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Heterogeneous effect of residency matching and prospective payment on labor returns and hospital scale economies

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Abstract

The paper evaluates heterogeneous effect of participation in a residency matching program and changeover from fee-for-service to a prospective payment system on labor returns and economies of scale at acute-care public hospitals in Japan. A range of frontier technologies for multi-product output function is introduced with panel data quantile regression models, where endogenous treatment variables account for the fact that participation in both the residency matching program and the prospective payment reform was voluntary. The analysis exploits nationwide longitudinal databases on Japanese hospital participation in each of the reforms and on financial performance of regional and municipal hospitals in 2006–2012. The results demonstrate a labor-capital trade-off and lower labor intensity in the most productive hospitals. The residency matching program is positively associated with hospital production and labor productivity, especially in medium quantiles. Prospective payment has a negative effect on labor productivity, but it is only significant for hospitals in the highest quantiles.

Keywords: quantile regressions, economies of scale, labor productivity, hospitals

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1 Introduction

Hospital production generally supports a classic rule about diseconomies of scale at the upper tiers of output and economies of scale at the lower tiers. Better division of labor and greater medical specialization, efficient use of indivisible fixed capital and hospital capacities, as well as lower unit managerial costs tend to give increasing returns to scale at hospitals with smaller outputs (Lynk (1995), Hefty (1969)). By contrast, excessive management, coordination costs and fewer fixed capital costs owing to labor intensive services, as well as the likelihood of managerial staff performing non-managerial tasks may result in diseconomies of scale at high-output hospitals (Dranove (1998), Zeira (1998), Berry (1967)).

Findings concerning returns to labor in hospital production are scarce and inconclusive, but labor is the major input contributing to hospital production and attracts most attention in policy interventions. Labor expenses constitute a substantial share of hospital costs, especially at rural and public hospitals, which play a significant role in healthcare supply (Ozcan et al. (1996), Ferrier and Valdmanis (1996)). The success of managerial performance in hospitals is often linked to benchmark figures for the share of labor expenses, implicitly assuming optimal technology and labor returns. Similarly, labor returns are crucial in deciding about the labor-capital mix in hospital planning. Finally, it is important to understand the association between remuneration schemes and labor returns, since financial incentives are the main instrument of policy reforms.

Although there are some estimates of labor returns in hospital groups, stratified according to capacities or output (Olsen et al. (2013), Sarma et al. (2010), Kimbell and Lorant (1977)), a little emphasis is put on technological variation. Indeed, the commonly used mean or median regressions have limitations for dealing with technological heterogeneity,[1] and various attempts to model optimal technology with non-parametric/parametric frontier methods may be criticized on various grounds.[2] Another shortcoming of the existing literature is the lack of general agreement about the impact of remuneration schemes on hospital production (Devlin and Sarma (2008)). Moreover, little is known about the effect of labor supply programs, such as residency matching.

The purpose of this paper is to provide a robust estimation of labor returns in hospital longitudinal production function, as well as to evaluate the change in labor returns due to hospital reforms. Our analysis exploits a quantile regression approach and introduces a range of frontier technologies to robustly account for potential technological heterogeneity. We estimate the differential effect of participation in the residency matching program and the switch from fee-for-service to prospective payment system on factor returns and economies of scale at acute-care public hospitals.

Our study builds upon three streams in the preceding literature. Firstly, we exploit multi-output distance functions and returns to scale in multi-product technology, developed in Shephard (1953), Shephard (1970), Panzar and Willig (1977) and Färe and Primont (1995). We also consider specification of production function and interpretation of its empirical estimates in hospital economics (Pauly (1980), Feldstein et al. (1974), Newhouse (1969).) Secondly, we use the theories on political economy regarding capital-labor augmenting/replacing technologies and division of labor (Acemoglu and Autor (2011), Zeira (1998), Becker

[1]For this reason mean regressions may provide opposite results about economies-diseconomies of scale for similar types of hospital care in different countries, e.g. increasing marginal cost for acute-care hospitals in California and New York and decreasing marginal cost for acute-care hospitals in Canada, measured in Hansen and Zwanziger (1996).

[2]Nonparametric methods, which use linear optimization techniques to construct a hull of observations (Charnes et al. (1978)), are sensitive to outliers, require large sample size owing to "curse of dimensionality", do not account for measurement error, and consider the observations on the constructed frontier as fully efficient. An alternative parametric method − stochastic frontier analysis imposes strict distributional assumptions on the error term (Aigner et al. (1977)). The debates in *Journal of Econometrics* (1980) and *Journal of Health Economics* (1994) have resulted in a conjecture that the scores estimated in the corresponding framework may be interpreted as no more than hints at possible inefficiency, and their reliability is limited to judgments about order of magnitude or inter-temporal dynamics (Rosko and Mutter (2008), Linna (1998), Hadley and Zuckerman (1994), Kooreman (1994)).

and Murphy (1994), Stigler (1951)); research on labor division in hospitals and the potential effect of involvement in prospective payment and teaching activities (Devlin and Sarma (2008), Custer et al. (1990), Baumgardner (1988b), Jensen and Morrisey (1986)). Thirdly, there is enormous research on straightforward classic parametric and non-parametric efficiency measurement, inspired by Farrell (1957)[3], as well as a gradually developing alternative methodology of quantile regressions, which provides for an ordered set of technological relationships and gives better estimates in economic simulations (Behr (2010), Liu et al. (2008), Koenker (2004), Hallock and Koenker (2001), Koenker and Bassett (1978)). Quantile regression is increasingly used to assess production in various industries (Mamatzakis et al. (2012), Chidmi et al. (2011), Bernini et al. (2004), Dimelis and Louri (2002), Levin (2001)). Indeed, linear quantile regressions have a property of equivalence to any monotonically increasing transformation, which is a useful feature for estimating log-linearized functions.[4] Other merits are robustness to deviations from distributional hypotheses and to outliers, which is particularly important for measurements with heterogeneous data (Bernini et al. (2004)).[5] However, to the best of our knowledge, applications of quantile regressions in health economics are limited to simulation analysis (Liu et al. (2008)) and pooled data estimates of efficiency in nursing facilities (Knox et al. (2007)).

The contribution of this paper to the above literature is threefold. To the best of our knowledge, the paper is the first application of a quantile regression approach to estimating longitudinal hospital production function. We provide estimates for a range of technologies, corresponding to various quantiles of output. Secondly, the paper is the first estimation of a panel data fixed effect model with endogenous treatment variables. For this purpose, we modify Canay's (2011) approach and extend Chernozhukov's and Hansen's (2004) instrumental variable estimations and grid-search procedure. Finally, while policy analysis commonly focuses on the outcomes of prospective payment reforms, this paper is the first study to assess the link between participation in residency matching and labor returns.

We use Japanese nationwide longitudinal samples of designated teaching hospitals taking part in a residency matching program (2003–2013), hospitals implementing a prospective payment system (2005–2013), and all municipal and regional public hospitals (1999–2013) to estimate the effect of participation in the residency matching program and changeover from fee-for-service to a prospective payment system. Both reforms have been available on a voluntary basis to Japanese municipal and regional hospitals.

The results demonstrate a labor-capital trade-off and lower labor intensity in the most productive hospitals. The residency matching program is positively associated with hospital output and labor productivity, especially in medium quantiles. Prospective payment only has a significant negative effect on labor productivity for hospitals in the top 25 percentiles of output.

The remainder of the paper is structured as follows. Section 2 proposes the methodology for fixed effect panel data quantile regression with endogeneity, as well as specifies the hospital production function and measurement of factor returns and inefficiency residual. Section 3 outlines the institutional features of the residency matching program and inpatient prospective payment system in Japan. The explanation of data and variables is given in section 4. Section 5 presents the results on heterogeneity of factor returns and the reform effects. In section 6 these results are discussed in light of existing theories on labor division.

[3] See review in Fried et al. (2008) and healthcare applications in Hollingsworth (2008).

[4] In this paper we exploit the fact that $Q_\tau(\log y|x) = \log(Q_\tau(y|x))$. This way residuals in quantile regression with logged dependent output variable show the value of inefficiency.

[5] Some literature incorporates quantile regression approaches into estimation of parametric (Koutsomanoli-Filippaki and Mamatzakis (2011)) and nonparametric efficiency (Wheelock and Wilson (2009), Aragon et al. (2005), Cazals et al. (2002)).

2 Methodology

2.1 Consistent estimation of a panel data quantile regression model with endogenous variables

The theory and inference for an instrumental variable approach, allowing consistent estimation of cross-sectional quantile regression with endogenous covariates, as well as practical implementation with a grid-search procedure were proposed in Chernozhukov and Hansen (2008), Chernozhukov and Hansen (2006), and Chernozhukov and Hansen (2004). Harding and Lamarche (2009) apply Chernozhukov's and Hansen's methodology to estimating Koenker's (2004) panel data quantile regression model with endogenous variables and quantile dependent fixed effects. Galvao (2011) shows consistency of Chernozhukov's and Hansen's approach in case of longitudinal data with endogenous variables, using an example of AR(1) dynamic panel data model. In technical terms, Galvao (2011) uses a grid-search procedure by Chernozhukov and Hansen (2004) to estimate a model with quantile dependent fixed effects, and numeric optimization for quantile independent fixed effects ("locational shift") model.

However, as regards panel data regression with quantile independent fixed effects, Canay (2011) proposes a computationally simple two-step estimator, which first, consistently estimates fixed effects under the assumption that they are "locational shifts" and computes fitted value of the dependent variable (subtracting the fitted value of "locational shifts"). Second, it applies panel data quantile regression methodology to the fitted value of the dependent variable. In this paper we use Canay's (2011) methodology for two-step estimation of panel data quantile regressions with endogenous variables. Adding an assumption about independence of the disturbance term from instrumental variables, we can, in the first step, consistently estimate fixed effects (e.g., using an OLS instrumental variable approach). In a second step we modify Chernozhukov's and Hansen's (2004) grid-search procedure for an instrumental variable estimation of a two-dimensional vector of endogenous variables D and a large number of instruments.We test the "locational shift" specification against a random effects model using the Hausman test (1978). The goodness-of-fit in the quantile regressions is assessed with the approach of Koenker and Machado (1999).

2.1.1 Random effects model

The model is the Koenker (2004) longitudinal version of Chernozhukov and Hansen (2008), specified as:

$$y_{it} = \mathbf{d}'_{it}\boldsymbol{\alpha}(u_{it}) + \mathbf{x}'_{it}\boldsymbol{\beta}(u_{it}) \tag{1}$$

$$\mathbf{d}'_{it} = \delta(\mathbf{x}_{it}, \mathbf{z}_{it}, \nu_{it}) \tag{2}$$

$$\tau \mapsto \mathbf{d}'_{it}\boldsymbol{\alpha}(\tau) + \mathbf{x}'_{it}\boldsymbol{\beta}(\tau) \tag{3}$$

where τ denotes the value of a given quantile for conditional distribution of the dependent variable y for observation i at period t, $\mathbf{d}$ is a vector of endogenous variables, $\mathbf{x}$ is a vector of exogenous variables, $\mathbf{z}$ is a vector of instruments (dim $\mathbf{z} \geq$ dim $\mathbf{d}$), ν_{it} is statistically dependent on u_{it}, $u_{it} \perp (\mathbf{x}_{it}, \mathbf{z}_{it}) \sim U[0,1]$, $i = 1, ..., N$, $t = 1, ..., T$.

A consistent estimation procedure (Galvao (2011), Chernozhukov and Hansen (2008)) involves minimizing the weighted quantile regression objective function

$$Q_{NT}(\tau, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}) := \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\rho_\tau(y_{it} - \mathbf{d}'_{it}\boldsymbol{\alpha} - \mathbf{x}'_{it}\boldsymbol{\beta} - \boldsymbol{\phi}'_{it}\boldsymbol{\gamma})v_{it} \tag{4}$$

where ρ_τ is the loss function (Koenker and Bassett (1978)), $\boldsymbol{\phi}_{it} = f(\mathbf{x}_{it}, \mathbf{z}_{it})$ and $v_{it} = v(\mathbf{x}_{it}, \mathbf{z}_{it})$ are weights.

The first step requires obtaining

$$\big(\hat{\boldsymbol{\beta}}(\boldsymbol{\alpha}, \tau), \hat{\boldsymbol{\gamma}}(\boldsymbol{\alpha}, \tau)\big) = \underset{\boldsymbol{\beta},\boldsymbol{\gamma}}{\operatorname{argmin}}\, Q_{NT}(\tau, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}) \tag{5}$$

Second, the value of $\boldsymbol{\alpha}$, so that $\hat{\boldsymbol{\gamma}}(\boldsymbol{\alpha}, \tau)$ becomes as close to zero as possible, is found as (Chernozhukov and Hansen (2004), eq.3.2):

$$\hat{\boldsymbol{\alpha}}(\tau) = \underset{\boldsymbol{\alpha}\in\mathcal{A}}{\operatorname{argmin}}\, W(\boldsymbol{\alpha}), \text{where} W(\boldsymbol{\alpha}) = \hat{\boldsymbol{\gamma}}(\boldsymbol{\alpha}, \tau)'\hat{A}(\boldsymbol{\alpha})\hat{\boldsymbol{\gamma}}(\boldsymbol{\alpha}, \tau) \tag{6}$$

where $A(\boldsymbol{\alpha})$ is uniformly positive definite matrix in compact parameter set $\mathcal{A}$ and $\hat{A}$ is a consistent estimate of A (may be set equal to the asymptotic variance-covariance matrix of $(\hat{\boldsymbol{\gamma}}(\boldsymbol{\alpha}, \tau), \tau)$ for treating W as Wald statistics).

The variance-covariance matrix $\mathbf{J}(\tau)^{-1}\mathbf{S}(\tau, \tau)[\mathbf{J}(\tau)^{-1}]'$ of $\hat{\boldsymbol{\gamma}}(\boldsymbol{\alpha}, \tau)$ is estimated as (Chernozhukov and Hansen (2006), eq.3.11–3.14):

$$\hat{\mathbf{S}}_{\boldsymbol{\psi}}(\tau, \tau') = (\min\{\tau, \tau'\} - \tau\tau')\frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\hat{\boldsymbol{\psi}}_{it}(\tau)\hat{\boldsymbol{\psi}}_{it}(\tau')' \tag{7}$$

$$\hat{\mathbf{J}}_{\boldsymbol{\psi}}(\tau) = \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N} I(|\hat{\epsilon}_{it}(\tau)| \leq h_{NT})\hat{\boldsymbol{\psi}}_{it}(\tau)\boldsymbol{\phi}'_{it} \tag{8}$$

where $\hat{\epsilon}_{it}(\tau) \equiv y_{it} - \mathbf{d}'_{it}\hat{\boldsymbol{\alpha}}(\tau) - \mathbf{x}'_{it}\hat{\boldsymbol{\beta}}(\tau) - \boldsymbol{\phi}'_{it}\hat{\boldsymbol{\gamma}}(\tau)$, $\boldsymbol{\psi}_{it}(\tau) \equiv v_{it}(\tau) \cdot [\boldsymbol{\phi}'_{it}(\tau), \mathbf{x}'_{it}]$ and bandwidth h_{NT} is chosen so that $h_{NT} \to 0$ and $NTh_{NT}^2 \to \infty$.

2.1.2 "Locational shift" fixed effects model

Denote $\tilde{y}_{it} = y_{it} + \eta_i$, $\tilde{\tilde{\mathbf{x}}}_{it} = [\mathbf{d}_{it}, \mathbf{x}_{it}]$. Consider a model specified for y_{it}, yet, with only $\tilde{y}_{it}$ being an observable variable:

$$y_{it} = \tilde{\tilde{\mathbf{x}}}'_{it}\boldsymbol{\theta}(u_{it}) \tag{9}$$

$$\tau \mapsto \tilde{\tilde{\mathbf{x}}}'_{it}\boldsymbol{\theta}(\tau). \tag{10}$$

Canay (2011) proposes a two-step consistent estimator for such model in case of with exogenous $\tilde{\tilde{\mathbf{x}}}_{it}$ under $y_{it}\perp\eta_i$ (assumption 1) and $u_{it}\perp(\tilde{\tilde{\mathbf{x}}}_{it}, \eta_i)$ (assumption 2). At the first stage, a least squares estimator of $\hat{\boldsymbol{\theta}}$ (consistent under $NT \to \infty$) is used to compute an estimator $\hat{\eta}_i \equiv \frac{1}{T}\sum_{t=1}^{T}[\tilde{y}_{it} - \tilde{\tilde{\mathbf{x}}}'_{it}\hat{\boldsymbol{\theta}})]$ (consistent under $T \to \infty$). The second stage defines $\hat{y}_{it} \equiv \tilde{y}_{it} - \hat{\eta}_i$ and estimates $\hat{\boldsymbol{\theta}}(\tau)$ as:

$$\hat{\boldsymbol{\theta}}(\tau) = \underset{\boldsymbol{\theta}}{\operatorname{argmin}}\frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\rho_\tau(\hat{y}_{it} - \tilde{\tilde{\mathbf{x}}}'_{it}\boldsymbol{\theta})v_{it} \tag{11}$$

However, as in our case with system (1)–(3) $\mathbf{d}_{it}$ are endogenous variables, assumption 2 should be modified into $u_{it}\perp(\mathbf{x}_{it}, \mathbf{z}_{it}, \eta_i)$. This allows the applicability of Canay's (2011) asymptotic theory and practical two-step procedure. Namely, consistent estimate of η_i, obtained through the least-squares instrumental variable regression, is employed for computing $\hat{y}_{it}$. Then, $\hat{y}_{it}$ becomes the dependent variable in the system (1)–(3), which is estimated with Galvao's (2011) and Chernozhukov and Hansen's (2008, 2006, 2004) procedure, applied to

$$Q_{NT}(\tau,\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma}) = \frac{1}{NT}\sum_{t=1}^{T}\sum_{i=1}^{N}\rho_\tau(\hat{y}_{it} - \mathbf{d}_{it}'\boldsymbol{\alpha} - \mathbf{x}_{it}'\boldsymbol{\beta} - \boldsymbol{\phi}_{it}'\boldsymbol{\gamma})v_{it} \tag{12}$$

In particular, in case of a panel data model with predetermined assignment of the labor and financial reforms (denoted respectively r_{it} and f_{it}, so $\mathbf{d}_{it} = (r_{it}, f_{it})$), we assume that $u_{it} \perp (r_{i,t-s}, f_{i,t-s}, \mathbf{x}_{it}, \eta_i)$, where $s = 1, 2, ..., T-1$. In other words, instruments for the reforms are their first lags.

