Medicare Hospital Payment Adjustments and Nursing Labor Markets

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Abstract

Compared to the extensive study on the effects of Medicare payment in hospital markets and on physician behavior, almost no work has been done on the effects of Medicare hospital payment on the labor market for nurses. This study deals with the hospital wage index (HWI) adjustment to Medicare payments, a geographic adjustment intended to compensate hospitals in high-cost labor markets, and examines two potential consequences of HWI adjustment on nurses' labor. First, we examine whether hospitals in highly-concentrated markets exploit their ability to influence their own wage index by paying nurses more. Second, we examine whether the Occupational Mix Adjustment (OMA) to the HWI affected nurse employment. We test for both consequences in U.S. hospitals between 1999 and 2009 and in empirical models that also allow us to examine support for classic monopsony power. We find no evidence that hospitals wield monopsony power to reduce nurses' wages or employment during our study period, nor do we find that existing HWI adjustment methods lead to higher wages. However, we do find evidence that hospitals responded to the implementation of the OMA by hiring fewer high-skilled nurses, which implies that hospitals were gaming Medicare wage adjustment rules prior to 2005.

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1. Introduction

Medicare, the largest payer of healthcare services in the U.S., relies on complex systems of administratively-set prices to reimburse providers. Changes in Medicare provider payments are often made with the intent of containing costs or improving quality. However, numerous empirical studies have documented unintended consequences such as increased supply of healthcare services when provider payments are cut (i.e., supplier induced demand), increased severity of patients' diagnoses under prospective payment systems (i.e., upcoding), and effects of physician payment changes on physician training and labor supply. In contrast, a very small literature has studied the effects of Medicare hospital payment on the labor market for nurses.

Our study provides new analysis of the link between Medicare hospital payment and the nurse labor market by examining the hospital wage index (HWI) adjustment to Medicare payments, a geographic adjustment intended to compensate hospitals in high-cost labor markets. We examine two potential consequences of the HWI adjustment. First, as noted by the Institute of Medicine or IOM, the process of making the HWI adjustment may unintentionally create "circularity" or endogeneity in the wage index (IOM, 2012a). That is, because Medicare calculates the HWI adjustment using wage data reported by hospitals themselves, hospitals in highly-concentrated markets can influence their own wage index and thus drive up their Medicare payments. We examine whether this HWI adjustment process leads to higher nurse wages in markets where hospitals have an increased ability ("opportunity") and a strong incentive ("motive") to game the HWI calculation.[1,2] Second, we examine an adjustment made to the HWI called the Occupational Mix Adjustment (OMA). Concerned that initial HWI calculations rewarded hospitals that hired more expensive higher-skilled labor, CMS

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[1] As such our paper looks for indirect evidence of hospital responses to Medicare payment rules. Direct evidence, in

[2] Hospitals could pay workers more, or inflate their reported wages, or both. An audit of 21 hospitals' wage data found that 17 hospitals overstated average hourly wage rates (OIG, 2007).

implemented the OMA in 2005 to remove skill-mix variation across hospitals from the wage index adjustment. We examine whether employment of higher-skilled nurses decreased after the implementation of the OMA. While both of our study questions pertain to nurses' labor, the HWI adjustment process could potentially affect other types of hospital workers. We focus on nurses because this occupation constitutes a significant fraction of the hospital workforce and because there is a rich existing theoretical and empirical literature on their labor.

Our study makes several contributions to the literature. First, we conduct the first study of whether Medicare administrative pricing impacts nurse wages. As noted above, existing critiques of Medicare geographic adjustments cite the potential for hospitals to drive their own wage index values, but to the best of our knowledge, no prior research has tested whether the wage index calculation process influences nurse wages. Second, we provide the first analysis of the impact of the occupational mix adjustment on nurse employment. Both of these contributions have important policy implications; moreover, they offer potential new insights on the links between healthcare and labor markets and previously unexamined welfare implications of Medicare payment policy.

Third, we contribute to the literature on classic monopsony in the market for nurses' labor. To examine the relationship between the HWI adjustment process and nurse wages, we regress nurse wage differentials with respect to alternative occupations on hospital market concentration. In this way, our work is similar to prior tests of classic monopsony (e.g., Hirsch and Schumacher, 2005), so our analysis allows us to provide updated tests for the classic monopsony model using more recent data. However, unlike those prior tests, we extend the basic model to allow the effect of market concentration to vary by the relevance of Medicare payments under the inpatient prospective payment system (IPPS) to hospitals' revenue. Finally, we add to literature on identifying the effects of the Medicare program through the use of a new version of a market-level “bite” or “pressure” variable.

We find no evidence that hospitals wield monopsony power to reduce nurses’ wages or employment during our study period (1999-2009). If anything, nurses’ employment and wages increase in locations where hospital market concentration increases. We find no support for the circularity critique of the HWI; that is, we find no evidence that existing HWI adjustment methods induce Medicare-intensive hospitals to use their influence on the index to increase wages. In fact, locations with Medicare-intensive hospitals experience declines in relative nurse wages as they become more concentrated. However, we do find evidence that hospitals responded to the implementation of the OMA by hiring fewer high-skilled nurses (RNs), which implies that hospitals were gaming Medicare rules prior to 2005.

Our paper proceeds as follows. In Section 2, we describe how the Medicare program uses the HWI to adjust hospital payments for geographic variation in labor prices, and how the current process of calculating the HWI and the implementation of the occupational mix adjustment may incentivize certain hospitals to alter nurse wages and employment. In Section 3, we describe how our analysis of nurse wages builds on a model of classic monopsony, and we summarize past findings from empirical tests of classic monopsony. Section 4 includes a description of our methods and data. Section 5 presents results and Section 6 concludes.

2. Background on the Hospital Wage Index and the Occupational Mix Adjustment

Since 1983, Medicare has paid hospitals for acute inpatient care provided to beneficiaries under the inpatient prospective payment system (IPPS); today some form of prospective payment is also used for inpatient rehabilitation care, inpatient psychiatric care, facility-based long-term care and skilled nursing care, home healthcare, and hospice care. Below we describe how the HWI enters into the IPPS payment calculation.[3] We then describe the role of the occupational mix adjustment in calculating the HWI.

Under IPPS, Medicare pays a lump sum for each hospital stay; the payment is determined up-front according to a formula that performs a series of adjustments to two base payments for the hospital's operating costs (i.e., labor and supply costs) and capital costs (MedPAC, 2014). The base payments are standardized amounts set by Medicare to reflect the typical costs of providing inpatient care; in 2015, the base operating payment was $5,431 and the base capital payment was $434. Base rates are first adjusted for differences in the resources used to treat different types of patients. Each hospital stay is assigned to a severity-adjusted diagnosis related group (or MS-DRG) based on the patient's condition at admission and the major procedures used in the patient's treatment, and each MS-DRG has a weight that reflects the complexity and severity of the treatment. Base rates are then adjusted by geographic factors, hospital factors (e.g., whether the hospital is a teaching hospital or qualifies for disproportionate share hospital (DSH) payments), whether the patient was an exceptionally costly case to treat (e.g., outlier payment), and other policy-related factors.

The HWI enters into the payment calculation when the operating and capital base payments are adjusted for geographic factors. Geographic adjustment is intended to raise or lower both base payments depending on the price of labor in the hospital's market. Table 1 illustrates the effect of the HWI adjustment on the larger of the two base payments – the operating payment. The table contains fiscal year 2011 data reported in IOM (2012a) for one of

[3] The HWI is also used to adjust prospective payments made by Medicare to other healthcare providers such as hospital outpatient departments, home health care providers, and skilled nursing facilities, to name a few (IOM 2012a, p. 22). As we describe below, however, only IPPS hospitals contribute wage data to the construction of the HWI.

over 700 MS-DRGs: MS-DRG 233, or coronary artery bypass grafting (CABG) with major a complication or comorbidity. Column (1) shows Stanford Hospital (in Palo Alto, CA), with the highest HWI value in 2011 and column (3) shows Medical Center Enterprise (in Enterprise, AL), with the lowest HWI value in that year. After the HWI is applied to operating payments for MS-DRG 233, Stanford's payment for this hospital stay is 71% higher than the payment received by Medical Center Enterprise.

For a given geographic area, the HWI is calculated as the ratio of the area's average hourly hospital wage to the national average hourly hospital wage. The average hourly wage is derived from data on wages, salaries, benefits, and hours provided by short-term acute care hospitals paid under the IPPS (hereafter referred to as "IPPS hospitals"), data that hospitals report to Medicare on Worksheet S-3 of the annual cost reports (Acumen, 2009). The HWI used to adjust base payments in a given fiscal year is calculated from cost report data submitted from four years prior; for example, wage index values for fiscal year 2010, which started October 1, 2009, were calculated from hospitals' fiscal year 2006 cost reports. The HWI is calculated at the geographic area level and then applied to all hospitals in a given area, although as we discuss below, hospitals can request reclassification.[4] Currently, Medicare uses core-based statistical areas (CBSAs) to define local markets in urban areas and designates a rest-of-state area for each non-urban local market; there are 432 such labor markets in the 50 U.S. states and DC.

The use of hospital-supplied data in calculating the HWI has been cited as an important limitation. In a comprehensive review of Medicare geographic adjustment, the IOM notes the potential for endogeneity or circularity in the wage index, or "the ability of hospitals to influence

[4] Medicare may adjust the HWI for certain groups of hospitals (IOM, 2012a, p. 86). The most common adjustment is reclassification of a hospital to a different labor market area with a higher HWI. Such adjustments are made at the request of an individual hospital and are reviewed and approved by the Medicare Geographic Classification Review Board (MGCRB). We discuss the potential impact of reclassification in the description of our empirical methods.

their own wage index value," a problem that is "especially likely to occur in areas containing only a few hospitals or in areas with one or a few dominant hospitals" (IOM, 2012a, p. 71). A significant number of markets fall into this group. For example, 2009-2011 data show that of 432 labor market areas, 59 markets had only one IPPS hospital, 98 markets had only two IPPS hospitals, and 56 markets had just three IPPS hospitals. As noted by the IOM, "[i]n these markets in particular, *the index can reflect hospitals' own decisions about what wages to pay* rather than the prevailing wage in the area" (p. 71, emphasis added).

The consequences of higher HWI values for hospitals and Medicare may be substantial. A higher wage index increases Medicare payments (i.e., revenue) for acute inpatient care, as well as payments for care delivered in other settings where the HWI is applied (e.g., hospital outpatient department services). In addition, there are potential productivity benefits to the hospital as predicted by efficiency wage theory. Artificially high values of HWI could contribute to higher Medicare program expenditures by decreasing the hospital's incentive to control labor costs. Out of concern about the poor accuracy of the HWI, the IOM recommends that Congress revise the HWI statute so that data on labor prices are drawn from Bureau of Labor Statistics (BLS) data on all healthcare sector employers, as opposed to cost report data submitted by IPPS hospitals. This recommendation is also made in other critiques of the hospital wage index (MedPAC, 2007; Acumen, 2009).

