0.042)	(0.0067)	(0.088)	(0.021)
ER × ln(cases)					0.14***	0.024*	0.068*	0.032***	0.14*	0.015
					(0.034)	(0.0095)	(0.031)	(0.0063)	(0.065)	(0.022)
Med/Surg × ln(cases)					0.23***	0.036**	0.18***	0.050***	0.23**	0.018
					(0.042)	(0.010)	(0.030)	(0.0057)	(0.071)	(0.018)
OR × ln(cases)					-0.00046	-0.0066	-0.0011	-0.0027	-0.11*	-0.026**
					(0.038)	(0.0058)	(0.030)	(0.0040)	(0.054)	(0.0094)
Other × ln(cases)					0.24***	0.0032	0.25***	-0.014	0.27***	0.0086
					(0.041)	(0.012)	(0.027)	(0.0080)	(0.052)	(0.022)
1 Week Lag	0.35***	0.051***	-0.42*	0.0030	0.22*	0.033*	0.20*	0.032*	0.20**	0.033*
	(0.021)	(0.0044)	(0.20)	(0.052)	(0.084)	(0.015)	(0.079)	(0.015)	(0.073)	(0.014)
N	9035	9035	1062	1062	23821	23821	23821	23821	23821	23821
R^2	0.60	0.48	0.66	0.58	0.56	0.44	0.59	0.47	0.64	0.53
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects			✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects			✓	✓						
Date Fixed Effects	✓	✓			✓	✓	✓	✓	✓	✓
Date-Specialty FE									✓	✓
State-Specialty FE							✓	✓	✓	✓
7-day Rolling Lags	1	1	1	1	1	1	1	1	1	1

This table reports estimates of equations (5) and (6) and includes lagged number of cases as a robustness check. 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-day level, cols. 3–4 are at the state-week-specialty level, and cols. 5–10 are at the state-day-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. Each specification also includes lagged number of COVID cases from the preceding 7 days. The number of lags indicate how many past 7-day periods have been included. Standard errors, in parenthesis, are clustered by state.

Table C.9: Regression Estimates with Lagged 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)	0.0057	-0.0039	0.50*	-0.016	-0.17*	-0.024	-0.13*	-0.037***	-0.17**	-0.015
	(0.021)	(0.0044)	(0.25)	(0.065)	(0.070)	(0.013)	(0.058)	(0.0093)	(0.061)	(0.018)
COVID-19 × ln(cases)			0.12***	0.043***						
			(0.035)	(0.0068)						
ICU × ln(cases)					0.27***	0.035**	0.18***	0.062***	0.26**	0.027
					(0.063)	(0.012)	(0.052)	(0.0075)	(0.086)	(0.021)
ER × ln(cases)					0.14***	0.023*	0.083*	0.037***	0.14*	0.017
					(0.039)	(0.010)	(0.038)	(0.0069)	(0.064)	(0.022)
Med/Surg × ln(cases)					0.25***	0.037**	0.20***	0.056***	0.23**	0.020
					(0.049)	(0.012)	(0.037)	(0.0062)	(0.071)	(0.019)
OR × ln(cases)					-0.0053	-0.0065	-0.0057	0.000051	-0.11	-0.023*
					(0.043)	(0.0066)	(0.034)	(0.0046)	(0.056)	(0.011)
Other × ln(cases)					0.25***	0.0031	0.27***	-0.013	0.26***	0.0061
					(0.047)	(0.013)	(0.033)	(0.0087)	(0.052)	(0.023)
1 Week Lag	0.25***	0.023***	-0.72**	-0.038	0.065	0.00095	0.052	0.0014	0.041	-0.0011
	(0.031)	(0.0064)	(0.25)	(0.072)	(0.082)	(0.015)	(0.075)	(0.014)	(0.070)	(0.014)
2 Weeks Lag	0.14***	0.036***	0.40**	0.082*	0.22***	0.044***	0.22***	0.043***	0.22***	0.046***
	(0.020)	(0.0042)	(0.12)	(0.037)	(0.057)	(0.012)	(0.055)	(0.011)	(0.055)	(0.012)
N	8741	8741	1043	1043	23512	23512	23512	23512	23512	23512
R^2	0.61	0.49	0.66	0.58	0.56	0.44	0.59	0.47	0.64	0.53
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects			✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects			✓	✓						
Date Fixed Effects	✓	✓			✓	✓	✓	✓	✓	✓
Date-Specialty FE									✓	✓
State-Specialty FE							✓	✓	✓	✓
7-day Rolling Lags	2	2	2	2	2	2	2	2	2	2

