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The efficiency of labor matching and remuneration reforms: a panel data quantile regression approach with endogenous treatment variables

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The efficiency of labor matching and remuneration reforms in health care: a panel data quantile regression approach with endogenous treatment variables

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Abstract

The paper evaluates the effect of residency matching and prospective payment on technical and cost efficiency of local public hospitals. Efficiency is estimated using panel data quantile regression models with two endogenous treatment variables. We exploit nationwide longitudinal databases on Japanese hospital participation in the two reforms and on financial performance of local public hospitals in 2005-2012. The results demonstrate that more efficient hospitals opt for each of the reforms, and participation further improves efficiency. The introduction of regional caps in residency matching resulted in efficiency losses, particularly in large prefectures, while a step towards best-practice rate setting in inpatient prospective payment system had no effect on efficiency dynamics.

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1 Introduction

Containing health care costs and reducing the burden of public health expenditure are major challenges for health systems of the developed countries. At the same time, there is a growing criticism of inefficiency of health care provision. The evidence of inefficiency is found in waiting lines, long lengths of stay, low bed occupancy rates, timely execution of tests and procedures, and lack of managerial efforts. The inefficiency may be driven by physician-induced demand under fee-for-service reimbursement, soft budget constraints, large subsidies, and rationing of doctor supply. Other inefficiency attributes are multiple objectives of health care systems and health care providers, uncertainty about prices and costs, and operational constraints (Hollingsworth and Street (2006), Hollingsworth et al. (1999)). As some of the unnecessary costs are speculated to be explained by provider inefficiency, there is an increasing need for a reliable measure of hospital efficiency. The measure would enable benchmarking best-performing providers to use them as reference points for various programs. Moreover, the change in provider efficiency owing to policy interventions may be used for evaluating the effect of the programs.

Efficiency changes in hospitals are often associated with the dynamics of length of stay, bed occupancy rates and various quality indexes. However, these indicators are not necessarily related to optimal technology or cost reducing efforts. Under a more general approach (Farrell (1957)), technical efficiency reflects an ability to produce maximum amount of output under a given set of inputs, or alternatively, use of minimum quantities of inputs for producing a given output mix. Allocative efficiency demonstrates whether inputs are exploited in optimal proportions to minimize costs under given input prices; or whether output mix maximizes revenues, given output prices. In health economics, efficiency reflects the relationship between labor, capital and other resources and health outcomes, given resource prices or renumeration for health care services. Since the precise measure of health outcome - change in patient's health owing to medical treatment (e.g. discharge status, survival rate) may be unavailable, the common proxies are intermediate outputs (bed-days, discharges, outpatient cases).

The two most common empirical methods of measuring technical or allocative efficiency are based on specific assumptions and have been criticized on several grounds. Nonparametric methods, which use linear optimization techniques to construct a hull of observations (data envelopment analysis, free disposal hull, see Charnes et al. (1978)), are sensitive to outliers, require large sample size owing to "curse of dimensionality", do not account for measurement error, and considers the observations on the constructed frontier as fully efficient. An alternative parametric method - stochastic frontier analysis treats the error term in either production or cost function equation as the sum of statistical noise and inefficiency component, imposing strict distributional assumptions (Aigner et al. (1977), Battese and Corra (1977), Meeusen and van den Broeck (1977)). The debates in *Journal of Econometrics* (1980) and *Journal of Health Economics* (1994, Vol.3) have resulted in conjecture that the scores estimated in the corresponding framework may be interpreted as no more than hints at possible inefficiency (Kooreman 1994), and their reliability is limited to judgments about order of magnitude or intertemporal dynamics (Rosko and Mutter (2008), Linna (1998), Hadley and Zuckerman (1994)).

Quantile regression approach (Koenker and Bassett (1978)), which unites the merits of two classic methods of efficiency estimation, has become an alternative tool for efficiency measurement. Quantile regression describe technological frontier for production (cost) function, [1] using firms in top (bottom) quantiles of con-

[1]For example, in case of conditional quantile production function $Q_\tau(y|\mathbf{x}) = \mathbf{x}'\boldsymbol{\beta}(\tau)$ for N producers, quantile regression estimates

$$\hat{\boldsymbol{\beta}}(\tau) = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \sum_{i=1}^{N} \rho_\tau(y_i - \mathbf{x}'\boldsymbol{\beta})$$

where $\rho_\tau(\cdot)$ is the loss function $\rho_\tau(u) = u(\tau - I(u < 0))$ (Koenker and Bassett (1978)).

ditional distribution of the corresponding dependent variable (Koenker (2005), Hallock and Koenker (2001)). The advantage of quantile regression is its ability to provide an ordered set of technological relationships, corresponding to different levels of efficiency. Linear quantile regressions have a property of equivalence to any monotonically increasing transformation,[2] which becomes a useful feature for estimating log-linearized production (cost) functions. Namely, (opposite of) residuals in quantile regression with logged dependent (cost) output variable show the value of inefficiency. [3] Other merits of quantile regression estimates include robustness to deviations from distributional hypotheses (e.g. compared to stochastic frontier assumptions, Bernini et al. (2004)) and to outliers, which is particularly important for measurements with heterogeneous data.[4] Simulation literature demonstrates reliability of quantile regression efficiency measures, if compared to classic parametric and nonparametric scores (Behr (2010), Liu et al. (2008)). There is growing literature on real-world applications in banking, hotel industry and diary firms (Mamatzakis et al. (2012), Chidmi et al. (2011), Bernini et al. (2004)). To the best of our knowledge, health economics applications are limited to simulation analysis (Liu et al. (2008)) and pooled data estimates of efficiency in Texas nursing facilities (Knox et al. (2007)).