Prior to 2005, the HWI adjustment process was also criticized for rewarding hospitals that pay higher wages not solely because they face higher prices of labor, but also because they choose to employ a more-skilled mix of labor. For example, a hospital could have a higher wage bill relative to the national average if managers hire more registered nurses (RNs) and fewer licensed practical nurses (LPNs) or nursing assistants. Because the intent of the hospital wage index is to adjust Medicare payments for geographic differences in costs (and not management decisions), CMS devised the Occupational Mix Adjustment to the HWI to remove the effect of skill mix differences from the wage index. As noted by the IOM (2012a), "IPPS hospitals are free to use whatever mix of occupations they need to treat their patients; the goal of the OMA is to avoid rewarding or penalizing hospitals per se for using a richer occupational mix" (p. 67). CMS implemented the OMA partially (a 10 percent adjustment) in fiscal years 2005 and 2006 and fully in fiscal year 2007 (Medicare Program, 2007).[5]

The process of making the OMA to the wage index is complex, and details can be found in a number of sources (e.g., Reiter, Slifkin, and Holmes, 2006; IOM, 2012a). Simply put, CMS combines the hospital-specific and national-level wage data used to calculate the HWI with additional hospital-specific data on the specific mix of clinical workers at each hospital. The latter data are collected from the Occupational Mix Survey (administered periodically to all IPPS hospitals starting in 2003) and are used to define, for each hospital and class of worker, an occupational mix adjustment factor. Occupational mix adjustment factors are calculated by comparing the hospital's skill-mix relative to the nation as a whole, and are carried forward into the calculation of the HWI adjustment for each market. Upon this adjustment, the resulting HWI is such that hospitals in markets with a below-average skill mix will receive larger HWI adjustments to their Medicare payments, and vice versa. Thus, the implementation of the OMA was expected to create an incentive for hospitals to cut back on high-skilled labor.

As with the HWI adjustment, hospitals that comprise a large share of their market contribute more to, and stand to be affected more strongly by, the OMA adjustment. The OMA is a market-level variable that makes the same proportional adjustment to the HWI for both large

[5] CMS justified its partial implementation (rather than full implementation) by noting that the data used to implement the OMA were not ideal. Litigation (Bellevue Hospital Center v. Leavitt) forced the full implementation in fiscal year 2007.

and small hospitals in a given area; therefore, the OMA can "affect the payment to a given hospital only to the extent that it [the given hospital] affects the market wage index" (Reiter, Slifkin, and Holmes, 2006, p. 7). Thus, the addition of the OMA to the calculation of the HWI adjustment is expected to create an incentive for hospitals to cut back on high-skilled labor especially when the hospital constitutes a large share of the market. In our analysis, we focus on the implementation of the OMA on the employment of RNs. Registered nurses are the highest skill level within the nursing classification, and the nursing classification accounts for 38% of all paid hours in hospitals nationally (2006 data reported in Reiter, Slifkin, and Holmes, 2006, p. 3).

While our study is the first to investigate whether the current method of making the HWI adjustment alters nurse wages and the first to examine whether the occupational mix adjustment altered nurse employment, numerous studies have examined other consequences of Medicare payment arrangements. For example, there is a sizeable literature on the impact of Medicare IPPS; Salkever (2000) and Chalkley and Malcomson (2000) provide detailed reviews of prior studies on the effects of Medicare IPPS on hospital costs and length of stay. In general, prior studies often report that hospitals respond to the financial incentives of IPPS by reducing inpatient lengths of stay and other measures of resource use, and thereby lowering costs.[6]

One notable prior study is Acemoglu and Finkelstein (2008) which also examines the impact of Medicare payment methods on nurse labor markets. Specifically, the authors test how IPPS affected hospitals' capital-labor ratios and use of high-skilled nursing labor. Noting that Medicare's adoption of IPPS reduced hospitals' reimbursements for labor while leaving capital payments unchanged, the authors hypothesize that the higher relative price of labor would cause

[6] Other studies have examined provider responses from the implementation of prospective payment in other settings of care with varying findings; see, for example, Norton et al. (2002) on Medicaid PPS in inpatient psychiatric care, Sood et al. (2008) on Medicare PPS in inpatient rehabilitation care, Grabowski et al. (2010) on Medicare PPS in skilled nursing facility care, and He and Mellor (2012) on outpatient PPS.

hospitals to increase their capital-to-labor ratios, technology adoption, and use of more-skilled nursing labor (to which technology is a stronger complement). Using hospital-level data from the 1980s, they show that hospitals with a higher share of revenues coming from the Medicare program (measured in a higher share of Medicare inpatient days at baseline) responded to the post-IPPS regime with significant increases in all three outcomes. Our study differs in several respects, namely in that we examine particular aspects of the IPPS payment, the HWI adjustment and the related occupational mix adjustment, and we focus on a time period after the rollout of IPPS.

3. Monopsony Power in Nurse Labor Markets and Medicare Hospital Reimbursement

To investigate how the HWI adjustment influences nurse wages, we build on the classic monopsony model, which is often applied to nurses' labor for several reasons. Employers of nurses tend to be large hospitals, and especially in rural areas, one or two hospitals often account for a large share of nurse employment. Nursing shortages are a longstanding concern (e.g., Yett, 1975) and are consistent with restricted employment by monopsony hospitals. Nurses' skills are specialized and not easily transferred to other industries. Finally, the female share among nurses is large (about 90 percent in our samples), and evidence of family ties in migration behavior has shown that women have been less geographically mobile in the context of job opportunities than men (Sloan, 1978; Mincer, 1978).

The simplest classic monopsony model for nurse labor markets has a single hospital that produces output q (health services) using only labor inputs E (nurses), and receives an output price p in a perfectly competitive output market. The labor market for nurses is not perfectly competitive, and the hospital faces the upward-sloping inverse labor supply curve $w(E)$. The monopsonist hospital's profit maximization problem is now

$$(1) \qquad \max_E \; pq(E) - w(E)E$$

and optimization implies

$$(2) \qquad (pq'-w)/w = 1/\delta_E$$

Equation (2) is the familiar statement that the "exploitation index" (the gap between the marginal benefit of a worker's labor to the firm and the wage) is inversely proportional to the wage elasticity of labor supply. As workers become more sensitive to wages (e.g., through improved job prospects at another firm), the monopsonist is less able to keep wages low.

Most studies on monopsony power in the nurse labor market appeal to the theoretical inverse relationship between the exploitation index and the wage elasticity of labor supply. The most common approach – and the one nearest to ours – proxies for the inverse of δ_E using hospital market concentration in geographical labor markets (e.g., Metropolitan Statistical Areas). Some early studies found lower nurse wages in locations with fewer or more-concentrated hospitals (Hurd, 1973; Link and Landon, 1975; Feldman and Scheffler, 1982; Bruggink et al., 1985) and concluded that monopsony power was evident in the market for RNs. However, subsequent studies showed that those results were not robust to the inclusion of reasonable controls like local wage levels in non-nursing (alternative) occupations or the use of alternative identification strategies (Adamache and Sloan, 1982; Hirsch and Schumacher, 1995 and 2005; Currie, Farsi, and MacLeod, 2005).[8] For example, Hirsch and Schumacher (2005)

[8] Another strand of literature estimates the elasticity of labor supply to individual hospitals. Staiger et al. (2010) exploit a sudden legislated increase in nurse wages at Department of Veterans Affairs hospitals and estimate quite small labor supply elasticities among RNs, which is evidence in favor of monopsony power. Matsudaira (2014) uses California's enactment of minimum staffing levels to identify labor supply elasticities and finds little evidence of monopsony power. However, those results are specific to the market for nurse aides, who have significantly lower skills and earnings than RNs.

found no evidence of classic monopsony in cross-sectional models of nurse wages using data collected around 2000. However, they also found that locations experiencing increased hospital consolidation through the 1990s saw relative wage reductions for nurses, which Hirsch and Schumacher interpret as evidence consistent with monopsony power in the short-run.

Our approach augments the classic monopsony model with insights from the HWI adjustment process; in doing so, it may provide a potential explanation for the weak or mixed evidence about monopsony power in the nurse labor market. As noted above, hospitals could game the HWI calculation process by paying nurses more in order ultimately to receive higher Medicare reimbursements (revenue). In investigating potential gaming of the HWI adjustment, we consider both the *opportunity* of hospitals in an area to exploit the adjustment process, and the hospitals' *motivation* to do so.

As noted above, the HWI adjustment process provides hospitals with the largest shares of their local market with the largest *opportunity* to influence their location's HWI. We exploit exogenous variation in this opportunity stemming from CMS's decision to define local areas as CBSAs (and not MSAs) circa 2005. This switch increased hospitals' opportunities in some markets and decreased opportunities in others, and we ask if increased opportunities for manipulating the wage index led to higher relative nurse wages. If so, we would expect to see that relative nurse wages increase as markets become more concentrated (i.e., become increasingly dominated by one or a few large hospitals). This is opposite the classic monopsony model prediction that nurse wages will decrease as markets become more concentrated. As a result, prior studies that do not take Medicare hospital payment features into account may yield attenuated estimates of monopsony power.

Further, to tease out the presence of both classic monopsony power and any gaming of the HWI, we also account for the *motivation* of area hospitals to raise the HWI. We argue that motivation will be greater the larger is Medicare's contribution to hospital revenue. Thus, if the wage index process creates circularity, then relative nurse wages will increase in those markets where hospitals with strong motives (those in Medicare-intensive areas) experience increased opportunity (increased market concentration). Markets with increased opportunities but low motivation may instead exhibit the classic monopsony prediction of reduced nurse wages in response to increased market concentration. In the next section, we describe the empirical model and data we use to account for both monopsony power and the Medicare HWI adjustments in the determination of nurse wages.

In addition to lower wages, the classic monopsony model implies lower employment levels among nurses. Robinson (1988) notes that registered nurses (RNs) have more extensive training and specific skills than licensed practical nurses (LPNs), so RNs are more exposed to monopsony power. Consistent with the monopsony model, Robinson (1988) finds that hospitals facing less local competition hire fewer RNs relative to LPNs. In contrast, other studies have found evidence inconsistent with hospitals using monopsony power to reduce RN employment (Hirsch and Schumacher, 1995; DePasquale, 2014). In the next section, we describe how our investigation of the Medicare occupational mix adjustment relates to hospital monopsony power and nurse employment levels.

