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THE IMPACT OF JAPANESE HOSPITAL FINANCING REFORM ON HOSPITAL EFFICIENCY: A DIFFERENCE-IN-DIFFERENCE APPROACH

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With Japanese hospital financing reform, a prospective payment system (PPS) has been established for inpatient care to replace the traditional fee-for-service remuneration of hospitals. This paper evaluates the effect of the reform on technical and cost efficiency of local public hospitals. Efficiency is estimated non-parametrically using two-stage data envelopment analysis with bias correction through bootstrap, and parametrically applying stochastic frontier analysis. The descriptive analysis shows that efficiency declines after the introduction of PPS. Difference-in-difference estimations reveal that PPS results in a limited efficiency gain, which might be related to inadequate incentives created by the two-part PPS tariff in Japan.
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1. Introduction

A prevalent form of volume-based reimbursement (fee-for-service, FFS) in the health-care industry leads to induced demand, increasing the consumption of medical goods and services suggested to patients by physicians. The resulting overuse of resources exacerbates a financial conflict between government and health-care providers. The problem is addressed through the development of reimbursement policies, which create incentives for health-care providers to contain costs. In particular, adequate remuneration is dependent on identifying hospitals' products and determining reasonable costs of each product. This is accomplished with the help of diagnosis-related groups (DRG), developed in the 1960s by the Yale University Center for Health Studies as a system for describing hospital production (Fetter and Freeman, 1986). DRG classify patients into a restricted number of medically-justified groups, with a statistically stable distribution of resource consumption in each group (Thompson *et al*., 1979). Such classification is an integral part of the prospective payment system (PPS), a method of reimbursement that establishes fixed payments for a patient in a given DRG. The PPS is a powerful means to curb medical inflation and to contain consumer demand for health care, which became worldwide problems in the 1970s and 1980s. Piloted in New Jersey in the 1980s and then applied at all Medicare hospitals in the USA, this managerial innovation (Kimberly and de Pouvourville, 1993) has now been adopted all over the world.

While FFS reimbursement provides an incentive for physicians to render unnecessary medical services and overprescribe drugs, the PPS is designed to change the decision-making process that determines the amount of health care to be consumed (Christianson and Conrad, 2011). Specifically, the PPS sets up a fixed payment for each DRG. Therefore, a hospital runs a deficit when its actual cost of treating a given patient exceeds the payment for the corresponding DRG. This financial risk motivates cost control, which should result in efficient use of hospital resources (Thompson *et al*., 1979; Rosko and Mutter, 2008). In this context, several theoretical and empirical studies focus on inputs, outputs, profits and quality of product to discuss the effect of the PPS on health-care providers (Cutler and Zeckhauser, 2000; Dranove and Satterthwaite, 2000; Rosenberg and Browne, 2001). The predictions of the models of hospital behaviour and empirical evidence (Rosko and Broyles, 1988; Suthummanon and Omachonu, 2004) demonstrate that the PPS generally leads to a decrease in average length of stay (ALOS) and cost per day. However, theoretical expectations regarding the effect of the PPS on hospitals' efficiency, defined as the ability to produce a maximal amount of medical services with a given set of inputs (technical efficiency) or with minimal cost of these inputs (cost efficiency), are controversial. Obviously, a decrease in hospital costs under the PPS might be achieved by lowering the amount of resources and sacrificing the quality of services. However, differences in practice style between hospitals (Ellis and McGuire, 1996) and efficiency efforts by specific hospitals (Ma, 1998) are also important factors in the PPS. Examples of such efforts include shortening of diagnostic and tests procedures (Suwabe, 2004), investing in better equipment and improving organizational structure (Chalkley and Malcomson, 2000).

The present paper assesses the effect of the PPS reform on hospital efficiency in order to understand whether this remuneration mechanism achieves its initial goals. The paper provides a robust estimate of efficiency scores using non-parametric and parametric methods of frontier analysis. In particular, we apply Simar and Wilson's (2002) return-to-scale test to raise the precision in the measurement of the boundary of the production possibilities set in the non-parametric analysis.[1] It should be noted that country studies generally use only one measure of efficiency (i.e. parametric or non-parametric) and address efficiency at hospitals that have undergone the PPS reform (Cromwell and Pope, 1989; Dismuke and Sena, 1999; Sommersguter-Reichmann, 2000; Biorn *et al*., 2003; Barbetta *et al*., 2007). Yet, such analysis does not enable a comparison of the post-reform efficiency of PPS hospitals with the would-be efficiency of the same hospitals if they had not participated in the reform. If the PPS is only introduced at some hospitals, the effect on hospital efficiency can be analyzed using a difference-in-difference (DiD) approach by constructing a control group of non-reformed hospitals. The case of Japan, where hospitals have joined the PPS reform gradually, is suitable for such analysis. There has been a considerable amount of research offering parametric and non-parametric point estimates of efficiency in Japanese local public hospitals, and a few studies (Kawaguchi, 2008; Takatsuka and Nishimura, 2008; Besstremyannaya, 2011) find a trend towards a decline of cost efficiency. However, assessment of the inpatient PPS on the efficiency of Japanese hospitals focuses on the analysis of reformed hospitals (Kawaguchi *et al*., 2010).

The novelty of this paper is twofold. To the best of my knowledge, the present paper is the first attempt to modify Simar and Wilson's (2002) returns-to-scale test and Simar and Wilson's (1998) bias correction through bootstrap in order to apply them to Tone's (2002) cost efficiency analysis, when input prices vary among producers. Second, the paper evaluates the effect of the inpatient PPS on the technical and cost efficiency of Japanese local public hospitals using DiD estimations.

The descriptive analysis of efficiency scores shows a decline in efficiency after a changeover to the PPS. However, the time profiles of efficiency scores are similar in the PPS and FFS groups of hospitals. DiD estimations show that the PPS results in a limited efficiency gain. The findings reveal that the system of economic stimuli of the Japanese

[1] Simar and Wilson (2002) show that a false assumption about constant returns to scale may lead to inconsistent efficiency scores, and a false assumption about variable returns to scale may cause a loss in statistical efficiency.

inpatient PPS does not lead to efficiency improvement as an immediate effect of the reform. Arguably, the explanation is related to inadequate incentives due to the composition of the two-part PPS tariff.

The remainder of the paper is structured as follows. Section 2 outlines the history of the inpatient PPS in Japan. Section 3 sets up models for estimating technical efficiency, cost efficiency and distance function scores. Section 4 describes the data on Japanese local public hospitals and input–output variables used in the analysis. Section 5 outlines the dynamics of estimated efficiency scores. Section 6 examines DiD in efficiency scores for the PPS hospitals and the control group of hospitals, and Section 7 addresses the potential reasons for a limited increase in efficiency of PPS local public hospitals in Japan.

2. Development of the Japanese prospective payment system

Japan has traditionally been known for relatively low health-care costs and high health outcomes. However, since the 1980s, Japan has faced ballooning health-care spending and growing regional disparities in health-care accessibility. In the 1990s, the average rate of real growth of Japanese total health-care expenditure started to exceed the rate of real GDP growth. The previously-used instruments for regulating health-care demand through coinsurance rates and tariff levels in the unified fee schedule proved insufficient to keep a lid on the amount of government financial support required for the health-care system. Therefore, Japan is seeking new means to contain health-care costs and reduce the burden of public spending. Replacing traditional FFS reimbursement of Japanese hospitals with the PPS might be an adequate instrument to achieve these goals. In particular, the Japanese PPS contains incentives for standardization of health care, accumulation of medical data and shortening patients' extremely long lengths of stay at hospitals.

To implement the inpatient PPS, in the late 1990s the Ministry of Health, Labor and Welfare (MHLW) developed a system of Diagnosis Procedure Combinations (DPC). DPC are based on the Dutch *Diagnose Behandeling Combinatie*, with an influence of French and Austrian approaches to regional health planning, and Belgian and British attitudes towards incremental development (Matsuda *et al*., 2008).

The unique feature of the Japanese inpatient PPS is the fact that it is divided into DPC and FFS components. The first component is constructed as a daily reimbursement rate, with the amount of per diem payment constant over each of three consecutive periods: period 1 represents the first quartile of ALOS in all the hospitals; period 2 encompasses the rest of the ALOS; and period 3 contains two standard deviations from the ALOS. To encourage a shorter length of stay, per diem reimbursement in the first period is established as 15% larger than the standard per diem reimbursement (Shokumura *et al*., 2005; Yasunaga *et al*., 2005a; Matsuda *et al*., 2008). The DPC component is related to the hospital fee and covers hospital expenditures on pharmaceuticals, injections, examinations and procedures costing under 10 000 yen. The FFS component covers the cost of surgical procedures, anaesthesia, endoscopies, pharmaceuticals, and materials used in operating theatres, as well as procedures worth more than 10 000 yen (Yasunaga *et al*., 2005a). The two-component system is justified in part by the historically developed variety of treatment patterns in Japanese hospitals. International Classification of Diseases (ICD) coding, which is a prerequisite for unification, had very low prevalence in Japan; it was used in only 10% of hospitals (Ikegami and Campbell, 2004, the data as of 1999).

