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Reinterpreting the Skill-biased Technological Change Hypothesis

A Study of Technology, Firm Size, and Wage Inequality in the California Hospital Industry

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Abstract: This study examines data from the 1983-1993 California hospital industry to test whether observed patterns of wage inequality growth can be explained by the skill-biased technological change hypothesis. The study finds little evidence of a direct link between technological inputs and skill premia, particularly when growth in firm size is taken into account. The findings challenge the notion that technological change is skill biased and suggest that economies of scale permit hospitals to compete for clientele on the basis of labor force quality. Since technological expenditures often promote consolidation, a reassessment of the relationship between wages and technology is suggested.

The wage premia associated with higher levels of skill rose notably throughout the 1980s and during particular periods in the 1990s. The college premium—the percentage by which the earnings of college graduates exceed those of high school graduates—rose from approximately 38 percent in 1979 to 73 percent in 1992, after which it slowed through 1997, increased again in the last part of the decade to 78 percent in 2001, and then leveled off somewhat.[1] Despite concern over increased inequality as a potential cause of social tension (see, for example, Riscavage, 1995), controversy has existed as to the underlying causes of the observed trends. Theories centering around global trade (Borjas and Ramey, 1994), factor outsourcing (Feenstra and Hanson, 1996), the weakening of labor unions (Mishel and Teixeira, 1991; Howell, 1994; Howell and Wieler, 1998), the failure of legislatures to maintain the real value of the minimum wage (DiNardo et al., 1996, Fortin and Lemieux, 1997), and influxes of low-skilled immigration (Borjas, 1994) have been advanced, but the most widely espoused theory has been that of skill-biased technological change (SBTC)—the notion that widespread advances in technology have intensified the demand for more highly skilled workers because these workers interact more productively than less skilled workers with technological inputs (Autor, Katz, and Kreuger, 1998; Berman, Bound and Griliches, 1994; Kreuger, 1993; Katz and Murphy, 1992, Murphy and Welch, 1992).

The general acceptance of the SBTC hypothesis in the early and mid 1990s created a preferential climate for policies promoting the acquisition of education and training for the low-skilled[2] rather than policies to regulate trade and the use of foreign

[1] Statistics were provided by the Bureau of Labor Statistics and based on median usual weekly earnings of full-time wage and salary workers 25 years and older from the Current Population Survey.

[2] See, for example, the School-to-work Opportunities Act of 1992.

labor, to shore up union power, or to restrict the entry of low-skilled workers into the U.S. As the growth in the college premium slowed in the mid-1990s, education- and training-related policies received less attention, but in light of more recent upturns, they may regain popularity.

Studies testing the SBTC theory have produced mixed results. The early case in support of the hypothesis was based primarily on the observation of concurrent trends at the macro level (e.g., Katz and Murphy, 1992, Murphy and Welch, 1992), but subsequent work attempted to link technology to wages within industries at the micro level. Although within-industry studies may present an incomplete picture of the wage determination process if the single industries under consideration are small actors within the larger labor supply and demand context, the fact that wage inequality growth in the 1980s and 1990s was stronger within industries than across them and linked more heavily to increases in the demand for skill rather than decreases in the supply (Autor, Katz, and Krueger, 1998; Berman, Bound, and Machin, 1998; Katz and Murphy, 1992) suggests that studies of firm-level wages and technology can offer valuable insights.

A few within-industry studies found a positive association between wages and technological inputs, particularly those related to computers (Autor, Katz, and Kreuger, 1998; Krueger, 1993). Doms, Dunne, and Troske (1997), using longitudinal data, however, found that high wages in technologically advanced firms were due to the high skill level of their workers but that this skill level was unrelated to the adoption of new technologies.

The research presented in this paper consists of a within-industry study that carries the analysis one step further. The findings support the insights offered by Doms, Dunne, and Troske (1997) and point to a possible explanation for the failure of technology to connect directly with wages despite the concurrence of trends.

This study examines longitudinal hospital-level data collected in California between 1983 and 1993 to determine if the wage and technology patterns observed in the industry were consistent with SBTC. The hospital industry provides a convenient context for this investigation for three reasons: 1) its wage inequality trends mirrored those of the national economy in the 1980s and 1990s, 2) it experienced a substantial growth in technology during the same time period, and 3) it is rich in the type of micro-level data on wages and technology that are needed to support a thorough analysis. The study finds little support for the SBTC hypothesis. Although the same prima facie association between technological sophistication and skill premia evident in the national context is also evident in the hospital industry, in-depth analysis challenges the notion that these premia are the result of a comparative advantage of skilled workers with technological inputs. The study raises questions about the traditional assertions of the SBTC hypothesis and provides new information that might lead to a reinterpretation.

The analysis reported in the study carries some limitations. Like other within-industry studies, it focuses on a subset of a larger labor market, and it takes a reduced-form approach to a general equilibrium problem. Auxiliary analyses comparing hospital and non-hospital wages suggest, however, that the restricted focus does not present a large problem for the validity of the findings, and although reduced-form models cannot strictly test the SBTC hypotheses, they reveal associations that cast doubt on its credibility.

Conceptual Framework

This section outlines the conceptual structure used to analyze hospital-level behavior regarding the compensation of high- and low-skilled labor. It assumes, in accordance with the neoclassical model of labor supply and demand, that wages for a particular category of labor (i.e., a skill or occupation group) are determined by the interaction of supply factors (e.g., the education and other pertinent characteristics of the labor pool, as well as the alternative opportunities available) and demand factors (e.g., the prices of outputs and all relevant inputs that affect the marginal product of labor) in a given labor market and that, within the context of its own particular market, a hospital takes the equilibrium wage as exogenous. The hospital then determines its own demand for labor following the framework outlined below, which extends the classical model of labor demand to conform to the realities of hospital production.

The hospital maximizes a preference function that includes profits and other variables, such as the quality of patient care, charity, status, or teaching (Newhouse, 1970; Lee, 1971) and produces more than one type of output—e.g., heart transplants, neonatal care, etc. In addition, hospitals utilize many types of labor inputs, such as registered nurses, technicians, nursing assistants, etc., as well as many types of capital inputs, such as X-ray machines, CT scanners, and blood pressure monitors. Therefore, subject to constraints on production technologies and the availability of specific inputs, one can say that hospital decision makers maximize utility according to the following specification in which profit and the other arguments are functions of the outputs, inputs, and prices:

$$Max\ Utility = U\ (\pi, other)$$

$$w.r.t. \quad y_i(i = 1,\ldots I) \quad l_j(j = 1,\ldots J) \quad k_m(m = 1,\ldots M)$$

$$s.t. \quad y_i = f_i(l_1,\ldots,l_j,k_1,\ldots k_m) \quad l_j \leq L_j \quad k_m \leq K_m$$

where f_i represents the production function for the *i*th output y and L_j and K_m represent external limits on the supply of labor l_j and capital k_m.

From the utility maximization process emerge the output supply functions y_i* and factor demand functions l_j* and k_m*, which are functions of prices, wages, and rents. It is expected that there will be variation in utility functions across hospitals, according to the degree to which factors other than profit are being maximized or the degree to which different types of outputs are being produced. In theory, a set of modified or reduced-form labor demand equations could be derived by substituting prices, wages, and rents with functions expressed in terms of output and capital choices to obtain equations of the form:

$$l_j* = g_j(y_1,\ldots,y_I,k_1,\ldots,k_m,w_1,\ldots w_j)$$

These modified labor demand equations incorporate direct links between labor usage and technology inputs in the form of physical capital.

Each l_j represents a particular type of hospital employee. As a first approach, one might consider each l_j to represent a different health care occupation. For example, l_1* might be the chosen quantity of hours of employment of hospital administrators, l_2* might be the chosen quantity of registered staff nurses, and so on. It is assumed that hospitals take as exogenous the wages assigned to various occupational categories by the interaction of supply and demand in their own geographically circumscribed labor markets, although this assumption is subject to controversy.[3]

Since the chosen proportions of workers in different occupational categories are observable, this occupation-based approach to defining the various l_j provides one with a framework within which the modified labor demand functions—*g(.)*—might be estimated to provide a measure of the association between technological input choices and the chosen number of hours of employment of particular occupation. Since some occupations require a higher degree of skill than others, one could draw some broad inferences regarding the relationship of technology to the demand for skill by observing the employment of high-skilled occupations relative to the employment of others.

A simplistic approach to testing the SBTC hypothesis might therefore involve checking for a positive association between some measure of technology and some measure of relative employment—the ratio of high-skilled to low-skilled full-time-equivalent employees (FTE), for example—within hospitals. A first hypothesis might therefore be the following:

H1) technological sophistication will be positively associated with the relative employment of high-skilled categories of labor.

