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Monopsony in Professional Labor Markets: Hospital System Concentration and Nurse Wages

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Working Paper No. 197

January 5th, 2023

ABSTRACT

Rolling waves of consolidation have significantly decreased the number of hospital systems in the U.S. potentially affecting industry quality, prices, efficiency, wages and more. This research concerns the growth in hospital system consolidation in local labor markets and its effect on registered nurse wages. We first use a nonparametric preprocessing data step via matching

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This research is part of a multi-year project, "Hospital Market Consolidation and Health Care Worker Wages," funded by Arnold Ventures (Grant ID: 19-03071). We thank Hunter Kellett and Alexandra Spratt for their support. We are thankful to those who provided comments and insights that greatly improved this work—Eileen Appelbaum, Rosemary Batt, Thomas Ferguson, John Schmidt, Dylan Gyauch-Lewis, Hayley Brown, Hye Jin Rho, and the team at Health Care Cost Institute who provided the hospital consolidation measures.

methods to define MSA-specific samples of workers analogous to nurses outside of the hospital sector. This step enables an accounting of heterogeneous MSA-specific baseline wage growth, and yields a standardized measure of nurse wage growth across MSAs used to set up a multi-site quasi-experiment. We then run a parsimonious linear model; market size matters, for every 0.1 increase in consolidation in smaller-MSAs, real hourly nurse wage growth decreased by \$0.70 (p-value of 0.038). Though not the primary aim of this study, a secondary finding is that real hourly wages for nurses grew less than that of comparable workers by \$4.08.

https://doi.org/10.36687/inetwp197

JEL Codes: C55, I11, J01, J42.

Keywords: monopsony, hospital consolidation, imperfect competition, matching methods for data preprocessing.

The issue of monopsony has increasingly become a focal point of research on the functioning of labor markets, particularly in the United States. Recent theory and evidence suggest that monopsony power can explain a wide range of labor market dynamics and outcomes (Manning 2021; Sokolova and Sorensen 2021). This paper is part of a diverse and quickly expanding body of literature that implicates noncompetitive markets as a contributing factor in some of the most intractable labor market trends in United States such as wage stagnation, increased inequality, and labor's falling share of national income.

The literature expands explanatory factors of labor market trends beyond the realm of perfectly competitive market models to include those where firms may have some degree of power such as in the case of monopsony (i.e., few buyers of production inputs).[1] For decades, traditional labor market foundations situated within competitive models were most used to explain workers' woes; such as the declining value of the real minimum wage, waning union density and strength, and massive industrial shifts due to globalization policies, search frictions, and economic slackness that all too often sideline workers.

Our contribution is to add to the empirical evidence on the role of growing concentration in local labor markets by focusing on higher earning professional workers with industry specific skills—in this case registered nurses. We focus on registered nurses (referenced as 'nurses' throughout) as a homogeneous group of workers that possess some degree of industry specific education and skills. Additionally, nurses represent the largest single occupational classification in hospitals and urgent care centers representing one in four workers. Growing hospital system concentration may affect nurses especially as outside employment options may be limited; in our sample, 70 percent of nurses, per metropolitan statistical area (MSA) average, work in the hospital and urgent care sectors.

We chose the hospital segment of healthcare as a case because it has undergone a radical transformation in recent decades, leading to dominant regional systems. Waves of consolidation have occurred since the 1980s in response to cuts or changes in government reimbursement rates. For example, the introduction of managed care plans drove mergers and acquisitions in the 1990s, followed by a surge in private equity buyouts of hospitals in the 2000s, and ongoing consolidation of hospitals in the 2010s in response to financial pressures as well as opportunities for growth under the Affordable Care Act (Appelbaum and Batt 2017). Today, concentration of U.S. hospital markets continues, creating geographic regions with fewer systems and less competition.

This research has important implications for policy makers, antitrust officials, healthcare decision makers, and practitioners. Antitrust authorities in the U.S. only investigate merger activity that results in high levels of concentration or those with evidence of anticompetitive conduct. Much of the research is focused on merger events and estimating effects on the merged

[1] We defined monopsony more broadly as is typical in the economics literature, as firms that have a degree of market share that gives them wage setting power as competitive constrains are weakened.

entities. In contrast, our study is not based on merger events but exploits the diverse rolling waves of consolidation in local labor markets across the country. Issues of concern, such as the potential for wage-setting power in highly concentrated markets, are not limited to distinct merger activity but to already high and ever-increasing concentration more generally. For example, concentration may increase due to hospital closures, not mergers. In addition, in markets with few competitors, the relative ease of collusion may result in wage suppression (FTC 2018). Thus, a focus limited to merger activity may miss increases in concentration that could also lead to anti-competitive practices. This study focuses on changes in hospital system concentration in which mergers have been a major, but not the only, relevant cause.

Understanding the dynamics of local healthcare labor markets is critical given the importance of the sector for the U.S. economy; even more so in the wake of the pandemic amid continued uncertainty around long term effects (e.g., early retirements, career shifts, education delays). Moreover, labor shortages among hospital-based nurses, which may be a symptom of monopsony, have been endemic in the industry for many years. The wages of nurses were stagnant between 1995 and 2015 despite increasing demand for healthcare over the same timeframe; it was the only sector that added employment during the Great Recession (Appelbaum and Batt 2017). Explanations for stagnation of nurse wages—in one of the more highly unionized professional occupations in the country—are not readily apparent.

This study exploits the intensity of MSA-level changes in hospital system consolidation over two periods to estimate its effect on the wage growth of registered nurses. A key challenge is to find a way of accounting for heterogeneous MSA-level baseline wage growth. We opt for a nonparametric preprocessing data step via matching methods that standardizes nurse wage growth across MSAs. The resultant standardized nurse wage growth is then used to estimate the effect of consolidation via a parsimonious linear model.

Literature

Manning (2021) provides a comprehensive review of evolving theoretical models of monopsony in labor markets. Monopsony, along with non-competitive markets, has the potential to explain an array of economic phenomena such as decreasing real wages that do not reduce employment, vacancies, wage dispersion, and labor's falling share of national income, to name a few. He summarizes "That labor markets have important elements of monopsony power is becoming clear beyond any reasonable doubt" (p. 21). Sokolova and Sorensen (2021) undertook a meta-analysis of monopsony in labor markets that synthesized 1,320 labor supply elasticities from 53 studies across 16 countries. Overall, Sokolova and Sorensen conclude that the studies included in their analysis "provides strong evidence for monopsonistic competition and implies sizable markdowns in wages" (p. 51). A historically situated white paper prepared by David Card for the 2022 annual meetings of the American Economic Association put forth "the time has come to recognize that many – or even most – firms have some wage-setting power" even as there remains much to learn about the mechanisms of such power (Card 2022, p.1).

Much of the discourse regarding labor market concentration as a potential source of monopsony power has focused on the low-wage workforce. For example, Kruger and Posner (2018) documented increases in monopsony and collusive practices by large firms and analyzed how no-poaching agreements and non-compete clauses affected low-wage workers. In particular, they underscored that regional labor markets dominated by few employers have wage setting power that has contributed to wage stagnation, rising inequality, and decreasing productivity growth. Kruger and Posner emphasized that noncompetitive labor market dynamics disproportionately affect low-wage workers. While this is undoubtedly true, it may also be the case that workers with higher earnings, especially those with industry specific education and skills, also face such forces.

This was certainly the case in the mid-2000s when "no-poaching" agreements among Silicon Valley technology firms were exposed. Adobe, Apple, eBay, Google, Intel, Intuit, Lucasfilm, and Pixar all agreed to abstain from recruiting or hiring each other's workers. Management at the highest levels was involved in the collusion. Using data from Glassdoor, Gibson (2022) estimated the effect of the poaching agreements on the salaries of workers within the named firms. Importantly, the Glassdoor data identified employers, thus allowed for a rich set of employer characteristics and job level controls. Gibson estimated the no-poaching agreements reduced salaries at colluding firms by an average of 4.8 percent, consistent with considerable employer market power. He found that stock bonuses and job satisfaction were also negatively affected.