4. Econometric Methods and Data

A. Testing for HWI Effects on Nurse Wages

To test whether the HWI determination process leads to higher nurse wages, we model the relationship between a market-level measure of nurse wages relative to other wage opportunities (i.e., the nurse wage differential) and hospital market concentration.[9] In the context of the monopsony literature, this relationship is a proxy for the inverse of δ_E. This basic specification also makes our analysis of nurse wages similar to prior tests of classic monopsony by Hirsch and Schumacher (2005). Unlike classic monopsony studies, however, we test whether the relationship between hospital market concentration and nurse wages varies with the importance of HWI adjustments to hospitals in the area. If hospitals are gaming Medicare payment rules by taking advantage of HWI circularity, we would expect to see a more positive relationship between higher nurse wages and hospital concentration in areas where a large share of hospital stays occur at IPPS hospitals and are paid by Medicare. We focus on first-difference models to account for any unobserved market-specific factors that potentially influence nurses' relative pay and hospital concentration.

Specifically, let φ_k be a measure of nurses' wages relative to alternative opportunities in location *k*. Equation (3) below describes determinants of changes over time in the nurse wage differential in location *k*:

$$(3) \qquad \Delta\varphi_k = \theta_0 + \theta_1 \Delta HHI_k + \theta_2 \Delta HHI_k \times BITE_{k,t-1} + \theta_3 \Delta X_k + \nu_k$$

HHI_{kt} is the Herfindahl-Hirschman Index for hospitals in location *k* at time *t*, a measure of the local concentration of hospitals. $BITE_{k,}$ measures the importance of HWI adjustments to hospitals in location *k*, and we define two variations of this measure from data on the inpatient days in an

[9] We looked for available data on nurse wages at the hospital-level. Sources like the AHA annual survey, the Medicare cost reports, and the Medicare IPPS impact file do not contain wage data by occupation. While there is some data on nurse wages from the Occupational Mix Survey, wage data are available starting in the 2006 survey, but were not collected on the 2003 survey (which collected data on hours, not wages). The 2006 and subsequent occupational mix surveys were not used because our identification strategy employs changes in the definition of Medicare markets used to make geographic adjustments, which occurred in 2005.

area occurring at IPPS hospitals and paid by Medicare (see below for variable definitions and construction). Since this type of measure may itself respond endogenously to changes in HHI, we measure each bite variable in the baseline period (*t-1*). This follows similar approaches in the literature on identifying Medicare program effects (e.g., Acemoglu and Finkelstein (2008) and numerous prior studies reviewed in Salkever (2000)). X_k is a vector of location-specific control variables including size (population) categories and average values of residents' characteristics (e.g., education level, age, race), and v_k is an error term that incorporates unobserved factors explaining the dynamics of nurses' relative wages. The coefficients of interest are θ_1 and θ_2. If monopsony power from market concentration lowers nurse wages relative to outside options, we expect our estimate of θ_1 to be negative. Further, if hospitals' incentive to game the HWI calculation process increases with the importance of the HWI in their revenues, we expect our estimate of θ_2 to be positive, meaning that Medicare reimbursement incentives attenuate the negative effect of hospital concentration on nurses' wages.

As noted earlier, hospitals can request reclassification to another market with a higher HWI. We argue that the ability to request reclassification does not remove the incentive for hospitals in Medicare-dependent, highly-concentrated markets to increase nurse wages. There is uncertainty about whether such requests will be approved or denied. A hospital's application must demonstrate that its wages exceed those paid by other hospitals in the market to which it was geographically assigned and are comparable to the higher-paying hospitals in the market to which it seeks assignment. The approval rate for applications varies substantially over time; we found evidence of approval rates around 50 percent in some years, although other years see 90 percent of applications approved.[10] At the same time, the ability of a hospital to request reclassification may lessen the relationship between highly concentrated/highly Medicare dependent markets and nurse wages, as the option to seek reclassification to a higher wage area provides an incentive for Medicare-dependent hospitals outside these areas to payer higher wages and meet the wage comparability criteria. For this reason, we expect that hospitals' ability to seek reclassification will attenuate our estimates of θ_2.

1. Data on Nurse Wages (φ) and Controls (X)

The dependent variable in the wage analysis, φ_k, is the area-specific wage differential between RNs and other workers, conditional on other controls. We follow Hirsch and Schumacher (2005) in calculating the area-specific nurse wage differentials from the wage regression shown below:

$$(4) \qquad \ln W_i = \alpha_t + \textstyle\sum_j \beta_{jt} X_{ij} + \sum_k \gamma_{tk} AREA_{ik} + \sum_k \varphi_{tk} RN_i \times AREA_{ik} + e_i$$

where i indexes individuals, t indexes time (year, either 2000 or 2010), k indexes areas, and j indexes individual traits (controls). W is hourly earnings and X is a vector of controls (sex, race, etc.). $AREA_{ik}$ is an indicator for person i living in location k. RN_i is an indicator for person i being a registered nurse. This approach accounts for higher wages of nurses in locations that have higher wages for all workers (say, to compensate for high costs of living), so estimates of φ_{tk} focus attention on local factors that specifically influence nurses' wages (such as hospitals' monopsony power or exploitation of Medicare rules).

[10] The approval rate in the Medicare Geographic Classification Review Board's first year was 90 percent (for fiscal year 1992). However, stricter requirements reduced reclassifications by about 60 percent in fiscal year 1994 (Dalton et al., 2007). CMS publishes recent MGCRB decisions on its web page. See http://www.cms.gov/Regulations-and-Guidance/Review-Boards/MGCRB/MGCRB_Decision_Listings.html (accessed July 3, 2015). We tabulated recent MGCRB activity and describe the results in Table 2 below. The MGCRB receives several hundred applications annually. The approval rate has been increasing recently from around 50 percent in 2012 to 87 percent in 2015.

The data used to estimate Equation (4) are derived from the 2000 Census and the pooled 2009-2011 annual American Community Surveys (Ruggles et al., 2010). The 2000 Census file is a 5 percent sample, and the 2009-2011 ACS file pools a 1 percent sample from each of three years 2009, 2010, and 2011. In each file, we select a sample of nurses and a comparison group. Both samples include only workers who are at least 18 years old. The sample of nurses includes only registered nurses (OCC1990=95) employed by the "Hospitals" industry (IND1990=831). The comparison group includes female (non-nurse) workers who have at least an associate's degree. We further restrict the comparison group to exclude workers in occupations that are related to the healthcare industry, in the military, with unknown occupations, or whose occupation is listed as unemployed.[11]

We calculate the hourly wage (*W*) as the annual wage and salary income from the prior year divided by the product of weeks worked and usual hours per week.[12] The Census Bureau imputes missing values, and we drop observations with imputed values for income, occupation, or industry. Measurement error in annual income, weeks worked, and hours worked increase the frequency of outlier observations, so we drop observations with hourly wages in the highest one percent and lowest one percent of the distribution in each sample (2000 and 2009-11). We control for various determinants of wages in *X*, including years of potential labor market

[11] Specifically, we exclude from the comparison group those with the following occupations: Medical scientists; Physicians; Dentists; Optometrists; Podiatrists; Other health and therapy; Pharmacists; Dietitians and nutritionists; Respiratory therapists; Occupational therapists; Physical therapists; Speech therapists; Therapists, not elsewhere classified; Physicians' assistants; Psychologists; Social workers; Clinical laboratory technologies and technicians; Dental hygenists; Health record tech specialists; Radiologic tech specialists; Licensed practical nurses; Health technologists and technicians, not elsewhere classified; Biological technicians; Private household cleaners and servants; Guards, watchmen, doorkeepers; Protective services, not elsewhere classified; Dental assistants; Health aides, except nursing; Nursing aides, orderlies, and attendants; Dental laboratory and medical appliance technicians; Military; Unemployed; and Unknown.

[12] The 2009-2011 ACS weeks worked variable is recorded in bins (1-13, 14-26, 27-39, 40-47, 48-49, and 50-52 weeks). We merge in a crosswalk created with the pooled 2005-2007 ACS samples that include this interval-valued variable and also its continuous-valued companion variable. For each weeks worked bin in the 2009-2011 ACS, we impute the average number of weeks reported by 2005-2007 ACS respondents in the same bin.

experience and indicators for sex, race/ethnicity (Black, Hispanic, white non-Hispanic, American Indian/Alaskan native, Asian and/or Pacific Islander, or other race), region (nine categories), marital status (married, separated/divorced/widowed, never married), education (high school or less, some college, associate's degree, bachelor's degree, master's degree or higher), public sector employment (federal, state, or local government), and part-time (fewer than 35 hours per week usual). We also include a control for the contemporaneous unemployment rate in the state using the 1999 and 2009 annual average unemployment rate for each state reported by the Bureau of Labor Statistics (BLS, various years).

Our definition of a geographic area is the CBSA, and we construct $AREA_{ik}$ indicators from Equation (4) accordingly as the CBSA in which individual i resides. Since census data report each respondent's location in a Public Use Microdata Area (PUMA),[13] we use a crosswalk from MABLE/Geocorr2K, available from the Missouri Census Data Center, to align PUMAs and CBSAs using a consistent definition of CBSA boundaries across years. Most PUMAs each correspond to a single CBSA. In cases where a single PUMA overlaps multiple CBSAs, we duplicate observations and assign the respondent to every overlapping CBSA; in regression models of Equation (4), we weight each observation by the share of the PUMA's population that overlaps the CBSA. Details of the crosswalk from PUMA to CBSA are available in section 1 of the Data Appendix.

We estimate Equation (4) separately for 2000 and 2009-2011 samples and collect the estimates of φ_{tk} for each location k. These are the estimated nurse wage differentials used to assess whether nurses are paid relatively more or less in locations with different hospital market

[13] A PUMA is a place (often following county or Census-defined "place" borders) including at least 100,000 residents.

structures and Medicare intensity. The change in this measure over time constitutes the dependent variable in our main empirical specification shown in Equation (3).

We also use data from the 2000 Census and pooled 2009-2011 ACS samples to calculate ΔX_k for use in estimating Equation (3). The vector X_{tk} represents CBSA-level control variables. These include: a set of indicator variables for the size of the CBSA population,[14] sample averages across CBSA residents of years of potential labor market experience and experience squared, the state unemployment rate and the shares of the CBSA residents in our sample in categories defined by sex, race/ethnicity,[15] education level,[16] public sector status, part-time status, and marital status.[17]

2. Data on Hospital Market Concentration (*HHI*)

To measure market-level hospital concentration in the nurse wage model, we use data from the annual hospital survey conducted by the American Hospital Association (AHA). We use the 1999 and 2009 annual surveys to align the time period to the timing of the Census-provided wage data (e.g., the 2000 Census data report 1999 wages, so we use the 1999 AHA survey). The AHA annual survey is a survey of all hospitals in the US. The 2009 survey database, for example, contains data on 6,269 hospitals in all U.S. states and the District of Columbia, including general hospitals (77.2%), psychiatric hospitals (7.5%), acute long-term

[14] We follow Hirsch and Schumacher (2005) in this regard. One size category is non-urban CBSAs, or CBSAs that are not "rest-of-state" areas. Since no CBSA in our sample period changes, this term falls out of the first-difference models. Among urban CBSAs, the categories are in bins with cut-off points of CBSA population equal to 200,000, 300,000, 500,000, 1 million, and 2 million, comparable to the cutoffs used in Hirsch and Schumacher (2005). The omitted category is CBSAs with populations less than 200,000.