This paper exploits quantile regression approach to estimate efficiency of hospitals. The novelty of the paper is twofold. To the best of our knowledge, the paper is the first estimation of panel data fixed effect model with endogenous treatment variables. For this purpose, we modify Canay (2011) approach and extend Chernozhukov and Hansen (2004) instrumental variable estimations and grid-search procedure. Secondly, the paper is the first application of quantile regression approach to measuring efficiency of hospitals and to evaluating the effect of endogenous reforms on the changes in hospital efficiency. Using nationwide longitudinal samples of Japanese prospective payment system hospitals (July 2005–March 2013), designated teaching hospitals (fiscal years 2003–2013) and local public hospitals (April 1999 – March 2013), we estimate the effect of the change from a fee-for-service to prospective payment system and the introduction of residency matching program, which are voluntarily exploited by local public hospitals since 2003-2004. Additionally, we focus at potential improvements in the design of each of the reforms. Residency matching program for medical school graduates and their employers has been suffering from incomplete match and imperfections of regional caps, introduced in 2010. Using the data for hospital demand for residents and actual outcomes of matching, we forecast potential output of each hospital, given the additional input were utilized at the same efficiency level. As regards prospective payment schedule, it was modified in 2012 towards best-practice tariff-setting. The length of our panel allows evaluating the effect of the both natural experiments within each reform, using treatment effect and matching estimators.

We discover that more efficient hospitals opt for each of the reforms, and participation further improves inefficiency dynamics. The introduction of regional caps in JRMP resulted in efficiency losses and deterioration of output of acute care local public hospitals in the six large prefectures. A step towards best-practice rate setting in inpatient PPS did not have an effect on inefficiency changes.

2 Hospital reforms in Japan

2.1 Inpatient payment system

Health care suppliers can voluntarily exercise cost-reducing efforts, such as shortening the diagnostic and tests procedures, improving utilization of operating theatres to increase the flow of patients, checking prices of

[2] In this paper we exploit the fact that $Q_\tau(\log y|x) = \log(Q_\tau(y|x))$.

[3] As well as may approximate the percentage change in the dependent variable.

[4] 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)).

different medications, investing in better equipment and perfecting organizational structure (Suwabe (2004), Biørn et al. (2003), Chalkley and Malcomson (2000)). However, cost-reducing efforts are not verifiable, which leads to a creation of an adequate reimbursement mechanism, stimulating an increase in such efforts (Holmstrom and Milgrom (1991)). An example of such mechanism - inpatient prospective payment system (PPS) is based on diagnosis related groups (DRGs), carefully developed as "a system of describing hospital production" (Fetter and Freeman, 1986). Piloted in New Jersey and then applied to all Medicare hospitals in the United States, the innovative system, reimbursing a fixed amount for treating a patient with a given DRG, has spread all over the world (Busse et al. (2011), France (2003)). Theoretical models of hospital behavior regard PPS as a reimbursement mechanism encouraging efficient use of resources, higher intensity, and improvements in productivity (Hodgkin and McGuire (1994)). However, the experience of countries introducing PPS (DRGs, global budget, etc.) fails to reveal a uniform pattern in hospital efficiency time profiles.

Japan has been gradually adopting per case financing since 2003. The country is known for its universal health insurance and equal access to any healthcare institution regardless of insurance type. Reimbursement of all healthcare institutions is implemented according to the fee-for-service principle, with rates for drugs and medical services set in the unifying fee schedule, which is biannually revised by the Ministry of Health, Labor, and Welfare. 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 (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. [5]. 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 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 the three consecutive periods: period 1 that represents the first quartile of the average length of stay (ALOS) in all the hospitals, period 2 encompassing the rest of the ALOS, and period 3 of two standard deviations from the ALOS. After the end of period III, hospitals are reimbursed according to the fee-for-service system. To create incentives for shorter lengths of stay, per diem payment in period I is higher than in period II,[6] and in period II is 15% higher than in period III.[7]

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. While MHLW annual hospital-level monitoring reports demonstrate that the reform reached its major goal of decreasing the long length of stay, the impact on hospital costs is unclear (Yasunaga et al. (2006)). Moreover, the accompanying rise in the early readmission rate, the fall in profit margins (Yasunaga et al. (2005a), Yasunaga et al. (2005b)) and increase of ALOS in some hospitals (Nawata and Kawabuchi (2013)) imply that productivity may not have increased.

In attempt to diminish the adverse effects of degressive tariff-setting and move towards best-practice rate

[5]For eaxample, 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))

[6]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.

[7]10% higher for a DPC with low medical cost at the beginning of the treatment.

setting, MHLW introduced a change in the price schedule: starting fiscal year 2012 no more that 50% of mean national length of stay for each diagnosis could be reimbursed according to the highest rate in period I (Ministry of Health, Labor and Welfare (2012a)).[8]

2.2 Residency matching program

Japan residency matching program was established in 2003 as a nationwide computer system which matches teaching hospitals and 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 formerly conducted at the individual hospital-student level and offer more options for graduates, resulting in weaker ties between universities and affiliated hospitals, improved quality of training programs and increase of standardization of medical care (Inoue and Matsumoto (2004)).