2.2 Specification

2.2.1 Production function

We followed the empirical literature on hospital production, which commonly exploits a translogarithmic production function, but collinearity among regressors did not enable its use.[6] Overall, the translog functional form may be a misspecification (Wilson and Carey (2004)) or inapplicable owing to collinearity among the cross-terms and quadratic terms (Knox et al. (2007)). Note that although the values may appear insignificant due to large standard errors, the presence of multicollinearity does not prevent consistent estimates of coefficients for the explanatory variables, and hence consistent estimation of factor returns and scale returns (Gonçalves and Barros (2013)). However, this paper deals with endogenous reforms and we use an instrumental variable approach. Multicollinearity with instrumental variable regression might result in even higher correlation between the fitted values of the endogenous variables at the first stage (Kritzer (1976), Farrar and Glauber (1967)) and, consequently, an upwards bias of the first stage F–statistics, leading to wrong conclusions about the absence of weak instruments (Stock et al. (2002)). Therefore, we use the Cobb–Douglas simplified form of translogarithmic production function, which yields variance inflation factors in the range of 2 to 8, signaling that the multicollinearity problem is unlikely to be present. Other arguments for use of the Cobb–Douglas production function are the absence of misspecification in case of quantile regressions in simulations with hospital data (Liu et al. (2008)), as well as the availability of real data estimates of labor and capital returns, which may be used for comparison with our findings (Knox et al. (2007)). Finally, as a special case of a homothetic production function, the Cobb–Douglas form has the useful property of a unity elasticity of substitution, allowing a simple computation of the ratio of optimal input costs as the ratio of corresponding factor returns (Pauly (1980), Shephard (1953), Douglas (1948)).

To estimate factor returns in a multi-product hospital we use production retransformation function $F(\mathbf{y}, \mathbf{x}) = 1$, which may be further specified as output distance function F_{it} ($0 < F_{it} \leq 1$) in the Cobb–Douglas form (Panzar and Willig (1977), Caves et al. (1981)):

$$\ln F_{it} = \sum_{m=1}^{M}\beta_m \ln y_{mit} + \sum_{k=1}^{K}\beta_k \ln x_{kit} + \sum_{j=1}^{J}\beta_j h_{jit}, \tag{13}$$

where i denotes hospital, t is time, m is the index for input, $M = dim(\mathbf{y})$, k indicates output, $K = dim(\mathbf{x})$, $\mathbf{h}$ are hospital control variables.

$F(\cdot)$ is homogeneous of degree 1 in $\mathbf{y}$ and homogeneity restrictions are imposed by dividing the distance function and all outputs by an arbitrarily chosen M-th output as a numeraire (in our case, the number of

[6]Various forms of the Reinhardt (1972) production function, which can deal with zero values for some labor inputs and is often favored in the analyses of primary care facilities, are not exploited in this paper, since total labor force is always positive (Pauly (1980))

outpatients). After rearranging terms, we obtain:

$$-\ln y_{Mit} = \sum_{m=1}^{M-1} \beta_m \ln \frac{y_{mit}}{y_{Mit}} + \sum_{k=1}^{K} \beta_k \ln x_{kit} - \ln F_{it} + \sum_{j=1}^{J} \beta_j h_{jit}. \tag{14}$$

Treating $-\ln F_{it}$ as a random error term (Coelli and Perelman (2000)), we can estimate the equation with quantile regression approach with a stochastic term u_{it} and fixed effect term v_i. As in this case the dependent variable is negative, bottom quantiles correspond to most efficient production path.

2.2.2 Scale and factor returns

Scale returns in a multi-output production function are defined as (Panzar and Willig (1977)):

$$s = -\sum_k \frac{\partial \ln F}{\partial \ln x_k} \Big/ \sum_m \frac{\partial \ln F}{\partial \ln y_m}, \tag{15}$$

where k is the index for input and $\partial \ln F/\partial \ln x_k$ is input elasticity (factor returns), further denoted as ϵ_k.

As F is homogeneous of degree 1 in $\mathbf{y}$, we may rewrite $F(\mathbf{y}, \mathbf{x}) = y_M \cdot F(\tilde{\mathbf{y}}, \mathbf{x})$, where $\tilde{\mathbf{y}} = \mathbf{y}/y_M$ and consider y_M as a function of $\mathbf{x}$ under given $\tilde{\mathbf{y}}$ (Sipiläinen et al. (2014)). Applying the implicit function theorem to the equation $y_M \cdot F(\tilde{\mathbf{y}}, \mathbf{x}) = 1$, we obtain:

$$\frac{\partial \ln y_M}{\partial \ln x_k} = -\frac{\partial \ln F}{\partial \ln x_k} \Big/ \frac{\partial \ln F}{\partial \ln y_M} \tag{16}$$

$F(\mathbf{y}, \mathbf{x}) = y_M \cdot F(\tilde{\mathbf{y}}, \mathbf{x})$ results in $\partial \ln F(\mathbf{y}, \mathbf{x})/\partial \ln y_M = 1$. So the denominator of the right-hand side of (16) is unity, and the equation becomes the expression for ϵ_k:

$$\frac{\partial \ln y_M}{\partial \ln x_k} = -\frac{\partial \ln F}{\partial \ln x_k} = \epsilon_k \tag{17}$$

Following Färe and Primont (1995), linear homogeneity of F in $\mathbf{y}$ is equivalent to:

$$\sum_m \partial \ln F(\mathbf{y}, \mathbf{x})/\partial \ln y_m = 1. \tag{18}$$

Combining (17) and (18) we reduce the expression for s in (15) to:

$$s = \sum_k \frac{\partial \ln y_M}{\partial \ln x_k}, \tag{19}$$

In other words, (19) is a simpler analogue of (15) for a numeraire output as a function of inputs, given the ratios of all outputs to the numeraire output are fixed.

Note that while factor returns require estimation with production function, returns to scale can be measured using production and cost function (Braeutigam and Daughety (1983), Panzar and Willig (1977)). However, we do not estimate cost function for several reasons. Firstly, there is a high possibility of endogeneity of output in the cost function of regional and municipal hospitals in Japan. Secondly, labor prices in Japanese hospitals are likely to be endogenous (Yamada et al. (1997)), and the only available information on average age and average tenure for each type of hospital labor may be insufficient for an instrumental variable estimation. Finally, to account for high reliance on pharmaceuticals in Japanese inpatient and outpatient treatment patterns we consider the total cost of medicines and medical materials as a quasi-capital input. But estimations with the cost function would require the price of this input, which is unavailable.[7] Moreover, owing to volatility of prices, cost function estimates may enable only short-term analysis, while production function measurement allows evaluating technological relationships within longer time periods (Banker (1984)).

2.2.3 Measure of inefficiency

We measure hospital output inefficiency te_{it} as

$$te_{it} = -\widehat{\ln}(y_{it}|\tau) - (-\ln y_{it}) = \ln y_{it} - \widehat{\ln}(y_{it}|\tau) \tag{20}$$

Given the range of values of y_{it}, the mean difference in logarithms of the actual and fitted value generally belongs to the $[-1, 0]$ segment, and therefore, may approximate the percentage change in inefficiency.

3 Background on hospital reforms in Japan

3.1 Inpatient payment system

Japan has been gradually adopting per case financing since 2003. The country is known for its universal health insurance and free access to any healthcare institution regardless of insurance type (Ikegami (2014), Kondo and Shigeoka (2013)).[8] Reimbursement of all healthcare institutions is implemented according to the fee-for-service principle, with tariffs for drugs and medical services set in the unifying fee schedule, which is biannually revised by the Ministry of Health, Labor, and Welfare (MHLW). Co-payment rates are at most 30%, and insurance contributions are rather low. Along with fee-for-service reimbursement this has lead to physician-induced demand, resulting in the growth of national health expenditure exceeding the growth of GDP (Shigeoka and Fushimi (2014), Bhattacharya et al. (1996)). Restraining health care demand demand by raising coinsurance rates and contributions in 1980s – 1990s, along with decreasing the prices in the unifying fee schedule did not lead to cuts in healthcare spending. [9] Therefore, a special case-mix system called Diagnosis Procedure Combinations (DPCs) was developed in Japan in the late 1990s as means to sustain hospital costs through raising efficiency. The unique feature of Japanese inpatient prospective payment system (PPS) is the fact that it is divided into DPC and fee-for-service components, with the shares 0.7 and 0.3, respectively (Okamura et al. (2005)). The first component is constructed as a daily reimbursement rate, with the amount of per diem payment constant over each of the three consecutive periods: period 1 that represents the first quartile of the average length of stay in all the hospitals, period 2 encompassing the rest of the ALOS, and period 3 of two standard deviations from the mean length of stay. After the end of period III, hospitals are reimbursed according to the fee-for-service system. To create incentives for shorter lengths

[7]The reported share of health insurance reimbursement of the cost of medicines and medical materials (often called the "drug margin rate"), which is defined as the ratio of a hospital's revenue from medicines and medical materials to incurred cost, might be used as the price variable. However, the share varies from 0.08 to 6 because the hospital's revenue potentially include some capital investment into medical materials. So some arbitrary rescaling of the drug margin rate (e.g. to make it in the range of zero to one) might be necessary.

[8]Enrollment in one of the mutually exclusive health insurance plans is obligatory and depends on an enrollee's age and status at the labor market. The following health insurance plans exist in Japan: 1) national health insurance, which is municipality-managed insurance for the self-employed, retirees and their dependents; 2) government-managed insurance for employees of small firms and their dependents; 3) company-managed insurance associations created by firms with over 300 workers for their employees and employees' dependents; 4) benefit schemes set up by mutual aid associations. Additionally, there is a separate plan of insurance for the elderly (Shigeoka (2014)). The users of any health insurance plan can choose any healthcare institution (e.g., private/public, hospital, clinic or ambulatory division of hospital), and payments for seeking the services of a large facility without referral are negligible (Ikegami and Campbell (1995)).

[9]For example, in 2002, 80% of insurers in the employee health insurance as well as the whole system of national health insurance operated with financial deficit (Abe (2007)).

of stay, per diem payment in period I is higher than in period II,[10] and in period II is 15% higher than in period III.[11]

DPC component is related to the hospital fee and covers hospital expenditures on pharmaceutical, injections, examinations, and procedures with a cost of less than 10,000 yen. The fee for service component covers the cost of surgical procedures, anesthesia, endoscopies, pharmaceuticals, and materials used in operating room, as well as procedures of more than 10,000 yen. The two-component system is justified in part by the historically developed variety of treatment patterns in Japanese hospitals (Ikegami (2014), Campbell and Ikegami (1998)). The reform reached its major goal of decreasing the long length of stay (Nawata and Kawabuchi (2013), Kondo and Kawabuchi (2012)), yet, the impact on factor returns is unclear. Overall, the inpatient prospective payment system, reimbursing a fixed amount for treating a patient with a given diagnosis group is generally viewed as a payment mechanism promoting efficient resource use. However, the experiences of various countries demonstrate different productivity dynamics and early results of the Japanese payment reform show potential heterogeneity of the effect (Kondo and Kawabuchi (2012), Besstremyannaya (2011)).

3.2 Residency matching program

Japan's residency matching program (JRMP) was established in 2003 as a nationwide computer system which matches teaching hospitals with final-year medical undergraduates, who are obliged to complete two-year postgraduate medical education. The objective of the program is to simplify the application process, which was previously conducted at the individual hospital-student level, and to offer more options for graduates, loosening ties between universities and their affiliated hospitals, improving the quality of training programs and increasing the standardization of medical care (Ikegami (2014), Inoue and Matsumoto (2004)).

Postgraduate training in Japan was mandatory in 1946–1968, but became non-compulsory after 1968 owing to inappropriate curricula, insecure status and low salary of trainees (Kozu (2006), Onishi and Yoshida (2004)). Nonetheless, 70–90% of graduates received training in 1980–2000, and about 80% of them spent their internship at a university hospital (Onishi and Yoshida (2004)). Moreover, it was a usual practice to take up an internship at the hospital, which was affiliated with the student's university (Campbell and Ikegami (1998)). Trainees were generally limited to working in a particular department or even in a certain ward, thus acquiring only a single specialty (Inoue and Matsumoto (2004), Onishi and Yoshida (2004))). Inadequate clinical skills of residents was the major reason for the introduction of a new postgraduate program in 2004.

The first year of the new postgraduate program is dedicated to internal medicine (at least 6 months), surgery and emergency medicine. The second year is spent acquiring skills in pediatrics, obstetrics-gynecology, psychiatry and primary care. The program establishes a high level of trainee salaries to discourage them from taking part-time jobs outside their training hospitals and also provides support for supervising doctors. In order to meet the criteria by the MHLW to receive status as a teaching hospital, an institution must: have departments for internal medicine, surgery, psychiatry, pediatrics, obstetrics-gynecology and (since 2010) anesthesiology; treat at least 3000 inpatients a year (relaxed in 2010 to more than 100 inpatients in each department); provide emergency care; use clinical pathology conference reports as medical records; have at least one supervisor (doctor with seven years of experience) per 5 trainees; have libraries, medical journals and Internet access (Ministry of Health, Labor and Welfare (2012), Nomura et al. (2008a)).

The first outcome of the JRMP was a decrease in the number of graduates selecting university hospitals for their internship from 58.8% in 2003 to 45.1% in 2013 (Japan Residency Matching Program (2013a)). The

[10] 15% higher for a standard DPC, 10% higher for a DPC with low medical cost at the beginning of the treatment, and varies for a DPC with high medical cost at the beginning of the treatment.

[11] 10% higher for a DPC with low medical cost at the beginning of the treatment.

share of same-university graduates among trainees, accepted to university hospitals, went down from 71.5% in 2003 to 63–64% in 2012–2013 (Japan Residency Matching Program (2013b)), and levels of professional competence of trainees increased (Nomura et al. (2008a)). However, a decrease in the number of doctors in rural areas, who often received their training at university hospitals may have been one adverse result of the JRMP (Nomura et al. (2008b)).

The number of vacancies in hospitals was larger than the number of medical school graduates, and several prefectures found it hard to fill vacancies. So regional caps were added to the JRMP in 2010 (Ministry of Health, Labor and Welfare (2009)). The caps are determined according to the share of regional population in the total population, share of regional medical students in the total national number, number of doctors per 100 square kilometers and regional population in remote islands (the cap may not exceed 90% of the previous year's sum of vacancies in the region). The ratio of the regional cap divided by the actual sum of vacancies in the prefecture is then applied to each hospital: maximum number of the hospital's residents in the previous three years is multiplied by the ratio to give actual vacancies. Hospitals, which send their doctors to other hospitals, receive additional quotas. The regional cap modification of the JRMP is argued to have led to inefficiencies in terms of unfilled vacancies (Kamada and Kojima (2010)).

3.3 Regional and municipal hospitals

Japanese local public hospitals constitute 10% of all hospitals in the country and half of public hospitals (Ikegami (2014)). They may be founded by prefecture, a city with special rights of their governments (designated city), city, town, village, or a union of towns/villages. With an increasing number experiencing financial deficit, Japanese local public hospitals are commonly criticized for weak financial constraints due to excessive subsidies (Ikegami and Campbell (1999), Iwane (1976)). Although this may be largely explained by the fact that many of these hospitals are understaffed (Campbell and Ikegami (1998)), the issue of resource use and labor/capital mix in regional and municipal hospitals has been reflected in the recent Japanese healthcare reforms (Ministry of Internal Affairs and Communications, 2007).

4 Data

4.1 Samples

The financial data employed in the analysis are annual surveys of all local public hospitals in Japan (The Yearbook of Local Government Enterprises, Hospitals, 1999-2012 fiscal years, Chihou kouei kigyou byouin-hen), published by the Department of Local Finance of the Ministry of Internal Affairs and Communications (Soumusho jichi zaiseikyokuhen).[12]

The data on hospital departments (as of 2014 or the last year of the hospital's functioning) and on hospital's location (urban/rural) come from "The Handbook of Hospitals", which contains the hospital name, address, and the list of departments. While a number of studies consider nursing standards, established by the MHLW (i.e. number of nurses per inpatients), as a quality characteristic (Takatsuka and Nishimura (2008), Kawaguchi (2008), Fujii (2001), Fujii and Ohta (1999), Yamada et al. (1997)), this paper uses data of the Japan Council for Quality Health Care (2014) on hospital accreditation. The third-party accreditation is started in Japan in 1997 and is granted to hospitals that fulfill seven standards: 1) mission, policy, organisation and planning; 2) community needs; 3) medical care and medical care support systems; 4) nursing care; 5) patient satisfaction and safety; 6) administration; 7) specific standard for rehabilitation and psychiatric hospitals (Hirose et al. (2003)).