In some instances, market dynamics limit competition in product markets, such as in the hospital market, where there is a real concern that some workers may face a monopsonist labor market. A regionally concentrated product market (i.e., a one-seller monopoly) may also lead to a concentrated labor market for at least some workers.

A review paper by David Wasser titled "Monopsony, Employer Consolidation and Health Care Labor Markets" (2022) supports the notion that monopsonist-type labor markets are more likely to occur in hospital markets due to their very nature. In particular, monopsony may arise in settings where a highly-localized demand for specialized occupations exists within geographic areas that may have limited outside options; singling out registered nurses given outsized relative demand for this occupation in areas where hospitals are located. Wasser's piece along with other review papers (Boal and Ransom 1997; Manning 2003, 2011) show that research going back to the 1970s indicates a large, negative relationship of nurse wages and hospital market concentration.

The consolidation of hospitals and health systems in local areas is well documented (Fulton 2017; Johnson, Kennedy, Rodriguez and Hargraves 2019). Research on the effects of consolidation has primarily focused on product market outcomes—prices charged for procedures and quality of care of patients. These studies found that consolidation increased market power of healthcare providers and led to higher prices for procedures (see for example, Cooper, Gaynor, and Van Reenan, 2015; Dafny and Lee 2016; Gaynor 2018; Gaynor, Ho, and Town, 2015).

Few papers, however, have examined whether hospital system consolidation in local areas extended to wage setting power. A recent paper by Prager and Schmitt (2021) is an exception and most relevant to our work. They looked at whether wage growth slowed due to increases in consolidation following hospital mergers. They focused on mergers because the Federal Trade Commission has a merger review process to regulate such market events.

The Prager and Schmitt event study found "evidence of reduced wage growth in cases where both (i) the increase in concentration induced by the merger was large and (ii) workers' skills were industry-specific" (2021 p. 307). When mergers resulted in a high degree of concentration (i.e., in the top quartile) the effects were most pronounced for medically skilled workers (i.e., nursing and pharmacy, -6.8 percent), less so for a group of other skilled, mostly white collar, non-medical workers (e.g., Administration, Employee Benefits, -4.0 percent). Moreover, there was no discernable effect for the group of mostly blue collar, non-medical workers (e.g., Maintenance & Repairs, Operations, Cafeteria). In sum, Prager and Schmitt attribute their findings of slower wage growth to a decline in labor market power from mergers that resulted in highly concentrated markets.

Hospital System Concentration

Like many studies of market concentration, we exploit a geographical location specific Herfindahl-Hirschman Index (HHI). We use HHI measures in lieu of hard-to-attain employer-employee linked data to measure the elasticity of labor supply—a widely used measure of the potential degree of monopsony power accessible to firms.

Wasser (2021) reminds us that concentration measures are not exogenous as they are also market determined. Thus, changes in concentration may not necessarily lead to less competition. However, the growing body of literature that negatively correlates concentration with wages and specifically to outcomes in hospital product and labor markets supports the use of HHIs as a proxy for potential market power (Wasser 2021). Extensively used by researchers, HHIs also assist the Department of Justice and the Federal Trade Commission to gauge merger activity (U.S. DOJ 2010).

We use HHI scores that reflect the number of hospital beds using American Hospital Association survey data.[2] Consolidation is without respect to cause—this is not an event study focused on mergers. We are interested in the growth of hospital system concentration within MSAs and its effect on local labor markets.

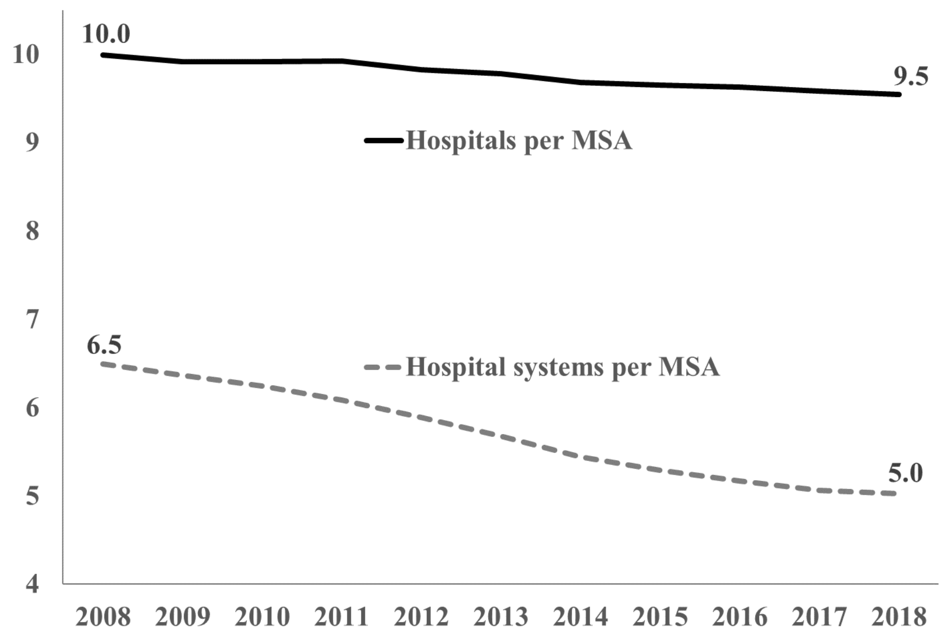
Figure 1 shows U.S. trends in the number of hospitals and hospital systems annually from 2008 through 2018 for the 214 MSAs used in this study—we note here that our final sample is out of a

[2] The Health Care Cost Institute, using American Hospital Associate data, provided within-MSA measures of hospital market concentration (HHI scores) and hospital characteristics. There were three HHI measures: number of beds, FTEs and number of admissions. We used number of beds but correlations with FTEs and admissions were 0.98 and 0.99.

possible 384 MSAs.[3] There were significant changes that occurred over this rather short period. The average number of hospitals, per MSA, fell from 10.0 to 9.5, while the average number of hospital systems decreased from 6.5 to 5.0—indicating markets becoming more concentrated.

Figure 1

Average Number of Hospitals and Hospital Systems, per MSA



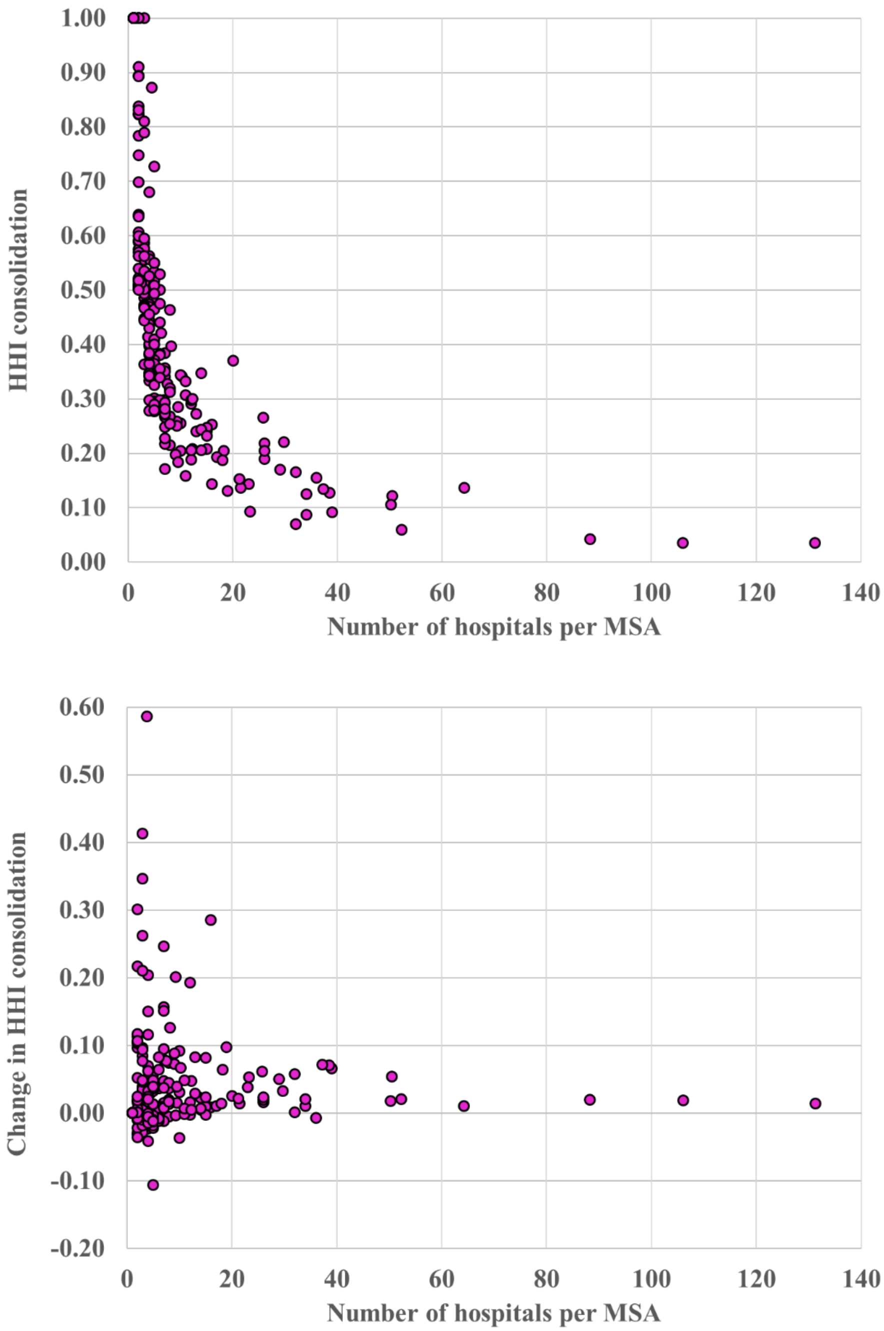
Source. American Hospital Association data.
Note. Data represents the 214 MSA's included in this study.