Postgraduate training in Japan was mandatory in 1946–1968, but became noncompulsory since 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 internship at university hospital (Onishi and Yoshida (2004)). Moreover, the tendency of applying to own university affiliated hospital was extremely prevalent (Campbell and Ikegami (1998)). Trainees were commonly restricted to work in a particular department or even in a certain ward, thus getting only monospeciality education (Inoue and Matsumoto (2004), Onishi and Yoshida (2004))). The resulting incompetence of residents in their clinical skills became the major cause for an introduction of a new postgraduate program in 2004. The first year of the postgraduate program is dedicated to internal medicine (at least 6 months), surgery and emergency medicine. The second year is spent to acquiring skills in pediatrics, obstetrics-gynecology, psychiatry and primary care. To guarantee absence of part-time jobs outside training hospitals the program establishes high level of trainee salaries and provides support for supervising doctors. The MHLW criteria for granting a status of teaching hospital include the presence of at least the departments for internal medicine, surgery, psychiatry, pediatrics, obstetrics-gynecology (and anesthesiology since 2010); treating at least 3000 inpatients a year (relaxed in 2010 to more than 100 inpatients in each department); providing emergency care; using clinical pathology conference reports as medical records; having at least one supervisor (doctor with 7-year experience) per 5 trainees; having libraries, medical journals and Internet access (Ministry of Health, Labor and Welfare (2012c), Nomura et al. (2008a)).

The first outcomes of the JRMP show that the number of graduates, selecting university hospitals decreased from 58.8% in 2003 to 45.1% in 2013 (Japan Residency Matching Program (2013a)). Additionally, the 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)). Moreover, the professional competence of trainees increased (Nomura et al. (2008a)). However, the adverse results of JRMP may have been a decrease of doctors in the rural areas, for which university hospitals were major suppliers of labor force (Nomura et al. (2008b)).

The number of vacancies in hospitals was larger than the number of medical school graduates, and several prefectures faced particularly low rate of filling vacancies. Accordingly, regional caps were added to 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. (Note that the cap may not exceed 90% of previous year's sum of vacancies in the region). The ratio of the regional cap divided by actual sum of vacancies in prefecture is then applied to each hospital. Namely, the maximum number of

[8]Moreover, the length of period I was decreased to only one day for 22 DPCs with particularly high medical cost at the beginning of the treatment (Ministry of Health, Labor and Welfare (2012b)).

hospital's residents in the previous 3 years is multiplied by the ratio to give actual vacancies, which may be announced. Hospitals, sending their doctors to other hospitals, receive additional quotas. The regional cap modification of JRMP is argued to have led to inefficiencies of the program in terms of unfilled vacancies (Kamada and Kojima (2010)).

2.3 Local public hospitals

Constituting 10% of all hospitals in the country, Japanese local public hospitals are founded by prefecture, designated city, city, town, village, or a union of several municipalities (usually towns or villages). With an increasing number being in the red, Japanese local public hospitals are commonly criticized for weak financial constraints due to over-subsidization by the government (Ikegami and Campbell (1999), Iwane (1976)). Although this may be largely explained by the fact that many of these hospitals are run-down and understaffed (Campbell and Ikegami (1998)), the issue of their financial deficit has become a particular topic in economic analysis of Japanese local public healthcare. Indeed, Newhouse (1969) argues that nonprofitable status, various subsidies, availability of cheap capital, desire to invest in capital equipment in search for prestige or as a form of market signaling add to economic inefficiency of a public hospital. [9]. Despite being publicly recognized, the issue of raising efficient resource use in local public hospitals has been weakly reflected in the Japanese healthcare reforms. As for particular policy issues for the local public hospitals, the guidelines on gradual changes of these institutions appeared only in December 2007 (Ministry of Internal Affairs and Communications, 2007).

3 Methodology

3.1 Endogeneity in quantile regression models

The theory and inference for an instrumental variable approach, allowing consistent estimation of cross-sectional quantile regression with endogenous covariates, as well as a 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 and Hansen (2004) methodology to estimating Koenker (2004) panel data quantile regression model with endogenous variables and quantile dependent fixed effects. Galvao (2011) shows consistency of Chernozhukov and Hansen (2004) 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 the fitted value of the dependent variable. In this paper we extend Canay (2011) methodology for two-step estimation of panel data quantile regressions with endogenous variables. Adding an assumption about independence of disturbance term from instrumental variables, at the first step we can consistently estimate fixed effects (e.g., with OLS instrumental variable approach). At the second step we modify Chernozhukov

[9] Although the above factors are particularly noticeable in local public hospitals, they may be justified by the fact that these institutions play a special role of guaranteeing certain types of healthcare provision in local areas. Therefore, subsidizing local public hospitals may be regarded as a regulator's attempt to correct for nonmarketability of medical care (Arrow (1963))

and Hansen (2004) grid-search procedure for an instrumental variable estimation of a two-dimensional vector of endogenous variables D and a large number of instruments.[10] We test the "locational shift" specification against a random effects model, as well as against a model with quantile dependent fixed effects.

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

3.2.1 Random effects model

The model is a 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):

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

[10] Chernozhukov and Hansen (2004) matlab code is modified by Sergei Golovan and Pavel Krivenko to contain two loops, have dim $\mathbf{z} \geq$ dim $\mathbf{d}$, and use arrayfun function to speed up computations.

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

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 $NTh^2_{NT} \to \infty$.

3.2.2 Quantile dependent fixed effects model

The list of exogenous covariates in the model (1)-(3) is $\tilde{\mathbf{x}}_{it} = [\mathbf{x}_{it}, \boldsymbol{\eta}_i]$, where $\boldsymbol{\eta}_i$ is $(N-1)$ vector of fixed effects and $\mathbf{x}$ includes constant term (Harding and Lamarche (2009)).

3.2.3 "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 a practical two-step procedure. Namely, a consistent estimate of η_i, obtained through a least-squares instrumental variable regression, is employed for computing $\hat{y}_{it}$. Then, $\hat{y}_{it}$ becomes a dependent variable in 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.