The first version of DPC consisted of 2,552 groups of diagnoses. Most of the groups (1,860) had sufficient cases and were rather homogeneous (Ikegami, 2005). For these groups, which corresponded to approximately 90% of admission cases, the rates were set. Each group of diagnoses (i.e. each DPC) incorporates three essential issues: algorithm, procedure and co-morbidity. Diagnoses are coded according to ICD-10 and, as for coding procedures, the Japanese Procedure Code, which is used in the unified fee schedule, is used (MHLW, 2004; Matsuda *et al.*, 2008). The original claim data were based on a special survey conducted by the MHLW in 2002 in the 82 hospitals that were designated for the PPS introduction. In 2004, the number of DPC was 3,074, of which rates were set for 1,726. In 2006, the total number of DPC dropped to 2,347, and in 2008 increased to 2,496.

Diagnosis Procedure Combinations-based hospital reimbursement is seen as an alternative to the FFS system, which leads to overutilization of hospital services. A preliminary study of the PPS applicability for acute care was conducted in 10 hospitals in 1998. The DPC reform for inpatient care started in 2003 in "specific function hospitals" providing high-technology health care (80 public and private university hospitals as well as two national centres: for cancer and cardiovascular diseases). The waves of 2004, 2006, 2008 and 2009 saw an increase in the number of PPS hospitals. Japanese local public hospitals started participating in inpatient PPS reform in 2006.

While MHLW annual hospital-level monitoring reports demonstrate that the reform reaches its major goal of decreasing the long length of stay (MHLW, 2008), the impact on hospital costs is unclear (Yasunaga *et al.*, 2005a, 2006; Nishioka, 2010). Moreover, the accompanying rise in the early readmission rate (Yasunaga *et al.*, 2005a) implies that efficiency might not have increased. The combination of a two-component system with DPC and FFS payments may not have even shorted the ALOS (Yasunaga *et al.*, 2006).

3. Efficiency measures

It has become a common pattern in Japanese ministerial, professional and academic literature to associate efficiency changes in PPS hospitals with the dynamics of ALOS. This parameter is discussed in annual DPC hospital monitoring reports by MHLW, in DPC seminars by the Japan Hospital Association, and in conferences of the *Journal for Hospital Administration*. However, ALOS does not necessarily reflect the issues relating to efficient combinations of hospital inputs and outputs under given prices.[2] Consequently, the present paper follows Kawaguchi *et al.* (2010) and analyzes the effect of the Japanese inpatient PPS using a more general approach of *frontier analysis*, which considers technical efficiency of a firm as "the ratio of its mean production (conditional on its levels of factor inputs and firm effects) to the corresponding mean production if the firm utilized its levels of inputs most efficiently" (Battese and Coelli, 1992, p. 154). The origin of the methodology is the seminal work of Farrell (1957), who suggests definitions of technical and price efficiency of a firm, and demonstrates a method of constructing a *frontier* as a linear convex hull surface to envelop observations. Charnes *et al.* (1978) develop data envelopment analysis (DEA) as a linear optimization problem for an input-oriented model with constant

[2] In fact, in productivity analysis, case-mix adjusted ALOS is commonly regarded as an exogenous variable (i.e. as an input not directly controlled by producers). However, due to the absence of case-mix variables in the Japanese local public hospital database, we could not adjust the average length of stay for corresponding diagnoses and, consequently, did not use ALOS among exogenous variables.

returns to scale.[3] An alternative parametric method, stochastic frontier analysis (SFA), regards the error term in either production or cost function equation as the sum of statistical noise and the inefficiency component (Aigner *et al.*, 1977; Battese and Corra, 1977; Meeusen and van den Broeck, 1977). DEA, which is a prevalent method for assessing hospital efficiency (Hollingsworth, 2008), has the following advantages: no assumptions about the functional form of production or cost function, absence of multicollinearity or heteroskedasticity problems, and non-vulnerability to small samples (Jacobs *et al.*, 2006). However, the drawbacks of DEA include: sensitivity to outliers, inability to account for measurement error and the fact that efficiency equals unity for the firms on the constructed frontier. SFA accounts for outliers and measurement errors by introducing statistical noise, and does not require that efficiency equal unity. The disadvantages of SFA are strict assumptions about the form of the production function and the distributions of errors, and the inability to explicitly introduce multi-output functions. Consequently, DEA and SFA may be regarded as alternative or complementary methods for estimating efficiency (Kooreman, 1994; Jacobs, 2001; Nakayama, 2003).

In Subsection 3.1, technical efficiency scores are estimated using data envelopment analysis. In Subsection 3.2, we construct a stochastic frontier analysis equivalent of DEA technical efficiency scores. Subsection 3.3 applies Tone's (2002) model of cost efficiency with varying input prices among producers.

3.1 Non-parametric model

The present paper uses an output-oriented DEA model that defines the frontier by maximizing hospital's outputs while holding the amounts of inputs constant. The choice of the output-oriented model is justified by the fact that Japanese local public hospitals are commonly noted as having insufficient medical staff to satisfy the demand for health care by the local population (Yamada *et al.*, 1997). Assuming that technology might change in the analyzed period of time, we consider annual frontiers, estimating separate DEA models for each of the years from 1999 to 2009.[4] Technical efficiency θ_j of the jth hospital in the M-output N-input model for J hospitals is estimated according to Equations (1)–(4) and is in the range of 0 to 1.

$$\min_{\boldsymbol{\theta},\boldsymbol{\lambda}} \theta_j \tag{1}$$

$$\text{s.t.} -y_{mj}/\theta_j + \sum_{i=1}^{J} \lambda_i y_{mi} \geq 0, \quad m = 1, \ldots, M, \tag{2}$$

$$x_{nj} - \sum_{i=1}^{J} \lambda_i x_{ni} \geq 0, \quad n = 1, \ldots, N, \tag{3}$$

$$\lambda_i \geq 0, \quad i = 1, \ldots, J, \tag{4}$$

[3] Subsequently, variable returns to scale, non-increasing returns to scale, output-oriented and other DEA models were introduced (Banker *et al.*, 1984; Fare *et al.*, 1985; Seiford, 1996).

[4] The code for DEA-related computations is written in R language (version R.2.14.1), with the use of (Hayfield and Racine, 2008, 2012), FEAR 1.15 (Wilson, 2008) and Rglpk 0.3–8 (Theussl and Hornik, 2012).

where j denotes hospital, m is the index for output, λ_j is the weight for the jth hospital and n is the index for input (i.e. y_{mj} is the mth output and x_{nj} is the nth input of the selected jth hospital).

Equations (1)–(4) represent a linear maximization program written in concise notation. Indeed, for each hospital j, Equation (2) denotes the set of M constraints, where each constraint corresponds to a particular output y_{mj} ($m = 1, \ldots, M$). Similarly, for each j, Equation (3) indicates N constraints on each input x_{nj}.