We exploit the within-MSA change in HHI between two periods under study: 2008-11 and 2015-18—using the MSA-average HHI for both periods. Our choice of periods, which pools annual data, is due to constraints on the availability of MSA-level worker data as described in the data section to come. The top of **Figure 2** plots HHI by the number of hospitals per MSA for the first time-period (i.e., 2008-11 average). Of the 214 MSAs under study, most have less than 20 hospitals and HHI scores that range from 0.035 to 1.00. Large MSAs that tend to have many hospitals, have the lowest levels of concentration in the base period. There are twenty fully consolidated (i.e., HHI of 1.00) MSAs in the first period—each has one, two or three hospitals (thus overlap in the figure). The majority (77 percent) of MSAs have an HHI index above 0.25, which is considered highly concentrated by the Federal Trade Commission.

[3] The ACS individual level data do not identify regional information when sample sizes are too small. MSAs left out of our study are due to this restriction. Analysis of AHA data show MSAs excluded for this reason are smaller-MSAs with two or fewer hospitals. Therefore, they are all highly concentrated with little room further increases. Administrative data to study these areas would be beneficial.

Figure 2

Scatter plot of HHI and HHI Change, by Number of Hospitals



Source. American Hospital Association data provided by Health Care Cost Institute.

Note. Herfindahl-Hirschman Index calculation based on total number of beds. Top figure represents baseline average for Period 1 (2008-11).

The bottom half of Figure 2 shows the average change in HHI over the two periods, also by the number of hospitals per MSA. Changes in consolidation range from -0.10 to 0.59; a few markets added hospital systems that reduced concentration, but most experienced an increase. The average change in HHI is 0.04, representing 147 MSAs or 69 percent that recorded an increase. Smaller markets experienced the largest increases. Market size, especially at the extremes, matters. It is perhaps expected that smaller (larger) markets, by nature of their size, have to experience a lower (higher) degree of concentration to record a significant change in HHI. The three largest markets (New York-New Jersey, Los Angeles, and Chicago) experienced only small increases in consolidation. As we discuss in the data section, the smallest MSAs are not included due to limitations on the American Community Survey data for smaller areas.

Research Design

The aim of our research design is to create a multi-site quasi-experiment that exploits the growth-intensity of MSA-level exposure to hospital system consolidation across two periods to estimate its effect on nurse wage growth. We first address two major challenges; their resolution motivates and clarifies our approach.

First, consolidation levels correlate negatively with population size; smaller MSAs, often with three or fewer hospitals, have higher degrees of consolidation. Furthermore, MSA population size correlates positively with wage levels for all workers, including nurses. We address these concerns by focusing not on consolidation and wage levels, but on the change in consolidation and the change in wages. That is, we are interested in the degree to which the growing trend in hospital consolidation affects nurse wage growth.

The second challenge concerns heterogeneous wage growth across MSAs. During the period under study real wages grew modestly in some areas and greatly in other areas—perhaps due to nonrandom state or local policies like minimum wages, or due to regional trends such as the growth in higher paying industries like the tech sector, or continued effects of globalization and deindustrialization. These heterogeneous trends also affect nurse wage growth and may confound the effect of consolidation; as such, it is necessary to account for MSA-specific 'baseline' wage growth.

How to account for the baseline wage trends? We opt to implement a nonparametric preprocessing data step via matching methods—made possible by ample American Community Survey data. This first phase offers a flexible method to net out potentially confounding MSA-specific baseline wage growth, and results in an MSA-standardized measure of nurse wage growth.

The choice of workers used for this task is important. We could use a sample of all workers or a subsample such as college educated workers. But matching offers the opportunity to net out baseline wage growth based on workers very similar to nurses—throughout we refer to this matched group as 'analogous' workers. In the next section, we describe the process used to construct MSA-specific analogous worker samples, outside of the hospital sector, *closely matched to each individual nurse*.

We then use wages from our sample of matched-analogous workers to net out MSA-specific baseline wage growth from our initial nurse wage growth for each MSA. We then model the new standardized nurse wage growth as a function of national trends in nurse wages, changes in hospital consolidation plus additional macro and hospital level controls that may also be important to wage growth. An attractive feature of using processed data is that the essential requirement of correctly specifying the functional form to estimate the effect of consolidation (i.e., an unknown sole-parametric model) is greatly reduced. Successful implementation of this approach may also reduce bias (Ho et al. 2007).[4]

Modeling Nurse Wage Growth

For ease of illustration, consider a single MSA such as Erie, Pennsylvania over two time-periods. We are interested in the wages of nurses in Erie, and those of a well-defined group of non-hospital workers with similar demographic, educational attainment, and employment characteristics of nurses (i.e., analogous workers). As we will show, the analogous group accounts for baseline wage growth in Erie across workers similar to nurses but not affected by hospital consolidation.

We use a notation convention with random quantities represented with uppercase symbols, and non-random quantities, such as sample sizes, fixed values and population parameters in lowercase that clearly specifies our source of statistical variation. Due to measurement error in the wage data, we pay particularly close attention to sampling error, which varies by region.

Define h_1 to be the mean wage of nurses in Erie in the first period, and a_1 to be the mean wage of all analogous workers during that same period. As noted, h_1 and a_1 are non-random parameters of the population within each MSA. We want to understand what is driving wage growth, thus we model the population of nurse wages in the second period, and the corresponding wage growth, as random. Let the average wages of the Erie analogous group in the second period be $a_2 = a_1 + baseline\_wg_a$ where $baseline\_wg_a$ is the change in their wages, and represents a regional nonrandom parameter specific to Erie.