3.3 Specification

3.3.1 Output distance function

Output distance function D_{it} $(0 < D_{it} \leq 1)$ for i-th hospital in M-output K-input model may be specified in translogarithmic form as (Coelli and Perelman (2000), eq. 5):

$$\begin{aligned}\ln D_{it} = &\sum_{m=1}^{M} \beta_m \ln y_{mit} + 0.5 \sum_{m=1}^{M}\sum_{q=1}^{M} \beta_{mq} \ln y_{mit} \ln y_{qit} + \sum_{k=1}^{K} \beta_k \ln x_{kit} \\ &+ 0.5 \sum_{k=1}^{K}\sum_{s=1}^{K} \beta_{ks} \ln x_{kit} \ln x_{qit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{nm} \ln x_{kit} \ln y_{mit} + \sum_{j=1}^{J} \beta_j h_{jit},\end{aligned} \tag{13}$$

where i denotes hospital, $M = dim(\mathbf{y})$, $K = dim(\mathbf{x})$, $\mathbf{h}$ are hospital control variables, and symmetry restrictions require $\beta_{ks} = \beta_{sk}$ and $\beta_{mq} = \beta_{qm}$. Homogeneity restrictions are imposed by dividing the distance function and all outputs by an arbitrarily chosen M-th output as a numeraire. After rearranging terms, the equation looks as follows (Coelli and Perelman (2000), eq. 11, 14):

$$\begin{aligned}-\ln y_{Mit} = &\sum_{m=1}^{M} \beta_m \ln \frac{y_{mit}}{y_{Mit}} + \sum_{m=1}^{M}\sum_{q=1}^{M} \beta_{mqt} \ln \frac{y_{mit}}{y_{Mit}} \ln \frac{y_{qit}}{y_{Mit}} + \sum_{k=1}^{K} \beta_k \ln x_{kit} \\ &+ 0.5 \sum_{k=1}^{K}\sum_{q=1}^{K} \beta_{kq} \ln x_{kit} \ln x_{qit} + \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{nm} \ln x_{kit} \ln \frac{y_{mit}}{y_{Mit}} - \ln D_{it} + \sum_{j=1}^{J} \beta_j h_{jit}.\end{aligned} \tag{14}$$

Assuming that the distribution of $-\ln D_{it}$ is a monotone function of a distribution of D_{it} and $D_{it} \sim U[0, 1]$, we can estimate the equation with quantile regression approach (adding a stochastic term u_{it} and fixed effect term v_i to the right-hand side). As in this case the dependent variable is negative, we estimate inefficiency using the bottom quantile observations.

3.3.2 Cost function

Since hospitals are generally modeled as cost-minimizing rather than profit-maximizing economic agents, this paper considers a panel data trans-logarithmic cost function. Cost function homogeneity of degree one in prices is exploited by division of costs and all prices by a numeraire price (following Yamada et al. (1997) we exploit the cost of medicines and materials per bed). Let

$$\begin{aligned}\ln \frac{c_{it}}{p_K} = &\sum_{m=1}^{M} \beta_m \ln y_{mit} + \sum_{k=1}^{K-1} \beta_k \ln \frac{p_{kit}}{p_K} + 0.5 \sum_{k=1}^{K-1}\sum_{o=1}^{K-1} \beta_{os} \ln \frac{p_{kit}}{p_K} \ln \frac{p_{kit}}{p_K} + 0.5 \sum_{m=1}^{M}\sum_{q=1}^{M} \beta_{mq} \ln y_{mit} \ln y_{mit} \\ &+ \sum_{k=1}^{K-1}\sum_{m=1}^{M} \beta_{km} \ln \frac{p_{kit}}{p_K} \ln y_{mit} + \sum_{j=1}^{J} \beta_j h_{jit} + \nu_i + \epsilon_{it}\end{aligned} \tag{15}$$

where i denotes hospital, $M = dim(\mathbf{y})$, $K = dim(\mathbf{x})$, p_K is a numeraire price, $\mathbf{h}$ are hospital control variables, and symmetry restrictions require $\beta_{os} = \beta_{so}$ and $\beta_{mq} = \beta_{qm}$.

3.4 Measure of inefficiency

We measure hospital output inefficiency te_{it} as

$$te_{it} = -\widehat{\ln}(y_{it}|\tau) - (-\ln y_{it}) = \ln y_{it} - \widehat{\ln}(y_{it}|\tau) \tag{16}$$

Similarly, hospital cost inefficiency ce_{it} is estimated as

$$ce_{it} = \widehat{\ln}(c_{it}|\tau) - \ln c_{it} \tag{17}$$

The change in output (cost) inefficiency in the post reform and pre-reform year are computed as

$$d_{it} = e_{it} - e_{i,t-1} \tag{18}$$

where e is output (cost) inefficiency, respectively. Given the range of values of our dependent variable $(y_{it} and c_{it})$, the difference in logarithms of the actual and fitted value (i.e. the inefficiency measures) may be approximately treated as the value in the $[-1, 0]$ segment. So the above defined change in inefficiency may be treated as percentage change in inefficiency.

3.5 The reform effect

3.5.1 Descriptive analysis

To assess the impact of JRMP on output and cost efficiency, we compare mean values of d^{te}_{it} (d^{ce}_{it}) in the three groups of hospitals:

1. with exact matching in year $t-1$,
2. with non-filled vacancies as a result of matching process in year $t-1$,
3. non-participants in the JRMP in year $t-1$.

Additionally, we estimate the effect of JRMP and PPS, focusing on only on those hospitals, which have introduced PPS by the corresponding year.