Note that Equations (1)–(4) assume that technology exhibits constant returns to scale (CRS). The problem changes to variable returns to scale (VRS) with the introduction of an additional constraint, $\sum_{i=1}^{J} \lambda_i = 1$, or to non-increasing returns to scale (NIRS) with the constraint $\sum_{i=1}^{J} \lambda_i \leq 1$. We apply Simar and Wilson's (2002) returns to scale tests, bootstrapping statistics $\hat{w} = \sum_{j=1}^{J} \theta_j^{CRS} \Big/ \sum_{j=1}^{J} \theta_j^{VRS}$, where θ_j^{CRS} and θ_j^{VRS} are technical efficiency scores calculated in Equations (1)–(4) under the assumptions of CRS and VRS, respectively.[5] For models with different combinations of inputs and outputs,[6] the tests demonstrate that the null hypothesis of CRS is rejected in favour of VRS, while the null hypothesis of NIRS is generally not rejected in favour of VRS.[7] Consequently, in our analysis, we estimate DEA models for corresponding returns to scale (NIRS or VRS). Furthermore, as DEA efficiency scores are upward biased due to the fact that the empirical frontier may fail to incorporate unobservable but very efficient firms (Simar and Wilson, 1998), we implement bias correction through Simar and Wilson's (1998) smoothed bootstrap with least-squares cross validation in the choice of bandwidth.[8]

To account for the influence of exogenous variables (Z) not controlled by producers, we use a two-stage procedure (Ray, 1991; Grosskopf, 1996) with bias correction. At the first stage, we obtain efficiency scores according to (1)–(4) with an additional constraint corresponding to the required returns to scale, and implement bootstrap bias correction. At the second stage, we regress the bias-corrected scores obtained in the first-stage DEA on the exogenous variables, and estimate the fitted values. We account for the fact that the DEA scores are in the range of 0 to 1 by treating the DEA scores as fractional data and using least-squares regression with logit transformation of the dependent variable (Papke

5 This is the statistic in equation 4.6 in Simar and Wilson (2002), which was shown to be the most powerful among other statistics. In the case of testing Ho of NIRS against Ha of VRS, the corresponding statistics is $\hat{w} = \sum_{j=1}^{J} \theta_j^{NIRS} \Big/ \sum_{j=1}^{J} \theta_j^{VRS}$, where θ_j^{NIRS} and θ_j^{VRS} are technical efficiency scores calculated in Equations (1)–(4) under the assumptions of NIRS and VRS, respectively.

6 Table 2 in Subsection 4.2 defines the eight models that we use in the analysis.

7 Exceptions are Models 5–8 in 1999–2000, Models 5–6 in 2001, Models 7–8 in 2002, Model 3 in 2003, Models 5–8 in 2004, Model 6 in 2005 and Models 1–3 in 2006. In these models, H_0 of NIRS is rejected and, consequently, we use VRS.

8 Simar and Wilson (2002) estimate the bias corrected technical efficiency score $\tilde{\theta}$ as $\tilde{\theta} = \hat{\theta} - bias(\hat{\theta}) = 2\hat{\theta} - \bar{\theta}*$, with $\bar{\theta}_j^* = \frac{1}{B}\sum_{b=1}^{B} \hat{\theta}_{b,j}^*$. Here, $\hat{\theta}$ is the "naive" DEA score obtained in Equations (1)–(4), with corresponding returns to scale, j is the index for hospital, b denotes the bootstrap iteration, B stands for the total number of bootstrap iterations, $\hat{\theta}_{b,j}^*$ is the efficiency score of the jth hospital obtained according to the bth bootstrap pseudo sample.

and Wooldridge, 1996; McDonald, 2009). This approach is less restrictive in terms of error specification and arguably provides goodness-of-fit at least as good as that according to conventional methodologies using Tobit or truncated regression models (Hoff, 2007; McDonald, 2009; Ramalho *et al*., 2010).[9] Note that an alternative one-stage procedure (Simar and Wilson, 2007)[10] imposes restrictions on the data generating process (e.g. separability of inputs and exogenous variables) and, therefore, might not be applicable to particular data sets, which is the case in our analysis.[11]

3.2 Parametric model

The parametric analogue of θ in Equations (1)–(4), output distance function D_{oj} for the jth hospital in the M-output N-input model may be specified in translogarithmic form as (Coelli and Perelman, 2000, equation (5)):

$$\begin{aligned}\ln D_{oj} = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln y_{mj} + 0.5 \sum_{m=1}^{M} \sum_{q=1}^{M} \alpha_{mq} \ln y_{mj} \ln y_{qj} + \sum_{n=1}^{N} \beta_n \ln x_{ni} \\ + 0.5 \sum_{n=1}^{N} \sum_{s=1}^{N} \beta_{ns} \ln x_{nj} \ln x_{sj} + \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{nm} \ln x_{nj} \ln y_{mj},\end{aligned} \tag{5}$$

where symmetry restrictions require $\alpha_{mq} = \alpha_{qm}$ and $\beta_{ns} = \beta_{sn}$, and homogeneity restrictions are imposed by dividing the distance function and all outputs by an arbitrarily chosen Mth output (in our case the variable *outpatients*) as a numeraire. All notations for inputs and outputs in Equation (5) have the same meaning as notations used in Subsection 3.1.

After rearranging terms, the equation appears as follows (Coelli and Perelman, 2000, equations 11 and 14):

$$\begin{aligned}-\ln(y_{Mj}) = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln(y_{mj}/y_{Mj}) + 0.5 \sum_{m=1}^{M-1} \sum_{q=1}^{M-1} \alpha_{mq} \ln(y_{mj}/y_{Mj}) \ln(y_{qj}/y_{Mj}) \\ + \sum_{n=1}^{N} \beta_n \ln x_{nj} + 0.5 \sum_{n=1}^{N} \sum_{s=1}^{N} \beta_{ns} \ln x_{nj} \ln x_{sj} + \sum_{n=1}^{N} \sum_{m=1}^{M-1} \delta_{nm} \ln x_{nj} \ln(y_{mj}/y_{Mj}) \\ - \ln(D_{oj}).\end{aligned} \tag{6}$$

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9 To compare different methods for second-stage estimations, we measure the fitted values of efficiency scores at the second-stage DEA according to ordinary least squares (OLS), Tobit and truncated regression models. The pairwise correlation coefficients between the fitted values in OLS, Tobit and truncated regression models are 0.95–0.99. Indeed, as after bias correction in the one-stage DEA, there are no exact zero or one values of efficiency scores at the second-stage DEA; Tobit and truncated regression models produce results similar to OLS.

10 In short, the one-stage procedure in Simar and Wilson (2007) uses environmental variables in the estimations of the bias-corrected DEA scores. Two algorithms are developed: algorithm 1 computes bias-corrected efficiency score $\tilde{\theta}$ as $\tilde{\theta} = \hat{\theta} - bias(\hat{\theta}) = \mathbf{z}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, where $\hat{\theta}$ is the "naïve" efficiency score measured in Equations (1)–(4), $bias(\hat{\theta})$ is the bias of the "naive" efficiency score, $\mathbf{z}$ is a vector of environmental variables and $\boldsymbol{\varepsilon}$ is a stochastic noise. Algorithm 2 (which has better statistical properties) further bootstraps the bias, and measures the bias-corrected efficiency score $\hat{\hat{\theta}}$ as $\hat{\hat{\theta}} = \hat{\theta} - \widehat{bias}(\hat{\theta})$.

11 We applied algorithms 1 and 2 from Simar and Wilson (2007) to obtain the fitted values for technical efficiency scores, and neither algorithm proved to fit our data.

Finally, $D_o = -\ln(D_{oj})$ is assumed to be a half-normal random variable. A normal random variable v is added to the right-hand side of Equation (6), so that a composite error term $\varepsilon = v + D_o$ satisfies the identification assumptions of stochastic frontier analysis (Barbetta *et al.*, 2007).

The distance function D_{oj} in Equation (6) is estimated using annual stochastic frontier analysis models in LIMDEP 9.0 with the Jondrow *et al.* (1982) estimator of the inefficiency term. To account for the influence of exogenous variables we add them to the right-hand side of Equation (6).

3.3 Cost minimization data envelopment analysis

Arguing that a conventional extension of a standard cost minimization DEA framework (Fare *et al.*, 1994) is inapplicable when input prices vary among such producers as Japanese local public hospitals, Tone (2002) introduces new cost efficiency for producer j as:

$$\bar{\gamma}^* = \frac{e\bar{x}_j^*}{e\bar{x}_j}, \tag{7}$$

with $\bar{x}_j^*$ being a solution to the below minimization problem:

$$\min \boldsymbol{e}\bar{x} \tag{8}$$

$$\text{s.t. } \bar{x} \geq \bar{X}\boldsymbol{\lambda} \tag{9}$$

$$\boldsymbol{Y\lambda} \geq \boldsymbol{y}_{\mathrm{j}} \tag{10}$$

$$\boldsymbol{\lambda} \geq \mathbf{0}, \tag{11}$$

where $\bar{x} = (w_{1j}x_{1j}, \ldots, w_{NJ}x_{NJ})^{\top}$, and $\boldsymbol{w}_{\mathrm{j}}$ is a vector of input prices for producer j, $\bar{X} = (\bar{x}_1, \ldots, \bar{x}_{\mathrm{J}})$, $\boldsymbol{Y} = (\boldsymbol{y}_1, \ldots, \boldsymbol{y}_{\mathrm{J}})$, $\boldsymbol{\lambda}$ is a vector of weights in R^{J}, and $\boldsymbol{e}$ is a unit vector in R^N. All other notations in the linear optimization problem in Equations (7)–(11) have the same meaning as in Subsection 3.1.