[15] We include the CBSA-level shares of residents who are black, Hispanic, American Indian/Alaskan native, Asian and/or Pacific Islander, or another race. The omitted category is the share of residents who are white non-Hispanic.

[16] We include the CBSA-level shares of residents that have some college education, an associate's degree, a bachelor's degree, and a master's degree or more. The omitted category is the share of residents whose highest level of education is high school or less.

[17] We include the CBSA-level shares of residents who are: 1) divorced, separated, or widowed; and 2) never married. The omitted category is the share of residents who are married.

care hospitals (5.7%), rehabilitation hospitals (3.8%), and a mix of other hospital types including children's hospitals and specialty hospitals (e.g., heart or cancer hospitals). Our preferred measure of the HHI includes all hospitals in the AHA annual survey; this version of the HHI is arguably most relevant for tests of classic monopsony since all such hospitals compete for nurse labor. It is also similar to the measure used in prior analysis of classic monopsony by Hirsch and Schumacher (2004, 2005).

We calculate the HHI as the sum of squared market shares for all hospitals in a market, where the market share for each hospital is the ratio of the hospital's number of staffed beds to the total number of staffed beds in the market.[18] We define two separate versions of the HHI: the first uses the market shares of all individual hospital units in each market, and the second treats hospitals belonging to the same system as a single unit. We call the latter the "system HHI." These two HHI measures are highly correlated, with a correlation coefficient of 0.96 in both years. Section 2 of the Data Appendix provides more details on the construction of these variables.

Recall that in calculating the area-level nurse wage differentials, we defined the area as the CBSA in both 2000 and 2009-11. In calculating the market-level *HHI*, however, we vary the level of geography by year. This is because Medicare adopted the use of metropolitan and rest-of-state CBSAs in its geographic adjustment process in 2005; prior to that year, Medicare used *MSAs* and rest-of-state rural areas. The switch from MSAs to CBSAs increased the total number of labor markets (including Puerto Rico) used by Medicare from 374 to 441 and changed the

[18] We also calculated alternate versions of the HHI in which hospital market shares are defined using either total inpatient days, adjusted inpatient days, or the average daily census, instead of the total number of staffed beds. These alternate measures are highly correlated with the HHI defined from the number of staffed beds. For example, in the 2009 AHA data, the correlation coefficients between each of the three alternate measures of HHI and the beds-based HHI measure range from 0.9845 to 0.9915. For simplicity we focus on the beds-based HHI in our analysis.

composition of numerous urban and rest-of-state areas. In our analysis, we construct the HHI using the Medicare geographic definition used in each year (that is, using MSAs in 1999 and CBSAs in 2009), and we match the CBSA-level nurse wage differentials to these HHI measures in each year. We merge 2009-2011 CBSA-level wage-differentials to CBSA-level HHI measures from 2009. For 2000, we match each of the CBSA-level nurse wage differentials to a single MSA's HHI in 1999 using a crosswalk based on population overlaps. Further details on this crosswalk are in the section 3 of the Data Appendix.

There are two advantages of matching 2000 CBSA-level nurse wage measures to the 1999 MSA-level HHI. First, we define the concentration of hospitals in the geographic units that Medicare uses in each year to construct the hospital wage index. Thus, our measure helps to identify hospital markets where large dominant hospitals would have the ability to drive the hospital wage index through decisions involving nurse wages. Second, the change in Medicare geography creates an exogenous source of variation in the HHI. That is, the variation over time in our measure of HHI comes from two sources: 1) changes in market concentration driven by hospital consolidation, expansion, entry, or exit; and 2) changes in market concentration driven by the switch from MSAs to CBSAs in making hospital wage index adjustments. Consider, for example, the consequences when a hospital is located in a CBSA that is newly formed from a portion of the old MSA. Even if there are no changes in the number and size of hospitals, our method will show an increase in the HHI over time if, say, the new CBSA in 2009 is dominated by a single hospital, whereas in 1999, that single hospital was one of many hospitals in the MSA. In this regard, our study bears some similarity to Clemens and Gottlieb (2014), which identifies the effect of physician payment changes in Medicare on physician treatment decisions and patient health using the price shock created when Medicare consolidated its physician payment areas from 210 to 89 regions in 1997.

To illustrate the variation in the HHI created by Medicare's adoption of CBSAs for the purpose of making geographic adjustments, we conduct the following exercise. We construct the HHI in each year according to the Medicare market definitions described above (i.e., the CBSA in 2009 and the MSA in 1999, mapping each CBSA in 1999 to a single MSA). We then define the change in this HHI measure for each CBSA. We regress that variable on a constant and a second measure of the change in HHI defined as the difference in CBSA-level HHI in both years (this measure is defined in section 5 of the Data Appendix). The R^2 from this regression defines the proportion of the variation in HHI across CBSAs explained by hospital decisions (such as consolidations, expansions, entry, exit). The residual variation ($1-R^2$) from this regression gives us the portion of the variation explained by changes in Medicare geography. In this model, the R^2 is 0.22, leaving 78% of the variation in our measure of the HHI coming from changes in Medicare geography.

3. Measuring the Importance of the HWI to Area Hospitals (*BITE*)

To measure the importance of HWI adjustments to hospitals in a given area, we construct two area-level "bite" measures using hospital-level data. In each case, we define the area as the CBSA using data from 1999 only. The first bite measure is defined as the share of all inpatient days in an area that occur in IPPS hospitals and are paid by Medicare. We hypothesize that the collective motivation of hospitals in the same market to raise nurse wages in response to the wage index adjustment increase with the share of all inpatient days in that market that occur at IPPS hospitals and are paid by Medicare. Using the 1999 AHA annual survey, we divide the number of Medicare inpatient days reported by IPPS hospitals in the area by the total number of inpatient days reported by all hospitals in the area. We refer to this as the "Medicare-IPPS share" of the market.

The second bite measure is an index that reflects the degree to which Medicare days at IPPS hospitals are concentrated in the market. We use this to explore whether the collective motivation of hospitals to raise nurse wages depends on having one or a small number of IPPS hospitals account for a large share of the inpatient days paid by Medicare. We expect this is likely, because only IPPS hospitals' wage data enter the calculation of CMS's hospital wage index. This measure helps to distinguish between two markets that might have the same Medicare-IPPS share, but differ in how those Medicare inpatient days are distributed across hospitals. For example, a market where one of five hospitals accounts for 80% of all Medicare days at IPPS hospitals would have a larger value of this bite measure compared to a market with the same Medicare-IPPS share, but where all five hospitals had an equal share of all Medicare days at IPPS hospitals. For this bite variable, we use the 1999 AHA data to calculate each hospital's share of the Medicare IPPS inpatient days in the market. For hospitals that are not IPPS hospitals or have zero Medicare days, this share is zero. We then square the hospital shares and sum for all hospitals in the market. See section 5 of the Data Appendix for additional details on the construction of both bite measures.

Table 3 reports means of the variables in our dataset for both time periods in the sample. Our main analysis excludes CBSAs located in Maryland, since hospitals in that state are not paid according to IPPS. This results in a sample of 424 CBSAs in each year.

B. Testing for OMA Effects on Nurse Employment

To test whether the 2006 implementation of the OMA reduced hospitals incentive to hire more-skilled labor, we model a hospital-specific measure of RN employment as described in Equation (5) below:

$$(5)\ RN\_EMP/BEDS_{ht} = \beta_0\, POST_t + \beta_1\, HHI_{kt} + \beta_2\, IPPSshare_{ht} + \beta_3\, IPPSshare_{ht} \times Medshare^{99}{}_h + \beta_4\, POST_t \times IPPSshare_{ht} + \beta_5\, POST_t \times IPPSshare_{ht} \times Medshare^{99}{}_h + \lambda_h + \varepsilon_{ht}$$

We estimate this model with two years of employment data from the AHA annual survey (1999 and 2009). The dependent variable is either a measure of the number of full-time or full-time equivalent registered nurses employed by hospital *h*, relative to its size (*BEDS*), in year *t*. We investigate employment of RNs specifically, because they are the higher-skilled nursing personnel we expect hospitals to favor if they respond to the HWI's implicit subsidy for a higher-skilled workforce (before the OMA). After the OMA, hospitals may substitute away from RNs and toward licensed practical nurses, nurse aides, orderlies, and other less-skilled workers for some tasks. HHI_k is the area-level HHI, defined from all hospitals in the market. $IPPSshare_h$ measures the influence of the hospital on the market-level OMA-adjusted HWI. It is the number of hospital *h*'s beds divided by the number of all IPPS hospital beds in the area and equals zero for hospitals that are not IPPS hospitals. $Medshare_h$ is the hospital's number of Medicare days divided by total inpatient days, defined in the first year of the data, to avoid issues where changes in the OMA cause changes in *Medshare*. $Medshare_h$ should measure how important Medicare reimbursements are for hospital *h*'s revenue and thereby proxy for its incentive to respond to the OMA. We include this variable since classic monopsony theory predicts that as market concentration increases, hospitals will hire fewer RNs. *POST* is a dummy equal to 1 in years after the OMA was implemented (2009), and 0 before (1999). Each hospital has its own intercept λ_h. If the OMA dampens hospital incentives to hire more RNs, we expect the estimated value of

β_5 to be negative, meaning that following the OMA, hospitals with an increased ability to influence the OMA and with a high importance of Medicare days will have a greater incentive to reduce RN employment.

1. Data on Hospital-specific Nurse Employment

Data on the number of full-time or FTE registered nurses employed by hospitals are from the AHA survey data from 1999 and 2009. We divide each by the hospital's beds count. We use a sample of hospitals in the AHA dataset that are either IPPS hospitals in both 1999 and 2009 or non-IPPS hospitals in both 1999 and 2009. This excludes hospitals that change IPPS status over the period; a large number of such hospitals changed from IPPS status to non-IPPS status and they are typically hospitals that became categorized as Critical Access Hospitals (CAHs) when the Balanced Budget Act of 1997 was implemented. CAHs are reimbursed based on cost of care, rather than PPS.

2. Data Sources for Explanatory Variables

We measure the hospital-specific share of the IPPS market from the AHA annual hospital survey. We define IPPS hospitals as described in section 5 of the Data Appendix, and we define the market as the MSA in 1999 and the CBSA in 2009, since Medicare changed the geographic area used to calculate HWI adjustments in 2005. The IPPS share is defined from data on the hospital's bed count relative to total beds in the market. Non-IPPS hospitals have a value of zero for this variable. We measure the hospital-specific Medicare share from the 1999 AHA annual survey. It is the hospital's number of Medicare inpatient days divided by the hospital's number of total inpatient days. The market-level hospital concentration (HHI) is included to control for potential monopsony labor market effects on employment; we define it from AHA data in 1999 and 2009, where the market is defined as the CBSA in both years. Details are found in section 4 of the Data Appendix.