3.5.2 Conditional average treatment effect and matching estimators

Average treatment effect, conditional on the sample distribution of covariates (CATE) is estimated as (Imbens (2004), Abadie and Imbens (2002))

$$\bar{\tau}(x) = \frac{1}{N}\sum_{i=1}^{N} E[y_i(w_i = 1) - y_i(w_i = 0)|\mathbf{z}_i] \tag{19}$$

where $i = 1, ..., N$ is the observed sample, y_i is the outcome, w_i is the treatment indicator, $\mathbf{z}_i$ are exogenous variables.

In constructing the control group we assume that PPS and JRMP are non-randomized treatments. Two issues justify the above premise. First, there are official criteria for participation in the programs. As regards inpatient PPS, a hospital has to meet the threshold value of MHLW "'nurse staffing ratio" of 2 inpatients per nurse; has to follow the methodology for accounting inpatient expenditure; and has to collect standardized data on prescribed drugs. In particular, the methodology for accounting inpatient expenditure implies employment of special administrative staff, detailed book keeping, ICD-10 coding, and data processing (Sato

(2007)). The eligibility criteria for JRMP are the presence of certain hospital departments, benchmark annual figures for inpatients (3000 before 2009 and 100 in each department since 2010), presence of physicians with at least 7 years of experience, dealing with emergency medicine, using clinical pathology conference reports, providing library facilities and Internet access. These requirements could be satisfied only by hospitals with certain characteristics. Second, voluntary participation in the PPS reform and JRMP might lead to self-selection. In particular, hospitals must have used them as a signaling tool to attract patients, or as means to enhance data management and promote treatment standardization. These incentives apply to some hospitals better than others, presumably leading to a selection bias in the Japanese PPS reform.

While a number of such methods exist in the literature (see review in Imbens (2004)), we used nearest neighbor matching with replacement which does not depend on smoothing parameters and enables increased precision [11] through increasing the number of matches (**?**). Using the STATA module nnmatch (Abadie et al. (2004)) we correct for the asymptotic variance of matching estimators (Abadie and Imbens (2002)) by combining regression and matching. As DPCs were primarily introduced in the local public hospitals which have appropriate medical data accounting systems, propensity score analysis (using probit model) is conducted in order to assess the overlap assumption (Crump et al. (2009), Rosenbaum and Rubin (1983)). Namely, to guarantee that

$$0 < Pr(w = 1|\mathbf{z}) < 1, \tag{20}$$

we follow Imbens and Wooldridge (2009) and check for the absence of observations with the propensity score out of the range (0.1, 0.9).

The major identifying assumption in the analysis of conditional average treatment effect is the premise that conditional on a given set of covariates (variables $\mathbf{z}$) participation in the reform is uncorrelated with the outcome in both states: participation and nonparticipation (Rosenbaum and Rubin (1983)). Called conditional independence (Heckman and Vytlacil (2007)) or unconfoundedness (Imbens (2004)), the assumption implies that

$$(D(w = 0), D(w = 1)) \perp w|\mathbf{z}, \tag{21}$$

where $y(w = 0)$ and $y(w = 1)$ are potential outcomes in case of absence of treatment and treatment, respectively. A justification for the unconfoundedness assumption may be revealed from the statements of health care officials who mention the development of standardization and uniform patterns for treatment of patients as the primary goals of hospitals' joining the PPS (Okuyama (2008), Saito (2007)). Moreover, the expectation about the rise in profits could not be considered as a reason for introducing DPCs (Nishioka (2010)). To assess unconfoundedness we adopt Imbens's (2004) approach and analyze the significance of CATE coefficient in matching and regression with lagged outcome. The results generally demonstrate insignificance of CATE coefficients, which may be interpreted as a validity of unconfoundedness assumption for most of the analyzed outcomes.[12]

[11] However, increased precision comes at the cost of bias of the estimator. Therefore, we use the models with 3 matches, which provide for most robust results.

[12] If the decision to participate in the reforms is endogenous (e.g., related to an unobservable parameter in hospital's objective function), the average treatment effect estimates are inconsistent (Greene (2012)). However, our use of instrumental variables for reform dummies in the quantile regressions and high goodness-of-fit statistics in the first stage minimize the possibility that such unobservable parameter would be correlated with the residual (i.e., efficiency score analyzed in this paper).

3.5.3 Forecasting

We find conditional quantile, so that hospital i were fully technically efficient in year t. Namely, using bisection method, for each $j = 1, ..., NT$ we run a set of quantile regressions in eq.(12) to find τ_j, so that

$$te_{it} = \ln y_{it} - \widehat{\ln}(y_{it}|\tau_j) \equiv 0 \tag{22}$$

Then, assuming that additional labor inputs (unmatched vacancies $\triangle\, l$) would be utilized with same efficiency as on the hospital-specific efficient technological frontier, we use quantile regression to estimate fitted value of output as

$$\hat{\ln}(y_{Mj}|\tau_j, l_j + \triangle\, l_j), \tag{23}$$

where l_j is the actual amount of doctors in hospital i in year t. The relative change in the fitted and the actual value of output $(\hat{y}_{Mj} - y_{Mj})/y_{Mj}$ gives potential gain in output, if the reform were effective in fully matching residents.

4 Data and variables

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).[13]

Owing to inavailability of the 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, efficiency 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 give the number of admissions or outpatient visits, reporting instead the daily number of inpatients and outpatients. However, the database allows reconstructing the number of discharges for the subsample of general hospitals with general 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 a subsample of hospitals with general beds. Labor inputs are doctors, total number of nurses (junior nurses and nurses proper), and other hospital personnel.[14] Beds are used as a proxy for capital.