[12] The length of panel is justified by data availability in electronic form.

Participation in hospital financing reform and data on treated patients are taken from an administrative nationwide database of the MHLW (September 20, 2013) with annual hospital-level aggregated information for major diagnostic categories and diagnosis-procedure combinations (July 2005 – March 2013). The data are voluntarily sent to the MHLW by hospitals, which opt for the prospective payment reform. Hospitals may join the reform after a trial period (commonly two years), or they may postpone the decision and continue submitting the data to the MHLW, or they may choose not to join the reform and stop sending data. Merging annual files by hospitals names[13] we create an unbalanced panel of 1837 hospitals.

Finally, we use nationwide data on hospital participation in Japan Residency Matching Program (2003–2013) to construct an unbalanced panel of 1157 hospitals (851 to 1052 hospitals in various years).

The non-anonymous character of the three databases allows them to be merged by hospital name. First, controlling for changes in name and affiliation, mergers and closures, we create an unbalanced panel of 1085 local public hospitals in Japan in 1999–2012. Owing to administrative reform, which resulted in change of affiliation and restructuring of up to 20% of local public hospitals in 2004–2005, our empirical estimations use the post-2005 data with annual samples of 834–970 hospitals.

Of the constructed unbalanced panel, 221–272 hospitals participated in the JRMP in various years. The inpatient prospective payment system was introduced in 29 hospitals in 2006, 96 hospitals by 2008, and 231–258 hospitals by 2009–2012. We drop the data for hospitals with average length of stay below 6 days[14] or over 90 days [15] and with missing numbers of doctors and other variables (about 5% of samples in various years).

Finally, to guarantee homogeneity of hospital production in the absence of any variable directly related to the prevalence of patients with different diagnoses (casemix), we concentrate exclusively on hospitals with acute-care (general) beds (Berry (1967)).[16] The following safeguards justify this choice. The prospective payment system applies solely to acute care beds. In theory, to qualify for participation in the JRMP a hospital must have a psychiatric department in addition to surgery, internal medicine, pediatrics, and obstetrics departments, all of which consist mainly of acute-care beds. However, this has not been a hard and fast rule: the probability of having a psychiatric department in a JRMP hospital is 0.57, which is close to the chance of not having it, so we should not expect a large bias owing to the selection effect. Also we do not necessarily exclude all hospitals with psychiatric departments, since beds in psychiatric departments are classified as exclusively psychiatric beds in only 29% of hospitals. Overall, we find that prevalence of hospitals with only acute-care beds does not differ considerably between JRMP participant and non-participant hospitals (37.8% and 44.8%, respectively).

Our estimations employ longitudinal subsamples of 298–358 hospitals, of which 82–96 participated in the JRMP in 2006–2012 and 9–93 have implemented the inpatient PPS by the beginning of the corresponding financial year (Table 1). Note that the prevalence of each of the reforms in the subsample of local public hospitals with acute-care beds and in the universe of local public hospitals is similar.

[13]We reconstruct anonymous names of 361 hospitals, which joined on trial in 2006, by matching the data on their performance in 2006 (average length of stay and readmission rate) with non-anonymous data, reported in subsequent years.

[14]With usual hospitalizations in Japan lasting at minimum a week, shorter stays are associated with preliminary diagnostics or further transferring to specialized hospitals (Nawata et al. (2006)).

[15]Hospital stays corresponding to long-term care.

[16]Overall, there is the following classification of beds in Japanese local public hospitals: acute care, long-term care, tuberculosis, psychiatric, and infection beds.

Table 1: **Universe and samples of Japanese local public hospitals**

	2006	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Universe	970	953	932	910	875	853	834
Sample, of which	924	901	875	849	808	787	760
JRMP	268	272	272	249	231	228	221
PPS	29	29	96	231	243	250	258
Acute care	381	374	371	365	352	344	336
Subsample, of which	358	329	344	338	322	311	299
JRMP	98	89	96	90	83	83	82
PPS	9	9	35	84	85	89	93

4.2 Inputs, outputs and exogenous variables

Owing to unavailability of hospital-level variables on the actual outputs (i.e., changes in patients' health due to medical treatment) in our database, we employ proxies for hospital outputs. Overall, production studies commonly use such outputs as outpatient visits, hospital admissions, or discharges (Rosko and Mutter (2008), Worthington (2004)). The Japanese local public hospitals database does not give the number of admissions or outpatient visits, reporting instead the daily number of inpatients and outpatients. However, the database allows reconstruction of the number of discharges for the subsample of acute-care hospitals with acute-care beds (Takatsuka and Nishimura (2008)). Consequently, to analyze the multi-output production function of hospitals, we use discharges and outpatients as proxies for hospital outputs for the subsample of hospitals exclusively with acute-care beds.

Production function often considers labor inputs by medical specialty. However, in case of endogeneity of certain medical specialties (e.g. nurses), the production function would be over-identified (Knox et al. (2007)). Our data demonstrates high collinearity among labor specialties: pairwise correlations between the number of physicians, nurses, technicians and other staff exceed 0.9. The reason might be that there are ministerial regulations which link the target number of each medical specialty in regional and municipal public hospitals to the number of beds (Yamada et al. (1997)). Therefore, to avoid the multicollinearity problem we consider total hospital staff as labor input.

Capital input is depreciable capital (building and equipment).[17] Owing to the emphasis of Japanese healthcare on pharmaceuticals, the cost of medicines and materials is also treated as an additional input (Besstremyannaya (2013)). This approach follows studies with data from the U.S. and U.K., where drugs are regarded as an input in the production function (Pauly (1980), Feldstein et al. (1974)).

Information about casemix is unavailable for Japanese hospitals, since the coding of diagnoses in non-prospective payment hospitals has always been very limited. Therefore, given data limitations, we follow the common approach of using proxies for casemix, which have been shown to be correlated with diagnostic measures in U.S. hospitals: teaching status, third-party accreditation, facility services (in our case, number of examinations per patient), and status as an emergency hospital (Becker and Sloan (1985), Sloan et al. (1983), Pauly (1980), Hefty (1969)).

Other hospital controls are dichotomous variables for urban hospitals, regional hospitals, designated local hospitals (which receive a special subsidy per admission) and hospitals in non-profitable areas, and bed-occupancy rate as a correlate of output (Hefty (1969)). Government subsidies are not included as

[17] Fujii (2001) and Fujii and Ohta (1999) use book value instead of the total number of beds as denominator. While their approach may be regarded as better justified, the post-1999 data do not allow computing capital book value for each hospital.

potentially endogenous variables. To incorporate geographic and socio-economic regional differences we include dichotomous variables for geographic zones of Japan: Hokkaido, Tohoku, Kanto, Kinki, Chugoku, Shikoku and Kyushu. Chubu zone, which contains the largest number of local public hospitals, is treated as a reference category. Annual dummies (using 2006 as a reference category) capture time effects (Table 2).

4.3 The reform effect

We use dichotomous variables for each of the two reforms: introduction of the PPS by the beginning of the financial year or participation in the JRMP in the autumn of the preceding year, so that residents would join the hospital in the analyzed financial year. Both reforms are considered endogenous. Indeed, theoretical analysis and empirical evidence suggest that the payment schedule of the Japanese prospective payment system links hospital's voluntary decision about an introduction of this remuneration mechanism to the marginal costs and length of stay, and the latter may be associated with hospital's productive efficiency (Besstremyannaya, 2014, 2011). Similarly, the participation in the residency matching program requires fulfillment of certain criteria, which may be considered endogenous to hospital's production and technology (e.g. capacities of each department, research infrastructure, use of of clinical pathology reports, presence of qualified supervisors). Moreover, self-selection may arise owing to hospital's potential use of each of the reforms as a signaling tool to attract patients, or as means to enhance data management and promote treatment standardization.

Our hypothesis assumes that the short-run influence of the reforms on hospital output comes primarily through labor returns. Further, we expect differential effect of the reforms in the top and bottom quantiles of output. Indeed, the early outcomes of the prospective payment system in Japan show that managerial efforts in cost containment are primarily related to enhancing labor productivity (e.g. through evidence-based management, early administering of pre-scheduled tests, Higuchi (2010), Hisamichi (2010)). Heterogeneity of the expected effect may be linked to perverse incentives within a step-wise payment schedule. The output of the best performing hospitals may decrease, since these hospitals do not bear any financial loss for increasing their length of stay up to the benchmark value. Longer length of stay with fully utilized capacities implies fewer discharges.

As for the residency matching program, the presence of trainees may help to refine labor division, thus increasing labor returns and raising production. These refinements may lead to efficient use of other medical specialties, such as technicians (Kimbell and Lorant (1977)). However, the effect may be less strong (or even opposite) in the most productive hospitals, which may invest in human capital of the trainees, sacrificing potentially lost output. At the same time, the least productive hospitals may not be able to effectively allocate residents, which might lead to negative effect of the reform on labor returns.

We are unable to include both reform dichotomous variables and corresponding labor-reform interaction terms owing to multicollinearity. Consequently, we consider specifications with dichotomous variables for the reforms and with interaction terms separately. The first lag of each reform is used as its instrument in the first specification. Since an interaction term is a factor of the reform, we take each lagged interaction term as an instrument in the second specification.

Table 2: **Descriptive statistics for subsample of acute-care local public hospitals in 2006-2012**

Variable	**Definition**	**Mean**	**Std.Dev.**	**Min**	**Max**
Outputs					
discharges	mean number of inpatient admissions and discharges	3238.6	3418.6	7.8	17781.1
outpatients	number of outpatients	141721.5	113701.7	365	724160
Inputs					
labor	number of employees	197.4	179.3	1	955
capital	depreciable fixed capital: building and equipment	4118	5097	1.3	42700
drugs	expenditure on medicines and medical materials	830	1019	0.019	6849
Reform participation					
PPS	=1 if introduced inpatient PPS by the beginning of the financial year	0.18	0.38	0	1
JRMP	=1 if participated in the JRMP in the autumn, preceding the financial year	0.27	0.44	0	1
Hospital variables					
designated	=1 if designated local hospital	0.04	0.18	0	1
accredited	=1 if given a third party accreditation of the Japan Council for Quality Healthcare by the beginning of the financial year	0.27	0.45	0	1
prefectural	=1 if governed by prefecture or designated prefectural city (with the rights of regional government)	0.21	0.41	0	1
urban	=1 if in the city, 0 if in town or village (chouson)	0.62	0.49	0	1
teach	=1 if has an affiliated college/nursery school	0.04	0.2	0	1
emergency	=1 if emergency hospital	0.86	0.35	0	1
nonprofit	=1 if in nonprofitable area	0.35	0.48	0	1
exam	mean number of examinations per patient	3.18	2	0	13.86
bed occupancy	bed occupancy rate, percent	69.88	16.86	0.9	103.2
beds	number of beds	190.71	150.07	20	810
Geographic regions					
Hokkaido	=1 if in Hokkaido prefecture	0.09	0.28	0	1
Tohoku	=1 if in Akita, Aomori, Fukushima, Iwate, Miyagi or Yamagata prefecture	0.16	0.36	0	1
Kanto	=1 if in Gunma, Tochigi, Ibaraki, Saitama, Tokyo, Chiba or Kanagawa prefecture	0.14	0.35	0	1
Kinki	=1 if Shiga, Kyoto, Osaka, Hyogo, Nara or Wakayama prefecture	0.18	0.39	0	1
Chugoku	=1 if Tottori, Shimane, Okayama, Hiroshima or Yamaguchi prefecture	0.08	0.28	0	1
Shikoku	=1 if Tokushima, Kagawa, Ehime or Kochi prefecture	0.05	0.21	0	1
Kyushu	=1 if Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima or Okinawa prefecture	0.11	0.31	0	1
Chubu	=1 if Niigata, Toyama, Ishikawa, Fukui, Yamanashi, Nagano, Gifu, Shizuoka, Aichi or Mie prefecture (the region is a reference category)	0.19	0.39	0	1

Notes: Total number of observations in the unbalance panel is 2310. The values of all variables are given on the annual basis. Financial variables in million yen. By law, the number of beds in Japanese hospitals may not be less than 20.

The status of designated local hospital and 10,000 yen per each admission is given to a hospital which: 1) has over 200 beds; 2) the share of patients referred from other facilities is over 60%; 3) shares its beds and expensive equipment (e.g. MRI, CT scanner) with other hospitals; 4) educates local health care officials; 5) has an emergency status.

A hospital in a non-profitable area: 1) has fewer than 100 beds (since 2009, relaxed to 150 beds) or fewer than 100 inpatients a day in the previous year; 2) the number of outpatients a day was less than 200 in the previous year; 3) there is at most only one other general hospital in the local municipal area or in the area of 300 sq. kilometers (relaxed to "the distance to another general hospital is over 15 kilometers, or another general hospital exists in other locality".)

5 Results

5.1 Factor returns and the reform effect

For ease of interpretation, the results are presented in terms of quantiles q for log output y_M, so higher values of q correspond to higher output quantiles. Here $q = 1 - \tau$, as the original computations deal with $-\ln y_M|\tau$, where lower values of τ are associated with higher productivity. Similarly, all coefficients discussed in this section are negative values of the original coefficients for the explanatory variables, estimated according to the equation (14).

As regards the consistent estimation of the fixed effect panel data model, the first-stage regressions show high values of overall F–statistics (above 40) and the significance of each corresponding reform lag in explaining the particular reform or interaction term (See Appendix A). This may be interpreted as absence of weak instrument problem in view of the approach used by Stock et al. (2002). Comparison of the random effects and fixed effects models for each quantile with the Hausman test, shows that the values of the test statistics are extremely low (Table 3).[18] This may signal the absence of correlation between the fixed effects and the error term. Nonetheless, we here present the results for the fixed effect specification, since we believe it to be justified on economic grounds. Formally, the negative values of the test statistics, which we obtain in more than half of the models, may be interpreted as an inconclusive outcome of the Hausman test (Schreiber (2008)). Moreover, owing to the close values of coefficients for the explanatory variables, our interpretation below is valid for the estimates in any model.

We discover three main results concerning heterogeneity of factor returns. Firstly, there is a negative relation between returns to labor and technology. Returns to labor are the highest in quantiles with the lowest output, and they gradually decrease as we move towards the top quantiles. The coefficient for log *labor* is significant in all output quantiles. Secondly, the relation between returns to capital and technology is positive: higher capital returns are found in quantiles with the highest output. Moreover, the log *capital* coefficient is insignificant in low-output quantiles. Medicines are a significant input for all output quantiles, with a U-shape relationship between returns to medicines and hospital capacity. Thirdly, there is a negative link between scale returns and technology. The decreasing returns to scale, which are observed in the top quantiles, gradually increase to unity (i.e. constant returns) in the bottom quantiles (Figure 1). The three results extend the findings with nursing facilities in the 0.8–0.95 quantile interval (Knox et al. (2007)) and with the hotel industry in the quantiles above the median (Bernini et al. (2004)). Our estimated values for returns to scale corresponds to the results of the literature with frontier methods (Besstremyannaya (2011)).

The values of labor returns (0.5–0.75) and capital returns (0.05–0.1) fall in the range of estimates made by earlier hospital studies with mean least-squares methodology (Conrad et al. (2002), Pauly (1980), Kimbell and Lorant (1977)).

The optimal share of labor costs in total costs calculated as the ratio of labor returns to returns to scale is in the range of (0.80–0.85) for low and medium output-hospitals both in the model with the reform dichotomous variables and with interaction terms (denoted as *share* in Tables 3–4). Relatively lower labor shares, which vary from 0.67 to 0.75 are observed only for most productive hospitals: $q \in 0.85, 0.90, 0.95$. These values are still higher than the recommended benchmark by the Ministry of Internal Affairs and Communications: the share of labor costs in medical revenues should not exceed 50%. However, our estimates may be upwards biased owing to inability of including other hospital outputs in the production function.

The dichotomous variable for the residency matching program in our first specification is positively significant for all quantiles, with slightly lower effect in low-output quantiles. The interaction term of the residency matching program and labor in the second specification is also positively significant for all quantiles,

[18]So the difference between the estimated coefficients in the random effects and fixed effects models is negligible.

and has smaller values not only in the low output quantiles but also in the highest output quantile (Figure 2). The reason for relatively smaller value of the reform and labor interaction term in the top quantile may be greater emphasis on teaching activities. In other words, while in most hospitals residents perform the usual duties of physicians, hospitals with the highest output may be able to afford using physician and nurse time on educating trainees, so the productivity of teaching personnel may decrease (Jensen and Morrisey (1986). Overall, the positive relation between technology and the effect of the residency matching program proves the prime importance of the efficient use of labor input in hospital production.

The dichotomous variable for the prospective payment system is insignificant. This may be explained by a trade-off between the length of stay and the readmission rate in Japanese prospective payment system hospitals, where the length of total hospitalization remained the same (Besstremyannaya (2014)). The interaction term between the prospective payment system and labor is negatively significant for top quantiles: $q \in [0.75, 0.95]$. This relates to the disincentive in the stepdown tariff, where the benchmark value for per diem reimbursement is established at the 25-th percentile of the nationwide length of stay. So when the best-performing hospitals in the top quantiles of output (and also in the lowest quantiles of length of stay) join the reform, they may increase their length of stay with resulting deterioration of labor productivity.