Similarly, the average wage of nurses in the second period is

$$H_2 = h_1 + baseline\_wg_a + nat'l\_nurse\_wg + \beta \Delta hhi + E_H.$$

In this simple model, wage growth of nurses in Erie is driven by local wage growth of analogous workers, $baseline\_wg_a$, and an intercept term *nat'l_nurse_wg* that captures the nationwide relative wage growth of nurses. Thus, we are not assuming that the wages of nurses grow at the

[4] Implementing matching techniques as a data preprocessing step before subsequent regression analyses has been used by economists for many decades in various types of research. It is perhaps most clearly articulated by Ho et al. (2007)—a paper with over 4000 citations.

same rate as comparable workers nationally. We also have Δhhi the local change in consolidation multiplied by β the main parameter of interest. E_H is a random error term specific to Erie nurses with expectation zero and variance σ^2 —it is the only random component in the model. To identify the model parameters, *nat'l_nurse_wg* and β, we move h_1 and $baseline\_wg_a$ to the left-hand side of the equation above so that

$$(H_2 - h_1) - (baseline\_wg_a) = nat'l\_nurse\_wg + \beta\Delta hhi + E_H.$$

The equation above shows that baseline wage growth has been accounted for within each MSA. Once calculated, the left-hand side now represents MSA-standardized nurse wage growth. This allows us to set up a multi-site quasi experiment that isolates the effect of consolidation on nurse wages apart from otherwise confounding MSA-specific baseline and national wage trends. That is, we first standardize nurse wage growth then specify a simple linear model to estimate β, our parameter of interest.

Furthermore, suppose that Δhhi is known but instead of observing the population mean wages of a_1, h_1, a_2, and H_2 we are only able to measure samples of each, or $\bar{A}_1$, $\bar{H}_1$, $\bar{A}_2$ and $\bar{H}_2$. Each sample average will differ with the population parameter by a measurement error, so that for the analogous group in the first period

$$\bar{A}_1 = a_1 - E_{\bar{A}_1}$$

where $E_{\bar{A}_1}$ is the sampling error for $\bar{A}_1$ with expectation zero and variance Var $(\bar{A}_1)$. Similarly,

$$\bar{H}_1 = h_1 - E_{\bar{H}_1},$$

$$\begin{aligned}\bar{A}_2 &= a_2 - E_{\bar{A}_2}\\ &= a_1 + baseline\_wg_a - E_{\bar{A}_2},\end{aligned}$$

$$\begin{aligned}\bar{H}_2 &= H_2 - E_{\bar{H}_2}\\ &= h_1 + baseline\_wg_a + nat'l\_nurse\_wg + \beta\Delta hhi\\ &\quad + E_H - E_{\bar{H}_2}.\end{aligned}$$

By substitution we have

$$\begin{aligned}(\bar{H}_2 - \bar{H}_1) - (\bar{A}_2 - \bar{A}_1) &= (\bar{H}_2 - \bar{H}_1) - \overline{BASELINE\_WG_a}\\ &= \overline{NURSE\_WG'}\end{aligned}$$

where $\overline{NURSE\_WG'}$ represents a standardized measure of nurse wage growth (i.e., net of baseline wage growth). Therefore,

(1) $\overline{NURSE\_WG'} = nat'l\_nurse\_wg + \beta\Delta hhi + E_H - E_{\bar{H}_2} + E_{\bar{H}_1} + E_{\bar{A}_2} - E_{\bar{A}_1}$

Equation (1) is the simplest form of our model where the wage sample means are a linear function of the change in consolidation with a random model term and four random sampling error terms.

Generalizing beyond Erie, consider a certain MSA$_j$, so that the regional equivalent of Equation (1) becomes

$$(2) \quad \overline{NURSE\_WG'}_j = nat'l\_nurse\_wg + \beta\Delta hhi_j + E_{H_j} - E_{\bar{H}_{2j}} + E_{\bar{H}_{1j}} + E_{\bar{A}_{2j}} - E_{\bar{A}_{1j}}$$

Equation (2) demonstrates the motivation for constructing analogous worker groups—to eliminate regional-baseline wage growth as a possible confounder. Now, linear regression estimates the model parameters, slope $\hat{\beta}$ and intercept $nat'l\_\widehat{nurse}\_wg$, across all MSAs using the standardized measure of nurse wage growth.

Unlike ordinary least squares, the left-hand side of each observation has a separate value for the variance. We address unequal variances by employing weighted least squares where MSA$_j$ is weighted by the inverse of its variance (see details in Appendix B).

Data and Sample Construction

We use the American Community Survey (ACS) as arranged by and accessed at IPUMS (Ruggles et al. 2021). The ACS is a survey administered annually to 3.5 million households. Among an array of queries, participants field questions concerning occupation, employment income, and hours worked for the previous year. We first identify workers potentially affected by hospital consolidation—registered nurses employed in the hospital and urgent care sectors. Then, we describe the statistical matching technique used to create an analogous non-hospital worker group within each MSA, year cohort.

Registered Nurses

To explore the effect of hospital consolidation on wages we focus on registered nurses. Nurses are the largest occupational group among patient-facing workers in hospitals and urgent care centers, and their earnings may be susceptible to industry consolidation. The ACS allows us to identify nurses by occupation to obtain work and demographic information needed for the analysis; it further provides geographic information, specifically place-of-work MSA, which we use to merge hospital consolidation information with the ACS sample by merging on MSA codes.

To reduce the measurement error in nurse wages within each MSA, we pool across multiple years, and inflation adjust all incomes to 2018 real dollars. Pooled data from 2007-2011 represents our first or baseline period and 2015-2019 represents the second period. The five-year pooling increases the sample size of nurses, allowing us to include smaller MSAs, and provides for a very large selection of non-hospital workers that represent the pool of candidates considered for the analogous worker group.

Hourly wages are calculated by dividing annual earnings by weeks worked multiplied by usual hours worked per week; discarded are observations with real hourly wages below $7.25 or above $200 to maintain data integrity. To maximize the quality of the wage information the sample of nurses is restricted to those who worked at least 50 weeks per year with 30 or more usual hours worked per week. Workers who are self-employed, enrolled in school, or have a missing place of work (i.e., MSA) distinction have been excluded.

Finally, the sample of nurses is restricted to those employed in hospitals or urgent care centers as hospital consolidation most directly affects these industry sectors. We omitted MSAs where data was sparse, defined as fewer than ten nurses in either period. This resulted in an unweighted sample of 110,074 nurses that met our criteria over the two periods representing 214 MSAs.[5]

Nurses are certainly not the only group of hospital workers potentially affected by hospital consolidation. We explored using other occupations such as licensed practical nurses, medical aides, physician assistants, and medical technicians. However, the ACS sample sizes for each were too small. In some instances, wages exhibited large variation, which in turn meant that they were not reliable due to considerable sampling error. Given the ACS as the source of wage data, nurses proved to be the only likely affected occupational group with sufficient data to carry out this analysis.

Analogous Worker Sample

The preprocessing data technique uses our sample of nurses to identify a matched sample of analogous workers. Here we describe our general approach. Appendix A provides more details regarding the matching methodology and our use of the *GenMatch* statistical package.

An "all donor pool" from the ACS represents *potential matches* and is restricted to non-nurses, employed in industries outside of hospital and urgent care, who meet the same work effort and other restrictions that define the sample of nurses. Each of the 110,074 nurses are matched to four analogous workers via a matching algorithm within MSA, year cohort.

The matching criteria are exact regarding gender and educational attainment. Meaning, the algorithm matches a female registered nurse with a bachelor's degree from Erie, Pennsylvania in the 2008 ACS sample with four analogous female workers with a bachelor's degree from Erie in the 2008 ACS sample (just one condition of satisfying a complex algorithm that determines the final sample of analogous workers). Other characteristics with categorical matching are: age

[5] There are 384 MSAs in the U.S., excluding Puerto Rico, according to the 2013 Office of Management and Budget. We use the ACS place-of-work variable, PWMET2013, which has data for 245 distinct MSAs. 216 MSAs have a consistent PWMET2013 definition across both periods and have HHI consolidation calculations. Two MSAs do not have at least 10 matched nurses in both periods, leaving us with a final sample of 214 MSAs.

(annual), race (6 categories) marital status (4) citizenship (3), and employment sector (2).[6] There were only a few instances where four nurse matches could not be found. The final (unweighted) sample consists of 108,515 nurses and 434,060 analogous workers. We then pool the annual samples of MSA-specific nurses and analogous workers into two periods: period 1 cohort from 2007-2011 and 2015-2019 for the period 2 cohort. Numerous matching strategies and software (Stuart 2010) would match nurses to analogous workers, and we use the *GenMatch* package (Diamond and Sekhon 2013) for this task. A key diagnostic criterion to evaluate the resultant matched data set is to attain a high degree of "covariate balance" defined as the similarity of the distributions of the full set of covariates. *GenMatch* considers this balance requirement, confirms its existence, and constructs a matched group, by design, to meet these criteria. Table A1 in Appendix A shows that the *GenMatch* algorithm was able to find a closely matched sample of analogous workers to our sample of nurses; illustrated by the substantial differences of the before-matched samples compared to the similarity of the covariate distribution across the post-matched samples, lending credence to our approach (see Appendix A for details).