5. Results

Before we present the results of our main empirical analysis of hospital gaming, we first use our data to update the basic tests for monopsony reported in previous studies. Recall that our specification is most similar to Hirsch and Schumacher (2005); in a first-difference model of RN relative wages estimated with data from 1993-1997 and 1998-2002, they found that increases in market-level hospital concentration had a negative and statistically significant effect on RN relative wages. This effect is robust to controlling for changes in hospital "average daily census" (an output measure), and is found in the sample of all markets as well as the subsample of urban markets. Their findings in these first-difference specifications are consistent with the prediction from classic monopsony theory. In Table 4, we update the analysis of Hirsch and Schumacher (2005) in several respects. We use more recent data on nurse wage changes from 2000 to 2009-2011, and newer data on hospital market concentration for 1999 and 2009. Our source of *HHI* is, like theirs, the AHA annual survey. Our definition of the market is the CBSA in both years (in this exercise), while their definition is the CMSA/MSA area and rest-of-state (non-urban area). As we show in Table 4, the estimated coefficient on *HHI* is smaller, statistically insignificant, and positive. This holds for the various samples examined (all vs. urban; including vs. excluding Maryland CBSAs). Thus we find no support for classic monopsony using the same estimation strategy as Hirsch and Schumacher (2005) but updated to more recent data.

We next present the results from estimating Equation (3), the first difference model of the effect of a change in the HHI on the nurse wage differential that allows us to test for potential hospital gaming in response to the HWI. The results are shown in Table 5 for various subsamples. As noted earlier we exclude Maryland CBSAs since hospitals in Maryland are exempt from IPPS.

In column (1) on Table 5, we again estimate a simple update to the classic monopsony test. The results from these regressions come from a model where the change in HHI is measured as the difference in CBSA-level HHI in 2009 from MSA-level HHI in 1999 (where the MSA-level HHI are assigned to CBSAs following our earlier description). We estimate this model for all CBSAs not including those in Maryland. Again, we see little evidence of classic monopsony. The estimated coefficients on the change in HHI are negative (meaning that markets becoming more concentrated experience reductions in relative RN wages), but they are small and statistically insignificant. This is also true when we exclude rural CBSAs, or CBSAs that were less similar to the MSA to which they are matched in assigning a measure of 1999 HHI to the 2000 nurse wage differential, or both.

Columns (2) and (3) of Table 5 report results from estimating Equation (3) for two alternative measures of *BITE*. In both sets of results, the pattern of the coefficient estimates is similar: the estimated coefficients on the change in *HHI* are positive, and the estimated coefficients on the interaction of the change in *HHI* and *BITE* are negative. These estimated coefficients on the interaction term are strongly significant when the second bite measure is used. The signs of the estimates once again contrast with the prediction of classic monopsony theory. They suggest that increases in hospital market concentration led to increases in RN relative wages in markets where Medicare shares were low and IPPS beds were diffused across hospitals. As noted by Hirsch and Schumacher (2005), a positive relationship between market concentration and nurse wages may be explained by rent sharing. That is, as hospital profits increase with monopoly power in the product market, those profits are shared with workers in the form of higher wages.

In addition, the signs of the coefficient estimates do not suggest that hospitals are gaming the HWI adjustment process by paying nurses higher wages. In contrast, the results suggest that hospitals in markets where there was increased opportunity to game the HWI (hospitals where markets become more concentrated over time) and where there was motive to game the HWI (in markets where Medicare/IPPS beds were concentrated at some hospitals), did not raise RN relative wages but instead *reduced* them. One possible explanation of this pattern is that market concentration increases rent-sharing, but hospitals that are highly dependent on Medicare prospective payment arrangements are less likely to share those rents with their workers, or have less profit to share.

As a robustness check on our main results, we calculate an alternate version of the HHI using only hospital bed size data from the Medicare Impact File and calculating market concentration changes for IPPS hospitals only. We had expected that we might find more evidence of classic monopsony when HHI is defined using all hospitals, and more evidence of gaming when HHI is defined for only those acute inpatient hospitals that contribute to the wage index calculations; as noted above, our Table 5 results offer little support for either monopsony or gaming when we use the AHA-defined HHI measures. Using the Impact File measure of HHI, as in Table 6, we observe smaller and statistically insignificant coefficients on the change in HHI. This is again no evidence of monopsony, and compared to Table 5, it provides less evidence of rent-sharing. We continue to see that RNs are paid lower wages in markets where hospitals are highly dependent on Medicare prospective payment arrangements. This is again no evidence of gaming, but could be the result of cost containment measures intended by the IPPS.

Finally, we turn in Table 7 to our analysis of nurse employment, or the estimation of Equation (5). The first two columns use counts of full time RNs and the next two use counts of full-time equivalent nurses as the dependent variable. All models adjust these counts for hospital size. The estimated effect of the *POST* variable is large, negative, and statistically significant, suggesting that over time, hospitals on average employed fewer RNs per bed. The estimated coefficient of the interaction of *POST* with Medicare share and IPPS share shows that the decline in RNs was *larger* for those hospitals that were more strongly impacted by the introduction of the OMA – hospitals with a high share of Medicare patients whose occupational mix data played an increasing role in the calculation of the market HWI adjustment. This finding is consistent with the OMA having the intended effect of reducing hospitals' use of high skilled labor. As in the previous analyses, we again find no evidence of classic monopsony in the market for nurses. The coefficient of *HHI* is positive and statistically significant, suggesting that market concentration leads hospitals to employ more RNs, opposite to the classic monopsony prediction.

The bottom panel of Table 7 uses the estimated coefficients from the top panel to calculate predicted effects of IPPS share on RN employment per bed in different contexts. The calculations show reversals of the IPPS share effect over time. In 1999, IPPS share is associated with fewer RNs per bed among hospitals with no Medicare business in that year, but in 2009 this association goes away or reverses for these same hospitals. For Medicare-intensive hospitals, IPPS share is positively associated with RNs per bed in 1999, but this effect reverses in 2009. Although the influence of a hospital's IPPS share on RN employment changed from negative to positive over this time period in hospitals with little to gain from Medicare reimbursement adjustments, the Medicare-intensive hospitals reduced their employment intensity for the highest-skilled nurses. This reduction is consistent with hospitals gaming the HWI by inflating their nursing skill mix prior to the 2005-2007 implementation of OMA and reducing the skill mix of their nurses when OMA implementation reduced the Medicare subsidy for skill.

6. Discussion and Conclusion

We model relative nurse wages and nurse employment in U.S. labor markets in the period from 1999 to 2009 to investigate whether hospitals engage in two different types of gaming of Medicare reimbursement rules. The results from these models have several implications for Medicare gaming as well as for hospital monopsony power.

One striking result from our study is that we consistently find no evidence of monopsony power among hospitals in our period of analysis (1999-2009). In contrast, increases in local-level hospital concentration are associated with higher nurse wages in some of our specifications.[19] When the estimated coefficients of changes in hospital concentration are negative, they are very small and somewhat precisely estimated. For example, the estimated HHI effect of -0.017 in the first column of Table 5 implies that a very large change in hospital concentration from 0.25 to 0.75 would reduce nurse wages by about 0.85 percent. Furthermore, in models of nurse employment, we find a positive association between HHI and hospital-level RNs per bed (Table 7). This is again the opposite of the monopsony prediction. Our findings are actually more consistent with higher hospital concentration leading to higher nurse wages and employment. One explanation for this result is that hospitals with more market power in the output market experience excess profits and share some of those profits with nurses.

Our findings about whether hospitals game Medicare reimbursement rules in decisions about nurse labor and wages are mixed. In models of nurse employment estimated with hospital-

[19] When we estimated the correlation between changes in HHI and changes in relative nurses wages directly (Table 4), the estimated HHI effect was positive; the lower bound of its 95 percent confidence interval was -0.07, which implies that a change of concentration from 0.25 to 0.75 would reduce nurse wages by about 3.5 percent.

level data, we find evidence that Medicare reimbursement rules influence hospital staffing decisions. In particular, those hospitals with Medicare-intensive caseloads employed fewer RNs (high-skilled personnel) when Medicare reimbursements ceased subsidizing greater skill mixes (i.e., with the implementation of the occupational mix adjustment). However, we find no evidence that average nurse wages are higher in locations where hospitals experienced increased opportunities to game the circularity of the hospital wage index. In fact, we find evidence of the opposite: in locations where hospitals had increased opportunities to influence the HWI by paying higher nurse wages *and* where hospitals had a strong motive to do so, there is a negative relationship between hospital concentration and relative nurse wages. Perhaps this is the case because hospitals cannot engage in profit sharing when Medicare is an important source of revenue. If this is because hospitals cannot accrue excess profits, this would be consistent with the cost-containment goal of Medicare's prospective payment systems.

We find reason to believe that, if anything, hospital concentration is good for nurses: their wages are not lower in more-concentrated markets and are perhaps higher. In addition, we find no reason to fear that circularity in the hospital wage index is taking place and leading to excessive costs for the Medicare program. The only evidence we find consistent with gaming is that hospitals hired more-skilled nurses (RNs) prior to CMS's implementation of the occupational mix adjustment in 2005-2007. That reform erased or at least mitigated hospitals' gaming incentives, so we are left with no evidence of continued gaming of Medicare's hospital reimbursement rules for the nurse labor market.

References

Acemoglu, Darren, and Amy Finkelstein. 2008. "Input and Technology Choices in Regulated Industries: Evidence from the Health Care Sector." *Journal of Political Economy,* 116 (5): 837-880.

Adamache, Killard W., and Frank A. Sloan. 1982. "Unions and Hospitals: Some Unresolved Issues." *Journal of Health Economics,* 1:1: 81– 108.

BLS (Bureau of Labor Statistics). Various years. Local Area Unemployment Statistics tables. Available at http://www.bls.gov/lau/.

Bruggink, Thomas H., Keith C. Finan, Eugene B. Gendel, and Jeffrey S. Todd. 1985. "Direct and Indirect Effects of Unionization on the Wage Levels of Nurses: A Case Study of New Jersey Hospitals." *Journal of Labor Research,* 6:407–16.

Chalkley, Martin, and James M. Malcomson. 2000. "Government Purchasing of Health Services", in *The Handbook of Health Economics*, A.J. Culyer and J.P. Newhouse, Eds. Volume 1A, Chapter 15, pages 847-890. Amsterdam: Elsevier Science.

Clemens, Jeffrey, and Joshua D. Gottlieb. 2014. "Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?" *American Economic Review,* 104 (4): *1320-1349.*

Currie, Janet, Mehdi Farsi, and W. Bentley MacLeod. 2005. "Cut to the Bone? Hospital Takeovers and Nurse Employment Contracts." *Industrial and Labor Relations Review,* (April) 58(3): 471-493.

Cutler, David M. 1995. "The Incidence of Adverse Medical Outcomes under Prospective Payment." *Econometrica*, 63 (1): 29-50.

