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MANAGED CARE

The impact of HMO penetration on the relationship between nurse staffing and quality

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Summary

While there are a number of studies examining the relationship between nurse staffing and quality, none has examined structural differences in the relationship between nurse staffing and quality contingent upon the level of managed care penetration. We used administrative data, and a dynamic panel data model to examine this relationship in a panel of 422 acute care hospitals from 1990 to 1995. We found that there were significant differences in the relationship between nurse staffing and both mortality and length of stay depending upon the level of HMO penetration in the hospital's market. Copyright © 2005 John Wiley & Sons, Ltd.

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The early 1990s witnessed dramatic changes in the operating environment for acute care hospitals due to the increasing dominance of managed care. From 1990 to 1996, HMO enrollment grew by 70% from 33 million members in 1990 to 63 million members in 1996 [1]. Hospitals responded by implementing a range of strategies aimed at improving the efficiency of their internal operations. With nursing personnel comprising approximately 30–40% of overall hospital FTE personnel and approximately 30% of the hospital budget [2], hospitals also responded with re-engineering and re-design strategies that frequently involved changes in nursing staff [3]. Together, the impact of these changes resulted in increased severity of illness for hospitalized patients who required more intensive nursing care [4]. Hospitals' efforts to reduce nurse staffing when patient acuity was increasing, however, raised concerns about whether these staffing changes affected quality of care.

In the 1990s researchers began to investigate the relationship between hospital nurse staffing and quality of care [5–12]. Despite the fact that changes wrought by increasing managed care penetration provided a critical impetus for hospital re-structuring, re-engineering, and staffing changes, none of these studies examined whether the extent of managed care penetration in the hospital's market affected the relationships between nurse staffing and quality. We used a panel of hospitals with data from 1990 to 1995 to examine whether managed care penetration affected the relationships between *change* in nurse staffing and *change* in quality of care. We improve upon prior analyses in several ways that allow stronger policy conclusions than earlier research. First, we controlled for hospital heterogeneity (omitted variable bias due to unmeasured time-invariant factors unique to

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each hospital) using a fixed-effects specification. Second, rather than assuming that measures such as quality of care adjust instantaneously to changes in the explanatory variables, we recognized the effect of history by including the lagged value of the dependent variable as a regressor [13]. Third, we made weaker assumptions about the exogeneity of staffing levels and other hospital characteristics (for example, between quality of care and staffing levels). The rest of the paper is organized as follows. First, we provide a brief literature review of studies examining nurse staffing and quality of care; discuss how increasing managed care penetration may affect quality; and then discuss how managed care penetration may affect the relationship between hospital nurse staffing and quality. The next section describes the data and measures and develops the rationale for using a dynamic panel model. We then present our findings and conclude with a brief discussion.

Background

Nurse staffing and quality of care

To date, eight studies have examined the relationship between nurse staffing and hospital quality of care, measured by mortality, length of stay (LOS) and/or patient complications [5–12]. With regard to mortality, Needleman *et al.* [8] found no significant relationship between nurse staffing and mortality, while Mark *et al.* [12] found a statistically significant decreasing marginal effect of nurse staffing on hospital mortality ratio (the ratio of actual to expected deaths). Four studies have provided support for the relationship between higher levels of nurse staffing and shorter LOS [5–8], while there have been mixed results in studies of staffing and specific patient complications for which nursing care is believed to play a critical role [5–12].

Effects of managed care penetration on quality

Because of HMOs' ability to obtain information about quality for its enrollees' providers, hospitals may have an incentive to increase quality in order to attract customers; conversely, HMO growth may reduce quality because HMOs force price competition, encouraging hospitals to cut costs, which then reduces profit margins [14]. Through selective contracting and volume discounts, these lower margins might, in turn, reduce inputs to care thus reducing hospital quality. Yet, three extensive reviews of the research on the effects of managed care on quality have concluded that although individual studies report statistically significant differences in quality between managed care enrollees and those in fee for service plans, there is little evidence to support claims of superior quality *overall* for either managed care or fee for service plans [15–17].

Managed care, competition and nurse staffing

The influence of managed care penetration and competition have also been examined in relation to nurse staffing. In an early study, Robinson [18] found that staffing levels were significantly higher in competitive than in non-competitive markets. In a series of studies, Buerhaus and Staiger [19–21] concluded that employment growth and earnings for RNs in the hospital sector had slowed significantly in states with high managed care enrollment, followed somewhat later in time by the same pattern in low-enrollment states. However, using data from California, Spetz [22] found that while HMO penetration had a significant negative effect on hours worked by LPNs and aides, HMO penetration had no statistically significant effect on hours worked by RNs. In addition, she found no direct effect of HMO penetration on RN staffing; rather, the effect was due to HMOs' impact on reducing hospital discharges, which then decreased demand for RNs.

Using stochastic frontier analysis, Mobley and Magnussen [23] studied the impact of managed care penetration on efficiency in hospital staffing. They suggest that hospital contracts with managed care organizations may make demand more predictable so that decisions about efficient staffing require trade-offs between cost savings that might arise from reducing slack in labor inputs and any potential effects on quality and continuity of care. They found that while market concentration was significantly associated with excess staffing (i.e. the proportion of staffed, but empty beds), HMO penetration did not have a significant impact on excess staffing.

Summary

In the early to mid-1990s, acute care hospitals responded to HMO growth by implementing initiatives designed to improve their internal operations, initiatives that raised concerns about quality of care. Further, there is a growing body of empirical evidence relating nurse staffing with quality of care. Given the financial pressures wrought by managed care penetration, we conjectured that different responses to these pressures by hospitals in high versus low managed care penetration markets might result in structural differences in the effect of nurse staffing on quality of care. For example, hospitals in high managed care penetration markets may have implemented a constellation of care management strategies such as stricter utilization controls, guidelines/evidence based practice protocols, or discharge planning programs. These hospitals may also have reduced a range of support services available to support clinical operations, thus influencing the relationship between nurse staffing and quality of care. Hospitals in high managed care penetration markets might be operating with less slack in labor inputs, so that the relationship between change in nurse staffing and change in quality of care might be more easily detected than in hospitals in low managed care penetration markets. No research has examined whether the extent of managed care penetration has any effect on the relationship between nurse staffing and quality of care. The study reported here attempts to address this gap in the literature.

Methods

Sample

We used the 422 hospitals in the 1990–1995 longitudinal cohort of the Healthcare Cost and Utilization Project (HCUP) National Inpatient Sample (NIS). The HCUP NIS contains all-payer data from a 20% probability sample of US community hospitals, stratified by ownership/control, bed size, teaching status, urban/rural location and US region. These 422 hospitals comprise 49% of the HCUP base year sample, and are located in 11 states (Arizona, California, Colorado, Florida, Illinois, Iowa, Massachusetts, New Jersey, Pennsylvania, Washington and Wisconsin). Compared to the population of US hospitals in 1995, our sample was 67% non-profit, 17% public, and 14% for profit, in contrast to the national figures of 58% non-profit and 27% public [24]. There was little difference between our sample and total US hospitals in terms of system affiliation (46% in our sample; 44% nationally) [24]. Hospitals in our sample were somewhat larger (190 beds vs 170 beds for US hospitals) and treated a somewhat more complex mix of patients (case mix index 1.33 vs 1.23 for US hospitals). Average HMO penetration in our sample in 1995 was 16%, identical to that of US hospitals [25], and the range in our sample (0–60.4%, which occurred in California) is nearly as large as the national range (0–73%). The largest *mean* increase in HMO penetration level occurred for hospitals in Washington, where HMO penetration doubled from 12.5% in 1992 to 24.6% in 1995. Thus, except for slight differences in ownership, size and complexity, our final sample reflects well the overall population of US hospitals.