A problem with this approach is that technologically advanced hospitals might plausibly seek to employ high levels of skill *within* both their high- and low-skilled

[3] Yett (1975) and Sullivan (1989) asserted that monopsony power existed in hospital labor markets. This assertion was challenged by Hansen (1991, 1992) who found no evidence of monopsony behavior. Robinson (1988a, 1988b) found evidence that hospitals in more competitive markets paid higher wages than those in less competitive markets, a finding consistent with monopsony theory. After controlling for supply difference, however, he finds that more competitive markets are also characterized by higher vacancy rates. The monopsony hypothesis, he claims, would predict the opposite, i.e., higher vacancy rates in less competitive markets, due to the fact that hospitals in these markets refuse collusively to raise wage rates. He therefore attributes higher wages in more competitive markets to non-price (i.e., quality-based) competition. In this model, I assume that higher wages represent a higher quality workforce.

occupational groups. If enough variation in skill level exists among workers within both groups, then a true positive association between technology and skill might fail to translate into a positive association between technology and relative employment.

Average Wage as a Proxy for Skill

A different approach to assigning meaning to the labor inputs *l*, and one that can better tease out the true association of technology with skill, would be to consider the *l* to represent *skill* rather than *occupation* categories. While occupational categories provide a rough measure of skill, heterogeneity of skill can occur within occupations, arising from differences in the education, training, experience, or ability of workers. The number of "skill categories" employed in a hospital may therefore far exceed the number of occupational categories. Differences across hospitals in the average skill level within an occupation category are not generally observable, but if they were, one could, in theory, relate these skill-based l_n* choices directly to capital input choices, by estimating the modified labor demand functions in the same manner as before.

A reasonable proxy for skill exists in the form of the average wage, however. Since a highly skilled registered nurse, for example, might command a higher wage than a less-skilled registered nurse because she or he may have a larger set of relevant alternatives or be in greater demand, a relatively high average wage for nurses in a particular hospital, after adjusting for cost of living and market supply tightness, would indicate a highly skilled nursing staff.[4] Using the hypothetical set of labor demand functions relating to each generic skill category, one can construct average wage

[4] It commonplace for nurses and aides, for example, to be assigned to categories based on education and experience and for their wages to be differentiated accordingly.

functions aw_j for each of the J occupational categories.[5] The effect of technology on the average wage is the derivative $\partial aw/\partial t$. If one assumes that hospitals paying a higher wage to workers in a particular occupation category are obtaining higher levels of skill within the category, it can be inferred that if the average wage of an occupation category increases with respect to technology, then the proportion of high- to low-skilled workers within that occupation increases with respect to technology, i.e., that technology and skill act as complements rather than substitutes.

Under this framework built upon modified *occupation-* and *skill-based* factor demands, it is therefore possible to determine the strength of the association of technology to relative wages, taking into account the entire picture, including across- and within-category heterogeneity. If the SBTC hypothesis is true, then one would expect to find a positive association between technology and the wages it pays to each category of workers—particularly those who are highly skilled. The following prediction should hold:

H2) technological sophistication will be positively associated with within-category average wages, particularly for high-skilled categories of labor.

In addition, if high- rather than low-skilled worker wages are primarily affected by the presence of sophisticated technologies, then a further hypothesis might be:

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[5] The equation for each category would be:

$$aw_j = \frac{\sum_{n=1}^{N} w_n * l_n(t,other)}{\sum_{n=1}^{N} l_n(t,other)}$$

where N is the number of skill categories within the jth occupational category, and the skill categories l are functions of technology t and other variables.

H3) higher levels of technological sophistication will be associated with higher relative wages (in the form of the ratio of high- to low-skilled wages, for example) within hospitals.

Data

The data used in this study were drawn primarily from the California Office of Statewide Health Planning and Development (OSHPD) annual surveys of hospitals.[6] California hospitals are required to submit two types of reports to OSHPD on an annual basis: 1) the Annual Disclosure Reports, which provide a wealth of detail regarding the characteristics and financial activities of each hospital, including information pertaining to the use of specific technologies and the hourly wages and hours of employment of different categories of labor, and 2) the Annual Patient Discharge Reports, which provide information regarding patient characteristics and revenue sources.

Of the different types of hospitals in California, I selected the subset of short-term general acute-care hospitals—approximately 80 percent of all hospitals—in order to obtain a sample of only those organizations for which it would be feasible or desirable to utilize similar technologies.[7] The period under consideration was limited to the span of years from 1983 to 1993, years that saw the beginning and end of a continuous increase in the wage gap between high- and low-skilled workers. The total number of observations in the panel composed of short-term general hospitals across the eleven years under consideration was 4,572. The number of these hospitals in California varied

[6] Data from the Current Population Survey (CPS) were also used to supplement some of the descriptive analyses. Sample weights were used in all calculations involving CPS data and wages were deflated to 1983 levels by the Consumer Price Index.

[7] Kaiser hospitals were also eliminated because OSHPD grants them a reporting exemption with respect to wages, and their wage data were therefore incomplete. Kaiser hospitals represented approximately five percent of the hospitals in California in 1993.

from 450 in 1983 to 384 in 1993, due to the fact that many hospitals closed or merged with others during the period under consideration. Sixty-nine percent of the hospitals in the sample were in operation in all eleven years. The total number of unique hospitals was 479; therefore, despite the general trend towards hospital attrition and consolidation, there were also some hospitals that came into operation during the period under consideration.

The Measurement of Employment and Wages

The OSHPD annual disclosure reporting forms ask hospitals to report the average hourly wages and hours worked of ten different categories of hospital workers within each unit of the hospital, with six of these representing approximately 98 percent of the hospital labor force. The six categories are 1) management and supervision (consisting of head nurses and hospital administrators), 2) technicians and specialists, 3) registered staff nurses, 4) licensed vocational or practical nurses, 5) aides and orderlies, and 6) clerical and administrative workers.[8] I included only the first five categories in my analysis, because they represented the largest groups of hospital workers with direct responsibility for patient care and because the technological inputs examined in this study were patient-care technologies. The unit-level data on wages and hours worked were aggregated to hospital-level hours and average wages for each of the five occupational groups for each hospital in each year. The wages were then deflated to 1983 levels by the Consumer Price Index to obtain real wages.[9]

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[8] The other categories are 7) environmental and food service specialists, 8) physicians, such as resident housestaff, 9) non-physician medical practitioners, such as physicians' assistants and nurse practitioners, and 10) other workers. Data on hospital-based physicians and non-physician practitioners were sparse and unevenly distributed.

[9] In addition, because California hospitals are required to submit the annual disclosure report at the end of their fiscal year and the fiscal year end varies from hospital to hospital, it was problematic to

From these five categories, two larger labor categories—one composed of highly skilled workers and the other composed of mid-to-low-skilled workers—were created. Using education as a metric for skill (see Table 1), I placed management and supervision, technicians and specialists, and registered nurses—who possessed on average 15 years of schooling—in the high-skill category and placed licensed vocational nurses and aides—who possessed on average 12 to 13 years of schooling—in the low-skill category. Average wages and hours worked for each of the two aggregate categories in each hospital and year were then calculated.[10]

The Measurement of Technology

A challenge faced by researchers who attempt to link technology to wages is to find a meaningful way to quantify technology. Since technology is embedded in capital and is not composed of homogeneous units that remain equally useful throughout time, the task is far from straightforward. As time passes, some technological services become less costly, less useful, or obsolete, and, at any given time, some types of services are more sophisticated than others. Many organizations—hospitals, in particular—use more than one type of technology in their production process, and the relative importance of these types must be weighed in assessing the organization's overall technological sophistication.

The characterization of technology for analytic purposes is further complicated by the fact that certain technologies are substitutes for skill while others are complements.

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compare data across hospitals that reported at different points in time. To resolve this problem, estimates of the values that would have been reported had the fiscal year end been the 31st of December of each year for every hospital were created using linear interpolation methods. Since approximately one quarter of the observations had a fiscal year end of December 31st, estimates were used in approximately three quarters of the observations.

[10] Average wages appeared unrealistically high in 22 observations and were set to missing.