Our approach with setting the production function generally follows the frontier studies of the Japanese local public hospitals' efficiency, where the most prevalent specification considers labor inputs by medical specialty.[15] In our baseline model labor input is doctors and beds is an input variable which serves a proxy for capital. Prices of labor are the earnings of a corresponding employee; capital price is the sum of depreciation and interest per bed[16]. Both these prices may be assumed exogenous in the framework of Japanese local public hospitals. Total cost and prices are normalized by the price of medicines (cost of medicines and materials per bed). In case of cost function we treat total labor force as labor input and use average earnings of an employee as labor price.

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

[14] To check robustness of our results we analyze models with different combinations of inputs and with 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 employing 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.

[15] See review in Besstremyannaya (2011).

[16] 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.

The data on hospital departments (as of 2014 or the last year of hospital's functioning) and on hospital's location (urban/rural) come from "Handbook of Hospitals", which contains hospital name, address, and the list of departments. While a number of studies consider nursing standards (established by the Ministry of Health, Labor, and Welfare) as a quality characteristic (Takatsuka and Nishimura (2008), Kawaguchi (2008), Yamada et al. (1997), Fujii and Ohta (1999), Fujii (2001)), this paper uses Japan Council for Quality Health Care (2014) data on hospital accreditation.

As regards the participation in hospital financing reform and data on treated patients, the analysis employs an administrative nationwide database from Japan's Ministry of Health, Labor, and Welfare (September 20, 2013) on annual hospital level aggregated information for major diagnostic categories and diagnoses-procedure combinations of patients, discharged in July-October 2005, July-December 2006-2010, July 2011-March 2012, and April 2012-March 2013. The data are voluntarily sent to MHLW by hospitals, which opt for the prospective payment reform. Hospitals may join the PPS reform after the trial period (commonly after two years), may postpone the decision and keep submitting the data to the MHLW, or may choose to never join the reform and discontinue sending their data. Merging annual files by hospitals names[17] we create an unbalanced panel for 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 merging them by hospital name. First, controlling for changes in name and affiliation, mergers and closures, we create an unbalanced panel of 1083 local public hospitals in Japan in 1999-2012. Owing to administrative reform, which has 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 914-984 hospitals.

Of the constructed unbalanced panel, 271-296 local public hospitals participated in JRMP in various years. As regards inpatient prospective payment system, it was introduced in 1 hospital by 2004, 33 hospitals by 2007, 108 hospitals by 2008, 260-309 hospitals by 2009-2012. We drop the data for hospitals with average length of stay below 6 days[18] or over 90 days [19], with missing numbers of doctors and with psychiatric beds.[20]Accordingly, the estimations with output distance (cost) function employ longitudinal subsamples of 626-785 (622-784) hospitals without psychiatric beds in 2005-2012 and 303-367 (300-366) hospitals with exclusively acute care (general) beds. Smaller subsamples in case of cost models are explained by missing values of employee earnings. Of the subsample of hospitals without psychiatric beds (with only general beds) 175-220 (80-98) participated in JRMP in 2005-2012 and 1-205 (1-93) have employed inpatient prospective payment system by the beginning of the corresponding financial year (Table 1).

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

		2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Universe	Total number	984	973	957	950	939	927	919	914
	PPS	1	33	33	108	260	286	295	309
	JRMP	293	293	296	296	278	272	271	271
	full match	145	131	94	88	121	121	124	113

[17]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.

[18]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)).

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

[20]To exclude this special type of patients and guarantee for certain homogeneity of hospital production in absence of any variable directly or indirectly related to the prevalence of patients with different diagnoses (casemix) in the local public hospitals database

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

		2005	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Acute care hospitals	Total number	367 (366)	364 (363)	326 (324)	347 (346)	340 (339)	325 (324)	315 (313)	303 (300)
	PPS	1	9	9	38	84	85	90	93
	JRMP	98	98	90 (89)	98	85	80	83	81
	full match	48	42	23	21	33	29	36	28
No psychiatric beds	Total number	785 (784)	769 (768)	697 (693)	721 (718)	701 (698)	671 (668)	652 (549)	626 (622)
	PPS	1	24	24	78	183	192	198	205
	JRMP	220	218	206	216	196	181	179	175
	full match	103	95	62	58	79	81	81	70

Note: Sub-samples of hospitals for cost models, if different from sub-sample in output distance function models, in parentheses.

5 Results and Discussion

5.1 Descriptive analysis

As the choice of benchmark quantile may influence the fitted values of residual (i.e. inefficiency, as defined in this paper), we experiment with bottom quantiles: $\tau \in \{0.1, 0.2\}$. The results of the estimates with our data demonstrate that the mean value of inefficiency in each subgroup of hospitals depends on the benchmark bottom quantile (Figures 1–2). However, the relative value of inefficiency in subgroups, as well as the time profile of changes in inefficiency scores may be regarded as independent of the chosen value of the bottom quantile