We eliminated data from six hospitals due to inability to match them across all data sets; two additional hospitals were eliminated because data were for a system rather than an individual hospital and two others were dropped because revenue information was missing from all CMS files. Hospitals with staffing outliers were also excluded. Additional exclusions were for hospitals with fewer than 15 expected mortalities [12].

Data

Data sources included the Area Resource Files, American Hospital Association Annual Survey, Centers for Medicare Services (CMS, formerly HCFA) Minimum Cost and Capital File, CMS Wage Rate File, CMS Provider of Services File, CMS Case Mix Index File, CMS Online Survey Certification and Reporting system (OSCAR) files, and HCUP files.

Measures

Table 1 provides definitions and data sources of all variables, measurement of most of these is straightforward. Here we provide additional information about selected variables.

Table 1. Variable definitions and sources of data

Variable	Definition	Source of data
Market characteristics		
Hospital use	In-patient days/1000 HSA population	Area resource files
Herfindahl index	Sum of squared market shares in an HSA	AHA survey
Number of HMOs	Number of HMOs in an HSA	Wholey/InterStudy
HMO penetration	% HMO enrollment as % of total HSA population	Wholey/InterStudy
Staffing		
RN staffing	RN FTEs/1000 in-patient days	AHA Survey, OSCAR files
LPN staffing	LPN FTEs/1000 in-patient days	AHA Survey, OSCAR files
Non-nurse staffing	Non-nurse FTEs/1000 in-patient days	AHA Survey, OSCAR files
Quality		
Mortality	Risk-adjusted ratio of observed/expected mortality	HCUP, MEDSTAT
Length of stay	Risk-adjusted ratio of observed/expected length of stay	HCUP, MEDSTAT
Control variables: *hospital characteristics*		
Operating margin	(Net patient revenue−operating expense)/ net patient revenue	CMS cost and capital files; Solucient data
Case mix index	Complexity of Medicare cases treated	CMS case mix index files
High tech services (Saidin index)	High tech services provided	AHA survey
Payer mix	Medicare + Medicaid discharges/total discharges	CMS cost and capital files
Beds	Number of open and operating beds	AHA survey
Ownership	Not for profit, for profit, or public	CMS cost and capital files
System affiliation	System affiliated or not	AHA survey

Market measures. Researchers have generally used one of three definitions of the 'market': standard geographic area definitions, such as counties or metropolitan statistical areas (MSAs); a fixed radius approach; or a variable market approach, often based on patients' residence zip codes [25]. We used the hospital service areas (HSAs) developed by Makuc [26] that groups counties into geographic regions based on flows of in-patient hospital admissions. By definition, each HSA includes at least one hospital. Wholey *et al.* [27] suggests that since over- or under-allocation pro-rating errors tend to be offset within a limited geographical area (over-allocation/under-allocation patterns occur in adjacent counties), aggregating to HSA or MSA levels will produce more reliable measures of HMO penetration.[a] We therefore measured market characteristics, hospital use, number of HMOs, HMO penetration and Herfindahl index (based on hospital in-patient admissions) at the HSA level.

Nurse staffing. Registered nurse (RN) staffing was measured as the number of registered nurse full-time equivalents (FTEs) per 1000 in-patient days. Licensed practical nurse (LPN) and non-nurse staffing were similarly defined. Prior to 1994, the AHA annual survey required hospitals to report staffing separately by hospital unit and nursing home/long term care unit. In subsequent years, reporting was done only for the total facility. Nursing homes, however, are required by CMS to comply with the Online Survey Certification and Reporting system (OSCAR). We obtained data on hospitals with nursing homes from the OSCAR system, which allowed us to subtract nursing home staffing from total facility staffing to arrive at hospital staffing. Another problem is that the AHA survey does not distinguish nurse staffing for in-patient and out-patient services, and, without an appropriate allocation method, estimates relating nurse staffing to quality of care would be biased. We followed Kovner *et al.* [9,10] in allocating staffing to the in-patient facility based on the ratio of in-patient to out-patient gross revenues.

Quality of care. Mortality was defined as deaths occurring during the patient's hospitalization. Risk adjustment for mortality and length of stay measures was performed using Medstat's Disease Staging methodology [28], which can be directly applied to HCUP data. Diseases are 'staged' into four substages (no complications through death) from UB-82/UB-92 information, including the patient's age, gender, admission type, admission source, and type of treatment (medical vs surgical). This information is used to derive a predicted probability of death and expected length of stay. For our study, the Disease Staging methodology generated an estimated probability of death and expected length of stay (LOS) for every discharge. These probabilities were summed over a hospital's discharges to yield an estimate of the number of deaths 'expected' for that hospital as well as the expected LOS.[b] Expected LOS for a hospital was obtained by calculating the geometric mean of expected LOS for all patients at a hospital for a given year (but patients with natural log of actual LOS four standard deviations above the mean were excluded). A mortality ratio greater than 1.0 indicates that the actual number of deaths exceeds the expected number, while a mortality ratio less than 1.0 indicates that the actual number of deaths was less than expected. LOS ratios are interpreted similarly.

Hospital characteristics. We also measured selected hospital characteristics as control variables. Because ours is the first examination of the impact of HMO penetration on the relationship between nurse staffing and quality of care, we chose hospital characteristics for which there was earlier research suggesting a relationship between the specific characteristic and either nurse staffing or quality of care. For example, hospital financial performance is a critical measure, since if hospitals cannot earn adequate operating profits, they may weaken their ability to generate sufficient cash to meet short-term obligations and accumulate the funds to acquire new and replacement plant and equipment. We therefore included operating margin as our measure of hospital financial performance [30]. There is also a substantial, although inconclusive, body of work relating hospital ownership to quality [31,32].

In addition, hospital size, case mix, and the availability of high technology services have been linked to quality of care [33,34]. While measurement of hospital size and case mix are straightforward, measurement of high technology services is more involved. Researchers frequently use a simple count of the number of services offered, which assumes that each extra service contributes the same 'amount' of additional high technology services. Instead, we applied the 'Saidin index' which is a weighted sum of the number of technologies and services available in a hospital, with the weights being the percentage of hospitals in the country that do not possess the technology or service [35]. Thus, the index increases more with the addition of technologies that are relatively rare than with the addition of technologies that are more common.

Empirical specification and analytic approach

The model we propose addresses important potential sources of bias that limit policy conclusions from previous research on staffing and quality of care. Previously we applied the model to the general question of quality of care and staffing level [12]; here we consider structural differences in this relationship depending upon the level of managed care penetration. We rely on Wooldridge's [36] approach to drawing conclusions about causal relationships from observational data: if the model is specified correctly, avoiding bias due to omitted variables, simultaneity, and so on, then we will obtain consistent estimates of the parameters, thus reflecting the real policy impact of changes in staffing on quality of care. Although the correctness of the specification cannot ultimately be verified, our approach contains several important elements to contend directly with potential sources of bias. These include incorporating hospital fixed effects, a dynamic, rather than static model, and an assumption that all hospital-level variables are predetermined, rather than strictly exogenous.