We note that our use of matching is strictly as a preprocessing data step with the goal of identifying and employing analogous workers to account MSA-specific heterogeneous wage growth. However, our use of matching provides a nonparametric approach to control for all worker level employment and demographic characteristics—thus, it is unwarranted to include worker attributes in the estimation of the parameters in Equation (2). We do not employ matching estimators, which are suited for binary treatment settings, because our main treatment variable Δhh_i is a continuous variable between zero and one. Ho et al. (2007) and Stuart (2010) suggest that processed data used in combination with parametric estimation works best even when direct matching estimators are possible.

In summary, we highlight three notable features of the model and estimation procedure. First, we do not assume a linear form for the demographic covariates, instead use a nonparametric matching technique. Second, we use matching simply as a preprocessing data step to create a group of analogous workers to account for MSA-specific heterogeneous baseline wage growth. Third, we do not assume a constant effect at the individual level for the change in consolidation (Δhhi). Rather, we assume a constant effect at the MSA level, a much weaker and more flexible assumption. This allows for any type of individual level data generating model with the aggregate effect at the level of the MSA being linear—leading to the estimation of Equation (2).

Parametric Estimation

We now move to estimating Equation (2) which represents the simplest form of linear regression. At this point, we greatly reduced model dependency and guesswork in favor of minimal linear modeling due to our use of the preprocessed data. Our use of processed data

[6] Exact matching may be difficult on all variables and result in too many dropped observations, resulting in large standard errors in the parametric estimation.

means worker characteristics have already been accounted for and are unwarranted in the regressions. However, it is the case that other factors may influence the degree to which the wage growth of nurses differs from that of the corresponding analogous workers—for example, nurses have much higher rates of union coverage than typical workers do, and unionization is associated with higher wage rates. Note that union status is not available in the ACS, thus could not be factored into the matching algorithm. We utilize two sets of covariates—one that accounts for overall labor market conditions, and one to account for hospital characteristics.

Descriptive Statistics

Table 1 reports averages across the 214 MSAs for both periods; we also note the pooled years and data source for each. MSAs-average 211 nurses (unweighted) in the first period and 263 in the second. The hourly earnings of nurses, on average, are higher than that of the analogous group by 39 percent and 36 percent, respectively, for periods one and two. Over the two periods, the wages of nurses increased by just 0.4 percent while they increased by 2.6 percent for the analogous group of workers. Average HHI scores increased from 0.45 to 0.48, reflecting that hospital were in amassed into fewer hospital systems over the two periods. In addition, fully consolidated MSAs in our sample (i.e., HHI equal to one) increased to 12.1 percent in period two, which reflects an increase of 2.8 percentage-points over the first period, an increase from 20 to 26 MSAs.

The business cycle reflects very different conditions over the two periods under study (2007-11 and 2015-19). The Great Recession, not uniformly felt across the country, officially dated December 2007 through June 2009 by the National Bureau of Economic Research. Economic recovery, too, was uneven; thus we control for state unemployment rates. The recession and recovery are reflected in these statistics. For example, across the two periods the national unemployment rate decreased significantly from 8.5 percent to 4.7 percent. State right-to-work laws are also important in determining wage growth. Table 1 includes the incidence of states that recently adopted the policy—from 36.8 percent to 47.5 percent, an increase of 10.7 percentage-points.

Hospital controls are near the bottom of Table 1. The average number of hospitals per MSA declined from 9.9 to 9.6 while the median number of beds was little changed. Hospitals admitted larger percentages of Medicaid (17.8 percent to 19.6 percent) and Medicare (45.5 percent to 48.6 percent) patients from period one to two. In addition, there was a shift away from public hospitals to private (a decline of 1.3 percentage-points). The prevalence of teaching hospitals declined from 8.8 percent to 8.0 percent, while there was a rather large increase in the share of critical access hospitals (7.3 percent to 10.5 percent).

Table 1

Descriptive Statistics of Regression Controls, MSA averages

Variables	Period 1	Period 2	Source: Period years 1, 2
Sample			ACS: 2007-11, 2015-19
Number of MSAs[a]	214	214	
Nurses	211	263	
Analogous workers	844	1051	
Average hourly wage			ACS: 2007-11, 2015-19
Nurses	$35.85	$36.00	
Analogous workers	$25.80	$26.48	
Hospital consolidation			AHA: 2008-11, 2015-18
HHI - hospital consolidation	0.45	0.48	
Fully consolidated MSA	9.3%	12.1%	
Labor market			CPS: 2008-11, 2015-18
Unionization rate[b]	12.6%	11.2%	
Unemployment rate[b]	8.5%	4.7%	
Right-to-work state[c]	36.8%	47.5%	
Hospital controls			AHA: 2008-11, 2015-18
Number hospitals	9.9	9.6	
Median number of beds	193.0	193.3	
Percent admits Medicaid	17.8%	19.6%	
Percent admits Medicare	45.5%	48.6%	
Percent public	13.9%	12.6%	
Percent private	86.1%	87.4%	
Percent teaching	8.8%	8.0%	
Percent critical access	7.3%	10.5%	

Source. ACS: American Community Survey; AHA: American Hospital Association; CPS: Current Population Survey; HHI: Herfindahl-Hirschman Index.
Note. [a]Removed two MSAs with fewer than ten nurses removed. Where MSA crosses state border linear combination of [b]state rates or [c]linear combination of state indicators. All statistics averages calculated across MSAs, unweighted.

Regression Specifications

We present two sets of regression results that follow from Equation (2). For each set, we start with the basic Equation (2). Next, we add in all the covariate controls from Table 1. Lastly, we run independent forward selection and backward elimination procedures where an algorithm determines what independent variables to include. The forward selection algorithm starts with a model without covariates. In the first stage, the algorithm finds and adds to the model the variable that most significantly reduces the model fit criteria. In the second stage, the algorithm selects a remaining variable that most significantly reduces the model's fit. This process repeats until an additional variable does not significantly reduce the model's fit.

Alternatively, the backward elimination algorithm starts with all covariates. In the first step, the algorithm eliminates the covariate that leads to the least statistically significant change in the model's fit, and only if the elimination is not significant. The process then repeats until no variables which could be removed without significantly worsening the fit of the model remain. We use the information criteria of Akaike (1974), commonly known as AIC, to assess fit. While the forward/backward selections may result in two different selected covariate sets, when both approaches yield the same final set of variables, this provides evidence that the selection procedure has arrived at a parsimonious, yet statistically relevant set of explanatory variables.

Results

Results for the first set of specifications are reported in **Table 2**. The main parameter of interest is β on the change in HHI. It gives the effect that the change in MSA-level consolidation has on nurse wage growth. The -5.57 coefficient from specification (1) indicates that, without including controls for other factors beyond the national trend (recall worker covariates have been accounted for via matching)—increases in HHI suppressed the wage growth of nurses. For ease of interpretation, for every 0.1 point-increase in HHI, real nurse wage growth was \$0.56 less per hour (statistically significant at the 10% level). Specification (2) includes all covariates, for every 0.1 point-increase in HHI nurse wages were \$0.51 less per hour.

Interestingly, the forward and backward procedures each selected the same specification—reported in specification (3) where most of the available covariates are not selected. HHI consolidation growth is selected, thus added to the model, but the coefficient is no longer statistically significant although the point estimate (-4.52) remained negative.

Thus far, results are weakly suggestive that increased hospital consolidation may suppress nurse wages within localized labor markets. However, these results may depend heavily on smaller MSAs where consolidation is most prominent as shown in Figure 2. Thus, we run a second set of regressions, where we interact HHI growth with MSA-size as measured by number of hospitals in the market. We designate a dichotomous distinction for small markets as those with four or less hospitals; otherwise, it is not a small market. 'Small-MSA' is a dummy variable entered into the model singularly and also interacted with HHI growth—leaving out HHI growth as a standalone independent variable.