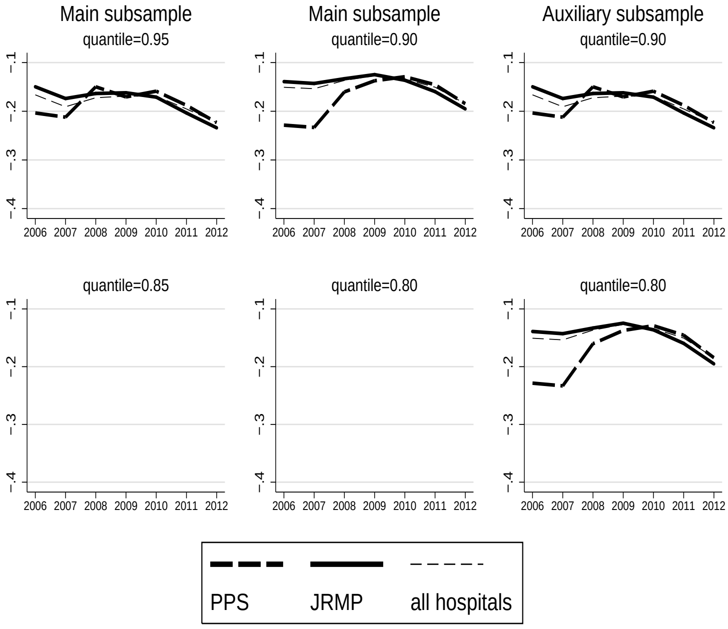

Figure 1: **Output inefficiency of Japanese local public hospitals**

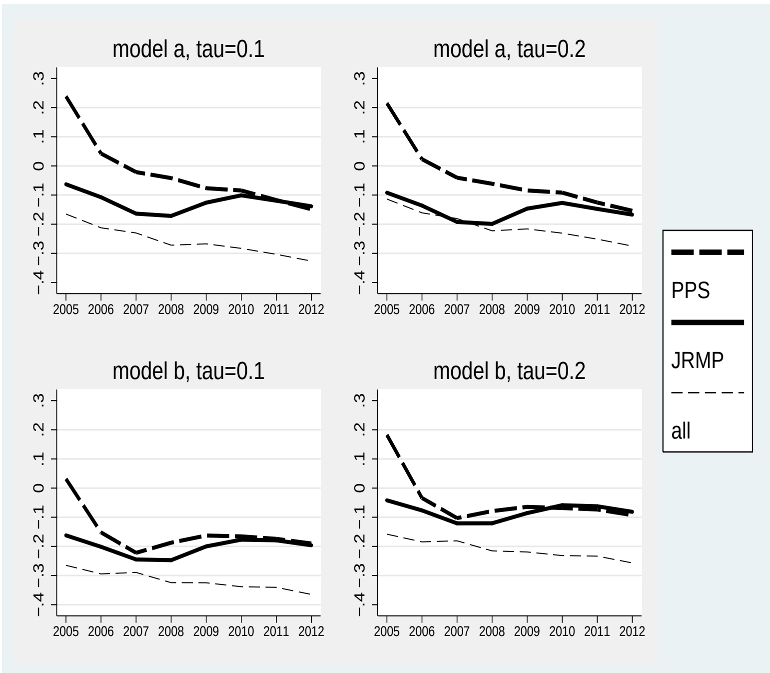

Figure 2: **Cost inefficiency of Japanese local public hospitals**

Notes: The results indicate estimates with Cobb-Douglass multi-output distance (cost) function. For each $t = 2005, ..., 2012$ the table demonstrates mean inefficiency, i.e. the values of $\bar{e}_{it} = \sum_{i=1}^{N} e_{it}$. Models (a) and (b) denote respectively, models with inpatients and outpatients, and discharges and outpatients.