Equation (1) describes our model for quality of care in hospital i in time period t (QC_{it}):

$$\mathrm{QC}_{it} = \alpha_i + \gamma_t + \delta \mathrm{QC}_{it-1} + ST'_{it}\beta + HC'_{it}\eta + MC'_{it}\pi + \varepsilon_{it} \tag{1}$$

Quality of care is assumed to be a function of hospital-specific intercepts (α_i) yearly time dummy variables (t), the lagged value of quality of care (QC_{it-1}), contemporaneous staffing levels (the vector STN_{it} which includes RN FTEs, LPN FTEs, and non-nurse FTEs all measured per 1000 in-patient days, as well as their squares and interactions), and, as described above, contemporaneous hospital characteristics (HCN_{it}) and market characteristics (MCN_{it}). Note that we control for the existence of unmeasured, time-invariant hospital-specific effects (the α_i). Failure to account for such hospital-specific effects yields biased parameter estimates if the fixed effects are correlated with the regressors. Equation (1) assumes that a dynamic process generates the dependent variable: Instead of assuming that quality of care adjusts fully and immediately to contemporaneous changes in the regressors, we allow for the possibility that past circumstances may continue to influence the current value of the dependent variable, with this influence captured through the lagged value of the dependent variable.

The within-group estimator (using information in deviations from time means for each cross-sectional unit) is commonly applied in order to estimate models incorporating fixed effects. But the lagged dependent variable in Equation (1) precludes use of this estimator: the within-group estimator, like the OLS estimator, yields inconsistent parameter estimates unless all regressors are strictly exogenous; that is, unless the error term is uncorrelated with the regressors in *all* time periods (see, for example [37]). Strict exogeneity is unambiguously violated in Equation (1) because $QC_{i,t-1}$ is correlated with $\gamma_{i,t-1}$.

The same difficulty with the within-transformation arises if there are feedback effects. Previous studies of staffing and quality of care [8–10] have assumed that staffing levels (as well as other hospital characteristics) are strictly exogenous, but this assumption is too strong if previous realizations of quality of care affect the current level of staffing (e.g. if unexpectedly high in-hospital mortality leads a hospital to increase staffing in a subsequent year). Instead of strict exogeneity, we allow for feedback effects by making the weaker assumption that staffing levels (and all other hospital-level regressors) are predetermined: the error term is uncorrelated with current and past values of the predetermined regressor but potentially correlated with future values of the regressor.

Anderson and Hsiao [38] showed that consistent estimates of a dynamic panel model such as Equation (1) may be obtained by applying a first difference transformation and using instrumental variable estimation. After applying the first-difference transformation to Equation (1) to eliminate the fixed effects, the dependent variable, ($QC_{i,t} - QC_{i,t-1}$), is to be regressed on ($QC_{i,t-1} - QC_{i,t-2}$) as well as the first differences of the other regressors in Equation (1). The error term is ($\gamma_{i,t} - \gamma_{i,t-1}$). Anderson and Hsiao noted that though ($QC_{i,t-1} - QC_{i,t-2}$) is correlated with the error term ($\gamma_{i,t} - \gamma_{i,t-1}$), the variables ($QC_{i,t-2} - QC_{i,t-3}$) or $QC_{i,t-2}$ can serve as instruments since both are uncorrelated with ($\gamma_{i,t} - \gamma_{i,t-1}$) as long as the original error term in Equation (1) is not serially correlated. The treatment of predetermined regressors (staffing levels and other hospital characteristics) is analogous: consistent parameter estimates may be obtained by using past values of the predetermined regressor as an instrument.

Although the instrumental variable estimation approach outlined in the paragraph above yields consistent estimates, we apply the Arellano and Bond [13] estimator which uses additional instruments for greater efficiency. For example, not only can $QC_{i,t-2}$ serve as an instrument for the regressor ($QC_{i,t-1} - QC_{i,t-2}$), but, in the periods when the lags exist, so too can $QC_{i,t-3}$, $QC_{i,t-4}$, and so on. Similar additional instruments are available for predetermined variables. When these additional instruments are translated to moment conditions, there are more moment conditions than parameters. Hence, Arellano and Bond construct a generalized method of moments estimator by weighting the different moment conditions to minimize asymptotic variance.[c]

In sum, we propose a model that avoids several potential sources of bias in previous studies of quality of care and staffing. By using fixed effects, we control for omitted variable bias due to unmeasured, time-invariant differences across hospitals that are correlated with the regressors. By using a dynamic model, we control for bias due to omission of past values of the regressors if quality of care adjusts over time, rather than immediately, to changes in the regressors. And, we control for bias due to possible feedback effects by assuming that staffing and other hospital-level variables are predetermined. Thus, our model should allow us to better measure the real policy impact of changing staffing levels.

Results

Table 2 provides means and standard deviations for variables separated by mean HMO penetration quartile in the years 1992–1995. In the dynamic panel model the first two observations (in our case, the observations for 1990 and 1991), are used to obtain the lagged value of the dependent variable and first differences. Hence, hospitals were assigned to an HMO penetration quartile based on their mean HMO penetration levels over the years 1992–1995, and the summary statistics in Table 2 reflect values in the years 1992–1995. Consequently, the number of observations reflects up to four observations per hospital.

In order to examine possible differences across HMO penetration levels, we partitioned the sample into quartiles. While it is possible that differences exist across HMO penetration levels at a finer level (e.g. deciles of HMO penetration), we believed that our sample size, while reasonably large, would have little power to detect such differences. Partitioning into quartiles was judged the appropriate partitioning, balancing the desire to capture different levels of HMO penetration with the need for parsimony. We tested for differences across HMO penetration quartiles in all the coefficients for the staffing variables. In addition, based on empirical research demonstrating the impact of managed care on hospital size [39], high tech services [40], case mix index, operating margin and payer mix [41], we tested for differences in the coefficients of these hospital characteristics as well.[d]

Results of tests for structural differences by HMO penetration quartile are given in Table 3. Hospitals in markets falling in the lowest quartile of HMO penetration (quartile 1, mean HMO penetration less than 7.5%) and hospitals in markets falling in the highest quartile of HMO penetration (quartile 4, mean HMO penetration >27.9%) were, in two separate regressions, compared to hospitals in the middle two quartiles of HMO penetration. We then tested the significance of the separate slope coefficients compared to HMO penetration quartiles 2 and 3. Given the lack of evidence of structural differences between quartiles 2, 3, and 4 for the mortality ratio, we pooled these quartiles and obtained even stronger evidence of structural differences compared to quartile 1. For the LOS ratio, however, it is quartile 4 for which structural differences are detected.