Dalton, Kathleen, Gregory C. Pope, Walter Adamache, Brian Dulisse, and Nathan West. 2007. "Potential Refinements to Medicare's Wage Indexes for Hospitals and Other Sectors" RTI International (June) No. 07-3.

DePasquale, Christina. 2014. "The Effects of Hospital Consolidation on Labor Market Outcomes" Emory University (June).

Feldman, Roger, and Richard Scheffler. 1982. "The Union Impact on Hospital Wages and Fringe Benefits." *Industrial and Labor Relations Review,* 35: 196–206.

Grabowski, David C., Christopher C. Afendulis, and Thomas G. McGuire. 2011. "Medicare Prospective Payment and the Volume and Intensity of Skilled Nursing Facility Services." *Journal of Health Economics*, 30 (4) 675-684.

He, Daifeng, and Jennifer M. Mellor. 2012. "Hospital Volume Responses to Medicare's Outpatient Prospective Payment System: Evidence from Florida." *Journal of Health Economics*, 31 (5): 730-743.

Hirsch, Barry T., and Edward J. Schumacher. 1995. "Monopsony Power and Relative Wages in the Labor Market for Nurses." *Journal of Health Economics,* 14: 443–476.

Hirsch, Barry T., and Edward Schumacher. 2004. "Classic Monopsony or New Monopsony? Searching for Evidence in Nursing Labor Markets." IZA Discussion Paper No. 1154.

Hirsch, Barry T. and Edward J. Schumacher. 2005. "Classic Monopsony or New Monopsony? Searching for Evidence in Nursing Labor Markets." *Journal of Health Economics,* 24: 969–989.

Hurd, Richard W. 1973. "Equilibrium Vacancies in a Labor Market Dominated by Non-Profit Firms: The Shortage of Nurses." *Review of Economics and Statistics*, 55: 234–240.

IOM (Institute of Medicine) 2012a. Committee on Geographic Adjustment Factors in Medicare Payment. *Geographic adjustment in Medicare payment. Phase I, Improving accuracy*. Committee on Geographic Adjustment Factors in Medicare Payment, Board on Health Care Services; Margaret Edmunds and Frank A. Sloan, editors.

IOM (Institute of Medicine) 2012b. Committee on Geographic Adjustment Factors in Medicare Payment. *Geographic adjustment in Medicare payment. Phase II, Implications for Access, Quality, and Efficiency.* Committee on Geographic Adjustment Factors in Medicare Payment, Board on Health Care Services; Margaret Edmunds and Frank A. Sloan, editors.

Link, Charles R., and John H. Landon. 1975. "Monopsony and Union Power in the Market for Nurses." *Southern Economic Journal,* 41: 649–659.

Matsudaira, Jordan D. 2014. "Monopsony in the Low-Wage Labor Market? Evidence from Minimum Nurse Staffing Regulations." *The Review of Economics and Statistics,* (March) 96(1): 92–10; Changes to the

Medicare Program; Hospital Inpatient Prospective Payment Systems and Fiscal Year 2007 Rates; Fiscal Year 2007 Occupational Mix Adjustment to Wage Index. 2007. 71 Fed. Reg. 47870 (August 18, 2006) (to be codified at 42 C.F.R. pts. 409, 410, 412, 413, 414, 424, 485, 489, and 505). Available at: https://www.federalregister.gov/articles/2006/08/18/06-6692/medicare-program-changes-to-the-hospital-inpatient-prospective-payment-systems-and-fiscal-year-2007#h-144.

MedPAC (Medicare Payment Advisory Commission). 2007. An alternative method to compute the wage index. In Report to the Congress: Promoting greater efficiency in Medicare. Washington, DC: MedPAC.

MedPAC (Medicare Payment Advisory Commission). 2014. Payment Basics: Hospital Acute Inpatient Services Payment System. Washington DC. Revised October 2014.

Mincer, Jacob. "Family Migration Decisions." 1978. *Journal of Political Economy*, (October) 86(5): 749-773.

Missouri Census Data Center, 2010. *MABLE/Geocorr2K: Geographic Correspondence Engine with Census 2000 Geography.* Version 1.3.3 (August, 2010). Available at http://mcdc2.missouri.edu/websas/geocorr2k.html. Last updated August 21, 2015.

Norton, Edward C., Coutney Harold van Houtven, Richard C. Lindrooth, Sharon-Lise T. Normand, and Barbara Dickey. 2002. "Does Prospective Payment Reduce Inpatient Length of Stay?" *Health Economics*, 11: 377-387.

OIG (Office of the Inspector General). 2007. Review of Hospital Wage Data Used to Calculate Inpatient Prospective Payment System Wage Indexes. A-01-05-00504. Washington DC: Department of Health and Human Services.

Robinson, James C. 1988. "Market structure, employment, and skill mix in the hospital industry." *Southern Economic Journal,* 55:315–25.

Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. 2010. *Integrated Public Use Microdata Series: Version 5.0* [Machine-readable database]. Minneapolis: University of Minnesota.

Salkever, David. 2000. "Regulation of Prices and Investment in Hospitals in the United States," in *The Handbook of Health Economics*, A.J. Culyer and J.P. Newhouse, Eds. Volume 1B, Chapter 28, pages 1489-1535. Amsterdam: Elsevier Science.

Shen, Yu-Chu. 2003. "The Effects of Financial Pressure on the Quality of Care in Hospitals." *Journal of Health Economics*, 22: 243-269.

Sloan, Frank A. 1978. *Equalizing Access to Nursing Services: The Geographic Dimension* DHEW publication no. (HRA) 78-51 (Department of Health, Education and Welfare, Washington, DC).

Sood, Neeraj, Melinda Beeuwkes Buntin, and Jose J. Escarce. 2008. "Does How Much and How You Pay Matter? Evidence from the Inpatient Rehabilitation Prospective Payment System." *Journal of Health Economics*, 27: 1046-1059.

Staiger, Douglas O., Joanne Spetz, and Ciaran S. Phibbs. 2010. "Is There Monopsony in the Labor Market? Evidence from a Natural Experiment." *Journal of Labor Economics*, 28 (2) (April): 211- 236.

Yett, Donald E. 1975. *An Economic Analysis of the Nurse Shortage*. Lexington, MA: Lexington.

Zwanziger, Jack, and Glenn A. Melnick. 1988. "The Effects of Hospital Competition and the Medicare PPS Program on Hospital Cost Behavior in California." *Journal of Health Economics,* 7: 301-320.

Table 1. Illustration of the HWI Effect on IPPS Payments

	Stanford Hospital Palo Alto, CA (1)	Emory University Hospital Atlanta, GA (2)	Medical Center Enterprise Enterprise, AL (3)
(1) FY 11 National Base Operating Payment	$5,164.11	$5,164.11	$5,164.11
(2) × Labor-related percent	68.8%	62%	62%
(3) = Labor-related portion	$3,552.91	$3,201.75	$3,201.75
(4) × Hospital Wage Index	1.6379	0.9522	0.7436
(5) = Labor-adjusted portion	$5,819.31	$3,048.70	$2,380.82
(6) + Non-labor portion	$1,611.20	$1,962.36	$1,962.36
(7) = Labor-adjusted standardized amount	$7,430.51	$5,011.07	$4,343.18
(8) × MS-DRG weight for "CABG with Major Complication or Comorbidity," (MS-DRG 233)	7.2081	7.2081	7.2081
(9) = Operating Payment Adjusted for Geographic Factors and Case Mix	$53,559.86	$36,120.29	$31,306.08

Source: IOM (2012a), p. 63.

Table 2. Applications and Approvals for Geographic Reclassification for the Hospital Wage Index (HWI)

Year	Cases (applications)	Reclassification approvals	Approval rate (%)
2012	413	219	53
2013	340	205	60.3
2014	408	311	76.2
2015	437	380	87

Source: Author's calculations from published Medicare Geographic Classification Review Board decisions accessed at http://www.cms.gov/Regulations-and-Guidance/Review-Boards/MGCRB/MGCRB_Decision_Listings.html (accessed July 3, 2015).

Table 3. Descriptive Statistics for Sample of 424 CBSAs

Variable	2000 Mean	2009-2011 Mean
RN wage differential	0.466	0.593
Mean years of experience	18.1	21.3
Mean state unemployment rate	4.1	9.2
Share with some college	0.01	0.004
Share with an associate's degree	0.34	0.34
Share with a bachelor's degree	0.64	0.65
Share with a master's degree or higher	0.01	0.01
Share employed in public sector	0.29	0.27
Share part-time	0.22	0.24
Share divorced/widowed/separated	0.16	0.16
Share never marked	0.19	0.19
Share male	0.01	0.01
Share black	0.06	0.06
Share Hispanic	0.01	0.01
Share American Indian/Alaskan native	0.02	0.03
Share Asian and/or Pacific Islander	0.001	0.001
Share other race	0.04	0.06
Pop 200-300K	0.10	0.13
Pop 300-500K	0.14	0.13
Pop 500K-1 mill	0.10	0.13
Pop 1-2 mill	0.08	0.07
Pop >2 mill	0.06	0.07
HHI (AHA based)	0.242	0.330
System HHI (AHA based)	0.280	0.375
Medicare-IPPS share	0.377	--
Medicare-IPPS concentration	0.076	--

Table 4. Effects of Hospital Concentration on Nurse Wage Differentials Based on the Hirsch and Schumacher (2005) Specification with Updated Data

	Dep. Var. is ΔRN Wage Differential, 2000 to 2009-11
All CBSAs (n=432)	
ΔHHI	0.062
	(0.070)
Urban CBSAs (n=384)	
ΔHHI	0.066
	(0.072)
All CBSAs excluding Maryland (n=424)	
ΔHHI	0.058
	(0.070)
Urban CBSAs excluding Maryland (n=377)	
ΔHHI	0.062
	(0.072)

Notes: Each cell reports the estimated coefficient and its robust standard error for the change in HHI from a separate model. As in Hirsch and Schumacher (2005), values of the HHI are defined from hospitals in the AHA annual survey and are defined at the same level of geography in each year (in this case, the CBSA). The dependent variable is defined as described in the text. All models include controls for changes in area level of education, years of experience and its square, race and ethnicity, part-time status, sex, marital status, public sector employment, the state unemployment rate, and the area population size.