The specification with labor-reform interaction terms allows computing labor elasticity, given the participation in the JRMP, PPS or both reforms as the sum of coefficient for the $\log labor$ and corresponding interaction term(s). Similarly, we estimate scale returns for the JRMP, PPS or both JRMP and PPS-participant hospitals adding this labor elasticity to the coefficients for $\log capital$ and $\log drugs$ (Figure 3). We discover that the JRMP increases labor and scale returns for all quantiles, while the PPS has a negative effect on labor and scale returns for hospitals in the high- and low-output quantiles. The effect of the JRMP is stronger in the absolute terms, so the net effect of participation in the two reforms is positive. Note that confidence intervals for labor and scale returns in presence/absence of the reform(s) are wide and overlap, so the influence of the reform(s) is statistically insignificant.

Annual dummies are positively significant for the fiscal year 2010 and negatively significant for 2011. This finding corresponds to a sharp increase of output in 2010, according to the 2010 revision of the national fee schedule, and a slight decrease in 2011, owing to an adjustment effect, since the fees are established on a biennial basis. It should be noted that the average value for medical fees in the fee schedule has been decreasing since 2002. However, the 2010 revision was an exception to this rule. As well as raising the average value for all fees, the schedule increased the fees for acute care hospitals (Ikegami (2014)), which may have resulted in increased profits starting from the 2010 fiscal year. Indeed, the share of non-deficit local public hospitals rose from 30% in 2009 to 54% in 2010, and higher unit prices for inpatient/outpatient care are noted as major factors for improvement of business performance (Yano Research Institute (2012)).

The proxies for case mix index are significant mainly in the top-output quantiles, indicating the importance of controlling for variation in diagnoses for hospitals with the largest capacities. As regards geographic differences, dichotomous variables are positively significant for top-output hospitals in the Tokyo metropolitan area and for medium- and low-output hospitals in Shikoku. The significance is negative for low-output quantiles of hospitals in Kanto, Kinki and Chugoku.

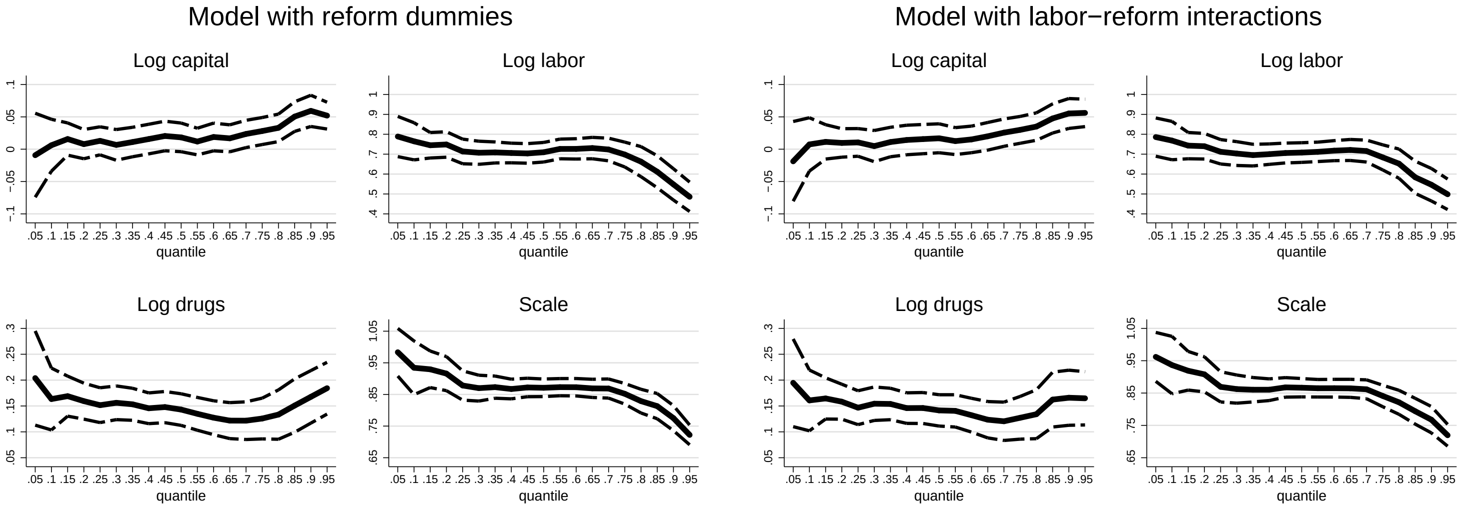

Figure 1: **Coefficients and 95% confidence intervals for factor and scale returns for various quantiles in the two models**
Note: Scale is the sum of coefficients for log capital, log labor and log drugs.

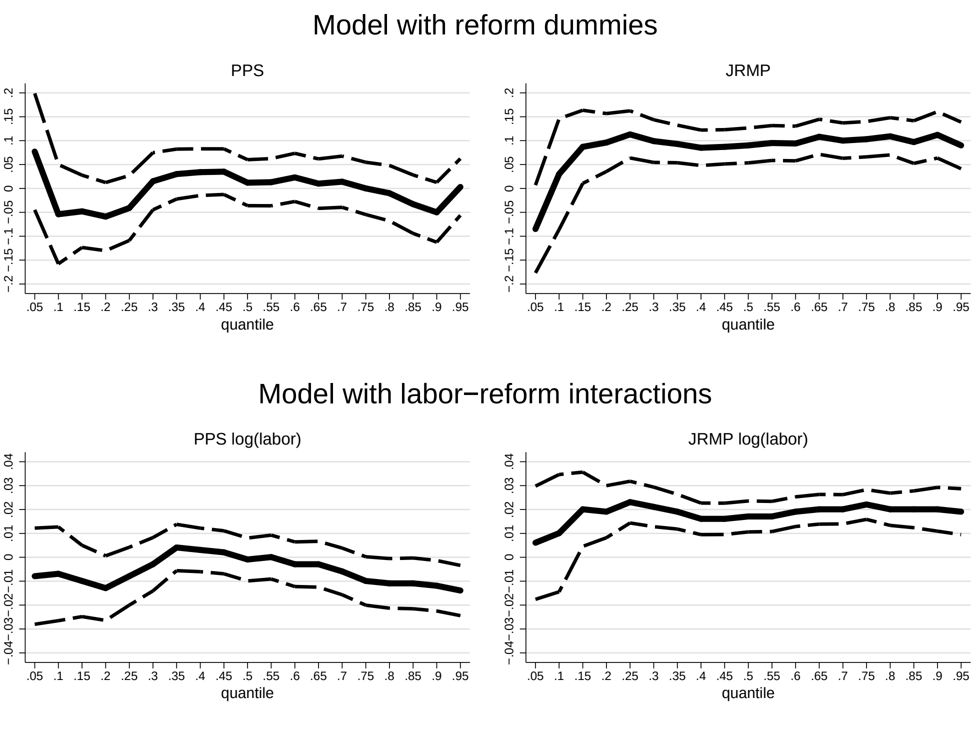

Figure 2: **Coefficients and 95% confidence intervals for the reform variables for various quantiles in the two models**

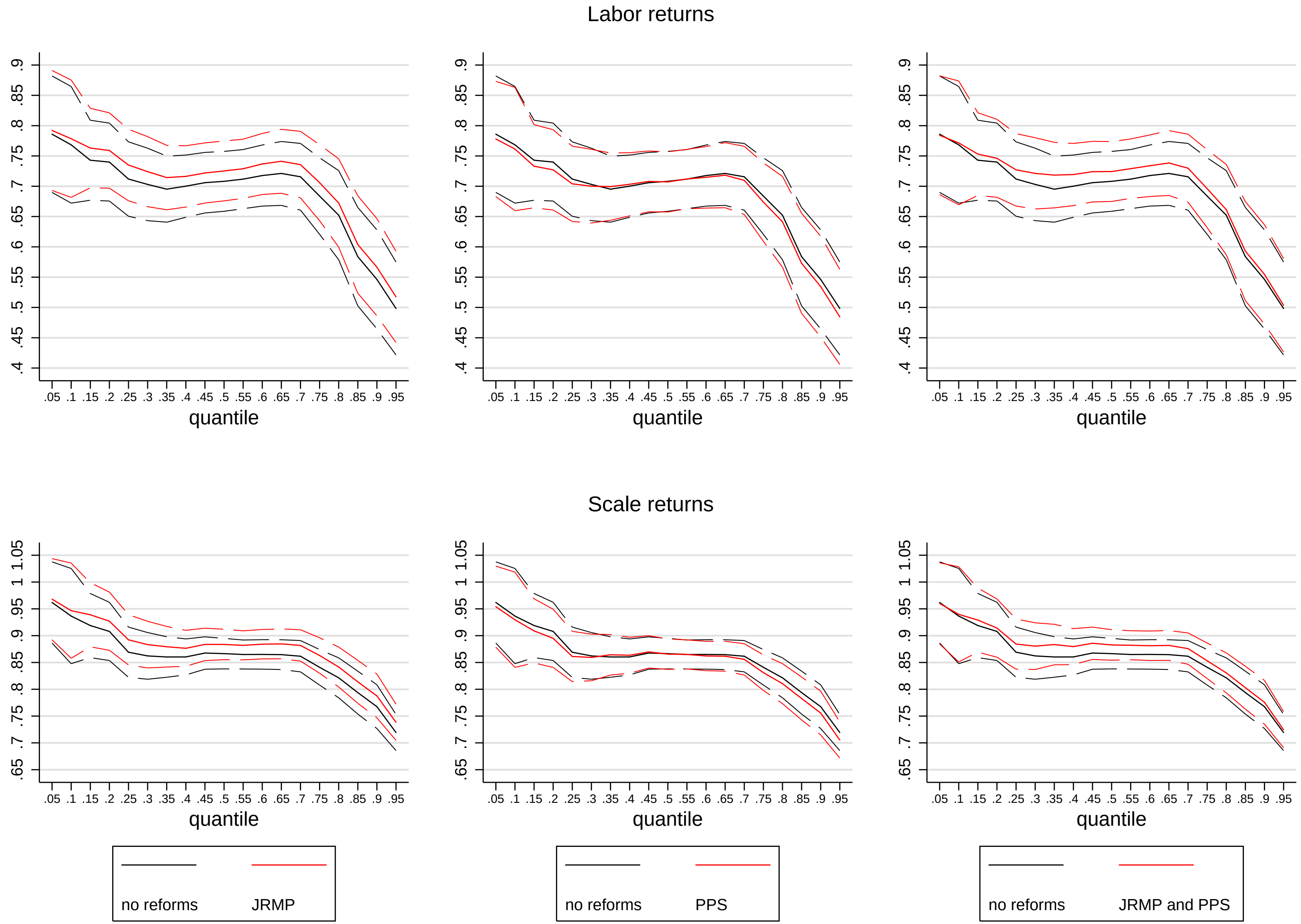

Figure 3: **Coefficients and 95% confidence intervals for labor and scale returns under participation and non-participation in the reforms for various quantiles, model with labor-reforms interactions**

Table 3: **Coefficients for the explanatory variables in quantile regressions, model with reform dummies**

quantile	**0.95**	**0.9**	**0.85**	**0.8**	**0.75**	**0.7**	**0.65**	**0.6**	**0.55**	**0.5**	**0.45**	**0.4**	**0.35**	**0.3**	**0.25**	**0.2**	**0.15**	**0.1**	**0.05**
PPS	0.0031	-0.0499	-0.0329	-0.0099	0.0001	0.0141	0.0101	0.0231	0.0131	0.0121	0.0351	0.0341	0.0301	0.0151	-0.0409	-0.0589	-0.0479	-0.0539	0.0771
	(0.0303)	(0.0319)	(0.0312)	(0.0296)	(0.0279)	(0.0273)	(0.0264)	(0.0257)	(0.0252)	(0.0245)	(0.0243)	(0.0249)	(0.0267)	(0.0305)	(0.0347)	(0.0364)	(0.0386)	(0.053)	(0.0622)
JRMP	0.0901***	0.1121***	0.0971***	0.1091***	0.1031***	0.1001***	0.1081***	0.0941***	0.0951***	0.0901***	0.0871***	0.0851***	0.0931***	0.0991***	0.1131***	0.0961***	0.0871***	0.0301	-0.0849
	(0.0249)	(0.0248)	(0.0228)	(0.0199)	(0.0189)	(0.0189)	(0.0187)	(0.0185)	(0.0186)	(0.0186)	(0.0183)	(0.0189)	(0.02)	(0.0228)	(0.0252)	(0.0309)	(0.039)	(0.0592)	(0.0469)
$\log y_1/y_2$	-0.3364***	-0.3731***	-0.4122***	-0.4625***	-0.4833***	-0.4968***	-0.4994***	-0.5118***	-0.5244***	-0.5187***	-0.521***	-0.5264***	-0.5341***	-0.5281***	-0.5546***	-0.5938***	-0.6227***	-0.6802***	-0.6685***
	(0.0278)	(0.0344)	(0.0328)	(0.0313)	(0.0286)	(0.0279)	(0.0272)	(0.0258)	(0.025)	(0.0242)	(0.0241)	(0.0242)	(0.0262)	(0.0297)	(0.0332)	(0.0323)	(0.0314)	(0.0555)	(0.0402)
log labor	0.4857***	0.5482***	0.6118***	0.6625***	0.6982***	0.7236***	0.7307***	0.7267***	0.7264***	0.7098***	0.7038***	0.706***	0.7088***	0.7071***	0.7138***	0.7487***	0.7448***	0.7648***	0.7889***
	(0.0377)	(0.0402)	(0.041)	(0.0385)	(0.0319)	(0.029)	(0.0274)	(0.0261)	(0.0252)	(0.0251)	(0.0251)	(0.0251)	(0.0269)	(0.0296)	(0.0316)	(0.0327)	(0.0327)	(0.0476)	(0.0516)
log capital	0.0519***	0.0593***	0.0504***	0.033***	0.0281***	0.0236***	0.0168*	0.0189	0.0119	0.0183	0.0205	0.0157	0.0111	0.0067	0.013	0.0078	0.0157	0.0061	-0.0093
	(0.0106)	(0.0123)	(0.0117)	(0.0108)	(0.0106)	(0.0108)	(0.0106)	(0.0109)	(0.0105)	(0.0113)	(0.0117)	(0.0117)	(0.0116)	(0.0121)	(0.011)	(0.0115)	(0.0127)	(0.0205)	(0.0331)
log drugs	0.1844***	0.1677***	0.1509***	0.1334***	0.1258***	0.1216***	0.1218***	0.1274***	0.1349***	0.1431***	0.1479***	0.1456***	0.1533***	0.1562***	0.1516***	0.1594***	0.169***	0.1635***	0.204***
	(0.0255)	(0.0259)	(0.0263)	(0.0243)	(0.0201)	(0.0186)	(0.0177)	(0.0167)	(0.0162)	(0.0156)	(0.0154)	(0.0152)	(0.0158)	(0.0166)	(0.0172)	(0.0177)	(0.0197)	(0.0305)	(0.0464)
designated	-0.03	-0.0216	-0.0206	-0.021	-0.0317	-0.0377	-0.0459	-0.0471	-0.0518	-0.0537	-0.087	-0.0792**	-0.06**	-0.0479	-0.0066	0.0007	0.0256	-0.0313	-0.2004
	(0.0258)	(0.0276)	(0.028)	(0.0293)	(0.0302)	(0.0317)	(0.032)	(0.0338)	(0.0348)	(0.0344)	(0.0355)	(0.0363)	(0.0338)	(0.0376)	(0.0386)	(0.042)	(0.0421)	(0.1215)	(0.1527)
accredited	-0.065*	-0.0497*	-0.0206	-0.0109	-0.0061	-0.0045	-0.0082	-0.0222	-0.0166	-0.0036	-0.0091	-0.001	0.0027	0.006	0.0241	0.0496	0.0978*	0.2211***	0.2977***
	(0.0227)	(0.0227)	(0.0189)	(0.0172)	(0.0163)	(0.016)	(0.0156)	(0.0154)	(0.0154)	(0.0156)	(0.0161)	(0.0166)	(0.0178)	(0.0202)	(0.0242)	(0.0306)	(0.039)	(0.0567)	(0.0588)
prefectural	0.0384	0.0049	-0.038*	-0.061***	-0.0882***	-0.0909***	-0.1016***	-0.0963***	-0.0922***	-0.1041***	-0.1025***	-0.1181***	-0.128***	-0.137***	-0.1675***	-0.2079***	-0.2364***	-0.344***	-0.4539***
	(0.019)	(0.0195)	(0.0194)	(0.0188)	(0.0171)	(0.0165)	(0.0161)	(0.0164)	(0.0166)	(0.0181)	(0.0189)	(0.021)	(0.0227)	(0.0259)	(0.032)	(0.0413)	(0.0517)	(0.0924)	(0.1106)
urban	-0.0099**	0.0115	-0.0205	-0.0183	-0.0258	-0.0264	-0.0348	-0.0201	-0.0136	-0.0091	-0.0137	-0.0122	-0.0134	-0.0072	-0.0168	-0.0061	-0.0146	0.0048	-0.0062
	(0.0194)	(0.0211)	(0.0211)	(0.0208)	(0.0204)	(0.0203)	(0.0198)	(0.0193)	(0.0194)	(0.0195)	(0.0196)	(0.0201)	(0.0206)	(0.0221)	(0.0235)	(0.0259)	(0.0255)	(0.0366)	(0.0429)
teaching	-0.0483***	-0.0385***	-0.044*	-0.0326*	-0.0421*	-0.0429***	-0.0476***	-0.0316	-0.0257	-0.032	-0.0353*	-0.0363*	-0.0458*	-0.0275	-0.0268	-0.0059	-0.0372	0.0031	-0.0142
	(0.0194)	(0.0193)	(0.0204)	(0.0201)	(0.0196)	(0.0196)	(0.0196)	(0.0196)	(0.02)	(0.0203)	(0.0203)	(0.0207)	(0.0213)	(0.0223)	(0.0232)	(0.0256)	(0.0263)	(0.0351)	(0.0432)
emergency	-0.0322***	-0.0286*	-0.0457*	-0.0279	-0.0314	-0.0428	-0.0376*	-0.0235	-0.0184	-0.0135	-0.023	-0.0238	-0.0292	-0.0149	-0.0123	0.0057	-0.0156	0.0261	-0.0148
	(0.0226)	(0.0218)	(0.0226)	(0.022)	(0.0209)	(0.0207)	(0.0207)	(0.0206)	(0.021)	(0.0216)	(0.0218)	(0.0225)	(0.0236)	(0.0253)	(0.027)	(0.0286)	(0.029)	(0.0427)	(0.0484)
nonprofit	-0.0425**	-0.0226	-0.0462	-0.0261	-0.0278	-0.0437*	-0.0417*	-0.0316	-0.0163	-0.0132	-0.0264	-0.0301	-0.0297	-0.0348	-0.0212	0.005	-0.0176	0.0294	-0.0173
	(0.0226)	(0.0229)	(0.0237)	(0.0232)	(0.0223)	(0.0216)	(0.0215)	(0.0213)	(0.0218)	(0.0223)	(0.0228)	(0.0236)	(0.0245)	(0.0264)	(0.0277)	(0.0288)	(0.0298)	(0.0435)	(0.0511)
exam	-0.0344***	-0.0196	-0.042	-0.0321	-0.0417	-0.0564	-0.0657**	-0.0439	-0.0296	-0.0236	-0.0307	-0.0327	-0.036	-0.0357	-0.0143	-0.002	-0.0313	-0.0002	-0.0404
	(0.0225)	(0.0227)	(0.0242)	(0.0242)	(0.0233)	(0.0229)	(0.0224)	(0.0221)	(0.0223)	(0.0224)	(0.0228)	(0.0236)	(0.0247)	(0.0266)	(0.0278)	(0.0304)	(0.0325)	(0.0479)	(0.0516)
BO	0.0042***	0.0038***	0.0032***	0.0037***	0.0036***	0.0037***	0.0041***	0.0045***	0.0046***	0.0044***	0.0048***	0.0051***	0.005***	0.0053***	0.0053***	0.0056***	0.0055***	0.0051***	0.0038***
	(0.0007)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0008)	(0.0012)
year2007	-0.0514***	-0.028	-0.0579*	-0.0502	-0.0614	-0.0731***	-0.0778***	-0.0608**	-0.0375	-0.038	-0.0541***	-0.0607***	-0.0534*	-0.0397	-0.0454	-0.024	-0.0615	-0.033	-0.0828
	(0.0228)	(0.0238)	(0.0248)	(0.0244)	(0.0237)	(0.0233)	(0.0229)	(0.0225)	(0.0229)	(0.0233)	(0.0237)	(0.0244)	(0.0253)	(0.0267)	(0.0292)	(0.0324)	(0.0374)	(0.0541)	(0.0562)
year2008	-0.0178	-0.0234	-0.0287***	-0.046***	-0.0366***	-0.0306***	-0.0347***	-0.0234**	-0.0232	-0.0306*	-0.0238	-0.0288	-0.0267*	-0.0124	-0.0127	0.0004	-0.0256	-0.0405	-0.0459
	(0.0161)	(0.0157)	(0.0156)	(0.0154)	(0.0153)	(0.0152)	(0.0151)	(0.0148)	(0.0149)	(0.0152)	(0.0151)	(0.0155)	(0.0162)	(0.0175)	(0.019)	(0.0205)	(0.0234)	(0.0362)	(0.0518)
year2009	-0.0556	-0.0362	-0.0404	-0.0092	-0.0261	-0.0402	-0.0462	-0.0654**	-0.072*	-0.059*	-0.1025***	-0.0817***	-0.0774***	-0.0798***	-0.0661***	-0.0487**	-0.0265	0.0268	0.0222
	(0.0275)	(0.0331)	(0.0322)	(0.0358)	(0.0347)	(0.0335)	(0.0327)	(0.0329)	(0.0328)	(0.0325)	(0.0277)	(0.0282)	(0.0263)	(0.0263)	(0.0266)	(0.0286)	(0.0314)	(0.0382)	(0.0642)