Table 2. Summary statistics by HMO penetration quartile, 1992–1995

	HMO penetration quartile							
	1		2		3		4	
Variable	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
Mortality ratio	0.994	0.241	1.026	0.236	0.987	0.218	1.014	0.218
LOS ratio	0.775	0.114	0.831	0.144	0.807	0.119	0.798	0.116
RN FTEs per 1000 IPD	3.190	1.063	3.268	1.010	3.531	1.014	3.662	1.069
LPN FTEs per 1000 IPD	0.756	0.489	0.638	0.401	0.551	0.396	0.535	0.390
Non-nurse FTEs per 1000 IPD	9.776	2.994	9.490	2.968	10.319	3.189	11.092	3.442
Operating margin	0.973	8.725	2.300	11.408	−2.452	16.803	0.814	7.349
Case mix index	1.227	0.207	1.301	0.201	1.365	0.209	1.359	0.213
Saidin index	2.584	2.098	3.328	2.212	3.849	2.368	4.193	2.531
Payer mix	63.76	10.31	57.29	12.25	55.10	15.67	51.13	13.83
Beds	133.93	136.11	190.35	186.06	237.59	202.44	213.35	147.45
System	0.382	0.487	0.486	0.501	0.539	0.499	0.564	0.497
Public	0.312	0.464	0.141	0.348	0.163	0.370	0.094	0.293
Profit	0.122	0.328	0.160	0.367	0.202	0.402	0.106	0.308
Hospital use	921.78	410.44	809.66	298.99	868.16	206.57	766.58	241.47
Herfindahl index	33.42	18.48	19.06	12.62	11.08	10.44	9.70	9.88
Number of HMOs	1.77	1.35	5.67	2.93	11.50	6.12	11.21	5.21
HMO penetration	3.26	2.98	12.57	4.71	21.31	5.44	35.59	8.31
Number of observations	353		362		362		360	

Table 3. Summary of parameter stability tests over HMO penetration quartiles[a]

	Mortality ratio		LOS ratio	
	Chi-squared statistic testing stability compared to		Chi-squared statistic testing stability compared to	
Quartiles	Quartile 1	Quartile 4	Quartile 1	Quartile 4
2 & 3	32.3*	22.7	16.8	29.9*
1, 2 & 3	—	—	—	33.0**
2, 3 & 4	37.7**	—	—	—

[a] Parameter stability tests for coefficients for all staffing variables and for the hospital characteristics Operating Margin, Case Mix Index, Saidin Index, Payer Mix, and Beds. Hospitals in HSAs with mean 1992–1995 HMO penetration $<7.5\%$ are assigned to HMO penetration Quartile 1; hospitals in HSAs with mean 1992–1995 HMO penetration $>27.9\%$ are assigned to HMO penetration Quartile 4. There were 14 degrees of freedom in each Chi-squared test.
*Significant at the 0.01 level.
**Significant at the 0.001 level.

Mortality ratio results

Table 4 provides the coefficient estimates for the dynamic panel model, and also shows the coefficient estimates we would obtain had we chosen the more commonly applied static models, OLS or within-group estimators, and assumed there were no feedback effects. As we note below, the different estimators lead to quite different conclusions. The coefficient estimates in Table 4 are grouped so that the first set applies to hospitals in HMO penetration quartiles 2–4, (which we call 'high' penetration), the second set to hospitals in HMO penetration quartile 1 (which we call 'low' penetration), and the third set common to both sets of hospitals.

The coefficient for the lagged value of the dependent variable of 0.154 ($z = 4.16$) demonstrates the meaningfully large influence of the past on the current value of the mortality ratio, an effect that cannot be estimated consistently using either the OLS or within-groups model.[e] Second, note the differences in sign, size, and statistical significance of coefficients between the OLS, within-groups, and dynamic panel models. After controlling for hospital specific effects, controlling for the influence of the past, and assuming that variables under the hospital's control are predetermined rather than strictly exogenous, variables that were significant in the simpler models (coefficients for hospital characteristics in the high penetration quartiles) are no longer significant and often change sign in the dynamic panel model.

Although we had found strong evidence of structural differences by HMO penetration in the dynamic panel model (Table 3), there is no indication from the coefficients in Table 4 that changing HMO penetration levels leads directly to changes in the mortality ratio. Increasing the number of HMOs, however, does have a statistically significant effect on reducing the mortality ratio. In addition, Table 4 demonstrates differences in the coefficients for the staffing variables between high and low managed care penetration markets, with Table 5 describing the impact of RN staffing changes by providing the marginal effect (and standard error) of a one-unit increase in RN FTEs per 1000 in-patient days at RN staffing levels corresponding to the 25th, 50th, and 75th percentile values in the sample. The marginal effects represent the contemporaneous effect of a change in nurse staffing on mortality ratio.[f] For hospitals in high HMO penetration markets, the estimates for the dynamic panel model indicate that increasing nurse staffing significantly reduces mortality ratio at the 25th percentile of nurse staffing and has a non-significant, but still negative, effect at the 50th percentile of nurse staffing, and no effect at the 75th percentile of nurse staffing.

In contrast to the effect of nurse staffing on mortality ratio in high HMO penetration hospitals, none of the estimation methods shows a statistically significant effect of nurse staffing on mortality ratio for hospitals in low HMO penetration markets. For the low penetration quartile the dynamic panel model marginal effects, -0.030 to -0.033, are relatively large, however. Some further information is provided in the table to demonstrate that this large marginal effect is entirely due to the implausibly large effect of the

Table 4. Estimation results measuring quality of care with the mortality ratio illustrating differences between hospitals in the lowest HMO penetration quartile and hospitals in the three highest HMO penetration quartile[a]

Variable	OLS	Within-groups	Dynamic panel model
HMO penetration quartiles 2–4 (High penetration)			
RN FTEs per 1000 IPD	−0.043*	−0.028	−0.099***
	(0.018)	(0.017)	(0.025)
RN FTEs per 1000 IPD^2	−0.003	0.002	0.010***
	(0.003)	(0.002)	(0.003)
LPN FTEs per 1000 IPD	−0.059	0.020	0.023
	(0.041)	(0.045)	(0.063)
LPN FTEs per 1000 IPD^2	0.016	0.043*	0.008
	(0.017)	(0.018)	(0.022)
Non-nurse FTEs per 1000 IPD	−0.002	−0.004	−0.004
	(0.006)	(0.006)	(0.008)
Non-nurse FTEs per 1000 IPD^2	−2.2E-4	2.1E-4	−1.6E-4
	(2.1E-4)	(1.8E-4)	(2.8E-4)
RN FTEs × LPN FTEs	0.014	−0.003	0.007
	(0.010)	(0.009)	(0.011)
RN FTEs × Non-nurse FTEs	0.003	8.5E-5	4.8E-4
	(0.001)	(0.001)	(0.002)
LPN FTEs × Non-nurse FTEs	−0.005	−0.008*	−0.005
	(0.004)	(0.004)	(0.005)
Operating margin	−0.001*	0.001	0.001
	(3.7E-4)	(3.4E-4)	(0.001)
Case mix index	−0.134***	−0.202***	−0.002
	(0.030)	(0.052)	(0.088)
Saidin index	0.012***	−0.008*	−0.012
	(0.003)	(0.004)	(0.007)
Payer mix	0.001*	2.5E-4	−2.9E-4
	(2.9E-4)	(0.001)	(0.001)
Beds	1.5E-4***	−2.1E-4*	1.9E-4
	(2.7E-5)	(9.8E-5)	(2.1E-4)
HMO penetration quartile 1 (Low penetration)			
RN FTEs per 1000 IPD	0.109	−0.021	0.005
	(0.057)	(0.052)	(0.081)
RN FTEs per 1000 IPD^2	−0.016	−0.003	−0.001
	(0.009)	(0.008)	(0.011)
LPN FTEs per 1000 IPD	−0.171	0.007	−0.193
	(0.147)	(0.136)	(0.205)
LPN FTEs per 1000 IPD^2	0.049	0.077	0.124
	(0.050)	(0.046)	(0.071)
Non-nurse FTEs per 1000 IPD	−0.063***	−0.015	−0.005
	(0.020)	(0.017)	(0.025)
Non-nurse FTEs per 1000 IPD^2	0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)
RN FTEs × LPN FTEs	0.038	0.003	0.018
	(0.037)	(0.030)	(0.037)
RN FTEs × Non-nurse FTEs	−0.001	0.002	−0.004
	(0.005)	(0.004)	(0.006)
LPN FTEs × Non-nurse FTEs	−0.004	−0.014	−0.003
	(0.014)	(0.012)	(0.014)
Operating margin	0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.002)

Table 4. (*Continued*).