This table reports estimates of equations (5) and (6) and includes lagged number of cases as a robustness check. 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-day level, cols. 3–4 are at the state-week-specialty level, and cols. 5–10 are at the state-day-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. Each specification also includes lagged number of COVID cases from the preceding 7 days. The number of lags indicate how many past 7-day periods have been included. Standard errors, in parenthesis, are clustered by state.

Table C.10: Regression Estimates with Lagged 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)	0.019	-0.0046	0.56*	-0.014	-0.19*	-0.026	-0.15*	-0.041***	-0.17*	-0.016
	(0.022)	(0.0046)	(0.28)	(0.072)	(0.073)	(0.014)	(0.061)	(0.010)	(0.064)	(0.019)
COVID-19 × ln(cases)			0.13**	0.038***						
			(0.048)	(0.0076)						
ICU × ln(cases)					0.27***	0.036**	0.18**	0.063***	0.25**	0.027
					(0.064)	(0.013)	(0.055)	(0.0080)	(0.085)	(0.021)
ER × ln(cases)					0.15***	0.022*	0.085*	0.038***	0.13*	0.016
					(0.039)	(0.011)	(0.041)	(0.0073)	(0.062)	(0.022)
Med/Surg × ln(cases)					0.25***	0.037**	0.22***	0.060***	0.23**	0.020
					(0.051)	(0.013)	(0.041)	(0.0069)	(0.071)	(0.019)
OR × ln(cases)					-0.013	-0.0081	-0.015	-0.00066	-0.12	-0.023
					(0.043)	(0.0069)	(0.035)	(0.0049)	(0.058)	(0.012)
Other × ln(cases)					0.26***	0.0030	0.29***	-0.016	0.26***	0.0058
					(0.048)	(0.014)	(0.035)	(0.0094)	(0.052)	(0.023)
1 Week Lag	0.17***	0.0085	-0.81**	-0.034	0.034	-0.0095	0.017	-0.0091	0.00055	-0.013
	(0.036)	(0.0075)	(0.30)	(0.084)	(0.081)	(0.014)	(0.073)	(0.014)	(0.069)	(0.014)
2 Weeks Lag	0.20***	0.043***	0.26	0.048	0.15*	0.040**	0.15*	0.039**	0.16*	0.041**
	(0.034)	(0.0071)	(0.20)	(0.056)	(0.062)	(0.014)	(0.060)	(0.013)	(0.061)	(0.013)
3 Weeks Lag	0.023	0.013***	0.17	0.033	0.12***	0.020*	0.13***	0.019*	0.12***	0.021*
	(0.019)	(0.0039)	(0.099)	(0.031)	(0.032)	(0.0091)	(0.032)	(0.0089)	(0.032)	(0.0091)
N	8396	8396	1021	1021	23191	23191	23191	23191	23191	23191
R^2	0.63	0.49	0.67	0.57	0.57	0.44	0.60	0.48	0.64	0.53
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects			✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects			✓	✓						
Date Fixed Effects	✓	✓			✓	✓	✓	✓	✓	✓
Date-Specialty FE									✓	✓
State-Specialty FE							✓	✓	✓	✓
7-day Rolling Lags	3	3	3	3	3	3	3	3	3	3

This table reports estimates of equations (5) and (6) and includes lagged number of cases as a robustness check. 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-day level, cols. 3–4 are at the state-week-specialty level, and cols. 5–10 are at the state-day-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. Each specification also includes lagged number of COVID cases from the preceding 7 days. The number of lags indicate how many past 7-day periods have been included. Standard errors, in parenthesis, are clustered by state.