Table 3: **Coefficients for the explanatory variables in quantile regressions, model with reform dummies**

quantile	**0.95**	**0.9**	**0.85**	**0.8**	**0.75**	**0.7**	**0.65**	**0.6**	**0.55**	**0.5**	**0.45**	**0.4**	**0.35**	**0.3**	**0.25**	**0.2**	**0.15**	**0.1**	**0.05**
year2010	0.1479***	0.1649***	0.2302***	0.2405***	0.238***	0.2447***	0.2656***	0.2767***	0.2899***	0.3152***	0.3203***	0.33***	0.3311***	0.3512***	0.3353***	0.3171***	0.282***	0.3307***	0.4449***
	(0.0451)	(0.0467)	(0.0326)	(0.0271)	(0.0245)	(0.0242)	(0.025)	(0.0264)	(0.0271)	(0.0277)	(0.0277)	(0.0293)	(0.031)	(0.0342)	(0.0358)	(0.0414)	(0.0467)	(0.0901)	(0.0896)
year2011	-0.1014***	-0.0798***	-0.0607***	-0.0868***	-0.0984***	-0.0765***	-0.0748***	-0.083***	-0.0928***	-0.0989***	-0.0841***	-0.0846***	-0.0886***	-0.0925***	-0.0992***	-0.0777**	-0.0662	-0.1761***	-0.1556***
	(0.0226)	(0.0228)	(0.0221)	(0.0221)	(0.0208)	(0.0199)	(0.019)	(0.0185)	(0.0188)	(0.0193)	(0.0201)	(0.0213)	(0.0231)	(0.0259)	(0.0297)	(0.0388)	(0.0435)	(0.0564)	(0.0717)
year2012	-0.018***	-0.0119**	-0.0074	-0.0057	-0.0039	-0.0024	-0.0014	-0.0001	0.001	0.0029	0.0066	0.0088	0.0062	0.0039	0.0069	0.0036	0.0015	-0.0066	-0.0317***
	(0.0054)	(0.0053)	(0.0052)	(0.0049)	(0.0047)	(0.0046)	(0.0044)	(0.0043)	(0.0043)	(0.0043)	(0.0041)	(0.0042)	(0.0045)	(0.0049)	(0.0052)	(0.0055)	(0.0058)	(0.0079)	(0.0092)
Hokkaido	-0.0063	0.0192	0.0499	0.021	0.0504	0.0273	0.0173	0.0055	-0.0001	-0.0006	0.0045	-0.016	-0.0202	-0.0481	-0.0795	-0.1065	-0.1451***	-0.0453	-0.053
	(0.0264)	(0.0299)	(0.0323)	(0.0309)	(0.0315)	(0.031)	(0.0305)	(0.0301)	(0.03)	(0.0304)	(0.0312)	(0.0344)	(0.0378)	(0.0452)	(0.0509)	(0.0553)	(0.054)	(0.0649)	(0.0884)
Tohoku	-0.085***	-0.0293	-0.0354	-0.037	-0.014	-0.008	-0.0077	-0.0115	-0.0042	0.0012	0.0126	0.0067	0.0195	0.0057	-0.0019	-0.0154	-0.0113	0.0239	0.0104
	(0.0214)	(0.0237)	(0.0217)	(0.0213)	(0.0203)	(0.0201)	(0.0197)	(0.0196)	(0.0196)	(0.02)	(0.0195)	(0.0201)	(0.021)	(0.0216)	(0.0233)	(0.0245)	(0.0246)	(0.0325)	(0.049)
Kanto	0.0352***	0.0492***	0.0218	-0.0126	-0.0223	-0.0446**	-0.0443**	-0.0587***	-0.062***	-0.0551***	-0.0611**	-0.0597***	-0.0829***	-0.1148***	-0.1458***	-0.1814***	-0.1852***	-0.1362*	-0.3187***
	(0.0234)	(0.026)	(0.0265)	(0.0235)	(0.0219)	(0.0209)	(0.0203)	(0.0208)	(0.0214)	(0.0221)	(0.0233)	(0.0246)	(0.029)	(0.0348)	(0.0408)	(0.0452)	(0.0497)	(0.0747)	(0.1477)
Kinki	-0.0082	0.0056	-0.0051	-0.0449	-0.0514**	-0.0527**	-0.0513**	-0.0595***	-0.0501***	-0.0413***	-0.0369**	-0.0348*	-0.0264**	-0.0371*	-0.0229	-0.0324*	-0.0276*	-0.0317	-0.039
	(0.0181)	(0.0193)	(0.0207)	(0.0207)	(0.0199)	(0.0197)	(0.0192)	(0.0185)	(0.0181)	(0.0177)	(0.0165)	(0.0165)	(0.0171)	(0.0179)	(0.0199)	(0.0219)	(0.0238)	(0.0316)	(0.0365)
Chugoku	-0.1594***	-0.1331***	-0.1016***	-0.0941***	-0.0753***	-0.0886***	-0.0971***	-0.1047***	-0.1092***	-0.1068***	-0.1116***	-0.112***	-0.102***	-0.1232***	-0.1203***	-0.1755***	-0.2103***	-0.2113***	-0.5535***
	(0.0225)	(0.0233)	(0.0245)	(0.025)	(0.0244)	(0.024)	(0.0238)	(0.0232)	(0.0231)	(0.0235)	(0.0241)	(0.025)	(0.0266)	(0.0293)	(0.0328)	(0.0482)	(0.0542)	(0.0741)	(0.1804)
Shikoku	-0.0536*	0.0076	0.0163	0.0253	0.0528**	0.0614	0.0789***	0.0831***	0.0722***	0.0813***	0.1098***	0.0829***	0.0809***	0.084***	0.0991***	0.1161***	0.1112***	0.1525***	0.1869***
	(0.0245)	(0.0269)	(0.0258)	(0.0271)	(0.027)	(0.0273)	(0.0279)	(0.0286)	(0.0296)	(0.0304)	(0.0305)	(0.0327)	(0.0328)	(0.0328)	(0.0343)	(0.0361)	(0.0377)	(0.0461)	(0.0478)
Kyushu	-0.0565	-0.0295	-0.0016	0.0077	0.0169	0.0211	0.0075	-0.0115	-0.007	0.0048	0.0079	0.0076	0.0113	-0.0022	0.0193	0.0452	0.043	0.0497	-0.043
	(0.0266)	(0.0276)	(0.0277)	(0.027)	(0.0255)	(0.0253)	(0.0252)	(0.0244)	(0.0241)	(0.0244)	(0.0242)	(0.0244)	(0.026)	(0.0273)	(0.0308)	(0.033)	(0.035)	(0.0515)	(0.0585)
Constant	4.7694***	4.3221***	4.1426***	4.1031***	3.9877***	3.8821***	3.8617***	3.6564***	3.5603***	3.4254***	3.2724***	3.2884***	3.1961***	3.1881***	2.988***	2.5781***	2.2609***	2.0443***	1.6437***
	(0.2437)	(0.2899)	(0.2419)	(0.2338)	(0.2262)	(0.2327)	(0.2387)	(0.2398)	(0.2385)	(0.2323)	(0.2289)	(0.2305)	(0.2456)	(0.2671)	(0.2899)	(0.3174)	(0.3275)	(0.5207)	(0.4498)
RTS	0.7221***	0.7752***	0.8131***	0.8289***	0.8521***	0.8688***	0.8693***	0.8729***	0.8731***	0.8711***	0.8722***	0.8673***	0.8732***	0.87***	0.8784***	0.9159***	0.9296***	0.9344***	0.9836***
	(0.0159)	(0.02)	(0.0202)	(0.0189)	(0.0164)	(0.0153)	(0.0145)	(0.0139)	(0.0137)	(0.014)	(0.0148)	(0.0157)	(0.0177)	(0.0206)	(0.0234)	(0.0272)	(0.0292)	(0.0428)	(0.038)
share	0.6727***	0.7072***	0.7524***	0.7992***	0.8194***	0.8329***	0.8406***	0.8325***	0.8320***	0.8148***	0.8070***	0.8141***	0.8117***	0.8128***	0.8127***	0.8174***	0.8013***	0.8185***	0.8021***
	(0.0426)	(0.0402)	(0.0372)	(0.0342)	(0.0277)	(0.0252)	(0.0239)	(0.023)	(0.0222)	(0.022)	(0.0215)	(0.0211)	(0.0214)	(0.0222)	(0.0224)	(0.0223)	(0.0229)	(0.0329)	(0.0435)
PseudoR2	0.7209	0.7314	0.7369	0.7396	0.7387	0.7364	0.7362	0.7299	0.7264	0.7268	0.73	0.7427	0.7554	0.7549	0.749	0.7324	0.727	0.6817	0.5857
Hausman	0.0012	-0.0055	0.0002	0.0001	-0.0022	0.0482	-0.0071	-0.0114	-0.0371	-0.0402	-0.0085	0.0073	0.0103	-0.0019	0.0022	-0.0068	0.0001	0.0003	-0.0003

Notes: The dependent variable is $log(outpatients)$. $\log y_1/y_2$ is log (discharged/outpatients), BO denotes "bed occupancy", RTS abbreviates returns to scale, which equal to the sum of coefficients for $\log labor$, $\log capital$ and $\log drugs$, $share$ is coefficient for $\log labor$ over RTS.
$PseudoR2$ is the Koenker and Machado (1999) R-squared, $Hausman$ is the statistics in Hausman (1978) test with the null hypothesis of the random effects model.
Robust standard errors (calculated for RTS and $share$ using delta method) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Coefficients for the explanatory variables in quantile regressions, model with labor-reform interaction terms**