Variable	OLS	Within-groups	Dynamic panel model
Case mix index	−0.014	−0.058	0.280
	(0.072)	(0.082)	(0.161)
Saidin index	−0.008	0.007	0.010
	(0.010)	(0.009)	(0.012)
Payer mix	−2.6E-4	−0.001	−0.007**
	(0.001)	(0.001)	(0.002)
Beds	2.4E-4*	−0.001***	−0.001*
	(1.1E-4)	(1.4E-4)	(2.9E-4)
All HMO penetration quartiles			
Mortality ratio$_{t-1}$			0.154***
			(0.037)
System	0.022**	0.004	0.003
	(0.008)	(0.011)	(0.015)
Public	−0.045***	−0.013	0.244
	(0.012)	(0.068)	(0.136)
Profit	−0.118***	−0.009	0.073
	(0.012)	(0.038)	(0.078)
Hospital use	1.4E-5	2.5E-5	2.0E-5
	(1.5E-5)	(5.7E-5)	(7.0E-5)
Herfindahl index	0.001*	−2.6E-4	−0.002
	(4.2E-4)	(0.003)	(0.004)
Number of HMOs	−0.003	−0.011***	−0.012***
	(0.002)	(0.002)	(0.003)
HMO penetration	0.003***	4.3E-4	−0.001
	(0.001)	(0.001)	(0.001)
HMOs × HMO penetration	−1.8E-4**	3.3E-5	1.3E-4
	(6.0E-5)	(8.9E-5)	(1.1E-4)
Fixed effects for years	*X*	*X*	*X*
Observations	2176	2176	1437
	$R^2 = 0.43$	$R^2 = 0.58$	

[a] Standard errors (in parentheses) beneath the coefficients.
*Significant at the 0.05 level.
**Significant at the 0.01 level.
***Significant at the 0.001 level.

RN-non-nurse interaction.[g] Note that the net impact of the other terms making up the marginal effect (based on the variables RN FTEs per 1000 in-patient days, its square, and the interaction between RN FTEs and LPN FTEs) is *positive* at each of the three levels of RN staffing (e.g. 0.007 at the 25th percentile value of RN staffing).

Table 5 also presents marginal effects for RN staffing implied by the OLS and within-group estimators. For hospitals in high managed care markets, OLS and within-group estimates of the marginal effects are quite different from those for the dynamic panel model. In particular, the within-group model marginal effects do not vary greatly at different staffing levels, while the dynamic panel model indicates a large, statistically significant marginal effect at the 25th percentile value of staffing, a marginal effect one-half as large at the median staffing level, and a marginal effect very near to zero at the 75th percentile level.[h]

Length of stay results

Estimation results for the LOS ratio are presented in Table 6. The dynamic effect is considerably larger for the LOS ratio than for the mortality ratio: the estimated coefficient for the lagged value of LOS is 0.681 ($z = 20.9$). Table 6 demonstrates that there are again many variables that appear to

Table 5. Illustration of the effect of a one-unit increase in RN FTEs per 1000 in-patient days on mortality ratio[a]

		Percentile value for RN staffing per 1000 in-patient days		
HMO penetration quartile(s)	Estimation method	25th 2.66	50th 3.34	75th 4.02
Quartiles 2–4 (High penetration)	OLS	−0.029***	−0.033***	−0.037***
		(0.006)	(0.005)	(0.007)
	Within-group	−0.015**	−0.013*	−0.010
		(0.006)	(0.005)	(0.006)
	Dynamic panel model	−0.026**	−0.012	0.002
		(0.008)	(0.007)	(0.008)
Quartile 1 (Low penetration)	OLS	0.016	−0.006	−0.027
		(0.015)	(0.016)	(0.025)
	Within-group	−0.017	−0.021	−0.024
		(0.014)	(0.015)	(0.021)
	Dynamic panel model	−0.030	−0.031	−0.033
		(0.022)	(0.022)	(0.030)
Further explanation of dynamic panel model marginal effect in Quartile 1:				
	w/o RN × Non-nurse interaction	0.007	0.005	0.003
		(0.058)	(0.065)	(0.075)
	RN × Non-nurse interaction		−0.036	
			(0.055)	

[a] Standard errors (in parentheses) beneath the estimates of the marginal effects. Marginal effects are calculated at the median values for LPN FTEs per 1000 IPD (0.55) and non-nurse FTEs per 1000 IPD (9.73).
*Significant at the 0.05 level.
**Significant at the 0.01 level.
***Significant at the 0.001 level.

have large, statistically significant effects in the OLS model, but the size of the effects and their statistical significance diminishes when we control for hospital-fixed effects, the influence of the past, and assume variables under the hospital's control are predetermined rather than strictly exogenous (e.g. system, public, profit, number of HMOs, and in the coefficients for HMO penetration quartiles 1–3 case mix index and beds).

Once more, there are important differences in the staffing coefficients between hospitals in high and low HMO penetration markets (and across estimation methods) and these differences are best illustrated in Table 7 showing the marginal effect of a one-unit increase in RN FTEs per 1000 in-patient days at the 25th, 50th, and 75th percentile values for RN staffing. For hospitals in high HMO penetration markets, increases in RN staffing significantly reduce length of stay ratio at both the 25th and 50th percentile of nurse staffing; the effect at the 75th percentile of nurse staffing, however, is negative but not statistically significant. In contrast, there is no statistically significant effect of RN staffing on length of stay ratio for hospitals in low HMO penetration markets. The dynamic panel model clearly shows a difference in marginal effects between high and low managed care quartiles and shows a slight diminishing effect of increasing RN staffing at higher RN staffing levels.

Conclusion

We observed no statistically significant direct effect of HMO penetration on quality of care, but we did find evidence to suggest differences in the relationship between RN staffing and quality of care dependent upon the level of HMO penetration in the hospital's market: increases in RN staffing for hospitals in higher HMO penetration markets were associated with lower mortality and length of stay ratios, but not for hospitals in low HMO

Table 6. Estimation results measuring quality of care with the LOS ratio illustrating differences between hospitals in the highest HMO penetration quartile and hospitals in the three lowest HMO penetration quartiles[a]