The difficulty of separating technologies of one sort from the other can obscure the mechanism by which technology might affect wages (Levin and Rumberger, 1989). Bartel and Lichtenberg (1987) hypothesized that the demand for skilled labor rises when technologies are first introduced into the productive process. They reasoned that skilled workers posses a comparative advantage with respect to unfamiliar technological inputs in that they are better able to adjust to and implement new techniques. Once diffused, they claim, a technology can be successfully and more cheaply operated by less educated workers and used as a substitute for skill. According to this theory, new technology initially increases the demand for skilled labor but later reduces it. The degree to which new technologies are skill-saving or skill-using may also depend upon contextual factors, such as the labor supply in the long term. Acemoglu (1998) theorized that the complementarity of technology is endogenous to the labor supply. If a large pool of skilled labor exists, the types of technology that will be utilized or invented will be those that are complementary to skill and vice-versa.

Not only the presence of technological inputs in a hospital, therefore, but also the particular features of those inputs are important in assessing their effect on skill-based wage gaps. An ideal technology measure would capture all of the relevant features—type, amount, newness, and skill complementarity. The data available specify the number and type of technologies possessed by hospitals but do not, however, directly indicate the degree to which these technologies are complementary to skill. The approach to technology measurement used in this study was to construct an index that captured the sophistication of the technological inputs present in a hospital by estimating the degree to which the hospital's technologies are relatively rare at a given point in time.

The index was created as follows. The OSHPD annual disclosure reports contain a list of the possible technical inputs that a hospital might utilize. Every hospital is asked to report whether or not it utilizes each type of input. In consultation with physicians, a subset of 85 technologies that reflected the machine-intensive, patient care-related technological capabilities of a hospital was drawn. Each observation in the dataset represented a hospital year, and for each technological input, a value of 1 was assigned if it was present in the hospital in that year and a value of 0 was assigned if it was absent.

The second step in creating the measure consisted of weighting the different technological capacities possessed by a hospital by an indicator of the degree to which they were rare. The weights were created by taking the mean value for each input across all hospitals in a given year and subtracting each mean from the number "1" to get the proportion of hospitals that did not use the input. Each weight, therefore, represented the degree to which the input was rare in a particular year. For each hospital in each year, the value of every service (0 or 1) was then multiplied by its year-specific weight. A list of the 85 selected inputs that a hospital might offer and the calculation of their "rareness" in the year 1983 is shown in Appendix 1.

The third and final step in creating the index,[11] was to average the products of inputs and weights for each hospital in each year in order to remove any unintended correlation with the size of the hospital. Thus, a small hospital that specialized in "high tech" services, such as cardiac care, could receive as high a score on the index as a large hospital with a similar spectrum of sophisticated technology.

[11] This index represents a modification of the Saidin index introduced by Spetz in her doctoral dissertation (1995) and named after the person who originated the idea.

Thus the index captured the technological sophistication of a hospital relative to other hospitals at a given point in time, based on the degree to which its technological services were rare. The initial selection of technologies, the weighting by rarity, and the averaging of the weights ensured that hospitals that invested in new technologies received higher values on the index than those that did not.

Control Variables

The empirical model expands upon the versions of the modified labor demand and average wage functions outlined in the conceptual framework by inserting control variables for hospital characteristics thought to predict different tradeoffs between profits and other factors, such as quality. Hospital level fixed effects account for differences in ownership status (i.e., whether the hospital was for-profit, nonprofit, religious, public, etc.) and union status, which was relatively stable during the 1983-1993 period.[12]

It was important to control for trends in the hospital industry that might affect wages. The industry experienced negative price shocks and increased competition in the 1980s, due to changes in domestic policy.[13] In response, hospitals tended to restructure their mix of both outputs and inputs. Changes in government financing parameters and an increasingly competitive economic environment caused hospitals to decrease the average length of a patient's stay during the 1980s, thus increasing the acuity level of the average hospital patient (Anderson and Wootton, 1991). Spetz (1995) reported that the

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[12] Unions representing high-skilled workers in California hospitals remained in the 20-25 percent range, and unions representing low-skilled workers remained in the 18-19 percent range between 1983 and 1993, according to survey data collected by the author.

[13] A payment scheme aimed at containing hospital care costs, known as the Prospective Payment System (PPS), was instituted by the federal government in 1983. It changed the method by which hospitals were reimbursed for treating Medicare patients. Under the PPS system, hospitals receive a diagnosis-specific lump sum for the treatment of each patient rather than reimbursement for the actual services provided.

number of registered nurses rose during this period while the number of practical nurses declined, as the need for medical expertise outweighed the need for simple bedside care. However, Aiken and Gwyther (1995) found evidence that hospitals began shifting to a work regime in which registered nurses were employed in smaller numbers as leaders of teams composed of less expensive practical nurses and assistants in the mid 1990s. Possible causes of these trends are accounted for in the empirical model by the inclusion of variables relating to patient acuity levels (casemix), the length of stay of the average patient, and patient revenue sources (i.e., the proportions of HMO and low-paying patients). Market competition was accounted for by the number of hospitals in the same health care finance planning area.[14] Indicator variables for each year of the panel were used to control for the pure effect of business cycle fluctuations, exogenous price shocks, and overall macroeconomic trends in the supply of labor, such as the percentage of immigrant workers entering the health professions, trends in the numbers of nursing graduates, etc., that would be expected to affect all regions in the state more or less equally over the time period under consideration.

I also included the number of full-time equivalent employees, in logged form, to represent the size of a hospital. The theoretical basis for a size-wage effect—the "scale of operations" effect (Sattinger, 1993)—stems from the notion that a firm's size influences its ability to specialize and exploit the comparative advantage of different types of labor inputs with technological inputs. Because size and technological sophistication were highly correlated, the inclusion of a size measure subjected the SBTC

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[14] The Health Care Financing Administration (HCFA) defined boundaries separating areas in which the health care institutions enclosed within them are thought to serve more or less the same geographical population.

hypothesis to a stronger test than would otherwise have been possible.[15] A list of the variables used in the analysis, along with their means and standard deviations, is presented in Appendix 2.

Empirical Model

Descriptive analyses are first presented to set the context. Next, three sets of regression models are used to relate technology to employment and wages in a manner that takes into account the influence of several additional factors. The models consist of reduced-form equations[16] that estimate the conditional expectations of relative employment, high- and low-skilled wages, and relative wages, given values of the technology index and other variables considered to influence these choices. I used logarithmic forms of four dependent variables: 1) the log of the ratio of high-skilled FTE[17] to low-skilled FTE, i.e., relative employment, 2) the log of high-skilled real wages, 3) the log of low-skilled real wages, and 4) the log of the ratio of high- to low-skilled real wages, i.e., relative wages.

The first set of regressions estimates the change in the dependent variable between 1983 and 1993 as a function of the change in the relative technological sophistication of the hospital and other time-varying factors. The basic model for these difference regressions is as follows:

$$\Delta y_i = \gamma \Delta TI_i + \Delta X_i \beta + \varepsilon_i \qquad \textit{(Model 1)}$$

where Δy_i is the 1993-1983 difference in the dependent variable of interest for hospital *i*, ΔTI_i is the difference in the technology index, and ΔX_i represents a vector of differenced

[15] The correlation between size and the technology index was .78.

[16] If wages are taken as exogenous, then the empirical model estimates equations that are derived directly from the structural labor demand equations.

[17] FTE measures full-time equivalent personnel.

time-varying control variables relating to hospital characteristics. The coefficient γ would be expected to be positive and significant to support the hypotheses stated in the conceptual framework.

In order to take advantage of the entire panel of data and to obtain more detail regarding the relationships under study, a second set of regressions is utilized. The basic model for the second set is as follows:

$$y_{it} = \alpha_i + \lambda_t + \gamma TI_{it} + X_{it}\beta + \varepsilon_{it} \qquad \textit{(Model 2)}$$

where α and λ are hospital and year fixed effects, *TI* is the technology index, and ***X*** is a vector of time-varying control variables relating to hospital characteristics. A positive and significant γ would provide evidence in favor of the SBTC hypothesis.

The third set of regression models—Model 3—consisted of Model 2 augmented to include interactions for all time-varying variables with the year indicators. In these regressions, the sum of the coefficients on technology and other covariates with the coefficients on the interaction terms—the "derivative" of the dependent variable with respect to each covariate in year *t*—was examined for sign and significance in each year and for changes over time. Changes over time in the derivatives relating to technology should be positive and significant if the hypotheses relating to SBTC are true.

Given the potential for bias in longitudinal models,[18] I checked for the presence of autocorrelation within hospitals panels. Regressions of residuals on their lags suggested that serial correlation was strong in the model, despite the inclusion of hospital-level fixed effects, and that the error followed a first-order autoregressive process

[18] See MaCurdy (1982).

$(\varepsilon_{it} = \rho\varepsilon_{it-1} + \nu_{it})$. I therefore estimated a generalized linear model that specified an AR(1) error structure.