Equations (7)–(11) assume CRS, and similarly to Equations (1)–(4) may be extended to VRS or NIRS by imposing a corresponding additional constraint. We adopt Simar and Wilson's (2002) returns-to-scale test and Simar and Wilson's (1998) bias correction for the new cost efficiency with the following rescaling within each of the algorithms:

$$\bar{x}_b = \frac{\bar{\gamma}^*}{\bar{\gamma}_b}\bar{x}, \tag{12}$$

where $\bar{x}_b$ denotes the bootstrapped input vector and $\bar{\gamma}_b$ stands for the bootstrapped $\bar{\gamma}$.[12]

Rescaling in Equation (12) corresponds to the logic of Simar and Wilson's (1998) bootstrap. Indeed, because technical efficiency is estimated as the distance to the produc-

[12] In the case of cost efficiency, according to the results of a returns-to-scale test, we employ VRS in most of the models. Exceptions are Models 1–4 in 2002, 2003 and 2008 and Model 2 in 2009, for which we use CRS, and Model 3 in 2009, for which we use NIRS.

tion possibilities frontier, in Simar and Wilson's (1998) bootstrap for input-oriented efficiency, each bootstrapped input equals the initial input multiplied by the ratio of optimal efficiency score to the bootstrapped score.[13] In this case, each component of the bootstrapped input becomes larger than the corresponding component of the initial input, and, consequently, bootstrapped inputs are pushed "inside" the production possibilities set. Tone's (2002) new cost efficiency deals with the distance to the point where the hyper plane set by the vector of unit prices **e** is tangent to the production possibilities frontier. Therefore, rescaling in Equation (12) guarantees that each component of $\overline{x}_b$ is larger than the corresponding component of $\overline{x}$, i.e. vector $\overline{x}_b$ lies in the necessary subspace relative to the above defined hyper plane.

Similarly to the estimations of technical efficiency in Subsection 3.1, we apply a two-stage procedure. In the first stage, we obtain bias-corrected DEA cost efficiency scores, and then in the second stage, we estimate fitted values for cost efficiency scores in an ordinary least squares regression with exogenous variables.

4. Data

4.1 Sample

The paper employs annual financial data on the local public hospitals for fiscal years 1999 to 2009 (Ministry of Internal Affairs and Communications, *The Yearbook of Local Government Enterprises*, Hospitals, Vol. 47–57). The data for participation in the PPS reform come from the MHLW. Japan Council for Quality Health Care (2011) data on hospital accreditation is used to construct a quality variable, which equals unity if the hospital is given accreditation by the beginning of the corresponding fiscal year.

We start with a balanced panel of 832 hospitals in fiscal years 1999–2009,[14] which existed within the whole time period and reported their data in all the years. The analysis is limited to the subsample of general hospitals with only general beds (the unbalanced panel of 521 hospitals) to guarantee homogeneity in the absence of a case-mix variable in the database (i.e. a variable that would account for the prevalence of patients with different diagnoses). Furthermore, the following data are dropped: hospitals with average length of stay below 6 days[15] or over 90 days,[16] and with missing numbers of doctors. This produced the unbalanced panel of 509 hospitals. Finally, as the year 2003 saw a sharp decline of hospitals with only general beds (due to an introduction of long-term care beds) in DiD estimations, the analyzed time period is decreased to the years 2003–2009. We concentrate on the first wave of Japanese local public hospitals, which have participated in the PPS since 2006. In the final unbalanced panel of 347 hospitals, 33 hospitals have used DPC

[13] For output-oriented efficiency, each bootstrapped output would equal the initial output multiplied by the ratio of bootstrapped efficiency to the optimal efficiency.

[14] Starting with the year 1999 is justified by the data availability in electronic form.

[15] With usual hospitalizations in Japan lasting at minimum 1 week, shorter stays are associated with preliminary diagnostics or further transferring to specialized hospitals (Nawata *et al*., 2006).

[16] These hospital stays correspond to long-term care.

since 2006.[17] The percentage of hospitals using DPC in the final sample corresponds to the percentage of hospitals that used DPC in the original sample of 832 local public hospitals.

4.2 Inputs, outputs and exogenous variables

Owing to the unavailability of hospital-level variables on the actual outputs (i.e. changes in patients' health due to medical treatment) in our database, we use proxies for hospital outputs. Frontier studies commonly use such outputs as outpatient visits, hospital admissions, discharges and patient-days (Rosko and Mutter, 2008; Worthington, 2004). The Japanese local public hospitals database does not provide the number of admissions or outpatient visits, reporting instead the daily number of inpatients and outpatients. However, the database allows us to reconstruct the number of discharges for the subsample of general hospitals with general beds (Takatsuka and Nishimura, 2008).[18] Consequently, to analyze the multi-output production function of hospitals, we use discharges and outpatients as proxies for hospital outputs.

Following the frontier studies of Japanese public hospitals' efficiency, this paper considers labour inputs by medical specialty. In the baseline model, labour inputs are doctors, total number of nurses (junior nurses and nurse proper) and other hospital personnel.[19] In our baseline model, labour inputs are doctors, total number of nurses (junior nurses and nurses proper) and other hospital personnel. Beds is an input variable that serves as a proxy for capital.[20] Prices of labour are the earnings of a corresponding employee; capital price is the sum of depreciation and interest per bed (Table 1).

To check the robustness of our results, we analyze models with different combinations of inputs and outputs (Table 2). In some models, we extend the list of inputs in the baseline model and introduce an additional input, expenditure on drugs and medical materials (Motohashi, 2009), as a proxy for the volume of drugs. The price of this input equals unity. It should be noted that using expenditure of drugs and materials as an input we implicitly assume that the types of drugs and materials used for treatment are similar in all hospitals.

Because a considerable amount of DEA and SFA studies (e.g. Aoki and Urushi, 1994; Nam and Gunji, 1994; Yamada *et al*., 1997; Fujii, 2001; Nakayama, 2003; Kawaguchi, 2008) use inpatients and outpatients as another possible combination of hospital outputs, we consider inpatients and outpatients as an alternative set of outputs.[21] For each combination of inputs and outputs, we measure technical efficiency, distance function score and

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[17] The sample of DPC hospitals includes hospitals preparing to introduce DPC ("*DPC jumbi byouin*") on the premise that the behaviour of such hospitals is similar to the incentives imposed on DPC hospitals.

[18] The database provides information on the numbers of inpatients and outpatients per day, and does not report the number of admissions. Takatsuka and Nishimura (2008) and Takatsuka and Nishimura (2008) propose deriving the arithmetic mean of the number of admissions and discharges from MHLW formulas for average length of stay and bed occupancy rate. Average length of stay, however, is reported only for general beds.

[19] It should be noted that there are formulas setting the benchmark numbers of doctors and nurses in the general hospital as a function of the numbers of daily inpatients and outpatients (Yamada *et al*., 1997, endnote 3). However, due to a shortage of doctors and nurses, the actual numbers of employed doctors and nurses might be smaller than the benchmark figures established by the MHLW.

[20] Note that although the data includes more professions (e.g. technicians and administrative personnel), the number of hospitals with complete sets of data drops significantly.

[21] We did not use patient-days because the variable was strongly correlated with the number of inpatients.

TABLE 1
Descriptive statistics for the unbalanced panel in 1999–2009

Variable	Definition	Observations	Mean	Standard deviation	Minimum	Maximum
Outputs						
Outpatients	Number of outpatients	3,884	171,681	137,641	18,250	879,864
Inpatients	Number of inpatients	3,884	53,247	47,010	2,920	265,716
Discharges	Average of admissions and discharges	3,884	2,910	2,992	68	16,796
Inputs						
Doc	Doctors	3,884	20	21	1	229
Nurse	Total nurses = nurses + junior nurses	3,884	106	102	1	1,048
Other1	Other personnel (1) = total staff – doctors – total nurses	3,884	48	39	1	353
Other2	Other personnel (2) = total staff – doctors	3,884	154	139	2	1,401
Bed	Total number of beds	3,884	183	143	25	810
Exp_med	Expenditure on drugs and medical materials	3,884	786,014	866,534	20,895	6,225,202
Input prices						
Doc_sal	Average salary of a doctor	3,072	17,400	5,023	575	66 200
Nurse_sal	Average salary of a nurse	3,072	6,009	639	239	8,611
Oth_sal1	Average salary of other personnel (1)	3,072	6,343	938	2,945	9,417
Oth_sal2	Average salary of other personnel (2)	3,072	6,095	671	1,826	8,630
Pk	Capital price = (depreciation + interest)/bed	3,072	1,431	905	61	6,108
Exogenous variables						
Regs	Regional government subsidy per bed	3,884	35	165	0	1,691
Teach	= 1 if has affiliated college for nurses or junior nurses, 0 otherwise	3,884	0.05	0.21	0	1
Ershare	Share of emergency beds	3,884	0.04	0.05	0	1
Rural	= 1 if in rural area (in town or village, as of 2007 administrative division), 0 otherwise	3,884	0.38	0.49	0	1
St	= 1 if in non-profitable area, 0 otherwise[22]	3,884	0.26	0.44	0	1
Accred	= 1 if received independent accreditation by Japan Council for Quality Healthcare, 0 otherwise	3,884	0.15	0.35	0	1
Drug margin ratio	= government reimbursement of the cost of prescribed drugs and injections/ the cost of prescribed drugs and injections	3,884	1.14	0.17	0.32	5.29

Notes: Variables are estimated on the annual basis. Monetary values are in thousands of yen. Prices are employed in the estimations of cost efficiency scores.