Variable	OLS	Within-groups	Dynamic panel model
HMO penetration quartile 4 (High penetration)			
RN FTEs per 1000 IPD	−0.073***	−0.022**	−0.028**
	(0.012)	(0.008)	(0.010)
RN FTEs per 1000 IPD^2	−0.002	−0.001	0.001
	(0.002)	(0.001)	(0.001)
LPN FTEs per 1000 IPD	−0.034	0.027	0.029
	(0.034)	(0.024)	(0.027)
LPN FTEs per 1000 IPD^2	0.016	−0.010	−0.008
	(0.013)	(0.009)	(0.008)
Non-nurse FTEs per 1000 IPD	−0.024***	−0.014***	−0.010**
	(0.004)	(0.003)	(0.003)
Non-nurse FTEs per 1000 IPD^2	4.6E-5	2.5E-4	2.3E-4
	(2.5E-4)	(1.4E-4)	(1.5E-4)
RN FTEs × LPN FTEs	0.025***	0.010*	0.010*
	(0.008)	(0.005)	(0.004)
RN FTEs × Non-nurse FTEs	0.005***	0.002**	0.001
	(0.001)	(0.001)	(0.001)
LPN FTEs × Non-nurse FTEs	−0.008**	−0.004*	−0.005**
	(0.003)	(0.002)	(0.002)
Operating margin	−3.7E-4	−1.1E-4	−2.6E-4
	(3.0E-4)	(1.8E-4)	(2.4E-4)
Case mix index	−0.034	−0.018	0.025
	(0.019)	(0.021)	(0.029)
Saidin index	−0.003	−0.002	−3.9E-4
	(0.002)	(0.001)	(0.002)
Payer mix	1.2E-4	−4.1E-4	−0.001*
	(2.1E-4)	(2.5E-4)	(3.1E-4)
Beds	2.1E-4***	1.8E-5	1.2E-4*
	(1.9E-5)	(3.7E-5)	(6.1E-4)
HMO penetration quartiles 1–3 (Low penetration)			
RN FTEs per 1000 IPD	−0.037*	−0.004	−0.013
	(0.015)	(0.009)	(0.011)
RN FTEs per 1000 IPD^2	−0.003	−0.003	−0.001
	(0.002)	(0.001)	(0.002)
LPN FTEs per 1000 IPD	0.010	0.017	0.039
	(0.031)	(0.022)	(0.025)
LPN FTEs per 1000 IPD^2	−0.016	−0.020*	−0.027**
	(0.013)	(0.008)	(0.009)
Non-nurse FTEs per 1000 IPD	−0.025***	−0.013***	−0.008*
	(0.005)	(0.003)	(0.004)
Non-nurse FTEs per 1000 IPD^2	1.3E-4	1.8E-4*	2.1E-4*
	(1.3E-4)	(7.9E-5)	(9.7E-5)
RN FTEs × LPN FTEs	0.004	0.008	0.015**
	(0.007)	(0.005)	(0.005)
RN FTEs × Non-nurse FTEs	0.004***	0.002**	0.001
	(0.001)	(0.001)	(0.001)
LPN FTEs × Non-nurse FTEs	−0.002	−0.001	−0.004
	(0.003)	(0.002)	(0.002)
Operating margin	−0.001***	−0.001***	−1.5E-4
	(2.3E-4)	(1.6E-4)	(2.2E-4)

Table 6. (*Continued*).

Variable	OLS	Within-groups	Dynamic panel model
Case mix index	−0.095***	−0.084***	−0.019
	(0.021)	(0.021)	(0.030)
Saidin index	0.001	0.003	0.002
	(0.002)	(0.002)	(0.002)
Payer mix	−9.1E-5	6.5E-5	−0.001**
	(0.000)	(2.5E-4)	(3.3E-4)
Beds	1.4E-4***	−3.7E-5	8.8E-5
	(1.9E-5)	(3.6E-5)	(5.9E-5)
All HMO penetration quartiles			
LOS ratio$_{t-1}$			0.681***
			(0.033)
System	−0.012**	−0.012**	−0.006
	(0.004)	(0.004)	(0.005)
Public	−0.039***	0.014	0.017
	(0.006)	(0.029)	(0.056)
Profit	−0.059***	−0.016	−0.025
	(0.008)	(0.017)	(0.030)
Hospital use	1.3E-4***	8.1E-5***	4.6E-5*
	(7.8E-6)	(2.1E-5)	(2.3E-5)
Herfindahl index	−2.0E-4	0.003*	0.002
	(2.1E-4)	(0.001)	(0.001)
Number of HMOs	0.005***	0.003***	0.001
	(0.001)	(0.001)	(0.001)
HMO penetration	−3.7E-4	0.001*	3.1E-4
	(3.4E-4)	(4.1E-4)	(4.2E-4)
HMOs × HMO penetration	−7.9E-5*	−9.5E-5**	−3.1E-5
	(3.3E-5)	(3.4E-5)	(3.4E-5)
Fixed effects for years	X	X	X
Observations	2176	2176	1437
	$R^2 = 0.99$	$R^2 = 0.87$	

[a] Standard errors (in parentheses) beneath the coefficients.
*Significant at the 0.05 level.
**Significant at the 0.01 level.
***Significant at the 0.001 level.

penetration markets. While prior research has demonstrated that HMOs force hospital price concessions and increases in efficiency [16,42], and some studies have found lower mortality and shorter length of stay in high HMO penetration markets [16,43], our study is the first to provide evidence of differential effects of nurse staffing in high vs low HMO penetration markets.

Earlier we suggested that, in contrast to hospitals in low HMO penetration markets, hospitals in high HMO penetration markets may have adopted a range of cost control mechanisms e.g. gate keeping, utilization control, evidence-based practice protocols, disease management, discharge planning, and changes in clinical support services [44]. In addition, widespread re-structuring transformed the nature of nursing work through reallocation of human resources, including nurse staffing, to maximize nursing time and cost–efficiency [45]. These changes may have reduced slack resources, making the effects of increases in nurse staffing on reducing LOS and mortality ratios more readily discernible. With nursing having been identified as the ‘primary surveillance system’ in hospitals [46], its proper operation depends upon having a sufficient number of registered nurses to observe patients directly, recognize an impending patient problem, and mobilize an intervention that often requires coordinating others’ activities to save a patient’s

Table 7. Illustration of the effect of a one-unit increase in RN FTEs per 1000 in-patient days on LOS ratio[a]

HMO penetration quartile(s)	Estimation method	Percentile value for RN staffing per 1000 in-patient days: 25th 2.66	50th 3.34	75th 4.02
Quartile 4 (High penetration)	OLS	−0.023***	−0.026***	−0.029***
		(0.004)	(0.003)	(0.005)
	Within-group	0.001	−0.002	−0.006
		(0.003)	(0.003)	(0.003)
	Dynamic panel model	−0.007*	−0.006*	−0.005
		(0.003)	(0.002)	(0.003)
Quartiles 1–3 (Low penetration)	OLS	−0.014**	−0.019***	−0.023***
		(0.005)	(0.004)	(0.005)
	Within-group	−0.005	−0.006**	−0.007**
		(0.003)	(0.002)	(0.003)
	Dynamic panel model	−0.001	−0.002	−0.003
		(0.004)	(0.003)	(0.004)

[a] Standard errors (in parentheses) beneath the estimates of the marginal effects. Marginal effects are calculated at the median values for LPN FTEs per 1000 IPD (0.55) and non-nurse FTEs per 1000 IPD (9.73).
*Significant at the 0.05 level.
**Significant at the 0.01 level.
***Significant at the 0.001 level.

life (reducing mortality ratio) or to ensure a smooth transition at discharge (reducing LOS ratio).

Most previous studies of staffing and quality of care rely on cross-sectional estimation methods and assume variables, such as staffing levels and other variables under the hospital's control, are strictly exogenous. Our application of a dynamic panel model (allowing controls for hospital specific effects and for differences in the history of circumstances) along with weaker assumptions about exogeneity (allowing for the possibility of feedback effects, e.g. from past realizations of quality of care to present staffing levels) leads to important differences in conclusions about the impact of changes in staffing levels on quality.