Table 5. Effect of Hospital Concentration and HWI on Nurse Wage Differentials
Hospital Concentration Measured from AHA Annual Survey

	Dep. Var. is ΔRN Wage Differential, 2000 to 2009-11		
	Baseline (1)	Bite is Medicare-IPPS Share (2)	Bite is Medicare-IPPS HHI (3)
All CBSAs, excluding MD (n=424)			
ΔHHI	-0.017	0.079	0.098*
	(0.029)	(0.095)	(0.057)
ΔHHI × Bite		-0.208	-0.625***
		(0.185)	(0.226)
All CBSAs, excluding MD (n=424)			
ΔSystem-HHI	-0.019	0.095	0.095*
	(0.028)	(0.109)	(0.057)
ΔSystem-HHI × Bite		-0.237	-0.604***
		(0.204)	(0.220)
All CBSAs (excluding MD) with similarity>0.9 (n=351)			
ΔHHI	-0.022	0.124	0.126**
	(0.031)	(0.102)	(0.060)
ΔHHI × Bite		-0.310	-0.780***
		(0.198)	(0.235)
Urban CBSAs, excluding MD (n=377)			
ΔHHI	-0.017	0.082	0.100*
	(0.029)	(0.097)	(0.058)
ΔHHI × Bite		-0.216	-0.635***
		(0.187)	(0.229)
Urban CBSAs (excluding MD) with similarity>0.9 (n=312)			
ΔHHI	-0.020	0.133	0.132**
	(0.032)	(0.103)	(0.061)
ΔHHI × Bite		-0.327	-0.804***
		(0.201)	(0.238)

Notes: Each column/panel reports results from a separate model of the change in the relative RN wage. Coefficient estimates are reported for the change in HHI (column 1), and the change in HHI plus the change in HHI interacted with a bite measure (columns 2 and 3)). Robust standard errors of estimates are shown in parentheses. HHI is defined from AHA data at the MSA-level in 2000 and the CBSA-level in 2010, as described in the text. All models include controls for area-level changes in average levels of education, years of experience and its square, race and ethnicity, part-time status, sex, marital status, public sector employment, the state unemployment rate, and the area population size.

Table 6. Effect of Hospital Concentration and HWI on Nurse Wage Differentials
Hospital Concentration Measured by Impact File

	Dep. Var. is ΔRN Wage Differential, 2000 to 2009-11		
	Baseline (1)	Bite is Medicare-IPPS Share (2)	Bite is Medicare-IPPS HHI (3)
All CBSAs, excluding MD (n=423)			
ΔHHI	-0.028 (0.025)	0.052 (0.067)	0.047 (0.053)
ΔHHI × Bite		-0.178 (0.129)	-0.416*** (0.169)
All CBSAs (excluding MD) with similarity>0.9 (n=350)			
ΔHHI	-0.029 (0.028)	0.083 (0.070)	0.067 (0.045)
ΔHHI × Bite		-0.248 (0.138)	-0.527*** (0.178)
Urban CBSAs, excluding MD (n=376)			
ΔHHI	-0.029 (0.026)	0.057 (0.069)	0.050 (0.045)
ΔHHI × Bite		-0.191 (0.133)	-0.434*** (0.174)
Urban CBSAs (excluding MD) with similarity>0.9 (n=311)			
ΔHHI	-0.028 (0.029)	0.092 (0.072)	0.074 (0.047)
ΔHHI × Bite		-0.266* (0.143)	-0.555*** (0.183)

Notes: Each column/panel reports results from a separate model of the change in the relative RN wage. Coefficient estimates are reported for the change in HHI (column 1), and the change in HHI plus the change in HHI interacted with a bite measure (columns 2 and 3)). Robust standard errors of estimates are shown in parentheses. HHI is defined from CM Impact File data at the MSA-level in 2000 and the CBSA-level in 2010. All models include controls for area-level changes in average levels of education, years of experience and its square, race and ethnicity, part-time status, sex, marital status, public sector employment, the state unemployment rate, and the area population size.

Table 7. Hospital Fixed Effects Models of RN Employment

	Dep. Var. is RN Employment/Beds			
	RN FTE employees/beds		RN FT employees/beds	
	(1)	(2)	(3)	(4)
Post (=1 if 2009; =0 if 1999)	0.378***	0.377***	0.341***	0.340***
	(0.012)	(0.012)	(0.011)	(0.011)
HHI (CBSA-level)	0.525**	0.705***	0.446**	0.585***
	(0.211)	(0.212)	(0.202)	(0.204)
IPPS share (hospital-level)	-1.130***	-0.419	-0.880***	-0.332
	(0.348)	(0.359)	(0.320)	(0.343)
IPPS share × Medicare share in 1999	1.830***	0.709	1.472***	0.607
	(0.629)	(0.642)	(0.569)	(0.611)
Post × IPPS share	1.237***	1.112***	1.117***	1.020***
	(0.196)	(0.195)	(0.180)	(0.187)
Post × IPPS share × Med share in 1999	-2.306***	-2.028***	-2.157***	-1.942***
	(0.373)	(0.369)	(0.341)	(0.354)
No. of beds		-0.002***		-0.001***
		(0.0001)		(0.0001)
N	6,338	6,338	6,338	6,338
Dep. Mean	1.317	1.317	1.054	1.054
Predicted IPPS share effect for:				
year =1999 and Medicare share=0	-1.130	-0.419	-0.880	-0.332
	(0.348)	(0.359)	(0.320)	(0.343)
year =1999 and Medicare share=1	0.701	0.290	0.592	0.275
	(0.301)	(0.300)	(0.269)	(0.287)
year =2009 and Medicare share=0	0.108	0.693	0.237	0.689
	(0.314)	(0.322)	(0.295)	(0.310)
year =2009 and Medicare share=1	-0.367	-0.626	-0.447	-0.647
	(0.259)	(0.259)	(0.236)	(0.250)

Notes: Each column reports results from a separate model of the ratio of RN employment to bed count. Sample includes hospitals in the AHA annual survey in both 1999 and 2009 that a) did not change in IPPS status, b) were general medical and surgical hospitals, and c) had available data on model variables in both years. All models are estimated as hospital fixed effects models without an intercept. Robust standard errors of estimates are shown in parentheses.

Data Appendix. Details on Variable Construction and Linkage by Geography

1. Nurse wage differentials

Area-level nurse wage differentials were constructed from respondent-level census data as described in the text. Areas were defined as CBSAs in both the 2000 Census and the pooled 2009-2011 ACS. Each CBSA is either a metropolitan or a micropolitan area. We follow CMS definitions and treat micropolitan CBSAs in the same state as part of a single "rest of state" area. In addition, eleven large CBSAs are divided into Metropolitan Divisions. CMS treats Metropolitan Divisions within a CBSA as separate areas, so we do the same. For example, there is a single CBSA code for Seattle, Tacoma, Bellevue, WA, but this large area is subdivided into Seattle-Bellevue-Everett, WA and Tacoma-Lakewood, WA. Finally, some parts of the country are not in CBSA-defined areas, and we count each of these as a part of its "rest of state" area. There are 940 CBSAs in our initial crosswalk file. We assigned some PUMAs to 46 rest of state areas in cases where the PUMA was not assigned to a CBSA. In addition, 574 CBSAs are micropolitan CBSAs that we assign to 47 rest of state areas. These two sets of rest of state areas contained different states, so the total number of rest of states created is 48. 11 CBSAs are subdivided into 29 Metropolitan Divisions. Thus, our analysis sample includes measures of nurse wages in 432 CBSAs.[20]

Individual respondents were assigned to CBSAs based on the PUMA of residence. We used two versions of the MABLE/Geocorr2k crosswalk (Missouri Census Data Center, 2010) between PUMAs and CBSAs; one version described overlaps between PUMAs and CBSAs with the population distribution in 2000, and the other used the 2009 population distribution. In cases where the PUMA matched to a single CBSA, this is a simple assignment. However, some PUMAs overlap multiple CBSAs. For respondents in these PUMAs, we duplicated their observations to include one in each overlapping CBSA. When we estimate the nurse wage differential regression, we weight each observation by the population overlap between that observation's original PUMA and the CBSA to which it was assigned. For example, suppose a PUMA shares 80, 15, and 5 percent of its population with CBSAs A, B, and C, respectively. Then each respondent in that PUMA becomes three observations in our regression sample, each assigned to a CBSA (A, B, and C). The respondents assigned to CBSA A, B, and C received a

[20] Specifically, we have 940-574+48-11+29=432.

regression weight of 0.85, 0.15, and 0.05, respectively. In our samples, 79 percent of respondents live in a PUMA that overlaps a single CBSA; among the remaining 21 percent of respondents, the average PUMA population share in the most-overlapping CBSA is 58 percent.

In Tables A1 and A2 below, we illustrate the number of observations used in the construction of CBSA-level nurse wages from the 2000 Census and the pooled 2009-11 ACS. Our concern is the precision with which we estimate nurse wage differentials at the CBSA (location) level. The average location-specific nurse wage differential relies on data from 189 RNs and 1,594 other workers in the 2000 Census, with somewhat smaller sample sizes for the pooled 2009-2011 ACS. While there are CBSAs with quite small samples of RNs (as few as 9), most CBSAs rely on much larger samples. We believe these are sufficient sample sizes to have confidence in our measures of nurse wage differentials across locations. The sample sizes in Table A2 support the pooling of multiple ACS surveys: CBSA-specific sample sizes would be quite small for individual years.

Table A1. Summary Statistics for Observation Counts, by CBSA, 2000 Census

	Mean	Std. Deviation	Minimum	Max
Counts of RNs per CBSA	189	271.4	9	1998
Counts of non-RNs per CBSA	1594	2390.9	99	18848

Table A2. Summary Statistics for Observation Counts, by CBSA, 2009-2011 ACS

	Mean	Std. Deviation	Minimum	Max
Counts of RNs per CBSA	165.8	233	9	1357
Counts of non-RNs per CBSA	1364.9	1997.2	91	14860

2. Herfindahl-Hirschman Index (HHI) Used in Nurse Wage Main Analysis

In our main analysis of nurse wages, we use area-level values of the Herfindahl-Hirshman index calculated from hospital-level data on the number of beds from the AHA annual survey in 1999 and 2009. In each year, we define the area based on the geographic area used by Medicare to construct hospital wage indices: the CBSA in 2009 and the MSA in 1999.

Hospitals in the 2009 survey were assigned to a CBSA using the FIPS county code in the AHA survey and a crosswalk from county-to-CBSA from Mable/Geocorr. Prior to its application, the Mable/Geocorr2K (Missouri Census Data Center, 2010) crosswalk was modified to account for two changes affecting Alaskan counties. First, for one Alaska county that was assigned to two CBSAs, we used population data to retain the CBSA with the larger share of that county's population, and to drop the other CBSA. Second, we added an Alaska county and its CBSA assignment for a county that was not in the Mable/Geocorr2K crosswalk. This allowed us to retain hospitals that appear in the AHA data with that county; we obtained the CBSA assignment for this county from an older version of a Mable/Geocorr county-CBSA crosswalk.

Hospitals in the 1999 survey were assigned to an MSA using FIPS county codes included in the AHA annual survey and a 2005 NBER/CMS crosswalk (NBER, 2012). This NBER/CMS crosswalk uses the same county borders in New England that CMS uses in the geographic adjustment of hospital payments, and is thus preferred in those states over the OMB-defined MSAs used in Mable/Geocorr, which follow town and city borders in New England. 2005 is the earliest year for which the NBER crosswalk is available.