Table 2

Estimates of Hospital Consolidation on Nurse Wages

	Specifications		
Controls	(1)	(2)	(3)
Intercept-national nurse wage	-0.66 ***	-6.29 **	-3.67 ***
	(0.24)	(2.74)	(1.28)
HHI consolidation growth	-5.57 *	-5.06 *	-4.52
	(2.97)	(3.03)	(2.84)
HHI consolidation score	-	2.04	3.11 ***
		(1.47)	(0.83)
Full consolidation	-	1.62	-
		(1.23)	
Unionization rate	-	14.78 ***	8.94 **
		(5.69)	(3.56)
Unemployment rate	-	32.34	21.61
		(38.98)	(14.23)
Unemployment rate growth	-	14.99	-
		(45.23)	
Right to work state	-	0.57	-
		(0.66)	
Right to work growth	-	0.03	-
		(0.81)	
Number of hospitals	-	0.00	-
		(0.01)	
Number of beds	-	0.00	-
		(0.00)	
Percent Medicaid admits	-	-7.01 *	-7.06 *
		(4.05)	(3.61)
Percent Medicare admits	-	2.79	-
		(3.27)	
Percent of hospitals public	-	0.84	-
		(1.27)	
Percent of hospitals private	-	1.07	-
		(1.03)	
Percent of hospitals teaching	-	0.12	-
		(1.48)	
Percent hospitals critical access	-	-0.81	-
		(1.43)	
Regression controls:			
HHI growth	Y	Y	Y
Full set of covariates		Y	Y
HHI growth X MSA size			

Note: Non-growth variables represent Period 1 averages; growth is the change over the two periods (see Table 1). Significance levels: ***1%; **5%; *10%.

Table 3

Estimates of Hospital Consolidation on Nurse Wages, by Size

	Specifications		
Controls	(4)	(5)	(6)
Intercept-national nurse wage	-1.22 ***	-6.54 **	-4.08 ***
	(0.31)	(2.76)	(1.27)
HHI growth x small (≤ 4 hospitals)	-8.95 **	-8.53 **	-7.03 **
	(3.69)	(3.87)	(3.37)
HHI growth x large (> 4 hospitals)	-0.40	0.80	-
	(4.83)	(5.18)	
Small MSA	1.37 ***	0.48	-
	(0.48)	(0.67)	
HHI consolidation score	-	2.29	3.49 ***
		(1.80)	(0.83)
Fully consolidation	-	1.40	-
		(1.27)	
Unionization rate	-	14.86 ***	8.43 **
		(5.73)	(3.54)
Unemployment rate	-	29.22	24.84 *
		(39.03)	(14.17)
Unemployment rate growth	-	5.23	-
		(45.71)	
Right to work	-	0.67	-
		(0.66)	
Right to work growth	-	-0.10	-
		(0.82)	
Number of hospitals	-	0.00	-
		(0.01)	
Number of beds	-	0.00	-
		(0.00)	
Percent Medicaid admits	-	-7.58 *	-7.18 **
		(4.07)	(3.59)
Percent Medicare admits	-	2.38	-
		(3.30)	
Percent of hospitals public	-	1.07	-
		(1.29)	
Percent of hospitals private	-	1.21	-
		(1.05)	
Percent of hospitals teaching	-	0.16	-
		(1.50)	
Percent hospitals critical access	-	-0.64	-
		(1.46)	
Regression controls:			
HHI growth	Y	Y	Y
Full set of covariates		Y	Y
HHI growth X MSA size			Y

Note: Non-growth variables represent Period 1 averages; growth is the change over the two periods (see Table 1). Significance levels: ***1%; **5%; *10%.

Reported in **Table 3** are the results that separate out size effects and HHI growth. Specification (4) includes only the intercept and the two controls on HHI growth and size. For this base model, the effect of HHI growth loads on to the interaction with Small-MSA; with small local area wages of nurses suppressed by $0.90 per hour for every 0.1 point-increase in HHI (statistically significant at the 5% level). The effect is similar in magnitude and statistical significance in specification (5), where nurses earned $0.85 less per hour with a full-set of controls included.

The forward selection and backward elimination procedures again selected the same subset of variables from those available in specification (5). They also correspond to those selected in specification (3); except we replace HHI growth with HHI growth x Small-MSA. Recall the estimate of HHI growth from specification (3) was -4.52 (not statistically significant), whereas the coefficient on HHI growth x Small-MSA from specification (6) is -7.03 (statistically significance at the 5% level). Importantly, HHI growth x Large MSA was not selected. Thus, the HHI effect attenuates with less statistical significance when market size is not explicitly considered.

The intercept, which captures the national relative trend in nurse wages, is important to consider. It is consistently negative (statistically significant at the 5% level or higher) across specifications—somewhat akin to a nurse-wage gap—as the wage growth of nurses fell behind that of analogous workers. From our preferred specification (6), the -4.08 coefficient indicates that nationally nurse wages increased by $4.08 less per hour than that of analogous workers over the two periods (statistically significant at the 1% level). This indicates that nurse wages have trended behind that of the analogous workers highly matched to nurses within each MSA—generally, that of other college educated females given our nurse sample is 88 percent female.

Results from this research are highly suggestive that growing hospital consolidation contributes to the suppression of nurse wages within local labor markets. It is reassuring that the forward/backward procedures landed on the same set of covariates, meaning that specifications (3) and (6) are equivalent in choice of independent variables (i.e., Intercept, HHI growth variables, HHI level, Unionization rate, Unemployment rate, and Percent Medicaid admits).

The estimated coefficients on the growth in HHI reported in Table 3 account for MSA-size, and are quite consistent across all three specifications—ranging from -8.95 to -7.03 (all significant at the 5% level; coefficients are not distinguishable statistically). MSA size is critically important, without such a distinction the HHI effect attenuates. Our results are similar to those by Prager and Schmitt (2021). They found that mergers that resulted in high rates of consolidation (those in the top quartile) were associated with the suppression of industry specific skilled worker wages (i.e., nurses and pharmacy), and this was not the case for other non-industry specific workers nor for any group in markets with lower concentration rates. Though not explicitly discussed, the Prager and Schmitt results depend on the smallest commuting zones, which is evident in their Table 2 (p. 408). It reports that the mergers at the highest quartile of change in HHI also had the smallest average populations compared to the lower quartiles.

Nurses are highly unionized, but data on MSA-level unionization rates for nurses is not available. Instead, we use MSA-level overall unionization for all workers which we view as a proxy for MSA-level nurse unionization in our regression models.[7] As expected given research on unions, the coefficients are positive, somewhat large, and statistically significant (at the 5% level or better). MSAs with higher unionization rates are associated with higher relative wage growth for nurses. Our analysis treats unionization and consolidation as separate factors; we are not able to test whether nurse unions pose a direct mitigating factor to growing concentration. However, Prager and Schmitt (2021) found a direct link as slower wage growth, due to mergers, was attenuated in markets with strong labor unions. Prager and Schmitt explored possible channels for this effect. They concluded that it is likely that labor market power is the main channel that explained wage suppression, not other merger-related explanations; stating "Wage growth slowdowns are attenuated in markets with strong labor unions, and wage growth does not decline after out-of-market mergers that leave local employer concentration unchanged" (Abstract, p. 397).

For a robustness check, we repeated our analyses using teachers to test for spurious results.[8] Across the six specifications using preprocessed data matched on teachers instead of nurses, all of the coefficients on hospital system HHI growth were positive (i.e., ranging from 2.06 to 4.13) instead of negative, and all were not statistically significant. Moreover, the forward/backward selection procedures never chose any of the HHI growth variables. Teachers were the only occupational group large enough for this exercise. Nevertheless, this lends credibility to our results.