For example, for both mortality and LOS ratio, when we apply OLS (that is, we do not control for fixed effects, feedback effects, or the history of past circumstances), the marginal effects generally indicate large and statistically significant decreases in both mortality and LOS across the range of RN staffing levels, results which are consistent with earlier research applying the same or a similar estimation method [5–8]. The dynamic panel model marginal effects are quite different, especially for hospitals in high HMO penetration markets: for LOS, the magnitude of the marginal effects is markedly reduced and decline with the level of nurse staffing, consistent with diminishing returns for increased RN staffing. For mortality ratio, the marginal effect is similar to the OLS marginal effect at the 25th percentile of nurse staffing, smaller by half at the 50th percentile and close to zero at the 75th percentile of nurse staffing, stronger evidence of diminishing returns for increases in RN staffing. The within-group marginal effects are essentially the same at different levels of RN staffing; hence, the dynamic panel model and within-group marginal effects are similar at the 50th percentile of RN staffing for the mortality ratio, but are quite different at both higher and lower staffing levels.

One difference in the findings for the two measures of quality of care is that the magnitude of the effect of increasing RN staffing on reducing mortality is larger than on reducing LOS ratio. This result may indicate that, of the two quality measures, mortality is more sensitive to changes in nurse staffing than is LOS, especially at lower levels of staffing.

From a policy perspective, the findings from our study indicate that increasing RN staffing achieves reduced mortality and LOS primarily for hospitals in high HMO penetration markets that are at lower levels of RN staffing, suggesting that policy recommendations and administrative decisions about nurse staffing, rather than being uniform and unvarying, should instead be responsive to local conditions. From a methodological perspective, our study has demonstrated how the selection of an estimation method can influence the findings. It further points out how using a method that controls for important sources of bias leads to different conclusions about the influence of HMO penetration on the relationship between nurse staffing and quality of care.

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Notes

a. HMO market measures were constructed using the data from HMO Census conducted by the Group Health Association of America for 1988–1991 and by InterStudy from 1992 to 1995. For the period of our study, InterStudy collected data from HMOs on their enrollment by metropolitan statistical area (MSA). Two sources of information from InterStudy are used to prorate enrollment: (a) a list of the counties served by each HMO in each year; and (b) enrollment by MSA served. MSA-level information was used to prorate an HMO's reported MSA enrollment to the MSA's constituent counties on the basis of county population. All prorating was based on county population weights (e.g. an HMO operating in two counties with populations of 100 000 and 200 000 would have 1/3 of its reported enrollment allocated to the smaller county and 2/3 to the larger county). HMO penetration was then measured as percent HMO enrollment as a percent of the total HSA population [Wholey, mimeograph, available from author].

b. The dependent variables, mortality ratio and LOS ratio, combine information about expected and observed quality of care in a ratio. The nature of the dependent variables suggests that the data should be weighted appropriately. The LOS ratio is calculated using the geometric mean of actual LOS and expected LOS; since there were quite different numbers of patients at different hospitals, we assume the error variance is inverse to the number of patients and weight the data accordingly. The standard error of the mortality ratio is (observed deaths)$^{0.5}$/expected deaths [29]. To normalize the error variance we weighted the data by the mean of the inverse of this standard error. For both mortality ratio and LOS ratio, we calculated weights using mean values in a panel; that is, we applied the same weights across different years for a given hospital so that changes in the values of the variables reflected change in the variable, not changes in the weights.

c. Arellano and Bond [13] also present two specification tests. The first is a test for serial correlation. If the error term is serially correlated then past values of the dependent variable are not valid instruments and their estimator should not be applied. The second is a test of overidentifying restrictions. We applied these specification tests to the models we estimate in the next section, and they gave no indication that the instruments were invalid.

d. We did not test for structural differences in the coefficients for the dummy variables system public, and profit: the dynamic panel model we apply uses information in first-differences and there were relatively few *changes* in system affiliation and ownership status. A reviewer suggested an alternate specification allowing such differences in market characteristics and allowing for differences in the coefficient for the lagged dependent variable for different quartiles, but we found no statistically or practically important differences in applying this specification. For example, for the mortality ratio when we estimate a dynamic panel model similar to that in Table 4 but also allowing differences in coefficients for the market characteristics between high and low HMO penetration markets as well as a different coefficient for the lagged dependent variable, we can easily accept the null hypothesis of stability across this additional set of coefficients ($X^2 = 1.84$, df = 6, $p = 0.93$). Similarly, the marginal effects of a one-unit increase in RN FTEs per 1000 in-patient days (Table 5) are essentially unchanged.

e. In the previous section, we explained that the within-groups estimator would not produce consistent estimates given the presence of the lagged dependent variable in Equation (1). To illustrate this point, we note that had we applied the within-group estimator to Equation (1) we would have obtained a coefficient estimate for the lagged dependent variable of -0.010 with a standard error of 0.037. Applying the Hausman specification test to this single parameter of interest [36], we would reject the null hypothesis of no significant difference in the coefficients ($t = 8.2$, $p = 5.4\text{E-}16$). Had we applied the OLS estimator to Equation (1) we would have obtained a coefficient estimate for the lagged dependent variable of 0.695 with a standard error of 0.019; the coefficient estimate is biased high presumably because of the failure to control for hospital-specific effects. Again, we would easily reject the null hypothesis of no significant difference in coefficients compared to the dynamic panel model. Similar sharp differences exist for the LOS ratio.

f. To illustrate the calculation of the marginal effects, given that β_1 is the coefficient for RN FTEs per 1000 IPD, β_2 is the coefficient for RN FTEs per 1000 IPD^2, β_7 is the coefficient for (RN FTEs per 1000 IPD) $\times$ (LPN FTEs per 1000 IPD), and β_8 is the coefficient for (RN FTEs per 1000 IPD) $\times$ (Non-nurse FTEs per 1000 IPD), and given the median values for LPN FTES per 1000 in-patients days (0.55) and Non-nurse FTEs/1000 in-patient days (9.28), the marginal effect of a one unit increase in RN FTEs per 1000 in-patient days from the 25th percentile value of 2.66–3.66 equals $\beta_2 + \beta_3(3.66^2 - 2.66^2) + \beta_8 0.55 + \beta_9 9.73$. As shown in Table 4, the marginal effect in the dynamic panel model in this instance is -0.026, with a standard error for the marginal effect of 0.008 ($z = -3.15$). Note also that the dynamic model implies that there would be a further impact of the change in staffing level in the current period on the mortality ratio in subsequent periods: for example, $\Delta QC_{i,t+1} = 0.154{*}\Delta QC_{i,t}$.

g. Recalling the marginal effect calculation explained in footnote[e], the marginal effect calculated at RN FTEs per 1000 IPD of 2.66, LPN FTEs per 1000 IPD of 0.55, and Non-nurse FTEs per 1000 IPD of 9.28 equals $0.109 + -0.016(3.66^2 - 2.66^2) + 0.038(0.55) + -0.004(9.73) = -0.03$. The last term is the part of the effect due to the RN FTE-Non-nurse FTE interaction and equals -0.036 ($z = -0.66$). Because the coefficient for the RN FTE-Non-nurse interaction for hospitals in the low HMO penetration quartile is imprecisely measured and is opposite in sign and an order of magnitude larger than the coefficient for this variable for high HMO penetration quartiles, we view the size of the marginal effect for the dynamic panel model for the low penetration quartile with greater skepticism even than would be justified due to its large standard error alone.

h. A reviewer suggested an alternate specification that included additional HSA variables. For both the mortality ratio results (Tables 4 and 5) and for the LOS ratio results (Tables 6 and 7), our conclusions are essentially unchanged when we estimate a model that includes the additional HSA variables natural log of population, natural log of inflation-adjusted per capita income, unemployment rate, and percentage of population over age 65.