[22] A hospital is situated in a non-profitable area if: (i) it had fewer than 100 beds or fewer than 100 inpatients a day in the previous year; (ii) the number of outpatients a day was fewer than 200 in the previous year; and (iii) there is at most only 1 other general hospital in the local municipal area or within 300 km^2.

TABLE 2
Models with different sets of input and output variables

	Model 1	2	3	4	5	6	7	8
Inputs								
Doctors	+	+	+	+	+	+	+	+
Nurses	+	+			+	+		
Other personnel (1)	+	+			+	+		
Other personnel (2)			+	+			+	+
Beds	+	+	+	+	+	+	+	+
Expenditure on drugs and medical materials		+		+		+		+
Outputs								
Discharges	+	+	+	+				
Inpatients					+	+	+	+
Outpatients	+	+	+	+	+	+	+	+

Note: The columns describe the models used in the analysis. The definitions of inputs and outputs are given in Table 1. "Plus" in each cell denotes that the corresponding input or output is included in the model. Model 1, which is the baseline model, uses doctors, nurses, other personnel (1) and beds as inputs, and discharges and outpatients as outputs. The estimations of cost efficiency scores use corresponding price variables for each input.

cost efficiency score according to the methodology described in Subsections 3.1, 3.2 and 3.3, respectively.

Exogenous variables include drug margin ratio, teaching and rural hospital dummies (Yamada *et al*., 1997), a hospital profitability dummy (Nakayama, 2003), bed occupancy rate (Yamada *et al*., 1997; Fujii, 2001), subsidies from regional governments, a dummy for hospital accreditation, and share of emergency beds (Besstremyannaya, 2011). Because the commonly used variable for severity of illness (i.e. the number of examinations per patient) is affected by PPS reform, this variable could not be used in the estimations that involve a construction of the control group. Therefore, we analyze the dynamics of this variable only in the descriptive analysis of efficiency scores of PPS hospitals.

It should be noted that the findings of our analysis are limited by the absence of a case-mix variable in the Japanese local public hospital database, so we are unable to study the severity bias and to follow the international literature in adjusting the numbers of patients. Although we attempt to incorporate health-care quality by using the dummy for independent hospital accreditation, the lack of data on other quality-related hospital-level variables (i.e. standardized mortality rate, as used in Kawaguchi *et al*., 2010, or parameters from qualitative surveys, as described in MHLW, 2005) represents a limitation of our analysis. Similarly, the unavailability of disaggregated data on DPC and FFS components means that a statistical analysis for each part of the PPS tariff is not possible.

5. Descriptive analysis of efficiency scores

The primary goal of our estimation of the efficiency scores is to analyze their dynamics with respect to the participation in PPS reform. Thus, in the two-stage DEA, we keep exogenous variables that are correlated with the binary indicator for participation in the reform but are not affected by the reform (Imbens, 2004; Angrist and Pischke, 2009). Two groups of covariates are used in the estimations: hospital variables (i.e. a teaching hospital dummy, a rural hospital dummy, regional subsidy per bed, share of emergency beds and drug margin ratio) and regional variables (i.e. per capita gross regional product adjusted for the difference in regional prices, share of population over 65 years and density of population).[23] The group of hospital variables incorporates parameters that are related to technology but are not directly controlled by hospitals. Indeed, teaching or rural hospital dummies and share of emergency beds might be associated with a special type of health care provided and different types of patients treated in each category of hospitals. High regional subsidies per bed and high drug margin ratios might become a disincentive for efficient production and, therefore, are commonly regarded as factors influencing the technology of local public hospitals (Yamada *et al*., 1997). To account for the fixed effects of secondary medical zones (*Nijiiryoken*), we take averages of non-dichotomous hospital variables (regional subsidy per bed, share of emergency beds and drug margin ratio) for each secondary medical zone.[24]

The group of regional (prefecture-level) variables includes the share of the population over 65 years, who are the major consumers of health care in local public hospitals. Per capita gross regional product adjusted for regional prices and population density capture the overall economic potential of the region.

Estimates of technical and cost efficiency according to two-stage DEA and the values of distance function scores show that PPS hospitals are more efficiency than hospitals operating according to FFS (Figs 1–3).[25] This suggests that per case financing reform was started in better performing hospitals. The dynamics of efficiency scores in the models we use in the analysis is similar to their dynamics in the baseline model: efficiency falls in the first 2 years of the reform and then it increases in the years 2008 and 2009.[26] Note that the time profile of efficiency scores in FFS hospitals resembles that of the PPS hospitals.

6. Estimating the effect of the prospective payment system

Efficiency scores of both PPS and FFS hospitals generally reveal negative dynamics in 2006 and 2007 and positive dynamics in 2008 and 2009. Although the observation is interesting by itself, it fails to disentangle differences between the two types of

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23 Due to data availability, per capita gross regional product adjusted for regional prices was held at the 2007 level in the years 2008 and 2009; share of population over 65 years was held at the 2002 level in 1999–2001, and at the 2005 level in 2006–2009; density of population in 1999 was held at the 2000 level.

24 A more precise approach of introducing dummies for secondary medical zones was inapplicable due to the small sample size of our data relative to the number of secondary medical zones (349 zones).

25 Correlation coefficients between the one-stage DEA measure of technical efficiency and distance function scores were significant and high (0.8–0.9 in different models in various years). However, correlation coefficients between the one-stage and the two-stage DEA scores were 0.2–0.3. Therefore, in the descriptive analysis in Figures 1–2, we provide both the one-stage and the two-stage DEA scores of technical efficiency.

26 Generally, efficiency scores decreased in the first two post-reform years and increased in the years 2008–2009. In most models, the value of the efficiency score in 2009 exceeded the value of 2008. In a few models, the efficiency score in 2009 was slightly lower than in 2008.

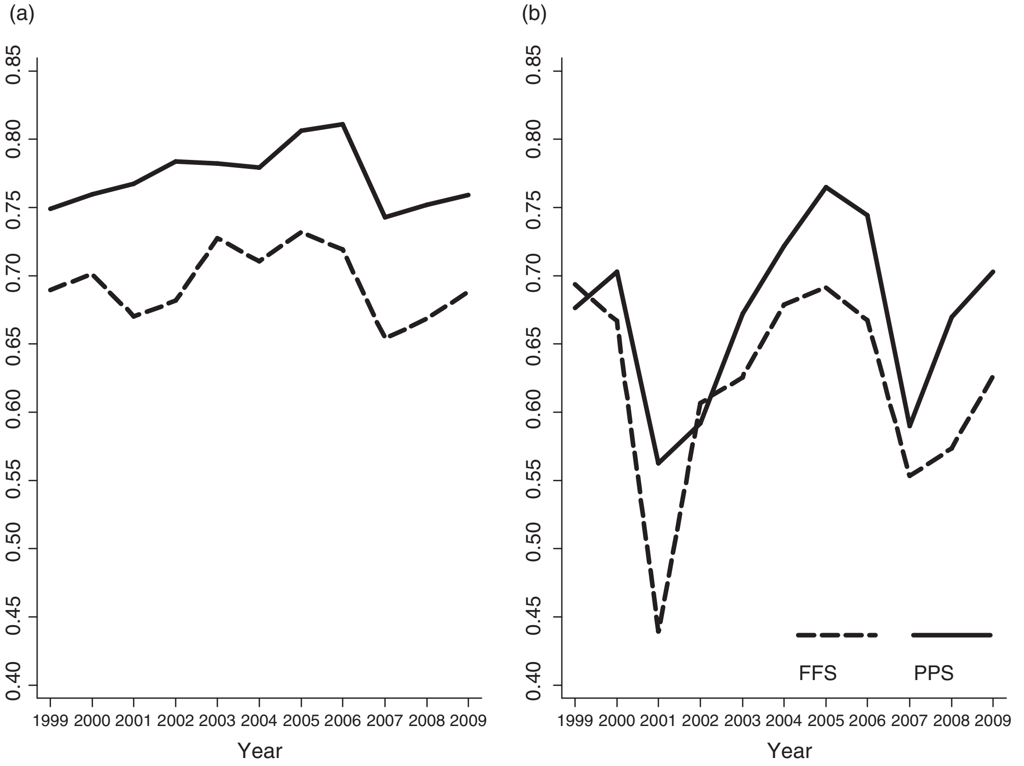

FIGURE 1. Bias corrected data envelopment analysis (DEA) score of fee-for-service (FFS) and prospective payment system (PPS) local public hospitals, baseline model. Notes: The figure shows (a) technical and (b) cost efficiency score obtained in the first-stage DEA (i.e. respectively, in Equations (1)–(4) and in (7)–(11)) and then corrected with Simar and Wilson's (1998) bootstrap. Local public hospitals that joined PPS reform in 2007 and later are excluded from the corresponding annual samples of FFS hospitals in 2007–2009