Final Thoughts

Joan Robinson introduced monopsony—a market dominated by a single buyer—in her 1933 book *The Economics of Imperfect Competition.* We defined the term more broadly as those firms that have a degree of market share that gives them some degree of wage setting power. Less competitive labor markets are gaining needed attention in U.S. The scrutiny is warranted in hospital markets as the DOJ and FTC report that approximately 80% of hospital markets in the U.S. are highly concentrated with HHI scores above 0.25; it is also the case for 77 percent of the 214 MSAs in this study.

A growing body of work has demonstrated that consolidation has adversely affected the quality of care, prices, and efficiency of hospitals. There has been much less investigation into the effect of ever-increasing hospital system consolidation on the wages of affected workers.

[7] At the state level, unionization rates from the CPS are available overall and for nurses. We calculated these rates across the 50 states and Washington DC from 2008 to 2018 and found the two unionization rates have a correlation value of 0.9. This high degree of linear association, which is close to perfectly collinear, indicates, at least at the state level, that unionization rates overall are a near substitute for unionization rates of nurses in linear regression models. Though the data is too sparse at the level of MSA, it seems likely a similar strong linear relationship would hold.

[8] Teacher results available upon request.

We exploit overall MSA-level growth in hospital system consolidation (otherwise, not limited to mergers) over two-periods to assess its effect on the wage growth of registered nurses. Nurses comprise the largest occupation in hospitals and urgent care facilities and they also have occupation-specific education and skills. Importantly, hospital system concentration is occurring in all markets, thus our study is akin to a dose-response type study.

We design an MSA-level quasi-experiment to estimate a simple linear equation that describes wage growth of nurses as a function of national wage trends, MSA-specific baseline wage trends, and changes in hospital consolidation. One challenge is how to account for heterogeneous MSA-level baseline wage growth that may cofound the effect of consolidation. We opt to incorporate a flexible nonparametric pre-processing data step via matching methods to define MSA-specific samples of workers that are very similar to nurses. Using a statistical package and worker and demographic characteristics from ACS data, a complex algorithm matched four 'analogous' workers to *each* nurse by MSA, year cohorts. Wage growth of the analogous workers gives MSA-specific baseline growth leaving a standardized measure of nurse wage growth used in subsequent parsimonious parametric linear regression analyses. Our use of data pre-pressing via matching methods is an excellent method to net out MSA-specific baseline wage growth of workers very similar to nurses.

The largest increases in consolidation have occurred in smaller MSAs and accounting for this pattern is crucial. Results are highly suggestive that increased hospital system consolidation in small-MSAs (i.e. MSAs with less than 5 hospitals) is adversely related to nurse wage growth. Coefficients from our set of regressions that interact HHI growth with a small-MSA dummy variable gives consistent results across the three specifications: -8.95, -8.53 and -7.03 (coefficients are significant at the 5% level, not statistically distinguishable). The effect attenuates without a control for size.

Estimates translate into a wage penalty for nurses of $0.70 to $0.90 per hour for every 0.1 increase in the HHI consolidation measure. The standard errors, however, are quite large—a 95 percent confidence interval around our preferred estimate spans from a large negative effect to a slight negative effect (-13.64 to -0.42 from a point estimate of -7.03). The average hourly wage of nurses in small-MSAs is $35.22 in the second period. Applying a 0.1 increase in consolidation—a typical increase for smaller MSAs with increasing consolidation—means that hourly wages could have been $0.70 higher, suggesting a 2% wage cut. A result that could add up to very large wage losses given high degrees of hospital consolidation. And, keep in mind our secondary finding that real hourly wages for nurses grew less than that of comparable workers by $4.08.

We showed that the largest markets, as of yet, are not highly concentrated, and we did not detect adverse effects of growing concentration in these markets. The largest markets (e.g., NY-NJ, LA, and Chicago) had beginning HHI scores of approximately 0.05 with increases of about 0.02 over our timeframe. It may seem these areas would have to experience significant consolidation to get to 0.25—deemed highly concentrated by the FTC. But now is the time for policy makers to study and understand growing market power in large cities to prevent high degrees of concentration that lead to anticompetitive markets and possible negative outcomes in the future.

The issue of causality is of critical importance but not easily claimed with quasi-experimental designs. This study adds to the limited but growing body of empirical evidence investigating whether there is a persuasive causal-link between hospital consolidation and the wages of affected workers—especially those with industry specific-skills and limited options within local labor markets.

Further exploration, perhaps utilizing administrative data on nurses, may provide much insight into concentrated markets in smaller-MSAs not included in this study due to data limitations and rural areas. Administrative data may also provide estimates with more precision, as our confidence interval spans large negative to slightly negative wage effects for registered nurses.

This research has policy implications for antitrust regulation and healthcare policy. Given that antitrust authorities have primarily focused their attention on merger activity, our study suggests that it behooves them to broaden their monitoring and enforcement lens to pay attention to other ways that consolidation occurs, for example through hospital closures, leading to heightened levels of concentration with degrees of monopoly and/or monopsony power.

Moreover, hospitals are often relatively small entities, potentially allowing mergers to escape regulatory oversight by the Federal Trade Commission because any one acquisition may typically fall below the FTC governing Hart-Scott-Rodino threshold ($50 million in 2001, $63.4 million in 2010, $76.3 million in 2015, $101 million in 2022) set by the Hart-Scott-Rodino (HSR) standard that would trigger an antitrust review (Dryden et al. 2021). Introducing reporting requirements for small mergers is central. Expansion of monitoring to cross-market activity is important as it is becoming more common and can also have associated adverse effects. All of which would require increased budgets at the DOJ and FTC. Hafiz (2020) argues for regulatory sharing between antitrust and labor law to combat the adverse narrow consumer-harm effects of employer power to include effects on workers.

Finally, healthcare policy makers and practitioners who must contend with ongoing labor shortages among nurses as well as other healthcare professionals may find this research suggestive of the factors shaping those shortages and point the way for policies to improve the wages and staffing levels of these essential workers.

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Appendix A. Constructing the Sample of Analogous Workers via Matching

Analogous Worker Sample

We use a nonparametric preprocessing data step via matching to define MSA-specific sample of workers analogous to nurses outside of the hospital sector. This step enables an accounting of heterogeneous baseline wage growth and is used to standardize nurse wage growth across MSAs setting up a multi-site quasi-experiment. We first describe our general approach, and then turn to the statistical matching package used to carry out the data-preprocessing step.

For each of the 110,074 nurses found in the ACS during our study period, we use the following algorithm to identify an analogous worker group. First, we develop an "all donor pool" of workers from the ACS that represents *potential matches* to the nurses in our sample. Workers in the donor pool are restricted to non-nurses, employed in industries outside of hospital and urgent care, who meet the same work effort and other restrictions that define the sample of nurses--those who worked at least 50 weeks per year with 30 or more usual hours worked per week. Workers that are self-employed, enrolled in school, or have a missing place of work (i.e., MSA) have been excluded. Second, using the all-donor pool, the algorithm searches for *four matches* to each nurse within MSA, year cohort as described below.

The matching criteria are such that gender (i.e., female, male) and educational attainment (i.e., categorized as high school degree or less, some college but no degree, Associate's degree, Bachelor's degree, and Master's degree plus) of the chosen analogous workers all match *exactly* to those fields of the particular nurse. The matching criteria also requires an exact match on year and MSA within the sample. For example, the algorithm matches a female registered nurse with a bachelor's degree from Erie, Pennsylvania in the 2008 ACS sample with four analogous female workers with a bachelor's degree from Erie in the 2008 ACS sample (just one part of satisfying a complex algorithm that determines the final sample of analogous workers).

Exact matching may drop too many observations and result in larger standard errors in the parametric estimation. Thus, we match analogous workers with six other important work and demographic characteristics without the stringent exact requirement. The six characteristics are age (annual), race (categorized as African American, White, Native American, Asian or Pacific Islander, Multiracial, and All Other), ethnicity (Latino/Hispanic or not), marital status (married, divorced/separated, widowed, or never married), citizenship (born US citizen, naturalized, or not a citizen), and employment sector (employed in the public or private sector). As we describe below, the matching algorithm constructs a matched group such that the distributions of the six non-exact covariates for the analogous workers are as similar as possible to the distribution of these characteristics for the nurses.