quantile	**0.95**	**0.9**	**0.85**	**0.8**	**0.75**	**0.7**	**0.65**	**0.6**	**0.55**	**0.5**	**0.45**	**0.4**	**0.35**	**0.3**	**0.25**	**0.2**	**0.15**	**0.1**	**0.05**
PPS·loglabor	-0.0139***	-0.0119**	-0.0109**	-0.0109**	-0.0099*	-0.0059	-0.0029	-0.0029	0.0001	-0.0009	0.0021	0.0031	0.0041	-0.0029	-0.0079	-0.0129*	-0.0099	-0.0069	-0.0079
	(0.0054)	(0.0054)	(0.0054)	(0.0053)	(0.0052)	(0.005)	(0.0049)	(0.0048)	(0.0047)	(0.0046)	(0.0046)	(0.0046)	(0.0049)	(0.0057)	(0.0062)	(0.0069)	(0.0076)	(0.01)	(0.0103)
JRMP·loglabor	0.0191***	0.0201***	0.0201***	0.0201***	0.0221***	0.0201***	0.0201***	0.0191***	0.0171***	0.0171***	0.0161***	0.0161***	0.0191***	0.0211***	0.0231***	0.0191***	0.0201***	0.0101	0.0061
	(0.0049)	(0.0047)	(0.0039)	(0.0034)	(0.0032)	(0.0031)	(0.0032)	(0.0032)	(0.0032)	(0.0033)	(0.0033)	(0.0034)	(0.0037)	(0.0042)	(0.0045)	(0.0056)	(0.0079)	(0.0125)	(0.0121)
log y_1/y_2	-0.3308***	-0.3713***	-0.408***	-0.4466***	-0.4746***	-0.4967***	-0.4979***	-0.5045***	-0.5189***	-0.52***	-0.5184***	-0.5217***	-0.5357***	-0.5289***	-0.5502***	-0.5933***	-0.6081***	-0.6781***	-0.6774***
	(0.0295)	(0.0346)	(0.0324)	(0.0312)	(0.0291)	(0.0279)	(0.0271)	(0.026)	(0.0249)	(0.0241)	(0.0239)	(0.0248)	(0.0267)	(0.0304)	(0.0326)	(0.0322)	(0.0328)	(0.0571)	(0.0413)
log labor	0.4984***	0.5463***	0.5839***	0.6523***	0.6839***	0.7157***	0.7212***	0.7177***	0.7118***	0.7081***	0.7059***	0.7002***	0.6953***	0.7031***	0.712***	0.74***	0.743***	0.7684***	0.786***
	(0.0391)	(0.0417)	(0.0414)	(0.0375)	(0.0322)	(0.0281)	(0.0269)	(0.0257)	(0.0249)	(0.0252)	(0.0255)	(0.0262)	(0.0278)	(0.0305)	(0.0313)	(0.0328)	(0.0337)	(0.0491)	(0.049)
log capital	0.0562***	0.0552***	0.0476***	0.035***	0.0299***	0.0256***	0.02*	0.0152	0.0125	0.0169	0.0156	0.0143	0.0111	0.0048	0.0105	0.0097	0.0114	0.0074	-0.0188
	(0.0108)	(0.0118)	(0.0115)	(0.0108)	(0.0106)	(0.0108)	(0.0109)	(0.0105)	(0.0106)	(0.0114)	(0.0115)	(0.0116)	(0.0116)	(0.0123)	(0.0109)	(0.0112)	(0.0136)	(0.021)	(0.0314)
log drugs	0.1649***	0.166***	0.1624***	0.1341***	0.1272***	0.1204***	0.1235***	0.1322***	0.1406***	0.1415***	0.1461***	0.1459***	0.1539***	0.1544***	0.1467***	0.1583***	0.1646***	0.1608***	0.1948***
	(0.0263)	(0.0272)	(0.027)	(0.0241)	(0.0211)	(0.0189)	(0.0179)	(0.0167)	(0.0159)	(0.0155)	(0.0153)	(0.0151)	(0.0155)	(0.0165)	(0.0167)	(0.0172)	(0.0203)	(0.03)	(0.0432)
designated	-0.0067	-0.0158	-0.0033	-0.001	-0.019	-0.0295	-0.0385	-0.0452	-0.0444	-0.0539	-0.0506	-0.0834**	-0.0727**	-0.0436	-0.012	-0.0003	0.0138	-0.0627	-0.1007
	(0.0264)	(0.0298)	(0.0311)	(0.0323)	(0.0332)	(0.0329)	(0.0335)	(0.0348)	(0.0354)	(0.0357)	(0.0352)	(0.0369)	(0.0352)	(0.0379)	(0.0375)	(0.0424)	(0.0481)	(0.1461)	(0.1501)
accredited	-0.0462*	-0.0408*	-0.0131	-0.0085	-0.0055	0.0001	-0.0009	-0.0047	-0.0097	0.0036	0.0044	0.0109	0.0051	0.0138	0.0131	0.038	0.0807*	0.1875***	0.2617***
	(0.024)	(0.0227)	(0.0193)	(0.0171)	(0.0159)	(0.0154)	(0.0152)	(0.0151)	(0.0151)	(0.0154)	(0.0157)	(0.0163)	(0.0173)	(0.0198)	(0.022)	(0.0287)	(0.0421)	(0.0662)	(0.0765)
prefectural	0.032	0.0081	-0.0368*	-0.0544***	-0.0719***	-0.0951***	-0.1002***	-0.0932***	-0.0996***	-0.1108***	-0.1172***	-0.1195***	-0.1234***	-0.1352***	-0.1759***	-0.2033***	-0.2306***	-0.3302***	-0.4581***
	(0.0195)	(0.0202)	(0.0198)	(0.0187)	(0.0176)	(0.0165)	(0.0165)	(0.0166)	(0.0171)	(0.0184)	(0.0195)	(0.021)	(0.0224)	(0.0261)	(0.0313)	(0.0395)	(0.0523)	(0.0979)	(0.1086)
urban	-0.0447**	-0.0078	-0.0159	-0.0122	-0.0208	-0.032	-0.0357*	-0.0271	-0.0142	-0.0083	-0.0179	-0.0133	-0.0194	-0.0117	-0.0104	-0.0016	-0.0034	0.0019	0.0026
	(0.0228)	(0.0221)	(0.0218)	(0.0213)	(0.0206)	(0.0206)	(0.0201)	(0.0195)	(0.0196)	(0.0195)	(0.0196)	(0.0202)	(0.021)	(0.0224)	(0.023)	(0.0256)	(0.026)	(0.0387)	(0.0392)
teaching	-0.0806***	-0.056***	-0.0371*	-0.0373*	-0.0376*	-0.0533***	-0.0497***	-0.0323	-0.0269	-0.0377*	-0.0357	-0.0386*	-0.0379*	-0.0246	-0.028	-0.005	-0.0252	0.005	-0.0147
	(0.0232)	(0.0208)	(0.0212)	(0.0204)	(0.0196)	(0.0196)	(0.0197)	(0.0197)	(0.02)	(0.0204)	(0.0203)	(0.0207)	(0.0213)	(0.0222)	(0.0227)	(0.0249)	(0.0263)	(0.0355)	(0.041)
emergency	-0.0507**	-0.0408*	-0.0397*	-0.031	-0.02	-0.0409**	-0.0366*	-0.0271	-0.0198	-0.0099	-0.0143	-0.0175	-0.0235	-0.0114	-0.0116	-0.0033	-0.0165	0.0129	0.0231
	(0.0258)	(0.0228)	(0.0223)	(0.0215)	(0.0207)	(0.0205)	(0.0204)	(0.0201)	(0.0202)	(0.0207)	(0.0209)	(0.0217)	(0.0227)	(0.0242)	(0.0251)	(0.0271)	(0.0285)	(0.0403)	(0.043)
nonprofit	-0.0593**	-0.0366	-0.0312	-0.0154	-0.0028	-0.041*	-0.0392*	-0.0277	-0.0087	-0.0136	-0.0274	-0.0245	-0.0302	-0.021	-0.0198	0.0062	-0.0061	0.0325	0.0642
	(0.0258)	(0.0239)	(0.0241)	(0.0237)	(0.023)	(0.0219)	(0.0217)	(0.0216)	(0.0218)	(0.0224)	(0.0229)	(0.0236)	(0.0245)	(0.0264)	(0.0274)	(0.0289)	(0.0309)	(0.0436)	(0.0493)
exam	-0.0586**	-0.0345	-0.0333	-0.023	-0.0229	-0.0465	-0.0528	-0.0353	-0.0335	-0.0196	-0.0305	-0.0306	-0.0265	-0.0267	-0.0132	0.0093	-0.0276	0.0016	-0.0017
	(0.0256)	(0.0238)	(0.0245)	(0.0245)	(0.0239)	(0.0234)	(0.0228)	(0.0225)	(0.0224)	(0.0226)	(0.0229)	(0.0239)	(0.0247)	(0.0268)	(0.0276)	(0.0295)	(0.0337)	(0.0481)	(0.0548)
BO	0.0041***	0.004***	0.0034***	0.0037***	0.0036***	0.0036***	0.004***	0.0044***	0.0045***	0.0045***	0.0048***	0.0049***	0.005***	0.0051***	0.0054***	0.0056***	0.0056***	0.0048***	0.0045***
	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0009)	(0.0013)
year2007	-0.0709***	-0.0408	-0.0435	-0.0352	-0.035	-0.062***	-0.0706***	-0.0516**	-0.0383*	-0.0296	-0.0559***	-0.0575***	-0.0483*	-0.0365	-0.033	-0.0092	-0.0434	-0.0342	-0.0297
	(0.0261)	(0.025)	(0.0254)	(0.0253)	(0.0247)	(0.0238)	(0.0231)	(0.0229)	(0.023)	(0.0234)	(0.0238)	(0.0246)	(0.0252)	(0.0269)	(0.0283)	(0.031)	(0.0379)	(0.0539)	(0.0582)
year2008	-0.0169	-0.0278	-0.0383***	-0.0411***	-0.0389***	-0.036***	-0.0385***	-0.0288*	-0.023	-0.0295*	-0.0236	-0.0281*	-0.0272*	-0.0243	-0.0144	-0.0054	-0.038	-0.0446	-0.0265
	(0.0163)	(0.016)	(0.0158)	(0.0157)	(0.0156)	(0.0154)	(0.0153)	(0.0151)	(0.015)	(0.0153)	(0.0153)	(0.0157)	(0.0162)	(0.0175)	(0.0183)	(0.0194)	(0.024)	(0.0366)	(0.0547)
year2009	-0.0433***	-0.0328***	-0.0335***	-0.029***	-0.0269***	-0.0323***	-0.0418***	-0.07***	-0.065*	-0.0623*	-0.0863***	-0.0856***	-0.0869***	-0.0823***	-0.0731***	-0.0603**	-0.0258	0.0288	0.0497
	(0.029)	(0.0336)	(0.0332)	(0.0352)	(0.036)	(0.0343)	(0.0341)	(0.0339)	(0.0333)	(0.0326)	(0.0296)	(0.0275)	(0.0261)	(0.0258)	(0.0259)	(0.0284)	(0.0312)	(0.0387)	(0.0536)

Table 4: **Coefficients for the explanatory variables in quantile regressions, model with labor-reform interaction terms**

quantile	**0.95**	**0.9**	**0.85**	**0.8**	**0.75**	**0.7**	**0.65**	**0.6**	**0.55**	**0.5**	**0.45**	**0.4**	**0.35**	**0.3**	**0.25**	**0.2**	**0.15**	**0.1**	**0.05**
year2010	0.1457***	0.176***	0.2341***	0.2406***	0.2484***	0.2477***	0.2601***	0.2744***	0.2847***	0.3018***	0.3142***	0.3336***	0.3365***	0.3436***	0.3262***	0.3046***	0.2987***	0.3372***	0.4503***
	(0.0455)	(0.0452)	(0.0329)	(0.0272)	(0.0242)	(0.0237)	(0.0249)	(0.0263)	(0.0269)	(0.0277)	(0.0285)	(0.0302)	(0.0313)	(0.0339)	(0.0351)	(0.0391)	(0.0574)	(0.0888)	(0.0873)
year2011	-0.1146	-0.086	-0.0843	-0.0997	-0.1026	-0.0902	-0.0803	-0.0879	-0.0933	-0.099	-0.0849	-0.0942	-0.1033	-0.1002	-0.1091	-0.0837	-0.0682	-0.1622	-0.2063
	(0.024)	(0.0231)	(0.0225)	(0.0218)	(0.0207)	(0.0199)	(0.0188)	(0.0187)	(0.0187)	(0.0193)	(0.0202)	(0.022)	(0.0237)	(0.0273)	(0.0297)	(0.0378)	(0.0455)	(0.0585)	(0.0746)
year2012	-0.0159***	-0.0122**	-0.0088	-0.0063	-0.0053	-0.0033	-0.0026	-0.001	0.0022	0.0033	0.005	0.0087**	0.0056	0.0041	0.0073	0.0053	-0.0007	-0.0051	-0.0268
	(0.0056)	(0.0056)	(0.0054)	(0.0051)	(0.0048)	(0.0045)	(0.0044)	(0.0044)	(0.0043)	(0.0042)	(0.0041)	(0.0043)	(0.0044)	(0.0049)	(0.005)	(0.0053)	(0.0062)	(0.0078)	(0.0092)
Hokkaido	0.0244	0.0421	0.0391	0.0364	0.0373	0.0254	0.0026	0.002	0.0005	-0.0033	-0.0028	-0.0208	-0.0268	-0.0452	-0.0842	-0.1048**	-0.1521***	-0.0488	-0.0294
	(0.027)	(0.031)	(0.0319)	(0.0311)	(0.0316)	(0.0315)	(0.0307)	(0.0299)	(0.0302)	(0.0306)	(0.0317)	(0.035)	(0.0375)	(0.0444)	(0.0514)	(0.0534)	(0.0538)	(0.0659)	(0.0843)
Tohoku	-0.0635***	-0.0289	-0.0396*	-0.0277	-0.0136	-0.0049	-0.0143	-0.0121	-0.0087	-0.0002	0.0096	0.009	0.0115	0.0091	0.0061	-0.0045	-0.0119	0.0288	0.0194
	(0.0217)	(0.0238)	(0.0224)	(0.0216)	(0.021)	(0.02)	(0.0197)	(0.0197)	(0.0196)	(0.0199)	(0.0197)	(0.0202)	(0.0207)	(0.022)	(0.0232)	(0.0239)	(0.0252)	(0.0334)	(0.0473)
Kanto	0.0718***	0.0641***	0.0191	-0.0084	-0.0275	-0.0411**	-0.0466***	-0.0588***	-0.0601***	-0.0541***	-0.0449**	-0.0603***	-0.0916***	-0.1137***	-0.1425***	-0.1839***	-0.1721***	-0.1244*	-0.3313***
	(0.0256)	(0.0272)	(0.0264)	(0.0232)	(0.0212)	(0.0204)	(0.0202)	(0.0205)	(0.0212)	(0.0222)	(0.0227)	(0.0258)	(0.0308)	(0.0362)	(0.0397)	(0.0442)	(0.0519)	(0.0718)	(0.1402)
Kinki	0.0345*	0.0162	-0.0009	-0.0186	-0.0412**	-0.0421**	-0.0448**	-0.0478***	-0.0507***	-0.0433***	-0.0348**	-0.0275*	-0.0358**	-0.0298*	-0.0184	-0.0377*	-0.0414*	-0.0252	-0.0116
	(0.0204)	(0.0198)	(0.0211)	(0.0205)	(0.02)	(0.0193)	(0.0193)	(0.0188)	(0.0183)	(0.0178)	(0.0167)	(0.0164)	(0.0168)	(0.018)	(0.0189)	(0.0214)	(0.0244)	(0.032)	(0.0316)
Chugoku	-0.1491***	-0.1289***	-0.1081***	-0.093***	-0.0812***	-0.0891***	-0.0967***	-0.1104***	-0.1076***	-0.1071***	-0.1126***	-0.1064***	-0.1118***	-0.1273***	-0.1247***	-0.1699***	-0.2113***	-0.2048***	-0.5817***
	(0.0221)	(0.0238)	(0.0252)	(0.0249)	(0.0247)	(0.0239)	(0.0238)	(0.0231)	(0.023)	(0.0234)	(0.0239)	(0.0248)	(0.0267)	(0.0306)	(0.0332)	(0.0466)	(0.0549)	(0.0781)	(0.1574)
Shikoku	-0.0387	-0.0003	0.0114	0.0229	0.0437	0.0571***	0.0697***	0.0744***	0.0745***	0.0717***	0.093***	0.0806***	0.0735**	0.0891***	0.0927***	0.1117***	0.0972***	0.1545***	0.175***
	(0.0246)	(0.0267)	(0.0266)	(0.0269)	(0.0271)	(0.0276)	(0.028)	(0.0285)	(0.0298)	(0.0308)	(0.0315)	(0.0325)	(0.0323)	(0.033)	(0.034)	(0.0354)	(0.0381)	(0.0469)	(0.0523)
Kyushu	-0.0415	-0.0243	-0.0022	0.0091	0.0135	0.0256	0.0103	-0.0092	-0.0149	0.0008	0.0066	0.0092	0.0028	0.0084	0.019	0.0433	0.0282	0.0612	0.0001
	(0.0262)	(0.0281)	(0.0285)	(0.0266)	(0.0251)	(0.025)	(0.0253)	(0.0248)	(0.0243)	(0.0245)	(0.0242)	(0.0245)	(0.0257)	(0.0275)	(0.0302)	(0.0322)	(0.0361)	(0.0513)	(0.0595)
Constant	4.9383***	4.4105***	4.1793***	4.1734***	4.0345***	3.9132***	3.8609***	3.7299***	3.5782***	3.4673***	3.3822***	3.3589***	3.2465***	3.2708***	3.1165***	2.6207***	2.4389***	2.0554***	1.7776***
	(0.2421)	(0.286)	(0.2457)	(0.2383)	(0.2347)	(0.2385)	(0.2422)	(0.2416)	(0.2366)	(0.2334)	(0.2317)	(0.2362)	(0.2552)	(0.2802)	(0.2909)	(0.3196)	(0.3442)	(0.5325)	(0.4185)
RTS	0.7194***	0.7675***	0.7939***	0.8214***	0.8410***	0.8617***	0.8646***	0.8650***	0.8649***	0.8665***	0.8676***	0.8604***	0.8603***	0.8623***	0.8692***	0.9080***	0.9189***	0.9366***	0.9620***
	(0.0172)	(0.0208)	(0.0204)	(0.019)	(0.0169)	(0.0149)	(0.0142)	(0.014)	(0.0138)	(0.0145)	(0.0154)	(0.0171)	(0.0193)	(0.0222)	(0.0239)	(0.0277)	(0.0305)	(0.0453)	(0.0386)
share	0.6928***	0.7118***	0.7355***	0.7941***	0.8132***	0.8305***	0.8341***	0.8297***	0.8230***	0.8172***	0.8136***	0.8138***	0.8082***	0.8154***	0.8191***	0.8150***	0.8085***	0.8204***	0.8170***
	(0.0434)	(0.0415)	(0.0387)	(0.0336)	(0.0287)	(0.0251)	(0.0241)	(0.0228)	(0.0221)	(0.022)	(0.0216)	(0.0213)	(0.0216)	(0.0225)	(0.022)	(0.0218)	(0.0243)	(0.0325)	(0.0401)
ϵ_{jrmp}	0.5175***	0.5664***	0.604***	0.6724***	0.7060***	0.7358***	0.7413***	0.7368***	0.7289***	0.7252***	0.7220***	0.7163***	0.7144***	0.7242***	0.7351***	0.7591***	0.7631***	0.7785***	0.7921***
	(0.0384)	(0.0409)	(0.041)	(0.0372)	(0.032)	(0.028)	(0.0269)	(0.0257)	(0.0249)	(0.0252)	(0.0253)	(0.0258)	(0.0271)	(0.0295)	(0.0301)	(0.0317)	(0.0335)	(0.0494)	(0.0505)
ϵ_{pps}	0.4845***	0.5344***	0.573***	0.6414***	0.674***	0.7098***	0.7183***	0.7148***	0.7119***	0.7072***	0.708***	0.7033***	0.6994***	0.7002***	0.7041***	0.7271***	0.7331***	0.7615***	0.7781***
	(0.0400)	(0.0425)	(0.0421)	(0.0382)	(0.0330)	(0.0287)	(0.0274)	(0.0259)	(0.025)	(0.0253)	(0.0256)	(0.0266)	(0.0283)	(0.0310)	(0.0317)	(0.0338)	(0.035)	(0.0519)	(0.0485)
$\epsilon_{jrmp\&pps}$	0.5036***	0.5545***	0.5931***	0.6615***	0.6961***	0.7299***	0.7384***	0.7339***	0.7290***	0.7243***	0.7241***	0.7194***	0.7185***	0.7213***	0.7272***	0.7462***	0.7532***	0.7716***	0.7842***
	(0.0393)	(0.0418)	(0.0417)	(0.0380)	(0.0328)	(0.0286)	(0.0273)	(0.0259)	(0.0250)	(0.0252)	(0.0255)	(0.0262)	(0.0276)	(0.0300)	(0.0305)	(0.0328)	(0.0348)	(0.0521)	(0.0500)
PseudoR2	0.7156	0.7272	0.734	0.7379	0.7364	0.7378	0.7365	0.729	0.7258	0.7264	0.7307	0.741	0.7542	0.7519	0.7498	0.7372	0.7265	0.6841	0.5951
Hausman	0.0001	-0.0087	0.0013	0.001	-0.0013	-0.0215	-0.008	0.0029	-0.0329	0.1615	0.0416	-0.0455	0.0013	0.001	0.0181	0.0006	0.0088	0.0001	0.00220

Notes: ϵ_{jrmp}, ϵ_{pps} and $\epsilon_{jrmp,pps}$ are returns to labor given the participation in the $JRMP$, PPS, or both the $JRMP$ and PPS respectively. Robust standard errors in parentheses (calculated using delta method for RTS, $share$ and labor returns, given reform participation). *** p<0.01, ** p<0.05, * p<0.1.