Findings

Descriptive Analyses

A plot of mean wages over time shows clearly that wage inequality between high- and low-skilled hospital occupations increased between 1983 and 1993 (see Figure 1a). Real high-skilled wages grew steadily, especially in the late 1980s, while real low-skilled wages remained at more or less the same level throughout.

Plots of total industry employment levels over time show that the employment of high-skilled workers was roughly double that of low-skill workers in 1983, rose steadily throughout the 1980s, and declined in the early 1990s (see Figure 1b). The employment of low-skilled workers fluctuated only slightly.

In order to get a sense of changes in the distributions of wages during the time period, I generated histograms of high- and low-skilled wages for 1983 and 1993 (see Figure 2). The changes are dramatic. The high-skilled wage distribution experienced a noticeable rightward shift and a definite widening over the ten-year period, while the low-skilled distribution shifted and widened only slightly.

The growth in both the wages and employment of high-skilled workers suggests that the demand for these workers shifted outward. The shift towards greater dispersion among high-skilled workers indicates that heterogeneity due either to skill level or to characteristics of the work environment played a greater role in their wage determination at the end of the period than at the beginning.

Table 2 compares the rate of growth in real wages between 1983 and 1993 for California hospital workers, calculated using the OSHPD data, to the same growth rates for working women in the State of California, calculated using data from the Current Population Survey (CPS). The purpose of this comparison is to obtain a sense of the degree to which hospital worker wages appear to follow outside—or non-hospital industry—wage trends.

The first part of the table displays the real hourly wages[19] and the change in these wages over time of four categories of California women.[20] The four categories are based on the educational level of the women and are the following: high school dropouts, high school graduates, workers who had obtained some but less than four years of college, and workers with four or more years of college. The second part of the table displays the wages and growth rates of high-skilled and low-skilled hospital workers. Recall from Table 1 that low-skilled hospital workers had approximately 12-13 years of schooling and were thus comparable to groups 2 and 3 of the California female workers. High-skilled hospital workers possessed an average of 14-15 years of schooling and were thus comparable to groups 3 and 4 of the California females. As can be seen from the table, low-skilled hospital workers experienced about the same gains as California females in their comparison groups, whereas high-skilled hospital workers enjoyed higher real wage gains than did the workers in their comparison groups.

The third part of Table 2 takes the comparison one step further. I divided hospitals into three groups of equal number based upon their level of technological sophistication as evidenced by the technology index. I then took average wages for high- and low-skilled workers in hospitals within each third of the technology distribution.

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[19] These were calculated by dividing real weekly earnings by real weekly hours.

[20] The vast majority of hospital workers are female (see Table 1), therefore female workers are the appropriate comparison group.

Average wages within the low and high technology hospitals are reported here.[21] As can be seen, high-skilled workers in high technology hospitals experienced the highest growth rates of all hospital and California worker categories.

From this analysis, it appears unlikely that labor market trends outside the hospital industry exerted a powerful influence on internal wage trends. Furthermore, the variation in technological sophistication among hospitals appears to be a plausible candidate in the search for factors contributing to the widening of the high-skilled wage distribution. This notion is reinforced by simple correlations of the technology index with the four outcome variables: 0.40 for the relative FTE measure, 0.35 for the high-skilled wage measure, 0.26 for the low-skilled wage measure, and 0.02 for the relative wage measure. The first three correlations were significant at the 1 percent level, and the last at the 10 percent level.

Regression Findings

Multivariate analyses erased the evidence in favor of a technology effect, however. Regression findings for Model 1—the difference model—provided no evidence of support for the SBTC hypotheses. Table 3 shows the estimated coefficients and t-statistics for the variables in these regressions. A change in hospital size is related to a change in relative employment, and changes in the percentages of low-paying and HMO patients were related to changes in the relative wage, but no associations with technological sophistication were evident.

Regression findings for Models 2 and 3 are presented in Tables 4 and 5. To facilitate the inspection of trends in the effects of the technology index and other

[21] Those in the middle range of technological sophistication are left out.

covariate, Table 5 shows the sums of the main and interaction effects for these variables for each year—i.e., the "derivative—and the p-values of tests of significance of each sum."[22] The technology index showed no significant relationship to any of the dependent variables in the Model 2 and Model 3 regressions, with the exception of a negative and significant main effect in the high-skilled wage regression in the interacted model.

Table 6 shows the results of a test aimed at identifying beginning to end of period changes. It lists the p-values for a test of the significance of the difference between the average of the first four and last four derivatives for the set of effects related to each time-varying variable.[23] The technology index showed a significant change in its association with only the low-skilled wage, a finding that does not help explain the overall wage inequality trends in the industry. The effect of the size of the hospital, however, represented by the log of total FTE, showed a positive and significant change in association with every dependent variable. The size variable, though negative in most cases, demonstrated a nearly monotonic upward trend in every regression and became positively associated with relative wages during the period.

Sensitivity analyses, in which slightly different models were estimated,[24] produced no notable differences in the patterns reported above.

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[22] Full regression results are available from the author upon request.

[23] For example, for the technology index, the test examined the significance of the sum of the coefficients on the first four technology-year interactions minus the sum of the last four technology-year interactions (dividing each sum by "4" to obtain the average was unnecessary).

[24] Technology-size interactions were included in one model. Another specification included a measure of occupational mix—i.e., the log of the ratio of high- to low-skilled FTE—on the right hand side of the wage regression to control for the possibility that hospitals with similar average wages might differ in important aspects of their work regime. Another specification used an IV model in which the share of medicare patients was used as an instrument, given that the proportion of elderly patients might potentially affect the demand for technology and, through this, the demand for skill. The instrument was not very powerful, however, and the small coefficient in the first stage led to implausibly large coefficients on the predicted technology variable in the second stage, although they were not significant and tended to be in

Discussion

The regression results revealed that the size of a hospital was more clearly associated with skill than technological sophistication. Although size and technological sophistication were highly correlated, the separation of the two effects via regression analysis showed that the size of a hospital was associated with wage inequality growth in a manner that was independent of investment in new technological equipment. Various interpretations could be offered to explain this phenomenon. The literature regarding size-wage premia offers limited insight, however, given that the size effect found here is negative and few prior studies address changes in this effect over time. The hypothesis that the premium reflects capital-skill complementarity (e.g., Griliches, 1969; Reilly, 1995) does not consider the effect of size independent of technological sophistication. Other hypotheses relating to trade-offs between wages and the cost of monitoring (Bulow and Summers, 1986) or the quality of management (Oi, 1983) might account for the findings, if it could be established that these issues became increasingly important to administrators of large hospitals over time. The hypothesis that the size-wage premium would be higher in the absence of high-skilled workers matching themselves to smaller firms (Idson and Feaster, 1990) might offer another explanation, if mergers offered workers fewer small firms to choose from. Hospital mergers were frequent in the decade under consideration. Building upon the concept of the influence of mergers, another possible interpretation is that the economies of scale that a hospital realized when it increases capacity may have been used to increase the quality of its staff in order to compete on a non-price basis for patients (Robinson, 1988a, 1988b). The fact that the

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the negative direction. Therefore the IV results are not presented here, although they provided no evidence to contradict the reported results.

size coefficients changed from positive to negative over time in the relative wage regressions might indicate that administrators in large hospitals perceived a particular benefit to hiring high-quality high-skilled workers and considered low skilled workers to be somewhat more generic.

If economies of scale were a factor driving the association of size and wage inequality in this manner, then perhaps the SBTC hypothesis can be reinterpreted. The results of the regression analyses presented in the previous section do not support a traditional interpretation of the hypothesis—i.e., that the presence of advanced technology in a hospital requires workers with greater skill to operate the equipment due to their comparative advantage with respect to technological inputs. Yet, it is plausible that the perceived need to acquire sophisticated and expensive technologies was a factor in promoting mergers and consolidation in the hospital industry in the 1980s and 1990s. Furthermore, the OSHPD data reveal that while overall patient days declined by 23 percent between 1983 and 1993,[25] the average size of a hospital, in terms of the number of FTE in the five categories of employment under consideration in this study, grew by 9 percent during the same period. If technology prices were one of a number of factors bringing about mergers and most of those newly formed large institutions decided to use their new-found economies of scale to compete for patients on the basis of quality, then the association of size with wages would be primary and the association of technology with wages would be secondary.

[25] This was due to the decrease in the average length of a patient's stay in the hospital.