hospitals.[27] Therefore, to understand the expected gain from participating in PPS reform, we measure the effect of the program carrying out DiD estimations. We compare the changes in pre-reform and post-reform efficiency scores of PPS hospitals with the changes in the control group of hospitals, which have not undergone the reform. It should be noted that the key identifying assumption of DiD estimations is the fact that trends in the outcome variables are the same in the reform and the control groups (Angrist and Pischke, 2009).

Using the database we find that there were no PPS hospitals situated in non-profitable areas, and that the nurse staffing ratio for PPS hospitals equals one of the two lower rank values for this variable in each corresponding year (i.e. 2 or 2.5 nurses per inpatient in

[27] Decline in the efficiency of Japanese local public hospitals in 2006–2007 may be explained by a combination of policy measures (e.g. decrease in the number of beds, tougher budget constraints due to full compliance with the local budget code and reduction of service reimbursement levels following revision of the unified fee schedule in 2006).

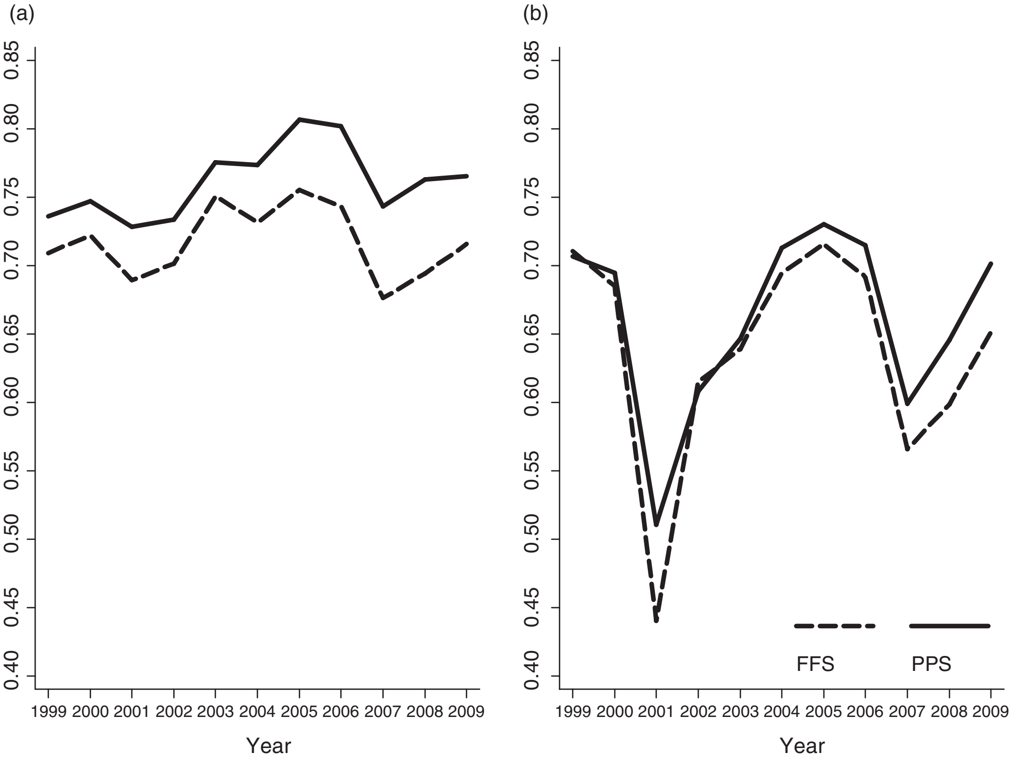

FIGURE 2. Fitted value in ordinary least squares regression for fee-for-service (FFS) and prospective payment system (PPS) local public hospitals, baseline model. Notes: The figure shows (a) technical and (b) cost efficiency scores derived in the second-stage data envelopment analysis (DEA) (i.e. when the bias-corrected DEA scores were regressed on exogenous variables). Local public hospitals that joined PPS reform in 2007 and later are excluded from the corresponding annual samples of FFS hospitals in 2007–2009

1999–2005 and 7 or 10 nurses per inpatient in 2006–2009).[28] Consequently, in constructing the control group, we exclude hospitals in non-profitable areas and with nurse staffing ratios higher than the second rank value from the controls. Local public hospitals that joined the PPS in 2007–2009 are excluded from the corresponding annual samples of the controls.

To distinguish between the immediate effect of the reform and the effect in the medium run, we follow Dafny and Dranove (2006) and study the difference between the average value of the outcome for the first k post-reform years and the average value for the 3 pre-reform years (2003–2005). Note that according to Bertrand *et al*. (2004), collapsing the data into two periods (pre-reform and post-reform) is a solution to the problem of the inconsistency of the standard errors of the coefficient for the effect. Let

$$\overline{e}_{t,k} = \frac{1}{k}\sum_{j=1}^{k} e_{t-1+j} \tag{13}$$

[28] We ignored the fact that two hospitals had the third rank value for nurse staffing ratio in some of the years.

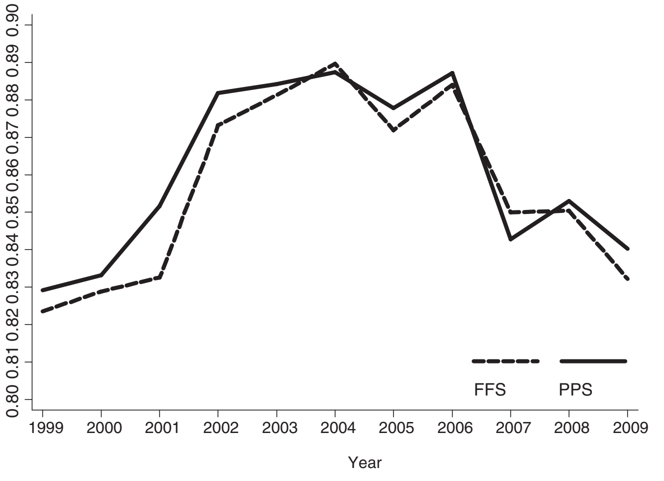

FIGURE 3. Distance function with exogenous variables for fee-for-service (FFS) and prospective payment system (PPS) local public hospitals, baseline model. Notes: The figure shows the efficiency score estimated according to parametric stochastic frontier analysis, with exogenous variables added to the right-hand side of Equation (6). Local public hospitals that joined PPS reform in 2007 and later are excluded from the corresponding annual samples of FFS hospitals in 2007–2009

$$\mathrm{D}_k = \bar{e}_{2006,k} - \bar{e}_{2003,3}, \tag{14}$$

where $\boldsymbol{e}_s$ is the efficiency score in year s, $\bar{e}_{t,k}$ is the average value of the efficiency score in time interval $[t, t + k - 1]$, D_k is the difference between the average values of the efficiency score in time interval $[2006, 2006 + k - 1]$ and in time interval [2003, 2005]. Given data availability, four dependent variables, D_k, corresponding to k equal 1, 2, 3 or 4 are constructed.[29]

6.1 Mean unconditional comparison

For each $k = 1 \ldots 4$, we estimate the following linear regression:

$$\mathbf{D}_k = \tau\mathbf{C} + \boldsymbol{\xi},\ \mathrm{E}\boldsymbol{\xi} = 0, \tag{15}$$

where the fitted value of τ gives the estimate of the reform effect.