References

1. Levitt L, Lundy J. *Trends and Indicators in the Changing Health Care Marketplace*. Kaiser Family Foundation Menlo Park: Menlo Park, California, 1998.
2. Witt Associates. *Today's Nurse Executive*: *Data analysis*, *1990 Survey*. Survey cosponsored by the American Organization of Nurse Executives. Witt/Kieffer, Ford, Hadelman & Lloyd: Oak Brook Terrace, IL, 1990.
3. American Nurses Association. Survey finds loss of RNs jeopardizes patient safety. *Am Nur* 1995; **30**: 1.
4. Shamian J, Hagen B, Hu T *et al*. The relationship between length of stay and required nursing care hours. *J Nurs Admin* 1994; **24**: 52–58.
5. American Nurses Association. *Implementing Nursing's Report Card*: *A Study of RN Staffing*, *Length of Stay and Patient Outcomes*. American Nurses Publishing: Washington DC, 1997.
6. American Nurses Association. *Nurse Staffing and Patient Outcomes in the Inpatient Hospital Setting*. American Nurses Publishing: Washington DC, 2000.
7. Lichtig L, Knauf R, Milholland K. Some impacts of nursing on acute care hospital outcomes. *J Nurs Admin* 1999; **29**: 25–33.
8. Needleman J, Buerhaus P, Mattke S *et al*. Nurse-staffing levels and the quality of care in hospitals. *N Engl J Med* 2002; **346**: 1715–1722.
9. Kovner C, Jones C, Chunliu Z *et al*. Nurse staffing and postsurgical adverse events: an analysis of administrative data from a sample of US hospitals, 1990–1996. *Health Serv Res* 2002; **37**: 611–629.
10. Kovner C, Gergen P. Nurse staffing levels and adverse events following surgery in US hospitals. *Image*: *J Nurs Scholarship* 1998; **30**: 315–321.
11. Cho S-H, Ketefian S, Barkausaks V *et al*. The effects of nurse staffing on adverse events, morbidity, mortality and medical costs. *Nurs Res* 2003; **52**: 71–79.
12. Mark B, Harless D, McCue M, Xu Y. A longitudinal examination of hospital nurse staffing and quality of care. *Health Serv Res* 2004; **39**: 277–298.
13. Arellano M, Bond S. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev Econ Stud* 1991; **58**: 277–297.
14. Shen Y. The effect of financial pressure on the quality of care in hospitals. *J Health Econ* 2003; **22**: 243–269.
15. Miller R, Luft H. Does managed care lead to better or worse quality of care? *Health Affairs* 1997; **16**: 7–25.
16. Miller R, Luft H. HMO plan performance update: an analysis of the literature, 1997–2001. *Health Affairs* 2002; **21**: 63–86.
17. Dudley RA, Miller R, Korenbrot T *et al*. The impact of financial incentives on quality of health care. *The Milbank Quart* 1998; **76**: 649–686.
18. Robinson J. Market structure, employment, and skill mix in the hospital industry. *South Econ J* 1988; **55**: 315–325.
19. Buerhaus P, Staiger D. Managed care and the nurse workforce. *JAMA* 1996; **13**: 1487–1493.
20. Buerhaus P, Staiger D. Future of the nurse labor market according to health executives in high

managed-care areas of the United States. *Image*: *J Nurs Scholarship* 1997; **29**: 313–318.
21. Buerhaus P, Staiger D. Trouble in the nurse labor market? Recent trends and future outlook. *Health Affairs* 1999; **18**: 214–222.
22. Spetz J. The effects of managed care and prospective payment on the demand for hospital nurses: evidence from California. *Health Serv Res* 1999; **34**(Part I): 993–1010.
23. Mobley L, Magnussen J. The impact of managed care penetration and hospital quality on efficiency in hospital staffing. *J Health Care Finance* 2002; **28**: 24–42.
24. American Hospital Assoc. *Annual Survey of Hospitals 1995*. American Hospital Association: Chicago, IL.
25. Baker L. Measuring competition in health care markets. *Health Serv Res* 2001; **36**(Part II): 223–251.
26. Makuc D, Haglund B, Ingram D, Kleinman J, Feldman J. The use of Health Service Areas for measuring provider availability. *J Rural Health* 1991; **7**: 347–356.
27. Wholey D, Christianson J, Engberg J *et al*. HMO market structure and performance, 1985–1995. *Health Affairs* 1997; **16**: 75–84.
28. Gonnella J, Hornbrook M, Louis D. Staging of disease: a case-mix measurement. *J Am Med Assoc* 1984; **215**: 637–644.
29. Breslow N, Day N. *Statistical Methods in Cancer Research*, *The Design and Analysis of Cohort Studies*, vol 2. International Agency for Research on Cancer: Lyon, France, 1987.
30. Zelman W, McCue J, Millikan A. *Financial Management of Health Care Organizations*. Blackwell: Malden, MA, 1999.
31. McClellan M, Staiger D. *Comparing hospital quality at for-profit and not-for-profit hospitals*. Working Paper 7324, National Bureau of Economic Research, 1999.
32. Sloan F, Picone G, Taylor D, Chou S. Hospital ownership and cost of quality of care: is there a dime's worth of difference? *J Health Econ* 2001; **20**: 1–21.
33. Hartz A, Krakauer H, Kuhn E *et al*. Hospital characteristics and mortality rates. *N Engl J Med* 1989; **321**: 1720–1724.
34. Keeler E, Rubenstein L, Kahn K *et al*. Hospital characteristics and quality of care. *J Am Med Assoc* 1992; **268**: 1709–1714.
35. Spetz J, Baker L. *Has Managed Care Affected the Availability of Medical Technology*? Public Policy Institute of California: San Francisco, 1999.
36. Wooldridge J. *Econometric Analysis of Cross Section and Panel Data*. The MIT Press: Cambridge, MA, 2002.
37. Anderson T, Hsiao C. Estimation of dynamic models with error components. *J Am Stat Assoc* 1981; **76**: 598–606.
38 Chernew M. The impact of non-IPA HMOs on the number of hospitals and hospital capacity 1995. *Inquiry* **32**: 143–154.
39. Young G, Burgess J, Valley D. Competition among hospitals for HMO business: effect of price and nonprice attributes. *Health Serv Res* 2002; **37**: 1267–1289.
40. McCue M. What determines hospital sponsorship of an HMO? *Inquiry* 2000; **37**: 268–281.
41. Morrisey M. Competition in hospital and health insurance markets: a review and research agenda. *Health Serv Res* 2001; **36**: 191–221.
42. Mukamel D. Zwanziger J, Tomaszewski K. HMO penetration, competition and risk-adjusted hospital mortality. *Health Serv Res* 2001; **36**: 1019–1035.
43. Mello M, Stears S, Norton E. Do Medicare HMOs still reduce health services use after controlling for selection bias? *Health Econ* 2002; **11**: 323–340.
44. Rosenthal M, Newhouse J. Managed care and efficient rationing. *J Health Care Finan* 2002; **28**: 1–10.
45. Hoover K. Nursing work redesign in response to managed care. *J Nurs Admin* 1998; **28**: 9–18.
46. Fagin C. *When Care Becomes a Burden*: *Diminishing Access to Adequate Nursing*. Milbank Memorial Fund: New York, 2001.