Conclusions

In the preceding section, a number of findings were presented. Descriptive analyses showed that wage inequality between high- and low-skilled workers grew during most of the period under consideration and that the growth was greatest in the late 1980s and the first two years of the 1990s, after which it leveled off. The level of employment of both high- and low-skilled California hospital workers increased in the mid-to-late 1980s and the beginning of the 1990s, but the employment of high-skilled workers grew at a faster rate. Wage inequality growth was due to an increase in high-skilled wages rather than a decrease in low-skilled wages, which remained at more or less the same level throughout the period. The high-skilled wage distribution widened considerably between 1983 and 1993, while the variance of the low-skilled wage distribution increased only slightly. Thus, there was growth in wage inequality between high- and low-skilled workers, but also within the category of high-skilled workers, indicating that greater levels of differentiation among high-skilled workers existed at the end of the period than at the beginning. It was also shown that hospital wages were located at the high end of the female wage scale, suggesting that the industry acted independently in raising wages for high-skilled workers. This finding reduced concerns that wage trends in the larger labor market engendered increased wage inequality in the hospital industry.

Further analysis indicated that the correlation between wages and technological sophistication was strong during this period but that this association may have been due more to the correlation between size and technology than to the technology itself. Regressions that investigated the relationship between changes in technology and changes in wages, relative wages, and relative employment revealed no evidence to support the SBTC hypothesis. The analyses suggested that size growth may have exerted a greater upward pressure on wage inequality than did technological advancement.

One possible explanation is that cost savings due to economies of scale enabled larger hospitals to invest in more highly skilled nurses, managers, and technicians. If this is the case, then the SBTC hypothesis could be reinterpreted. Instead of hypothesizing that skill complements technology, one might hypothesize that the high cost of technology is a factor encouraging consolidation and that the resultant economies of scale allow firms to compete for clientele on the basis of labor force quality.

The findings presented in this paper weaken the assertion that a direct link exists between technological advancement and wage inequality growth. Although caution in interpretation is warranted due to the reduced-form nature of the analysis, the findings challenge the notion that technological change is, in and of itself, skill biased and raise issues for future study. Research designed to examine the separate effects of technology and firm size in association with wage inequality in other industries and research designed to determine the degree to which technology is a factor leading to consolidation within industries would be important next steps.

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Appendix 1: List of the 85 Services Used in Computing Technology Index in Order of Rareness in 1983

Percentage of Hospitals Not Offering Service	Name of Service
0.96	organ transplant surgery
0.96	hyperbaric chamber services
0.96	organ acquisition
0.95	developmentally disabled nursery care
0.93	burn intensive care
0.92	research
0.89	otolaryngology clinic
0.89	ophthamology clinic
0.89	electroconvulsive (shock) therapy
0.85	cobalt therapy
0.83	open heart surgery
0.82	radioisotope decontamination room
0.78	radiation therapy
0.78	neonatal intensive care
0.77	radium therapy
0.75	cardiac catheterization
0.68	pediatric intensive care
0.67	hemodialysis
0.57	neonatal acute care
0.54	electromyography
0.51	premature nursery care
0.40	pulmonary intensive care
0.38	necropsy lab
0.34	newborn nursery care
0.32	electroencephalography
0.31	blood bank
0.30	neurological surgery
0.28	diagnostic radioisotope
0.28	trauma treatment E.R.
0.27	anatomical pathology lab
0.25	orthopedic emergency services
0.20	pulmonary function services
0.18	coronary intensive care
0.18	plastic surgery
0.18	podiatry surgery
0.18	anesthesia services
0.17	ophthamolgic surgery
0.17	dental surgery
0.15	emergency room service
0.15	otolaryngolic surgery
0.14	surgical intensive care
0.13	physical therapy
0.12	medical intensive care

0.12	cystoscopy lab
0.10	microbiology lab
0.09	urologic surgery
0.09	hematology lab
0.08	orthopedic surgery
0.07	serology lab
0.06	electrocardiology
0.06	chemistry lab
0.05	gynecological surgery
0.04	respiratory therapy

Source: OSHPD

Appendix 2: Means and Standard Deviations of Variables Used in Analyses

	1983		1993	
	Mean	**Std Dev**	**Mean**	**Std Dev**
High-skilled real wage	13.20	1.32	15.76	2.06
Low-skilled real wage	8.04	1.15	8.30	1.42
Log of high-skilled real wage	2.58	0.10	2.75	0.13
Log of low-skilled real wage	2.07	0.14	2.10	0.17
Technology Index	0.23	0.06	0.28	0.06
Log of FTE	5.11	1.09	5.43	1.02
Average Length of Stay	5.86	3.08	4.60	2.84
Casemix	0.90	0.14	1.01	0.21
Share of Low Payers	0.15	0.12	0.27	0.21
Share of HMO Payers	0.02	0.15	0.16	0.16
HFPA Competition	9.10	8.88	8.12	7.12

Source: OSHPD

Table 1: Characteristics of the Five Major Hospital Occupation Groups Dealing with Patient Care

	Management and Supervision	Technicians and Specialists	Registered Nurses	Licensed Vocational Nurses	Aides and Orderlies
Percent of Labor in 1983	7.9	20	34.6	12.3	14.7
Percent of Labor in 1994	6.3	21.9	39.7	7.7	13.4
Percent Female in 1983	66	74	95	96	90
Percent Female in 1994	73	78	95	94	83
Average Age in 1983	39.2	34.8	36.3	36.5	36.8
Average Age in 1994	40.4	36.9	38.9	39.7	37.4
Ave Yrs of School 1983	15	14.6	15	13.1	12
Ave Yrs of School 1991	15	14.7	15.5	13.2	12.3

Source: OSHPD and CPS

Notes: "Percent of Labor" is the average percentage of the California short-term general hospital labor force. "Percent Female" is the average percentage of workers in this occupation in the U.S. that are female. "Average Age" is the average age of workers in this occupation in the U.S. "Average Years of School" is the average number of years of schooling of workers in this occupation in the U.S. This is taken for 1991 rather than 1993 because the CPS reports degree completion rather than years of schooling after 1991.

Table 2: Comparison of Real Hourly Wages and Wage Growth Rates

A.Wages and wage growth rates of female California workers by educational category

	Group 1: High School Dropouts		Group 2: High School Graduates		Group 3: Some College		Group 4: Four or more Years of College	
	Real Wage	Change	Real Wage	Change	Real Wage	Change	Real Wage	Change
1983	5.30	1.00	7.14	1.00	8.14	1.00	10.34	1.00
1993	4.83	0.91	7.45	1.04	8.68	1.07	11.95	1.16

Source: CPS

B. Wages and wage growth rates of California Hospital Workers

	Low-skilled Group		**High-skilled Group**	
	Real Wage	Change	Real Wage	Change
1983	8.04	1.00	13.20	1.00
1993	8.30	1.03	15.76	1.19

Source: OSHPD

C.Wages and wage growth rates of California hospital workers in low- and high-tech hospitals

	Low-skilled Group				**High-skilled Group**			
	Lo Tech	Change	Hi Tech	Change	Lo Tech	Change	Hi Tech	Change
1983	7.67	1.00	8.40	1.00	13.02	1.00	13.47	1.00
1993	7.93	1.03	8.57	1.02	14.83	1.14	16.54	1.23

Source: OSHPD

Table 3: Regressions of Changes in Wages and FTE on Changes in Technological Sophistication and Other Variables: 1983 to 1993

Dependent Variable	Δ Relative FTE	Δ Relative Wage	Δ High-skilled Wage	Δ Low-skilled Wage
Δ Technology Index	1.083	0.258	0.264	0.043
	(-1.286)	(-1.482)	(-1.618)	(-0.198)
Δ Total FTE	-0.320**	0.024	-0.015	-0.049
	(-3.467)	(-0.862)	(-0.681)	(-1.571)
Δ Length of Stay	-0.023	0.002	0	-0.002
	(-1.921)	(-0.749)	(-0.004)	(-0.596)
Δ Casemix	-0.065	0.103	0.084	-0.023
	(-0.257)	(-1.961)	(-1.547)	(-0.373)
Δ Share of Low-paying Patients	0.243	0.123*	0.043	-0.033
	(-1.071)	(-2.076)	(-0.728)	(-0.471)
Δ Share HMO Payers	0.234	0.136**	0.028	-0.1
	(-1.241)	(-2.727)	(-0.637)	(-1.755)
Δ HFPA Competition	0.003	0.007	0.002	-0.004
	(-0.281)	(-1.780)	(-0.518)	(-1.253)
N	347	345	354	346
R2	0.064	0.046	0.016	0.026

Source: OSHPD

Note: T-statistics in parentheses.