6.2 Mean conditional comparison

For each $k = 1 \ldots 4$ we run a regression:

$$\mathbf{D}_k = \tau\mathbf{C} + \boldsymbol{\gamma}'\mathbf{Z}^{\mathrm{pre}} + \boldsymbol{\zeta},\ \mathrm{E}\boldsymbol{\xi} = 0, \tag{16}$$

[29] In these notations, the first post-reform year ($k = 1$) denotes the year that the reform was implemented (i.e. 2006).

where Z^{pre} denotes the average values of exogenous variables in the 3 pre-reform years (2003–2005), and the fitted value of τ provides the estimate of the reform effect.

6.3 The size of the effect

The coefficients of the effect are slightly smaller and less significant in mean conditional comparison than in mean unconditional comparison (Table 3). The coefficients are positively significant in a few models, which may be interpreted as a minor positive effect of the PPS reform on technical and cost efficiency of Japanese local public hospitals (Table 4). The coefficient values show that PPS reform generally leads to a 1–3-percent increase in mean post-reform technical and cost efficiency (relative to mean pre-reform scores) in 2006–2009.

Finally, we focus on two groups of PPS hospitals, where the reform leads to an increase and a decrease in technical efficiency, respectively (Table 5). With one exception, PPS hospitals showing increases in technical efficiency are non-teaching urban hospitals that have received independent accreditation. The rise in technical efficiency at these institutions is associated with a decrease in profit, ALOS, and drug margin ratio. Because the change in the number of examinations per patient is lower in the group of hospitals with a positive post-reform change in technical efficiency (except in the first post-reform year), the rise in technical efficiency is most probably the result of lower resource consumption. However, hospitals might achieve greater technical efficiency through specific efforts: indeed, the drop in bed occupancy rate is smaller in better performing PPS hospitals. The results indicate that government support is targeted at hospitals with lower technical efficiency: starting from the second post-reform year, the increase in regional and government subsidies per bed is generally smaller at hospitals where the PPS leads to a rise in technical efficiency.

Our results demonstrate that a rise in technical efficiency is associated with a fall in cost efficiency. According to Biorn *et al*. (2003), the opposite dynamics of technical and cost efficiency scores in PPS hospitals might be explained by an upward bias in technical efficiency due to an underestimated volume of inputs (i.e. the failure to include overtime work in technical efficiency estimations).

It should be noted that our analysis does not enable incorporation of quality-related variables such as mortality rates or readmission rates. The failure to include a quality variable in the production function pushes the production possibility frontier downwards, because, *ceteris paribus*, it is always possible to produce the same amount of product, but with lower quality. This causes an upwards bias in the estimated technical efficiency scores. Similarly, costs decrease for a product of lower quality and missing quality variables lead to a downward bias in the estimated cost efficiency scores.

7. Discussion

In theoretical models of hospital behaviour, the PPS is regarded as a reimbursement mechanism encouraging efficient use of resources, higher intensity and improvements in productivity (Hodgkin and McGuire, 1994; Epstein and Mason, 2006; Sanchez-Martınez *et al*., 2006). In practice, the choice of DRG rates and short-term/long-term hospital incentives vary in different health systems. Consequently, the experience of countries

TABLE 3
Coefficients of the effect in the linear difference-in-differences estimations, baseline model

	D_1		D_2		D_3		D_4	
Outcome	a	b	a	b	a	b	a	b
Technical efficiency,	0.036***	0.029***	0.031***	0.024	0.025*	0.018	0.026	0.017
Bias corrected DEA	[0.011]	[0.012]	[0.011]	[0.016]	[0.015]	[0.016]	[0.016]	[0.017]
Technical efficiency,	0.019***	0.019***	0.022***	0.018***	0.027***	0.022***	0.024***	0.019***
Fitted value in OLS regression	[0.006]	[0.007]	[0.006]	[0.006]	[0.005]	[0.005]	[0.005]	[0.004]
Distance function without	0.007	0.004	0.008	0.003	0.007	0.003	0.010	0.006
Exogenous variables	[0.005]	[0.005]	[0.006]	[0.007]	[0.007]	[0.008]	[0.008]	[0.009]
Distance function with	0.004	0.001	0.004	0.0003	0.002	0.001	0.006	0.004
Exogenous variables	[0.005]	[0.006]	[0.006]	[0.006]	[0.008]	[0.007]	[0.009]	[0.009]
Cost efficiency,	0.035***	0.024	0.010	0.020	0.027	0.024	0.043*	0.028
Bias corrected DEA	[0.015]	[0.021]	[0.020]	[0.024]	[0.022]	[0.021]	[0.023]	[0.025]
Cost efficiency,	0.006	0.002	0.009	–0.001	0.016***	0.006***	0.019***	0.012***
Fitted value in OLS regression	[0.004]	[0.002]	[0.006]	[0.001]	[0.005]	[0.002]	[0.005]	[0.003]

Notes: The value of each cell corresponds to the coefficient of the effect in difference-in-difference estimations, with the dependent variable D_k measured using corresponding outcome indicated in each row. "a" and "b" indicate models with unconditional mean comparison and mean comparison conditional on covariates, respectively. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. Robust standard errors are in brackets. DEA, data envelopment analysis; OLS, ordinary least squares.

TABLE 4
Coefficients of the effect in mean conditional comparison

Outcome	Model	D_1	D_2	D_3	D_4
Technical efficiency, fitted value in OLS regression	1	0.019 [0.007]***	0.018 [0.006]***	0.022 [0.005]***	0.019 [0.004]***
	2	0.013 [0.005]**	0.014 [0.005]***	0.019 [0.004]***	0.016 [0.003]***
	3	0.023 [0.007]***	0.018 [0.006]***	0.020 [0.006]***	0.018 [0.004]***
	4	0.017 [0.005]***	0.015 [0.005]***	0.018 [0.004]***	0.015 [0.004]***
	5	0.014 [0.005]**	0.017 [0.005]***	0.020 [0.005]***	0.019 [0.004]***
	6	0.009 [0.004]**	0.013 [0.004]***	0.016 [0.004]***	0.015 [0.003]***
	7	0.014 [0.006]**	0.014 [0.005]***	0.016 [0.004]***	0.014 [0.004]***
	8	0.009 [0.004]**	0.011 [0.004]***	0.012 [0.004]***	0.011 [0.003]***
Distance function with exogenous variables	1	0.001 [0.006]	0.0003 [0.006]	0.001 [0.007]	0.004 [0.009]
	2	−0.003 [0.007]	−0.003 [0.007]	0.0003 [0.008]	NA
	3	0.002 [0.007]	0.001 [0.008]	0.0004 [0.007]	0.004 [0.008]
	4	−0.0002 [0.006]	−0.0003 [0.007]	−0.0004 [0.008]	0.001 [0.010]
	5	0.002 [0.009]	0.007 [0.010]	0.009 [0.012]	0.015 [0.013]
	6	−0.003 [0.009]	0.004 [0.010]	0.012 [0.012]	NA
	7	−0.001 [0.007]	0.004 [0.010]	0.007 [0.011]	0.015 [0.012]
	8	−0.004 [0.007]	0.001 [0.009]	0.007 [0.010]	NA
Cost efficiency, fitted value in OLS regression	1	0.002 [0.002]	−0.001 [0.001]	0.006 [0.002]***	0.012 [0.003]***
	2	0.002 [0.002]	−0.001 [0.001]	0.006 [0.002]***	0.011 [0.003]***
	3	0.002 [0.002]	−0.001 [0.001]	0.006 [0.002]***	0.011 [0.003]***
	4	0.002 [0.002]	−0.001 [0.001]	0.006 [0.002]***	0.012 [0.003]***
	5	−0.005 [0.002]**	−0.001 [0.001]	0.004 [0.002]**	0.007 [0.002]***
	6	−0.005 [0.002]**	−0.001 [0.001]	0.005 [0.002]**	0.007 [0.002]***
	7	−0.005 [0.002]**	−0.001 [0.001]	0.004 [0.002]**	0.007 [0.002]***
	8	−0.005 [0.002]**	−0.001 [0.001]	0.004 [0.002]**	0.007 [0.002]***

Notes: The value of each cell corresponds to the coefficient of the effect in difference-in-difference estimations, with the dependent variable D_k measured using corresponding outcome. Covariates are listed at the beginning of Section 5. Models are defined in Table 2. Convergence was not achieved in estimating distance function score in 2009 in case of Models 2, 6 and 8. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. Robust standard errors are in brackets. NA, not applicable; OLS, ordinary least squares.