5.2 Efficiency values

As there is no general agreement in the literature about the value of the appropriate benchmark quantile, we measure residuals for several top-output quantiles, so $q \in \{0.80, 0.85, 0.90, 0.95\}$. The results demonstrate similar annual trends for mean inefficiency regardless of the choice of the benchmark quantile (Figure 4). The lowest inefficiency is on average associated with the introduction of the inpatient payment system (PPS). Hospitals, participating in the residency matching program (JRMP) have smaller average values of inefficiency than all remaining hospitals. The gap between the mean inefficiencies for hospitals with full and incomplete match decreased in 2010, as an immediate effect of the revision of the unified fee schedule. Yet, it further sharply increased in 2011 (Figure 5).

The data does not show the presence of scale economies for inefficiency scores both for rural and urban hospitals. Indeed, the plots of individual inefficiency against the number of hospitals beds reveal no pattern in terms of mean inefficiency or standard deviation for various capacities (Figure 6).

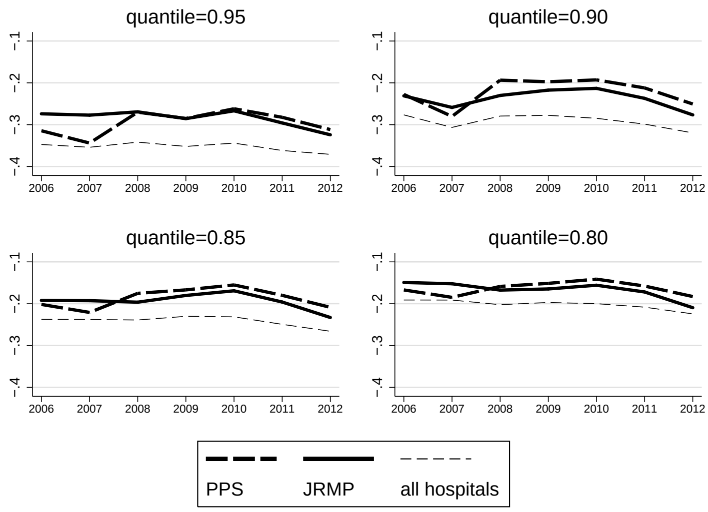

Figure 4: **Annual reform participation and mean output inefficiency (y-axis).**

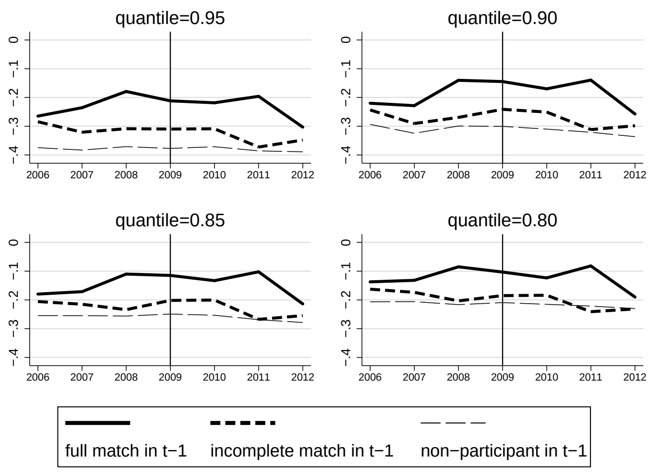

Figure 5: **Annual match of residents and mean output inefficiency (y-axis).**

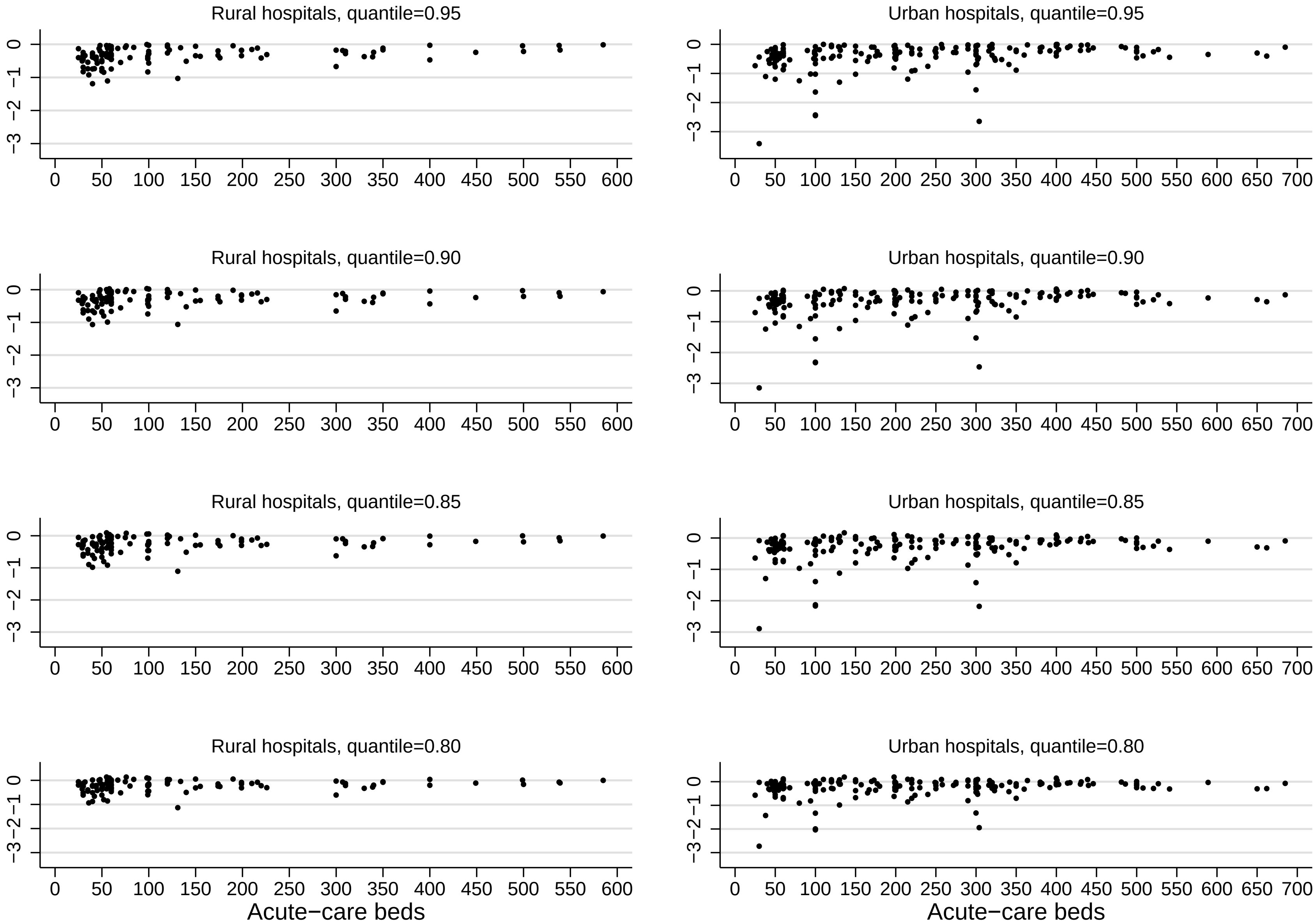

Figure 6: **Number of acute-care beds (x-axis) and output inefficiency (y-axis) of rural and urban local public hospitals in 2012.**

6 Discussion and Conclusion

The importance of measuring technological relationship has been constantly emphasized in the economic literature. Indeed, knowledge about factor substitution makes it possible to determine the shares of factor costs, which is crucial for various policy regulations aimed at promoting the optimal input mix (Douglas (1948), Shephard (1953), Pauly (1980)). The early estimations of the production function demonstrate substantial heterogeneity of producers, justifying the existence of a range of technologies both across and within industries. While a number of methods may be exploited to account for such heterogeneity (e.g. median regression or least-squares analyses by subgroups), the quantile regression approach gives more robust and accurate estimates, as it measures the output conditional on *all* covariates.

The quantile regression estimations of production functions in various industries are still limited. But the results of our study correspond to the findings with healthcare and hotel services on the negative relation between labor returns and output, while capital returns are positively associated with the output quantile (Knox et al. (2007), Bernini et al. (2004)). So, the more productive a hospital is, the more effectively it exploits capital relative to labor.

Lower returns to labor in high-output local public hospitals may be related to a higher degree of labor specialization, possibly owing to larger size of the local market size. The argument may be linked to the theory of local demand shifters of labor specialization in service industries, developed in Baumgardner (1988a) as an extension of the Stigler (1951) model on market size influence, and originally stemming from the seminal Adam Smith's theorem. The empirical proof for the hospital industry may be found in Baumgardner (1988b).[19]

The values for factor substitution across the output quantiles may be explained by the theory put forward by Zeira (1998) on association between technical progress and capital investment. According to this theory, increase in capital leads to the adoption of a new technology, so the marginal productivity of capital does not fall. Acemoglu and Autor (2011) extend this framework, allowing for an endogenous assignment of labor tasks, which may be linked to labor specialization.

Our findings, however, may be viewed as specific for service industries with labor-augmenting technologies. Indeed, estimations with the data for manufacturing firms show smaller values of the capital intensity coefficient (capital over by labor) in the higher quantiles of the dependent variable, which is measured as output over labor (Dimelis and Louri (2002)).

As regards heterogeneous impact of financing reforms, the effect of the change from fee-for-service to prospective payment is forecast to vary owing to unobservable firm heterogeneity. Although the existing theoretical papers model this heterogeneity through the cost function (Miraldo et al. (2011), Siciliani (2006), Laffont and Tirole (1993)), the duality approach explains that differential costs are essentially related to variations in technology (Shephard (1953)). Therefore, technological heterogeneity of hospital production may result in heterogeneous impact of prospective payment on output. Our empirical estimates confirm the presence of such heterogeneity: the negative impact of the switch from fee-for-service to a prospective payment system on hospital output is discovered for all quantiles, but it is only significant for the top 25 percentiles of the output. In the case of Japanese hospital financing reform this effect may be linked to the built-in differential stimuli within the step-wise prospective tariff. It should be noted that the decrease of output owing to prospective financing, found for Japanese acute-care hospitals, is similar to theoretical results of Custer et al. (1990) and to empirical findings about the negative impact of prospective schemes on hospital volume and the output of general practices (Devlin and Sarma (2008), Custer et al. (1990)).

[19] Additionally, Becker and Murphy (1994) state that the extent of labor specialization is explained by the balance between higher productivity (owing to the division of labor) and increased costs of labor coordination.

Teaching activity is likely to have differential impact on capital and labor productivity. Consequently, the net effect of teaching on a firm's output may be related to technology. Indeed, in the case of hospital production Jensen and Morrisey (1986) show a negative impact of residents on the productivity of labor specialists (e.g. doctor and nurses) and positive impact on the productivity of capital. Combined with our finding about lower elasticity of labor substitution in high output quantiles, we can conclude that the positive effect outweighs the negative, suggesting net positive impact from participation in the residency matching program. Moreover, the net impact is stronger in the higher output hospitals. An exception may be found in the highest quantiles, which invest in teaching, so the net effect becomes weaker. Another explanation of the negative results of teaching activity for the most productive hospitals could be our failure to include teaching as an additional output of hospitals involved in the residency matching (Jensen and Morrisey (1986)).

We should note several limitations of our analysis. Because consistent estimates cannot be obtained with an instrumental variable regression under multicollinearity, we employ total labor input, which does not enable the analysis of labor mix and returns to various labor specialties. We exploit hospital accreditation as a proxy for hospital quality, but inability to directly incorporate quality prevents us from assessing the quality-quantity tradeoff in evaluating the effect of prospective payment (Custer et al. (1990)). Moreover, the absence of healthcare quality variable biases the measurement of output and may lead to underestimation of the returns to labor and scale returns in hospitals with higher output (Dranove (1998)). Inability to observe the quality of labor may result in the underestimation of labor returns in high-output hospitals, where the human capital is likely to be relatively high. Similarly, the unavailability of casemix and the use of proxy variables permits only tentative conclusions about the estimated effects and does not enable the analysis of production heterogeneity for various diagnoses. The exclusion of non-acute care hospitals prevents generalization of the results to hospitals with other types of beds.

Finally, the results of this research are based exclusively on estimates of production function, which are considered to be only supplementary to cost efficiency measurement. So the interpretation of our findings in terms of policy implications would require analysis with the cost function (Knox et al. (2007)). Along with the data caveats for estimation of the cost function, unavailability of output prices (e.g., claim per discharge, claim per outpatient) precludes evaluation of economies of scope and allocative efficiency.

Appendix A Results of the first-stage regression

	Model 1		Model 2	
VARIABLES	JRMP	PPS	JRMP$\cdot \log labor$	PPS$\cdot \log labor$
$\log(discharged/outpatients)$	-0.0181	0.0901***	-0.0799	0.5044***
	(0.0119)	(0.0251)	(0.0645)	(0.1387)
$\log labor$	0.0070	0.0206	0.1667	0.2341
	(0.0189)	(0.0400)	(0.1017)	(0.2185)
$\log capital$	-0.0138**	-0.0206	-0.0765**	-0.1178
	(0.0062)	(0.0131)	(0.0334)	(0.0717)
$\log drugs$	-0.0071	-0.0247	-0.0594	-0.1187
	(0.0119)	(0.0252)	(0.0641)	(0.1376)
l.JRMP	0.4445***	0.0211		
	(0.0186)	(0.0395)		
l.PPS	-0.0222***	0.6560***		
	(0.0081)	(0.0171)		
l.(JRMP$\cdot \log labor$)			0.4124***	0.0006
			(0.0184)	(0.0395)
l.(PPS$\cdot \log labor$)			-0.0334***	0.6536***
			(0.0080)	(0.0171)
designated	0.0100	-0.0013	0.1183	0.0331
	(0.0181)	(0.0384)	(0.0979)	(0.2103)
accredited	-0.0094	0.1770***	-0.0217	0.9998***
	(0.0186)	(0.0395)	(0.1003)	(0.2155)
prefectural	0.0050	0.1362***	0.0280	0.6815**
	(0.0233)	(0.0494)	(0.1255)	(0.2696)
teaching	0.0107	-0.8280***	0.1768	-4.4479***
	(0.0956)	(0.2024)	(0.5137)	(1.1038)
emergency	-0.0114	0.0637	-0.0573	0.3223
	(0.0195)	(0.0414)	(0.1050)	(0.2255)
nonprofit	0.0006	0.0113	0.0039	0.0594
	(0.0088)	(0.0187)	(0.0474)	(0.1019)
exam	0.0003	0.0028	0.0091	0.0092
	(0.0031)	(0.0065)	(0.0166)	(0.0356)
bed occupancy	0.0004	-0.0009	0.0016	-0.0062*
	(0.0003)	(0.0006)	(0.0016)	(0.0035)
Constant	0.3257*	0.9193**	1.5545*	4.5188**
	(0.1728)	(0.3660)	(0.9312)	(2.0009)
Observations	2310	2310	2301	2301
R-squared	0.236	0.502	0.222	0.505
Number of hospitals	400	400	399	399
F-statistics	41.88	136.5	38.46	137.7

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

References

Abe, Y. (2007). The effectiveness of financial incentives in controlling the health care expenditures of seniors. *Japan and the World Economy*, 19(4):461–482.

Acemoglu, D. and Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, 4:1043–1171.

Aigner, D., Lovell, C., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, 6(1):21–37.

Aragon, Y., Daouia, A., and Thomas-Agnan, C. (2005). Nonparametric frontier estimation: a conditional quantile-based approach. *Econometric Theory*, 21:358–389.

Banker, R. D. (1984). Estimating most productive scale size using data envelopment analysis. *European Journal of Operational Research*, 17(1):35–44.

Baumgardner, J. R. (1988a). The division of labor, local markets, and worker organization. *The Journal of Political Economy*, 96(3):509–527.