Table 4: Model 2 Panel Regression Results

	Relative FTE		High-skilled Wage		Low-skilled Wage		Relative Wage	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Intercept	-0.06	-1.11	0.20	11.60	0.15	9.10	0.00	-0.19
Technology Index	-0.09	-0.70	0.04	1.25	0.04	0.99	0.00	-0.13
Log of Total FTE	-0.23	-7.64	-0.07	-9.75	-0.07	-7.98	0.00	0.31
Length of Stay	0.00	-1.76	0.00	-1.25	0.00	-0.55	0.00	-0.10
Casemix	-0.06	-0.78	0.06	3.12	0.02	0.73	0.03	1.56
Share Low-pay Patients	-0.09	-1.17	0.05	2.67	0.00	0.08	0.05	2.08
Share HMO Patients	0.12	1.90	0.02	1.47	-0.02	-1.06	0.04	2.37
Hospital Competition	0.01	1.87	0.00	-1.35	0.00	-1.54	0.00	0.70
Year 84	0.73	10.94	1.01	44.51	0.81	34.39	0.16	6.60
Year 85	1.29	11.20	1.65	44.76	1.34	34.50	0.26	6.72
Year 86	1.68	11.12	2.07	45.26	1.70	34.85	0.33	6.84
Year 87	1.93	10.93	2.33	45.51	1.92	34.79	0.39	7.10
Year 88	2.11	10.78	2.52	46.20	2.07	34.90	0.44	7.58
Year 89	2.23	10.60	2.65	46.52	2.17	34.83	0.48	7.95
Year 90	2.29	10.36	2.73	46.73	2.23	34.68	0.52	8.24
Year 91	2.38	10.34	2.79	46.79	2.27	34.48	0.54	8.50
Year 92	2.44	10.33	2.83	46.77	2.30	34.29	0.56	8.65
Year 93	2.47	10.29	2.84	46.72	2.31	34.21	0.57	8.73
N	3954		4053		3948		3946	

Source: OSHPD

Table 5: Model 3 Panel Regression Results: Sums of Coefficients on Covariates and Covariate-Year Interactions and P-values of Significance Tests

		Relative Employment		High-skilled Wage		Low-skilled Wage		Relative Wage	
Variable	Year	Derivative	P-value	Derivative	P-value	Derivative	P-value	Derivative	P-value
Technology Index	84	-0.47	0.26	-0.19	0.10	-0.15	0.27	0.01	0.94
	85	-0.13	0.46	-0.03	0.46	-0.01	0.83	-0.01	0.86
	86	0.09	0.71	0.08	0.22	-0.05	0.56	0.08	0.28
	87	-0.05	0.85	0.14	0.06	-0.04	0.65	0.12	0.16
	88	-0.29	0.34	0.20	0.01	0.04	0.63	0.13	0.17
	89	0.25	0.46	0.14	0.11	0.27	0.01	-0.09	0.37
	90	0.54	0.12	0.10	0.27	0.12	0.28	-0.09	0.37
	91	0.46	0.13	0.04	0.66	0.20	0.04	-0.20	0.04
	92	-0.13	0.56	0.08	0.18	0.08	0.24	-0.02	0.81
	93	0.05	0.89	0.21	0.03	0.19	0.09	0.03	0.81
Log of Total FTE	84	-0.36	0.00	-0.13	0.00	-0.13	0.00	-0.01	0.52
	85	-0.34	0.00	-0.10	0.00	-0.10	0.00	-0.01	0.43
	86	-0.31	0.00	-0.09	0.00	-0.07	0.00	-0.02	0.14
	87	-0.25	0.00	-0.08	0.00	-0.06	0.00	-0.01	0.29
	88	-0.21	0.00	-0.07	0.00	-0.06	0.00	-0.01	0.53
	89	-0.21	0.00	-0.07	0.00	-0.08	0.00	0.01	0.27
	90	-0.21	0.00	-0.06	0.00	-0.07	0.00	0.02	0.08
	91	-0.19	0.00	-0.06	0.00	-0.06	0.00	0.02	0.16
	92	-0.19	0.00	-0.06	0.00	-0.06	0.00	0.01	0.48
	93	-0.21	0.00	-0.06	0.00	-0.06	0.00	0.01	0.56
Length of Stay	84	-0.02	0.03	0.00	0.02	0.00	0.65	0.00	0.03
	85	-0.01	0.33	0.00	0.30	0.00	0.18	0.00	0.10
	86	-0.01	0.23	0.00	0.67	0.00	0.29	0.00	0.41
	87	0.00	0.72	0.00	0.33	0.00	0.47	0.00	0.82
	88	0.00	0.81	0.00	0.03	0.00	0.64	0.00	0.04
	89	0.01	0.03	-0.01	0.00	0.00	0.49	0.00	0.00
	90	0.01	0.09	0.00	0.36	0.00	0.58	0.00	0.51
	91	0.00	0.65	0.00	0.74	0.00	0.51	0.00	0.68
	92	-0.01	0.01	0.00	0.74	0.00	0.50	0.00	0.44
	93	-0.02	0.00	0.00	0.08	0.00	0.01	0.00	0.23
Casemix	84	-0.16	0.35	-0.03	0.58	-0.04	0.47	0.02	0.73
	85	-0.14	0.24	0.03	0.32	0.01	0.82	0.01	0.68
	86	-0.07	0.53	0.08	0.01	0.02	0.49	0.03	0.36
	87	-0.08	0.44	0.07	0.01	0.06	0.07	0.00	0.96
	88	0.03	0.80	0.08	0.00	0.08	0.01	-0.01	0.69
	89	-0.12	0.23	0.09	0.00	0.07	0.03	0.02	0.47
	90	0.05	0.63	0.07	0.01	0.04	0.22	0.02	0.45
	91	0.00	0.98	0.05	0.05	0.00	0.95	0.05	0.12
	92	0.02	0.85	0.08	0.01	0.03	0.34	0.04	0.17
	93	-0.02	0.85	0.08	0.01	-0.01	0.86	0.08	0.03
Share Low-pay Patients	84	0.01	0.93	0.14	0.00	0.06	0.19	0.08	0.08
	85	-0.09	0.43	0.10	0.00	0.03	0.34	0.07	0.05

	86	-0.17	0.11	0.08	0.00	0.03	0.32	0.04	0.17
	87	-0.27	0.01	0.05	0.07	0.02	0.52	0.03	0.39
	88	-0.22	0.04	0.03	0.28	0.01	0.76	0.02	0.58
	89	-0.25	0.01	0.03	0.30	0.01	0.73	0.02	0.51
	90	-0.14	0.17	0.03	0.19	0.02	0.57	0.02	0.58
	91	-0.15	0.13	0.02	0.45	-0.05	0.11	0.07	0.03
	92	0.01	0.89	0.05	0.05	0.00	0.97	0.05	0.11
	93	0.11	0.39	0.04	0.22	-0.01	0.73	0.05	0.13
Share HMO Patients	84	0.23	0.19	0.00	0.92	0.03	0.61	-0.02	0.70
	85	0.16	0.25	0.04	0.28	0.04	0.29	0.00	0.94
	86	0.00	0.98	0.03	0.26	0.01	0.70	0.02	0.57
	87	-0.02	0.82	0.00	0.87	0.00	0.90	0.01	0.75
	88	0.01	0.88	0.00	0.98	-0.03	0.29	0.03	0.31
	89	0.05	0.61	0.00	0.97	-0.01	0.73	0.02	0.55
	90	0.09	0.30	0.05	0.05	0.02	0.49	0.03	0.26
	91	0.07	0.47	0.05	0.08	-0.01	0.78	0.06	0.06
	92	0.35	0.00	0.02	0.43	-0.04	0.23	0.06	0.04
	93	0.33	0.01	0.01	0.85	-0.06	0.06	0.08	0.02
Hospital Competition	84	0.00	0.93	0.00	0.83	0.00	0.86	0.00	0.52
	85	0.00	0.73	0.00	0.44	0.00	0.67	0.00	0.74
	86	0.01	0.27	0.00	0.22	0.00	0.44	0.00	0.86
	87	0.01	0.06	0.00	0.14	0.00	0.26	0.00	0.97
	88	0.01	0.05	0.00	0.25	0.00	0.48	0.00	0.98
	89	0.01	0.04	0.00	0.31	0.00	0.72	0.00	0.78
	90	0.01	0.21	0.00	0.39	0.00	0.45	0.00	0.76
	91	0.01	0.11	0.00	0.36	0.00	0.60	0.00	1.00
	92	0.02	0.01	0.00	0.20	0.00	0.65	0.00	0.75
	93	0.02	0.02	0.00	0.03	0.00	0.41	0.00	0.68