TABLE 5
The percentage change in the values of selected variables in prospective payment system (PPS) hospitals, baseline model

	1 year		2 years		3 years		4 years	
	I	II	I	II	I	II	I	II
Technical efficiency								
Mean	3.96	−2.46	2.93	−2.89	3.30	−2.59	2.61	−2.60
Standard deviation	3.59	2.08	3.21	2.07	2.60	1.57	1.62	1.67
Cost efficiency								
Mean	2.99	1.19	−8.76	−5.01	−9.04	−5.80	−8.10	−4.20
Standard deviation	1.68	3.00	2.10	3.37	2.06	1.99	0.05	1.53
Bed occupancy rate								
Mean	−3.39	−6.12	−4.27	−4.77	−4.89	−5.54	−5.37	−4.45
Standard deviation	5.46	9.78	3.81	8.77	3.40	9.57	5.26	9.17
Average length of stay								
Mean	−7.39	−6.96	−10.85	−7.47	−8.82	−10.10	−13.65	−10.22
Standard deviation	4.20	5.65	4.25	4.20	4.69	5.93	3.17	7.61
Drug margin ratio								
Mean	−5.97	0.14	−18.52	−0.06	−31.49	−5.39	−26.92	−9.28
Standard deviation	14.37	3.12	26.05	6.12	27.41	9.25	31.67	13.17
Profit								
Mean	−1010.71	−35.79	−7.42	7.34	−33.10	30.66	−85.53	−61.52
Standard deviation	4205.65	157.88	56.31	149.60	40.74	148.16	57.98	369.51
Regional subsidy per bed								
Mean	−21.91	−33.92	8.76	5.97	−16.51	45.64	−17.35	112.21
Standard deviation	61.88	59.83	96.15	112.66	118.07	159.04	109.24	211.57
Government subsidy per bed								
Mean	80.59	13.56	52.50	60.62	38.99	75.01	81.70	84.73
Standard deviation	125.36	51.24	77.17	81.36	75.47	97.63	75.37	101.83
Examinations per patient								
Mean	19.03	8.35	13.66	23.32	13.28	24.78	9.38	27.67
Standard deviation	36.55	28.26	10.47	43.92	16.31	43.94	29.66	44.15
Observations	20	7	6	18	4	19	4	18

Note: The table reports the mean percentage change in the average value of each variable in the post-reform year(s) relative to the average value of the variable in the 3 pre-reform years (2003–2005). "I" and "II" indicate groups of observations with, respectfully, non-negative and negative change in technical efficiency (measured in the baseline model) over the corresponding period. Due to data availability there were fewer observations in the case of cost efficiency, regional subsidy per bed and government subsidy per bed.

introducing the PPS (e.g. DRG and global budget) fails to reveal a uniform pattern in hospital efficiency. Indeed, purchaser/provider split and output-based reimbursement have helped to improve the cost efficiency of Swedish hospitals (Gerdtham *et al*., 1999). Technical efficiency of Norwegian hospitals increased and cost efficiency may have decreased as a result of activity-based financing reform (Biorn *et al*., 2003; Bibbee and Padrini, 2006). In Portugal, while introduction of DRG had a positive impact on hospital productivity, technical efficiency went declined in certain types of hospitals for some diagnoses (Dismuke and Sena, 1999). At the same time, several empirical studies show that the inpatient PPS is not necessarily an efficiency enhancing tool (Barbetta *et al*., 2007 for Italy, Sommersguter-Reichmann, 2000 for Austria and Borden, 1988 for USA).

The findings of DiD estimations demonstrate that the reform has a limited positive effect on the technical and the cost efficiency of Japanese local public hospitals. A twofold explanation for non-increase in the efficiency of Japanese local public hospitals is attempted.

First, there are common reasons related to the introduction of a new technology. Specifically, the adoption of Japanese DPC required improvements in accounting and standardization. The attendant increase in work intensity of doctors and nurses due to the need to code diagnosis and drugs (Sato, 2007; Okuyama, 2008) may have reduced the technical efficiency of hospitals.

Similarly, a fixed cost of 20 to 30 million yen for data management software in DPC hospitals (Saito, 2007) must have contributed to an increase in the total cost of PPS hospitals. Moreover, while the PPS tariff is generally aimed at shortening ALOS, it does not necessarily result in cost reduction (Yasunaga *et al*., 2005a, 2006).

Growing costs may be inferred from the profitability patterns of PPS local public hospitals. Following Hsiao *et al*. (1986), we grouped Japanese local public hospitals according to their operating surplus (surplus, breakeven and deficit hospitals) and found that profitability kept decreasing in all three groups during the 2 post-PPS years. This should be compared with the results at 82 specific function hospitals, where indicators of medical treatment did not deteriorate after introduction of DPC (Suka *et al*., 2006). It should be noted that local public hospitals are presumably smaller in size than specific function hospitals, offer conservative (non-surgical) rather than surgical treatment, and are commonly situated in low populated areas where the demand for health care tends to remain unchanged. Therefore, local public hospitals could not easily compensate for the drop in revenue by attracting new patients or changing the case-mix.

The second group of reasons relate to specific features of the Japanese PPS tariff, which might have become disincentives for efficiency. Japanese DPC are calculated *per day*, rather than *per case*. As was described in Section 2, the tariff is the sum of a fixed FFS payment per day and a DPC component based on the ALOS. The FFS payment is supposed to cover the cost of medical materials; therefore, when the cost of medical materials is high relative to FFS reimbursement, the hospital may opt for longer hospitalizations to cover the shortfall (Yasunaga *et al*., 2005a, 2006). However, Japanese hospitals face administrative pressure to shorten the ALOS, so they may choose to adhere to the recommended time for patient discharge and suffer financial losses as a result. In an attempt to minimize these losses, PPS hospitals strive to reduce the use of drugs in the course of treatment (Ikeda *et al*., 2005; Onda *et al*., 2010). Moreover, a survey of DPC hospitals by the Japan Hospital Association showed that 80% of hospitals consider DPC reimbursement inadequate for covering the full cost of medicines and materials (Saito, 2007). In this regard, Yasunaga *et al*. (2005b) suggest that changing the ratio between the DPC and FFS components of the PPS tariff might be the only way to solve the problem.

Finally, DPC rates for conservative treatment might not be as generous as the pre-reform FFS rates (Yasunaga *et al*., 2005b), which might have negatively affected small and medium size hospitals, leading to financial losses.

It should be noted that the Japanese inpatient PPS is a voluntary program. This special feature of the reform might lead to self-selection and heterogeneity in the effect of the program. Indeed, the coefficients of the effect obtained for the sample of hospitals that joined the PPS in 2007 are different from the coefficients of the effect for the hospitals that joined the PPS in 2006. In fact, Kawai and Maruyama (2000) argue that the voluntary character of PPS reform contradicts the original goals of this reimbursement mechanism.

In regards to the internal validity of our analysis, the lack of readmission data makes it impossible to account for the increase in the readmission rate, which is particularly noticeable in PPS hospitals after the reform. The rise in readmissions supposedly led to an artificial increase in the numbers of inpatients who were readmitted with the same diagnosis a short period after discharge (Nishioka, 2010). In the framework of our DEA and SFA models, increased readmissions imply positive biases in post-reform hospital output and efficiency scores. The final limitation of the present paper concerns post-reform data availability: we compared the pre-reform efficiency scores with those in the four post-reform years (2006–2009). However, even if hospitals adopt better technologies as soon as the PPS is introduced, resulting improvements in technical efficiency may take some time to appear (Sommersguter-Reichmann, 2000).

8. Conclusion

The introduction of a prospective payment system for inpatient care in various countries has attracted the attention of empirical analysts. These analysts have been measuring the impact of this financing reform on hospital efficiency. However, the methods commonly used for analysis of efficiency scores do not enable a comparison of the post-reform efficiency of PPS hospitals with the would-be efficiency of the same hospitals if they had not participated in the reform.

The present paper addresses the problem by analyzing the effect of the PPS reform in Japan through study of the DiD of pre-reform and post-reform efficiency scores in the reformed and control groups of local public hospitals with general beds in 1999–2009. The descriptive analysis of technical and cost efficiency scores of both PPS and FFS hospitals generally reveals negative dynamics in 2006 and 2007 and positive dynamics in 2008 and 2009. DiD estimations generally indicate that the PPS has a minor positive effect on technical and cost efficiency.

The findings of this paper suggest that the system of economic stimuli of the Japanese inpatient PPS does not lead to improvement in local public hospitals' efficiency as an immediate effect of the reform. Arguably, adequate incentives in the Japanese PPS might be created by the introduction of a suitably balanced two-part PPS tariff.

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