Table C.11: Regression Estimates with Lagged 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)	0.0092	-0.0067	0.61*	-0.0069	-0.20*	-0.027	-0.17**	-0.043***	-0.18**	-0.016
	(0.023)	(0.0048)	(0.28)	(0.076)	(0.075)	(0.015)	(0.064)	(0.011)	(0.061)	(0.020)
COVID-19 × ln(cases)			0.11*	0.035***						
			(0.055)	(0.0091)						
ICU × ln(cases)					0.28***	0.035*	0.20**	0.065***	0.26**	0.027
					(0.067)	(0.013)	(0.059)	(0.0085)	(0.078)	(0.021)
ER × ln(cases)					0.14***	0.020	0.083	0.037***	0.12*	0.013
					(0.038)	(0.011)	(0.042)	(0.0073)	(0.059)	(0.022)
Med/Surg × ln(cases)					0.26***	0.037**	0.24***	0.063***	0.23**	0.019
					(0.052)	(0.013)	(0.042)	(0.0073)	(0.067)	(0.019)
OR × ln(cases)					-0.017	-0.0092	-0.024	-0.0014	-0.13*	-0.022
					(0.045)	(0.0072)	(0.037)	(0.0048)	(0.058)	(0.012)
Other × ln(cases)					0.26***	0.0015	0.30***	-0.019	0.26***	0.0028
					(0.050)	(0.014)	(0.037)	(0.0096)	(0.049)	(0.023)
1 Week Lag	0.20***	0.0081	-0.76*	-0.039	0.020	-0.014	-0.00017	-0.014	-0.011	-0.019
	(0.038)	(0.0080)	(0.30)	(0.091)	(0.086)	(0.016)	(0.077)	(0.015)	(0.072)	(0.014)
2 Weeks Lag	0.24***	0.051***	0.19	0.036	0.13*	0.035*	0.13*	0.034*	0.14*	0.036**
	(0.038)	(0.0079)	(0.22)	(0.062)	(0.063)	(0.014)	(0.061)	(0.013)	(0.061)	(0.013)
3 Weeks Lag	-0.052	-0.017**	-0.24	0.0070	0.099*	0.0059	0.10**	0.0056	0.096*	0.0100
	(0.029)	(0.0062)	(0.13)	(0.046)	(0.040)	(0.0088)	(0.037)	(0.0084)	(0.037)	(0.0083)
4 Weeks Lag	0.0073	0.021***	0.38***	0.034	0.083*	0.026*	0.079	0.025**	0.073	0.024**
	(0.017)	(0.0036)	(0.078)	(0.026)	(0.042)	(0.0096)	(0.041)	(0.0090)	(0.040)	(0.0083)
N	8055	8055	1004	1004	22832	22832	22832	22832	22832	22832
R^2	0.63	0.49	0.68	0.57	0.57	0.44	0.60	0.48	0.65	0.53
State Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Specialty Fixed Effects			✓	✓	✓	✓	✓	✓	✓	✓
Week Fixed Effects			✓	✓						
Date Fixed Effects	✓	✓			✓	✓	✓	✓	✓	✓
Date-Specialty FE									✓	✓
State-Specialty FE							✓	✓	✓	✓
7-day Rolling Lags	4	4	4	4	4	4	4	4	4	4

This table reports estimates of equations (5) and (6) and includes lagged number of cases as a robustness check. 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-day level, cols. 3–4 are at the state-week-specialty level, and cols. 5–10 are at the state-day-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. Each specification also includes lagged number of COVID cases from the preceding 7 days. The number of lags indicate how many past 7-day periods have been included. Standard errors, in parenthesis, are clustered by state.