Source: OSHPD

Table 6: P-values in Tests of Significance of Changes Over Time in Model 3 Regressions

	Relative FTE	High-skilled Wage	Low-skilled Wage	Relative Wage
Technology Index	0.18	0.13	0.02	0.15
Log of Total FTE	0.02	0.00	0.03	0.07
Length of Stay	0.95	0.12	0.72	0.27
Casemix	0.35	0.31	0.93	0.37
Share Low-pay Patients	0.46	0.05	0.16	0.81
Share HMO Patients	0.31	0.74	0.23	0.11
Hospital Competition	0.38	0.80	0.91	0.78

Source: OSHPD

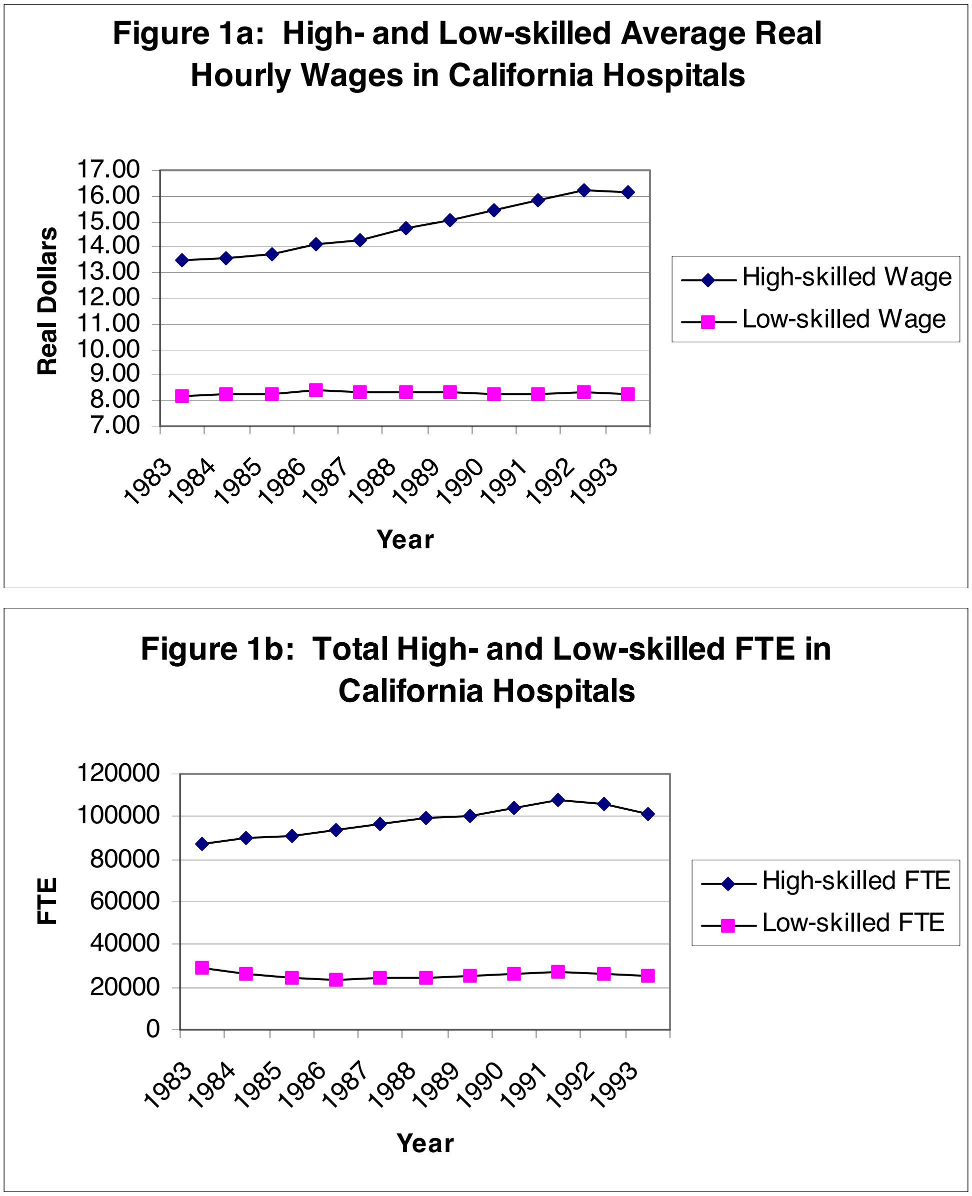

Figure 1: Wage and Employment Trends in the California Hospital Industry 1983-1993