In both years of the AHA survey data, observations from hospitals in U.S. territories (e.g., Puerto Rico) were excluded. Also in both years of the AHA data, FIPS county codes were manually replaced for a small number of hospitals, namely: 1) 33 hospitals in Miami-Dade county (where the FIPS county code changed from 12025 to 12086 in 1997); 2) one hospital in South Boston City (FIPS 51780), an area that become part of Halifax County (51083) in 1995; and 3) two Virginia hospitals for which the FIPS county code was not assigned in the AHA data.

3. Assigning 2000 CBSA-level Nurse Wage Differentials an MSA-level HHI

CBSA-level nurse wage differentials from the 2000 ACS were assigned an MSA-level HHI value constructed from the 1999 AHA survey (or the 2000 Impact file) using a crosswalk that maps each CBSA to a single MSA.

The CBSA-single MSA crosswalk was constructed for this project from a 2005 crosswalk based on CMS data and available from NBER (NBER, 2012). This crosswalk lists both the CBSA and the MSA to which each U.S. county is assigned. As noted above, the NBER/CMS crosswalk uses the same county borders in New England that CMS uses in the geographic adjustment of hospital payments, and is thus preferred in those states over the OMB-defined MSAs used in Mable/Geocorr, which follow town and city borders in New England. Since the crosswalk reflects assignments as of 2005 and our goal is to assign CBSAs from 2010 to an MSA, we updated the crosswalk for changes in CBSA definitions that took place between 2005 and 2010. These changes include accounting for two CBSAs that were named, and several counties that were re-assigned to a different CBSA after 2005. All changes are shown in Table A3 below.

Table A3. CBSA Re-Assignments

Geographic area	Re-assignment	Effective date
CBSA 46940	CBSA 42680	2006
CBSA 37764	CBSA 21604	2008
FIPS county 04015	CBSA 29420	2008
FIPS county 12035	CBSA 37380	2008
FIPS county 12115	CBSA 14600	2009
FIPS county 12081	CBSA 14600	2009
FIPS county 40047	CBSA 40	2009
FIPS county 36013	CBSA 36	2009
FIPS county 37167	CBSA 16740	2009
FIPS county 20061	CBSA 31740	2009
FIPS county 20149	CBSA 31740	2009
FIPS county 20161	CBSA 31740	2009
FIPS county 17003	CBSA 16020	2010
FIPS county 29017	CBSA 16020	2010
FIPS county 29031	CBSA 16020	2010
FIPS county 27103	CBSA 31860	2010
FIPS county 27013	CBSA 31860	2010

We then combined this crosswalk with county-level population data from the U.S. Census Bureau to define the share of CBSA residents that lived in a given MSA for each possible CBSA-MSA match. The CBSA-single MSA crosswalk was produced by assigned each CBSA to the MSA in which the greatest share of its residents lived. To illustrate this process, Table A4 shows five hypothetical counties that comprise a single CBSA (CBSA C1), four of which fall into MSA M1 and one of which falls into MSA M2. Since 85% of the CBSA residents lived in counties located within MSA M1, and only 15% lived in the county located within MSA M2, CBSA C1 would be assigned to MSA M1.

Table A4. Illustration of CBSA-MSA Crosswalk Construction

CBSA ID	County ID	MSA ID	County population	CBSA population
C1	A	M1	100	655
C1	B	M1	101	655
C1	C	M1	204	655
C1	D	M1	150	655
C1	E	M2	100	655

Tables A5 and A6 provide additional details on the crosswalk. As shown in Table A5, some CBSAs overlapped with as many as five different MSAs, but a large majority of CBSAs

(64.8%) overlapped with only one MSA, and another large share overlapped with only two MSAs (29.2%). Similar to Table A5, Table A6 shows that in 280 of the 432 CBSAs in our sample, 100% of CBSA residents lived in a single MSA. Another 78 CBSAs were matched to an MSA where more than 90% (but less than 100%) of residents lived, and another 52 CBSAs were matched to an MSA where more than 80% (but less than 90%) of residents lived.

Table A5. MSA-CBSA Overlap

No. of MSAs that overlap with a CBSA	No. of CBSAs of this type	% of CBSAs of this type
1	280	64.8%
2	126	29.2%
3	18	4.2%
4	6	1.4%
5	2	0.5%
Total	432	100%

Table A6. Percent of the CBSA Population Residing in its Matched MSA

% of the CBSA population residing in the single MSA to which it is matched	No. of CBSAs of this type	% of CBSAs of this type
100%	280	64.8%
More than 95% but less than 100%	36	8.3%
More than 90% but less than 95%	42	9.7%
More than 80% but less than 90%	52	12%
More than 70% but less than 80%	13	3%
More than 60% but less than 70%	6	1.4%
More than 50% but less than 60%	3	0.7%
Total	432	100%

We examined the group of CBSAs that matched to a single MSA more closely. This group consists of two types of CBSAs: 1) CBSAs that were formed from identical boundaries as a single MSA (these may be either urban or rest-of-state areas), and 2) CBSAs that were formed from a sub-area within a single MSA (again these may be either urban or rest-of-state areas). Of the 280 CBSAs that match to a single MSA, 153 are of the first type, and 127 are of the second type. This latter group is especially interesting to us for two reasons. The first is that the switch to defining the market as the CBSA (as opposed to the MSA) creates some exogenous variation in the concentration of hospitals in the market. The second is that because the new CBSA was formed from a subset of one MSA, we can be confident about linking the CBSA-level nurse wage differential in 2000 to the MSA-level market concentration measure in that year, since all the nurses residing in that CBSA were living in areas that were part of the MSA.

We also examined the CBSAs that match to more than one MSA (prior to our selection of the single MSA) and found that this may be the case for various reasons. For example, in some cases, one urban CBSA was formed from two or more urban MSAs; in other cases, one urban CBSA was formed from one or more urban MSAs and part of a rest-of-state area. In some cases, a rest-of-state CBSA was defined using parts of a rest-of-state MSA combined with part or all of one or more urban MSAs. In these cases, the switch to CBSAs for defining the market also creates exogenous variation in the concentration of hospitals in the market. Because the new CBSA was formed from multiple MSAs, this introduces some noise into the assignment of the CBSA to a single MSA for the purposes of linking the CBSA-level nurse wage differential in 2000 to the MSA-level market concentration measure in that year. For this reason, we use the data on population overlap in Table A6 to conduct some sensitivity test of our results, as described in the text.

4. Other HHI Measures Used in Additional Analysis

In a robustness check on our main results from nurse wage models, we use area-level values of the Herfindahl-Hirshman index calculated from hospital-level data on the number of beds from the CMS Medicare IPPS Impact Files. Each year's Impact File contains data collected in the summer preceding the start of the federal fiscal year (NBER, 2014). For example, the 2000 Impact File included data collected in the summer of 1999, since fiscal year 2000 began October 1, 1999. Thus, for aligning annual market conditions with nurse wage differential estimates, we use Impact File data for 2000 and 2010.

In each year, we define the area based on the geographic area used by Medicare to construct hospital wage indices; in the 2000 Impact File, we thus define the HHI at the MSA level. Because the 2000 Impact File does not report the MSA for hospitals in the Indian Health Service, we first obtain the missing MSA identification codes for these hospitals from the 1999 AHA annual survey (using a merge by hospital Medicare Provider Number, or MPN). We then define the MSA-level HHI using the hospital-specific shares of beds out of all beds at Impact File hospitals in the MSA.

In the 2010 Impact File, we define the HHI at the CBSA-level. The 2010 Impact File does not contain the CBSA for hospitals in the Indian Health Service, so to assign missing CBSAs for these hospitals, we merge the Impact File observations to a Mable/Geocorr county-to-CBSA crosswalk. Because this crosswalk uses FIPS county codes and the Impact File contains only SSA county codes, the merge requires the additional use of a SSA county-to-FIPS county crosswalk, available from NBER (2012). We then define the CBSA-level HHI using the hospital-specific shares of beds out of all beds at Impact File hospitals in the CBSA.

In other analysis of nurse wages and RN employment, we use area-level values of the HHI calculated from the AHA data, but using CBSAs to define areas in both years. This requires the use of a CBSA-level measure of HHI defined from 1999 AHA annual survey data. To construct this measure, we assign each hospital in the 1999 AHA survey to a CBSA using the 2010 CBSA definitions. For this step we use the 2005 NBER/CMS county-to-CBSA crosswalk (NBER, 2012) described in Section 2 above. Before applying this crosswalk to the 2010 Impact File, we first update the crosswalk for the CBSA changes that occurred between 2006 and 2010 shown in Table A3 above, and we manually replace FIPS county codes for a small number of hospitals in the AHA data, namely: 1) 33 hospitals in Miami-Dade county (where the FIPS county code changed from 12025 to 12086 in 1997); 2) one hospital in South Boston City (FIPS 51780), an area that become part of Halifax County (51083) in 1995; and 3) two Virginia hospitals for which the FIPS county code was not assigned in the AHA data. The CBSA-level HHI is defined using hospital specific shares of beds out of all beds at all hospitals in the AHA survey.

5. Bite measures

We construct the two bite variables following the description in the text. In both cases, we define IPPS hospitals from the hospitals in the 1999 AHA annual survey in two ways. First, we define hospitals with MPNs in which the last four digits range from 0001-0879 as IPPS hospitals, per CMS documentation.[21] For hospitals with missing MPN or MPN equal "777777," we identify potential IPPS hospitals based on whether the hospital was a community, general hospital based on two fields in the AHA survey. Each hospital's MPN was obtained from an online search and then the last 4 digits were used to designate it as an IPPS hospital or not. In three cases, we could not obtain the MPN through a manual lookup; two of these hospitals were

[21] See page 2-164 of DHHS (2001).

designated IPPS hospitals because they did not appear on a list of Critical Access Hospitals (which are not paid according to IPPS rules).

Data Appendix References

DHHS (Department of Health and Human Services). 2001. *Medicare State Operations Manual Provider Certification, Transmittal 26*. Department of Health and Human Services, Health Care Financing Administration, March 1, 2001. Available at: www.cms.gov/Regulations-and-Guidance/Guidance/Transmittals/downloads/r26som.pdf. Last updated August 21, 2015.

Missouri Census Data Center. 2010. *MABLE/Geocorr2K: Geographic Correspondence Engine with Census 2000 Geography.* Version 1.3.3 (August, 2010). Available at http://mcdc2.missouri.edu/websas/geocorr2k.html. Last updated August 21, 2015.

NBER. 2012. *CMS's SSA to FIPS CBSA and MSA County Crosswalk*. Available at: www.nber.org/data/cbsa-msa-fips-ssa-county-crosswalk.html. Last updated June 8, 2015.

NBER. 2014. *CMS Impact File Hospital Inpatient Prospective Payment System (IPPS).* Available at: www.nber.org/data/cms-impact-file-hospital-inpatient-prospective-payment-system-ipps.html. Last updated June 11, 2014.