We then pool the annual samples of MSA-specific nurses and analogous workers into two periods: period 1 cohort from 2007-2011 and 2015-2019 for the period 2 cohort. Again, the pooling of years ensures an adequate sample size to minimize wage measurement error particularly for smaller MSAs. Thus, each of the 214 MSAs has a sample of nurses and a corresponding sample of analogous workers that is four times as large for each of the two periods.

Importantly, we note that our use of matching is strictly as a preprocessing data step with the goal of standardizing nurse wages across MSAs. However, our use of matching offers a nonparametric approach to control for all available employment and demographic characteristics—thus, when moving to estimating the parameters in Equation (2), controls on worker characteristics are unwarranted. We do not employ matching estimators, which are suited for binary treatment settings, because our main treatment variable Δhh_i is a continuous variable between zero and one. Ho et al. (2007) and Stuart (2010) suggest that processed data used in combination with parametric estimation works best even when matching estimators are used.

Data Preprocessing via Matching

We use the *GenMatch* package (Diamond and Sekhon 2013) to construct a sample of analogous workers. Numerous matching strategies and software (Stuart 2010) are available to match a nurse with an analogous worker with similar characteristics. A key diagnostic criterion to evaluate the resultant matched data set is to attain a high degree of "covariate balance" defined as the similarity of the distributions of the full set of covariates. *GenMatch* considers this balance requirement, confirms its existence, and constructs a matched group, by design, to meet this criterion.

We choose a matching strategy without replacement so that, for some nurses, the algorithm may not be able to find four matches as described—in that case, we drop those nurses from our sample without bias (see Ho et al. 2007, p. 206). A second important criterion in the preprocessing data step is not dropping too many observations from the matching sample—nurses in our case. The choice of the four matches is somewhat arbitrary. The larger the number matches for each nurse, the smaller the sampling error of the analogous worker wages. However, the larger the number of matches the greater likelihood that nurses will be dropped from the sample. We ran our analysis with 1, 2…10 matches. Four matches seemed to strike the right balance of retaining nurses while providing a large enough group of analogous workers to minimize sampling error.

Table A1 summarizes the samples and distribution of covariates before and after matching. The first data column reports the distribution, using sample weights, for the 110,074 nurses in the ACS—our starting sample of nurses that met the worker criteria. The second data column reports the complete 'all donor pool' of 5,777,473 non-nurses, non-hospital, and non-urgent care workers in the ACS that met our worker criteria; they represent *potential* matches for the matching algorithm to consider. The third data column represents the final sample of nurses—those where the algorithm successfully found four matches, and the last column represents the final analogous worker sample.

Table A1 shows that the *GenMatch* algorithm was able to find a closely matched sample of analogous workers to our sample of nurses; illustrated by the substantial differences of the before-matched samples compared to the similarity of the covariate distribution across the post-matched samples, lending credence to our approach. First, compare the ‘all nurses” sample to the ‘all donor pool’ sample of potential matches in data columns one and two. Workers in the all-donor pool are typically a bit younger, far less likely to be female, considerably less educated, less likely to be married, significantly more likely to identify as Latino/Hispanic, equally likely to be a citizen, and somewhat more likely to be employed in the private sector.

The third data column represents the final sample of nurses, those that we are able to find four matched workers from the donor pool. Importantly, there remain 108,515 of the original 110,074 nurses, representing a 98.6% rate of successful matching—a critical criterion that gives confidence in the success of our match procedure. The last column is our final analogous workers sample of 434,060—which remains quite large given our stringent matching criteria.

The distributions of the original nurse sample (first data column) and nurses that were successfully matched (third data column) are nearly identical; this is expected given the high match rate of the nurses. The last column reports statistics for our final analogous group sample. The ‘all donor pool’ looks quite different from the final nurse and analogous worker samples. The matching procedure drew a subsample of analogous workers that has a highly similar distribution of covariates compared to the final sample of nurses. By all accounts, the resultant final samples via *GenMatch* demonstrates a highly successful matching procedure.

Table A1

Sample Statistics, Before and After Matching

	Before matching		After matching	
Variables	All nurses	All donor pool	Nurses	Analogous workers
Total unweighted sample	110,074	5,777,473	108,515	434,060
Average age	43.8	42.8	43.8	43.7
Percent female	88%	42%	88%	88%
Marital status				
Married	61%	57%	61%	60%
Divorced	16%	14%	16%	16%
Widowed	2%	2%	2%	2%
Never married	21%	27%	21%	22%
Education attainment				
High School deg. or less	2%	40%	2%	2%
Some college, no degree	3%	15%	3%	3%
Associate's degree	28%	8%	27%	29%
Bachelor's degree	52%	24%	53%	51%
Master's degree plus	14%	13%	15%	14%
Race				
White	73%	74%	72%	74%
Black	11%	12%	11%	10%
Chinese, Japanese	1%	2%	1%	3%
All other Asian/PI	11%	5%	12%	8%
Multiracial/other	3%	8%	3%	4%
Percent Latino/Hispanic	7%	18%	7%	8%
Citizenship				
Born citizen	81%	81%	81%	82%
Naturalized	15%	9%	15%	13%
Not citizen	4%	10%	4%	4%
Class of worker				
Private	89%	83%	89%	88%
Public	11%	17%	11%	12%

Source. American Community Survey data pooled 2007-11 and 2015-19 averages.

Note. Worker restrictions: 50+ weeks, 30+ hours, designated place of work MSA, not in school, not self-employed, and working for wages. Real $2018 hourly wages from $7.25 to $200 an hour. Nurses in Hospital and Urgent Care, while controls are sans these industries.

Appendix B. Variance Calculation for Weighted Least Squares

Unlike ordinary least squares, the variance of the error term will be different for each observation. We address unequal variances by employing weighted least squares where MSA$_j$ is weighted by the inverse of its variance. Since our measure for the standardized wage growth, $\overline{NURSE\_WG'}_j$, is equal to $(\overline{H}_{2_j} - \overline{H}_{1_j}) - \overline{BASELINE\_WG_{aJ}}$, which is equal to $\left(\overline{H}_{2_j} - \overline{H}_{1_j}\right) - (\bar{A}_{2_j} - \bar{A}_{1_j})$, we weight each observations with

$$1/Var((\overline{H}_{2_j} - \overline{H}_{1_j}) - (\bar{A}_{2_j} - \bar{A}_{1_j})).$$

To calculate the inverse variance weights, we assume modeling error is uncorrelated with the sampling error, and that the sampling error terms across the two periods are uncorrelated with each other. This gives

$$\text{(B1)}\ Var\left[(\overline{H}_{2_j} - \overline{H}_{1_j}) - (\bar{A}_{2_j} - \bar{A}_{1_j})\right] = Var\left[E_{H_j} - E_{\overline{H}_{2j}} + E_{\overline{H}_{1j}} + E_{\bar{A}_{2j}} - E_{\bar{A}_{1j}}\right]$$
$$= \sigma^2 + Var\left(\overline{H}_{1j}\right) + Var\left(\overline{H}_{2j}\right) + Var\left(\bar{A}_{1j}\right) + Var\left(\bar{A}_{2j}\right)$$
$$- 2Cov(\overline{H}_1, \bar{A}_1) - 2Cov(\overline{H}_2, \bar{A}_2).$$

Where each term on the final right-hand side of the equation above: $Var\left(\overline{H}_{1_j}\right), Var\left(\overline{H}_{2_j}\right), Var\left(\overline{A}_{1_j}\right)$ and $Var\left(\overline{A}_{2_j}\right)$, are estimated with standard replication weight packages. The two-covariance terms $Cov\left(\overline{H}_1, \overline{A}_1\right)$ and $Cov\left(\overline{H}_2, \overline{A}_2\right)$ are estimated with replicate weights with additional programming (see IPUMS 2021). However, in practice we found these to be negligible in comparison to the size to the variance terms. Finally, the estimate of σ^2, the modeling error, is calculated with an initial unweighted regression, that is, using ordinary least squares, of the MSA level data. We substitute the estimates of all variance components into the right-hand side of Equation (B1), using the plug-in principal estimate of the variance of the standardized nurse wage growth for each MSA