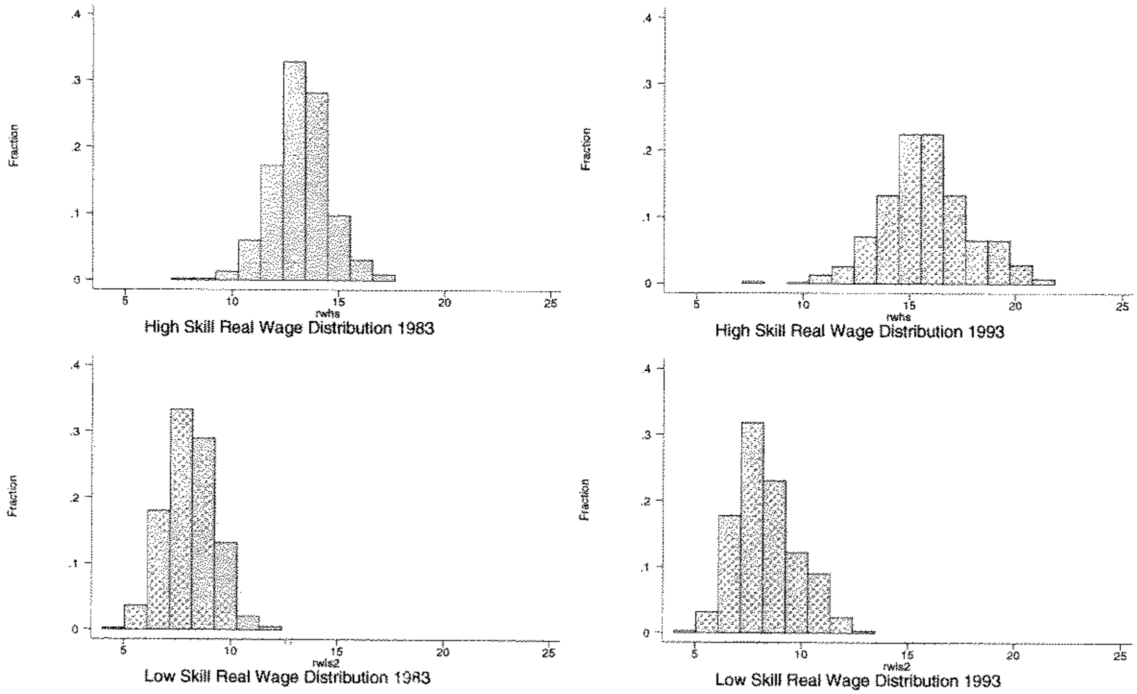

Figure 2: Hospital Wage Distributions 1983 and 1993

Supplemental Appendix for the Reviewers: Full Regression Results for Model 3

	Relative FTE		High-skilled Wage		Low-skilled Wage		Relative Wage	
	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic	Coefficient	T-statistic
Intercept	-0.04	-0.73	0.16	9.44	0.14	8.46	-0.02	-1.03
Technology Index	-0.29	-0.41	-0.49	-2.20	-0.39	-1.54	-0.03	-0.11
Log of Total FTE	-0.45	-4.45	-0.16	-5.38	-0.18	-4.87	-0.02	-0.40
Average Length of Stay	-0.03	-3.21	0.01	3.52	0.01	1.66	0.00	1.26
Casemix	0.01	0.04	-0.17	-2.06	-0.14	-1.39	0.01	0.06
Share Low Payers	-0.06	-0.25	0.22	2.81	0.10	1.13	0.14	1.49
Share HMO Payers	-0.07	-0.19	-0.09	-0.79	0.04	0.34	-0.14	-1.04
Hospital Competition	-0.01	-0.42	0.00	0.23	0.00	0.62	-0.01	-0.73
Year 84	0.67	5.61	0.97	29.53	0.75	19.91	0.18	4.78
Year 85	1.21	7.20	1.59	34.49	1.22	23.66	0.31	6.08
Year 86	1.52	7.45	1.99	35.94	1.54	24.96	0.40	6.59
Year 87	1.61	7.09	2.25	37.42	1.73	25.92	0.47	7.18
Year 88	1.67	6.88	2.45	39.14	1.87	26.76	0.54	7.89
Year 89	1.82	7.12	2.58	39.68	2.02	28.05	0.52	7.43
Year 90	1.71	6.40	2.66	40.10	2.13	28.66	0.49	6.76
Year 91	1.84	6.67	2.75	40.88	2.19	28.97	0.52	7.23
Year 92	1.94	6.80	2.75	40.22	2.18	28.24	0.54	7.35
Year 93	2.11	7.10	2.76	39.30	2.23	28.09	0.50	6.62
Technology Index*Year 84	-0.18	-0.41	0.30	2.10	0.24	1.48	0.04	0.24
Technology Index*Year 85	0.16	0.25	0.46	2.17	0.38	1.58	0.02	0.08
Technology Index*Year 86	0.38	0.53	0.57	2.49	0.35	1.33	0.11	0.41
Technology Index*Year 87	0.24	0.32	0.63	2.66	0.36	1.31	0.15	0.53
Technology Index*Year 88	0.00	0.01	0.69	2.86	0.44	1.58	0.16	0.54
Technology Index*Year 89	0.54	0.68	0.63	2.56	0.66	2.35	-0.06	-0.21
Technology Index*Year 90	0.83	1.04	0.59	2.38	0.51	1.79	-0.06	-0.22
Technology Index*Year 91	0.75	0.97	0.53	2.17	0.59	2.12	-0.17	-0.58
Technology Index*Year 92	0.16	0.22	0.57	2.43	0.47	1.77	0.01	0.05
Technology Index*Year 93	0.34	0.42	0.71	2.83	0.59	2.05	0.06	0.19
Total FTE*Year 84	0.09	2.11	0.03	2.18	0.05	2.76	0.00	0.04
Total FTE*Year 85	0.11	1.73	0.05	2.57	0.08	3.07	0.00	0.14
Total FTE*Year 86	0.14	1.73	0.07	2.58	0.11	3.39	0.00	-0.04
Total FTE*Year 87	0.20	2.16	0.08	2.80	0.12	3.41	0.00	0.13
Total FTE*Year 88	0.24	2.36	0.08	2.76	0.12	3.22	0.01	0.23
Total FTE*Year 89	0.23	2.22	0.09	2.92	0.10	2.70	0.03	0.67
Total FTE*Year 90	0.24	2.15	0.09	2.97	0.11	2.84	0.03	0.84
Total FTE*Year 91	0.26	2.29	0.10	3.04	0.12	2.94	0.03	0.73
Total FTE*Year 92	0.26	2.30	0.10	3.07	0.13	3.11	0.02	0.55
Total FTE*Year 93	0.24	2.07	0.10	3.08	0.12	3.05	0.02	0.53
Length of Stay*Year 84	0.02	2.09	-0.01	-3.11	-0.01	-2.49	0.00	0.12
Length of Stay*Year 85	0.03	2.70	-0.01	-3.18	-0.01	-2.35	0.00	-0.48
Length of Stay*Year 86	0.03	2.45	-0.01	-3.52	-0.01	-2.02	0.00	-0.86
Length of Stay*Year 87	0.03	3.04	-0.01	-3.58	-0.01	-1.80	0.00	-1.23
Length of Stay*Year 88	0.03	2.65	-0.01	-4.09	0.00	-1.26	-0.01	-2.01

Length of Stay*Year 89	0.04	3.82	-0.02	-4.73	0.00	-1.22	-0.01	-2.38
Length of Stay*Year 90	0.04	3.63	-0.01	-3.54	0.00	-1.26	-0.01	-1.41
Length of Stay*Year 91	0.03	2.55	-0.01	-3.23	0.00	-1.17	-0.01	-1.31
Length of Stay*Year 92	0.02	1.71	-0.01	-3.33	-0.01	-1.78	0.00	-0.88
Length of Stay*Year 93	0.01	1.02	-0.01	-3.88	-0.01	-2.65	0.00	-0.57
Casemix*Year 84	-0.17	-1.09	0.14	3.03	0.10	1.68	0.01	0.22
Casemix*Year 85	-0.15	-0.67	0.20	2.93	0.14	1.78	0.01	0.10
Casemix*Year 86	-0.08	-0.31	0.24	3.14	0.16	1.72	0.02	0.25
Casemix*Year 87	-0.09	-0.31	0.24	2.91	0.19	1.94	-0.01	-0.08
Casemix*Year 88	0.02	0.06	0.25	2.91	0.21	2.09	-0.02	-0.17
Casemix*Year 89	-0.13	-0.45	0.26	2.99	0.20	1.95	0.02	0.15
Casemix*Year 90	0.04	0.13	0.24	2.73	0.17	1.66	0.02	0.16
Casemix*Year 91	-0.01	-0.04	0.22	2.50	0.13	1.27	0.04	0.39
Casemix*Year 92	0.01	0.03	0.24	2.78	0.17	1.56	0.04	0.34
Casemix*Year 93	-0.03	-0.11	0.24	2.72	0.13	1.19	0.07	0.63
Low Payers*Year 84	0.08	0.50	-0.08	-1.58	-0.04	-0.71	-0.05	-0.92
Low Payers*Year 85	-0.02	-0.11	-0.12	-1.79	-0.07	-0.90	-0.07	-0.89
Low Payers*Year 86	-0.10	-0.44	-0.14	-1.86	-0.07	-0.80	-0.09	-1.05
Low Payers*Year 87	-0.21	-0.82	-0.17	-2.11	-0.08	-0.87	-0.11	-1.16
Low Payers*Year 88	-0.16	-0.59	-0.19	-2.29	-0.09	-0.96	-0.12	-1.23
Low Payers*Year 89	-0.19	-0.70	-0.19	-2.29	-0.09	-0.94	-0.12	-1.19
Low Payers*Year 90	-0.08	-0.27	-0.18	-2.19	-0.08	-0.86	-0.12	-1.21
Low Payers*Year 91	-0.09	-0.33	-0.20	-2.36	-0.15	-1.56	-0.07	-0.71
Low Payers*Year 92	0.08	0.27	-0.16	-1.92	-0.10	-1.02	-0.08	-0.85
Low Payers*Year 93	0.17	0.59	-0.18	-2.12	-0.11	-1.15	-0.08	-0.83
HMO Payers*Year 84	0.29	1.13	0.09	1.13	-0.02	-0.16	0.11	1.19
HMO Payers*Year 85	0.23	0.69	0.13	1.24	0.00	0.01	0.13	1.10
HMO Payers*Year 86	0.07	0.18	0.12	1.08	-0.03	-0.24	0.15	1.18
HMO Payers*Year 87	0.05	0.13	0.09	0.82	-0.05	-0.37	0.14	1.09
HMO Payers*Year 88	0.08	0.22	0.09	0.77	-0.07	-0.57	0.16	1.23
HMO Payers*Year 89	0.12	0.31	0.09	0.76	-0.05	-0.41	0.15	1.14
HMO Payers*Year 90	0.16	0.43	0.14	1.18	-0.02	-0.18	0.17	1.24
HMO Payers*Year 91	0.14	0.38	0.14	1.17	-0.05	-0.40	0.19	1.43
HMO Payers*Year 92	0.42	1.10	0.11	0.95	-0.08	-0.63	0.20	1.47
HMO Payers*Year 93	0.40	1.04	0.10	0.81	-0.11	-0.82	0.21	1.58
Competition*Year 84	0.01	1.04	0.00	-0.87	0.00	-1.25	0.00	0.82
Competition*Year 85	0.01	1.02	0.00	-0.78	-0.01	-1.20	0.00	0.90
Competition*Year 86	0.01	1.11	0.00	-0.67	-0.01	-1.03	0.00	0.83
Competition*Year 87	0.02	1.21	0.00	-0.63	-0.01	-0.99	0.01	0.80
Competition*Year 88	0.02	1.04	0.00	-0.50	-0.01	-0.80	0.01	0.74
Competition*Year 89	0.02	1.02	0.00	-0.46	0.00	-0.69	0.00	0.66
Competition*Year 90	0.01	0.78	0.00	-0.43	-0.01	-0.77	0.01	0.77
Competition*Year 91	0.02	0.89	0.00	-0.45	-0.01	-0.71	0.01	0.68
Competition*Year 92	0.03	1.22	0.00	-0.55	0.00	-0.68	0.00	0.59
Competition*Year 93	0.02	1.15	-0.01	-0.78	-0.01	-0.78	0.00	0.56
N	3954		4053		3948		3946	

Source: OSHPD