Baumgardner, J. R. (1988b). Physicians' services and the division of labor across local markets. *The Journal of Political Economy*, 96(5):948–982.

Becker, E. R. and Sloan, F. A. (1985). Hospital ownership and performance. *Economic Inquiry*, 23(1):21–36.

Becker, G. S. and Murphy, K. M. (1994). The division of labor, coordination costs, and knowledge. In *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education (3rd Edition)*, pages 299–322. The University of Chicago Press.

Behr, A. (2010). Quantile regression for robust bank efficiency score estimation. *European Journal of Operational Research*, 200:568–581.

Bernini, C., Freo, M., and Gardini, A. (2004). Quantile estimation of production function. *Empirical Economics*, 29:373–381.

Berry, R. E. (1967). Returns to scale in the production of hospital services. *Health Services Research*, 2(2):123.

Besstremyannaya, G. (2011). Managerial performance and cost efficiency of Japanese local public hospitals. *Health Economics*, 20(S1):19–34.

Besstremyannaya, G. (2013). The impact of Japanese hospital financing reform on hospital efficiency. *Japanese Economic Review*, 64(3):337–362.

Besstremyannaya, G. (2014). The impact of Japanese hospital financing reform on hospital efficiency. *Health Economics*, doi:10.1002/hec.3128.

Bhattacharya, J., Vogt, W., Yoshikawa, A., and Nakahara, T. (1996). The utilization of outpatient medical services in Japan. *The Journal of Human Resources*, 31(2):450–476.

Braeutigam, R. R. and Daughety, A. F. (1983). On the estimation of returns to scale using variable cost functions. *Economics Letters*, 11(1):25–31.

Campbell, J. and Ikegami, N. (1998). *The Art of Balance in Health Policy. Maintaining Japan's Low-Cost, Egalitarian System.* Cambridge University Press: Cambridge.

Canay, I. (2011). A simple approach to quantile regression for panel data. *The Econometrics Journal*, 14(3):368–386.

Caves, D. W., Christensen, L. R., and Swanson, J. A. (1981). Productivity growth, scale economies, and capacity utilization in us railroads, 1955–74. *The American Economic Review*, pages 994–1002.

Cazals, C., Florens, J., and Simar, L. (2002). Nonparametric frontier estimation: a robust approach. *Journal of Econometrics*, 106:1–25.

Charnes, A., Cooper, W., and Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2:429–444.

Chernozhukov, V. and Hansen, C. (2004). Instrumental variable quantile regression. Working Paper, available at http://www.mit.edu/∼vchern.

Chernozhukov, V. and Hansen, C. (2006). Instrumental quantile regression inference for structural and treatment effect models. *Journal of Econometrics*, 132(2):491–525.

Chernozhukov, V. and Hansen, C. (2008). Instrumental variable quantile regression: A robust inference approach. *Journal of Econometrics*, 142(1):379–398.

Chidmi, B., Solís, D., and Cabrera, V. E. (2011). Analyzing the sources of technical efficiency among heterogeneous dairy farms: A quantile regression approach. *Journal of Development and Agricultural Economics*, 3(7):318–324.

Coelli, T. and Perelman, S. (2000). Technical efficiency of european railways: a distance function approach. *Applied Economics*, 32(15):1967–1976.

Conrad, D. A., Sales, A., Liang, S.-Y., Chaudhuri, A., Maynard, C., Pieper, L., Weinstein, L., Gans, D., and Piland, N. (2002). The impact of financial incentives on physician productivity in medical groups. *Health Services Research*, 37(4):885–906.

Custer, W. S., Moser, J. W., Musacchio, R. A., and Willke, R. J. (1990). The production of health care services and changing hospital reimbursement: the role of hospital–medical staff relationships. *Journal of Health Economics*, 9(2):167–192.

Devlin, R. A. and Sarma, S. (2008). Do physician remuneration schemes matter? The case of Canadian family physicians. *Journal of Health Economics*, 27(5):1168–1181.

Dimelis, S. and Louri, H. (2002). Foreign ownership and production efficiency: a quantile regression analysis. *Oxford Economic Papers*, 54(3):449–469.

Douglas, P. H. (1948). Are there laws of production? *The American Economic Review*, 38(1):1–41.

Dranove, D. (1998). Economies of scale in non-revenue producing cost centers: implications for hospital mergers. *Journal of Health Economics*, 17(1):69–83.

Färe, R. and Primont, D. (1995). *Multi-Output Production and Duality: Theory and Applications: Theory and Applications*. Kluwer Academic Publishers.

Farrar, D. E. and Glauber, R. R. (1967). Multicollinearity in regression analysis: the problem revisited. *The Review of Economic and Statistics*, pages 92–107.

Farrell, M. (1957). The measurement of productive efficiency. *Journal of Royal Statistical Society, Series A (General)*, 3:253–281.

Feldstein, M., Intriligator, M., and Kendrick, D. (1974). Econometric studies of health economics. *Frontiers of Quantitative Economics II, Vol. 2*.

Ferrier, G. D. and Valdmanis, V. (1996). Rural hospital performance and its correlates. *Journal of Productivity Analysis*, 7(1):63–80.

Fried, H. O., Lovell, C. K., and Schmidt, S. S. (2008). *The Measurement of Productive Efficiency and Productivity Growth*. Oxford University Press.

Fujii, A. (2001). Stochastic cost frontier and cost inefficiency of Japanese hospitals: a panel data analysis. *Applied Economics Letters*, 8:801–812.

Fujii, A. and Ohta, M. (1999). Stochastic cost frontier and cost inefficiency of Japanese hospitals: a panel data analysis. *Applied Economics Letters*, 6:527–532.

Galvao, A. (2011). Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics*, 164(1):142–157.

Gonçalves, R. and Barros, P. P. (2013). Economies of scale and scope in the provision of diagnostic techniques and therapeutic services in Portuguese hospitals. *Applied Economics*, 45(4):415–433.

Hadley, J. and Zuckerman, S. (1994). The role of efficiency measurement in hospital rate setting. *Journal of Health Economics*, 13(3):335–340.

Hallock, K. and Koenker, R. (2001). Quantile regression. *Journal of Economic Perspectives*, 15(4):143–156.

Hansen, K. K. and Zwanziger, J. (1996). Marginal costs in general acute care hospitals: a comparison among california, new york and canada. *Health Economics*, 5(3):195–216.

Harding, M. and Lamarche, C. (2009). A quantile regression approach for estimating panel data models using instrumental variables. *Economics Letters*, 104(3):133–135.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, pages 1251–1271.

Hefty, T. R. (1969). Returns to scale in hospitals: a critical review of recent research. *Health Services Research*, 4(4):267.

Higuchi, S. (2010). Chuusho jichitai byouin-no genjo-to kadai (current situation and tasks for small and medium local public hospitals). *Journal of Japan Hospital Association*, 5:95–101.

Hirose, M., Imanaka, Y., Ishizaki, T., and Evans, E. (2003). How can we improve the quality of health care in Japan? Learning from JCQHC hospital accreditation. *Health Policy*, 66:29–49.

Hisamichi, S. (2010). Byouin keiei koto hajime. byouin jigyou kanri-no tachiba kara. (starting hospital management. point of view of a hospital manager). *Journal of Japan Hospital Association*, 2:98–119.

Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health Economics*, 17:1107–1128.

Ikegami, N. (2014). *Universal Health Coverage for Inclusive and Sustainable Development: Lessons from Japan*. International Bank or Reconstruction and Development /The World Bank: Washington DC.

Ikegami, N. and Campbell, J. (1995). Medical care in Japan. *New England Journal of Medicine*, 133:1295–1299.

Ikegami, N. and Campbell, J. C. (1999). Health care reform in Japan: the virtues of muddling through. *Health Affairs*, 18(3):56–75.

Inoue, K. and Matsumoto, M. (2004). Japan's new postgraduate medical training system. *The Clinical Teacher*, 1(1):38–40.

Iwane, T. (1976). Wa-ga kuni-no kouritsu byouin-ni tsuite. Byouin koudou-no riron-to jisshotekikenkyu (on the public hospitals in Japan: a behavior model of hospitals and some empirical studies). *Osaka Economic Papers*, pages 35–54.

Japan Residency Matching Program (2013a). Byouinsuu, gakuseisuu, boshuuteiinsuu, mattingushasuu-no sui (heisei15nendo). (Dynamics of number of hospitals, graduates, vacancies and matched graduates since fiscal year 2003).

Japan Residency Matching Program (2013b). Kakonendo-no rinshoubyouin mattingu toukei. Daigakuin (shisetsubetsu)-niokeru jidaigakushusshinsha-no hiritsu (Previous year's matching statistics. Share of each medical school's students in affiliated university hospital).

Jensen, G. A. and Morrisey, M. A. (1986). Medical staff specialty mix and hospital production. *Journal of Health Economics*, 5(3):253–276.

Kamada, Y. and Kojima, F. (2010). Improving efficiency in matching markets with regional caps: The case of the Japan residency matching program. Discussion paper, Stanford Institute for Economic Policy Research.

Kawaguchi, H. (2008). *Iryono koritsusei sokutei. (Estimating Health Care Efficiency)*. Keisoushobou, Tokyo.

Kimbell, L. J. and Lorant, J. H. (1977). Physician productivity and returns to scale. *Health Services Research*, 12(4):367.

Knox, K., Blankmeyer, E., and Stutzman, J. (2007). Technical efficiency in Texas nursing facilities: a stochastic production frontier approach. *Journal of Economics and Finance*, 31(1):75–86.

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, 91(1):74–89.

Koenker, R. and Bassett, G. (1978). Regression quantiles. *Econometrica*, 46:33–50.

Koenker, R. and Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association*, 94(448):1296–1310.

Kondo, A. and Kawabuchi, K. (2012). Evaluation of the introduction of a diagnosis procedure combination system for patient outcome and hospitalisation charges for patients with hip fracture or lung cancer in Japan. *Health Policy*, 107:184–193.

Kondo, A. and Shigeoka, H. (2013). Effects of universal health insurance on healthcare utilization, and supply-side responses: evidence from Japan. *Journal of Public Economics*, 99:1–23.

Kooreman, P. (1994). Nursing home care in the Netherlands: a nonparametric efficiency analysis. *Journal of Health Economics*, 13(3):301–316.

Koutsomanoli-Filippaki, A. and Mamatzakis, E. (2011). Efficiency under quantile regression: What is the relationship in the EU banking industry? *Review of Financial Economics*, 20:84–95.

Kozu, T. (2006). Medical education in Japan. *Academic Medicine*, 81(12):1069–1075.

Kritzer, H. M. (1976). Problems in the use of two stage least squares: standardization of coefficients and multicollinearity. *Political Methodology*, pages 71–93.

Laffont, J. and Tirole, J. (1993). *A Theory of Incentives in Procurement and Regulation*. MIT Press.

Levin, J. (2001). For whom the reductions count: A quantile regression analysis of class size and peer effects on scholastic achievement. *Empirical Economics*, 26(1):221–246.

Linna, M. (1998). Measuring hospital cost efficiency with panel data models. *Health Economics*, 7(5):415–427.

Liu, C., Laporte, A., and Ferguson, B. S. (2008). The quantile regression approach to efficiency measurement: insights from Monte Carlo simulations. *Health Economics*, 17(9):1073–1087.

Lynk, W. J. (1995). The creation of economic efficiencies in hospital mergers. *Journal of Health Economics*, 14(5):507–530.

Mamatzakis, E., Koutsomanoli-Filippaki, A., and Pasiouras, F. (2012). A quantile regression approach to bank efficiency measurement. MPRA Paper 51879, Munich Personal RePEc Archive.

Ministry of Health, Labor and Welfare (2009). Rinshouseido-noarikata nado-nikansuru kentoukai (Study on the implementation of clinical training).

Ministry of Health, Labor and Welfare (2012). Kikangata rinshoukenshuu byouin-no shiteikijun-ni tsuite (On requirements for designated teaching hospitals).

Miraldo, M., Siciliani, L., and Street, A. (2011). Price adjustment in the hospital sector. *Journal of Health Economics*, 30(1):112–125.

Nawata, K. and Kawabuchi, K. (2013). Evaluation of the dpc-based inclusive payment system in Japan for cataract operations by a new model. *Mathematics and Computers in Simulation*, 93:76–85.

Nawata, K., Nitta, A., Watanabe, S., and Kawabuchi, K. (2006). An analysis of the length of stay and effectiveness of treatment for hip fracture patients in Japan: Evaluation of the 2002 revision of the medical service fee schedule. *Journal of Health Economics*, 25:722–739.

Newhouse, J. P. (1969). Toward a theory of non-profit institutions: An economic model of a hospital. Technical Report RAND-P-4022, RAND CORP Santa Monica CA.

Nomura, K., Yano, E., Aoki, M., Kawaminami, K., Endo, H., and Fukui, T. (2008a). Improvement of residents' clinical competency after the introduction of new postgraduate medical education program in Japan. *Medical Teacher*, 30(6):e161–e169.

Nomura, K., Yano, E., Mizushima, S., Endo, H., Aoki, M., Shinozaki, H., and Fukui, T. (2008b). The shift of residents from university to non-university hospitals in Japan: a survey study. *Journal of General Internal Medicine*, 23(7):1105–1109.

Okamura, S., Kobayashi, R., and Sakamaki, T. (2005). Case-mix payment in Japanese medical care. *Health Policy*, 74:282–286.

Olsen, K. R., Gyrd-Hansen, D., Sørensen, T. H., Kristensen, T., Vedsted, P., and Street, A. (2013). Organisational determinants of production and efficiency in general practice: a population-based study. *The European Journal of Health Economics*, 14(2):267–276.

Onishi, H. and Yoshida, I. (2004). Rapid change in Japanese medical education. *Medical teacher*, 26(5):403–408.

Ozcan, Y. A., Yeh, S.-C., McCollum, D., and Begun, J. W. (1996). Trends in labor efficiency among American hospital markets. *Annals of Operations Research*, 67(1):61–81.

Panzar, J. C. and Willig, R. D. (1977). Economies of scale in multi-output production. *The Quarterly Journal of Economics*, 91(3):481–493.

Pauly, M. (1980). *Doctors and Their Workshops: Economic Models of Physician Behavior*. University of Chicago Press, A National Bureau of Economic Research monograph.

Reinhardt, U. (1972). A production function for physician services. *The Review of Economics and Statistics*, 54(1):55–66.

Rosko, M. and Mutter, R. (2008). Stochastic frontier analysis of hospital inefficiency. a review of empirical issues and an assessment of robustness. *Medical Care Research and Review*, 65(2):131–166.

Sarma, S., Devlin, R. A., and Hogg, W. (2010). Physician's production of primary care in ontario, canada. *Health Economics*, 19(1):14–30.

Schreiber, S. (2008). The hausman test statistic can be negative even asymptotically. *Jahrbücher für Nationalökonomie und Statistik*, pages 394–405.

Shephard, R. (1970). *Theory of Cost and Production Functions*. Princeton University Press.

Shephard, R. W. (1953). Cost and production functions. In Beckmann, M. and Kunzi, H., editors, *Lecture Notes in Economics and Mathematical Systems*, Berlin Heidelberg New York. Springer-Verlag.

Shigeoka, H. (2014). The effect of patient cost sharing on utilization, health, and risk protection. *American Economic Review*, 104(7):2152–2184.

Shigeoka, H. and Fushimi, K. (2014). Supplier-induced demand for newborn treatment: Evidence from Japan. *Journal of Health Economics*, 35:162–178.

Siciliani, L. (2006). Selection of treatment under prospective payment systems in the hospital sector. *Journal of Health Economics*, 25(3):479–499.

Sipiläinen, T., Kumbhakar, S. C., and Lien, G. (2014). Performance of dairy farms in Finland and Norway from 1991 to 2008. *European Review of Agricultural Economics*, 41(1):63–86.

Sloan, F. A., Feldman, R. D., and Steinwald, A. B. (1983). Effects of teaching on hospital costs. *Journal of Health Economics*, 2(1):1–28.

Stigler, G. J. (1951). The division of labor is limited by the extent of the market. *The Journal of Political Economy*, 59:185–193.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4).

Takatsuka, N. and Nishimura, S. (2008). Oderingu shistemu ga byoinseisansei, kouristusei nioyobosu eikyono hyouka. (Effect of order entry system on hospital productivity and efficiency for inpatient care in Japan). *Japanese Journal of Health Economics and Policy*, 20(1):15–33.

Wheelock, D. and Wilson, P. (2009). Robust nonparametric quantile estimation of efficiency and productivity change in U.S. commercial banking, 1985-2004. *Journal of Busines & Economic Studies*, 27(3):354–368.

Wilson, P. W. and Carey, K. (2004). Nonparametric analysis of returns to scale in the US hospital industry. *Journal of Applied Econometrics*, 19(4):505–524.

Worthington, A. (2004). Frontier efficiency measurement in healthcare: a review of empirical techniques and selected applications. *Medical Care Research and Review*, 61(2):135–170.

Yamada, T., Yamada, T., Kim, C., and Noguchi, H. (1997). Efficiency and costs in hospitals: a stochastic frontier approach. Discussion Paper 748, University of Tsukuba, Institute of Policy and Planning Sciences.

Yano Research Institute (2012). National and public hospitals reform in Japan: key research findings 2012.

Zeira, J. (1998). Workers, machines, and economic growth. *Quarterly Journal of Economics*, 113:1091–1117.