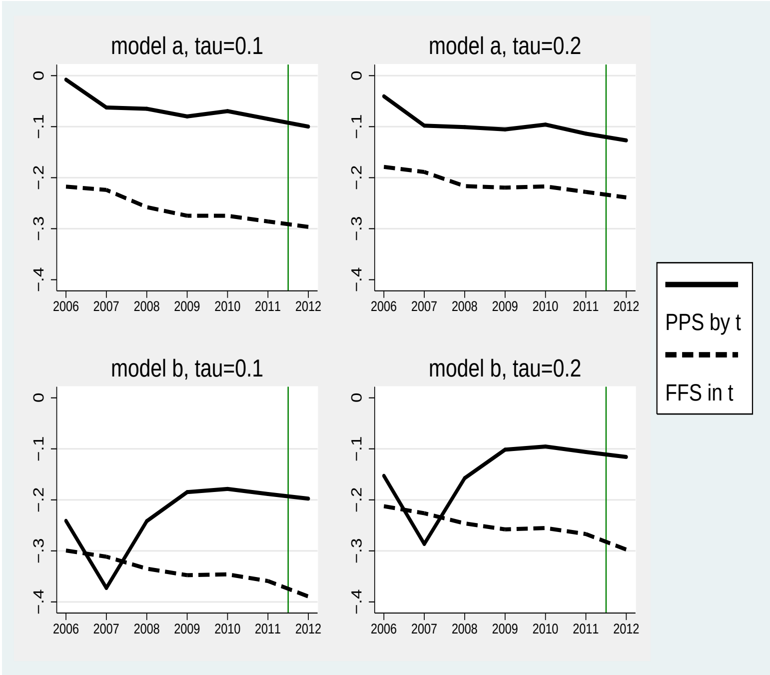

Figure 3: **Effect of PPS on change in output inefficiency**

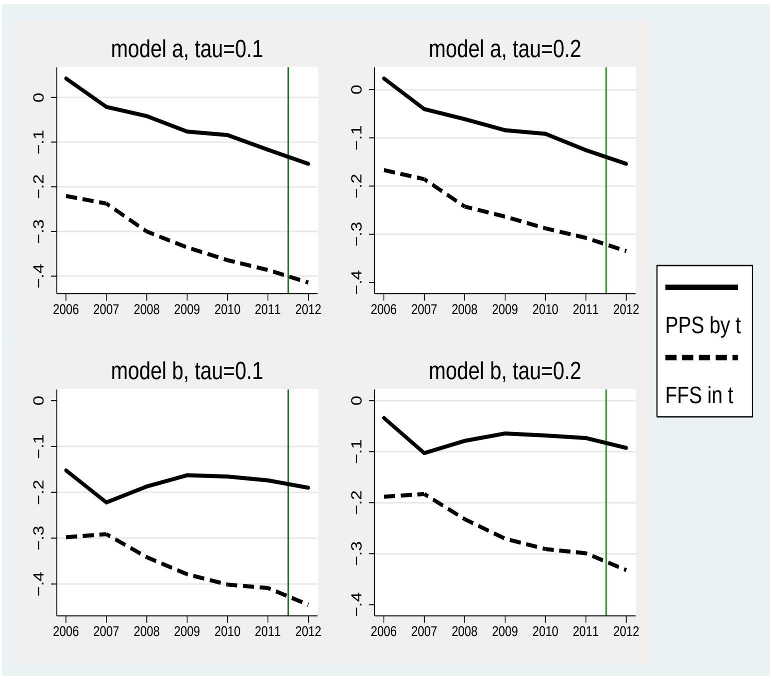

Figure 4: **Effect of PPS on change in cost inefficiency**

Notes: The results indicate estimates with Cobb-Douglass multi-output distance (cost) function. For each $t = 2006, ..., 2012$ the table demonstrates mean inefficiency change in subgroup g (PPS by t, or FFS in t), i.e. the values of $\bar{d}_{it} = \sum_{i_g=1}^{N_g}(e_{i_g,t} - e_{i_g,t-1})$. Models (a) and (b) denote respectively, models with inpatients and outpatients, and discharges and outpatients.

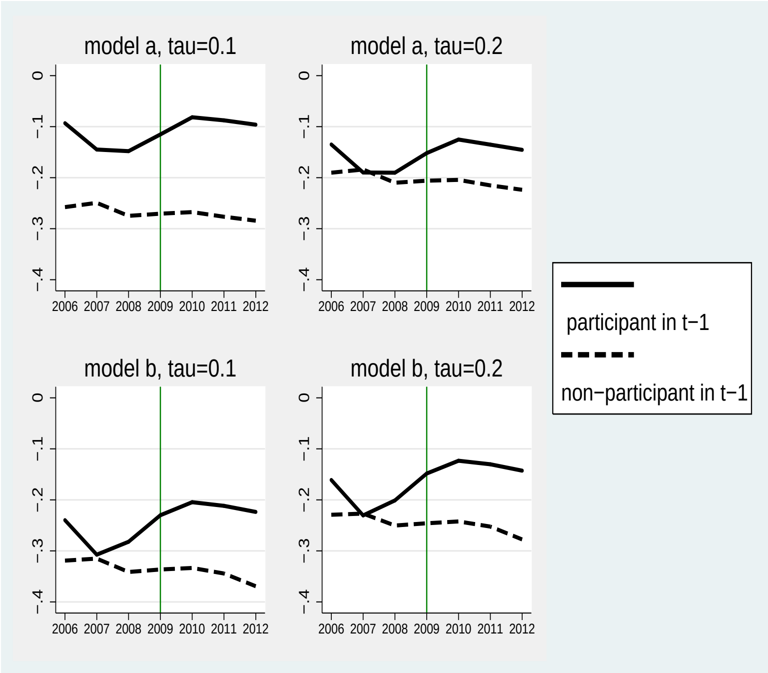

Figure 5: **Effect of JRMP on change in output inefficiency**

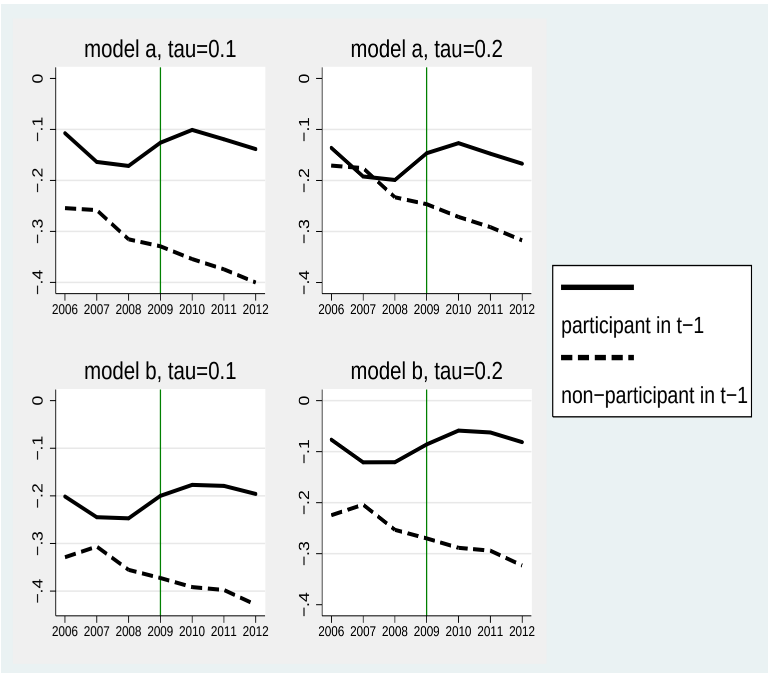

Figure 6: **Effect of JRMP on change in cost inefficiency**

Notes: The results indicate estimates with Cobb-Douglass multi-output distance (cost) function. For each $t = 2006, ..., 2012$ the table demonstrates mean inefficiency change in subgroup g (participants or non-participants in JRMP in $t-1$), i.e. the values of $\bar{d}_{it} = \sum_{i_g=1}^{N_g}(e_{i_g,t} - e_{i_g,t-1})$. Models (a) and (b) denote respectively, models with inpatients and outpatients, and discharges and outpatients.

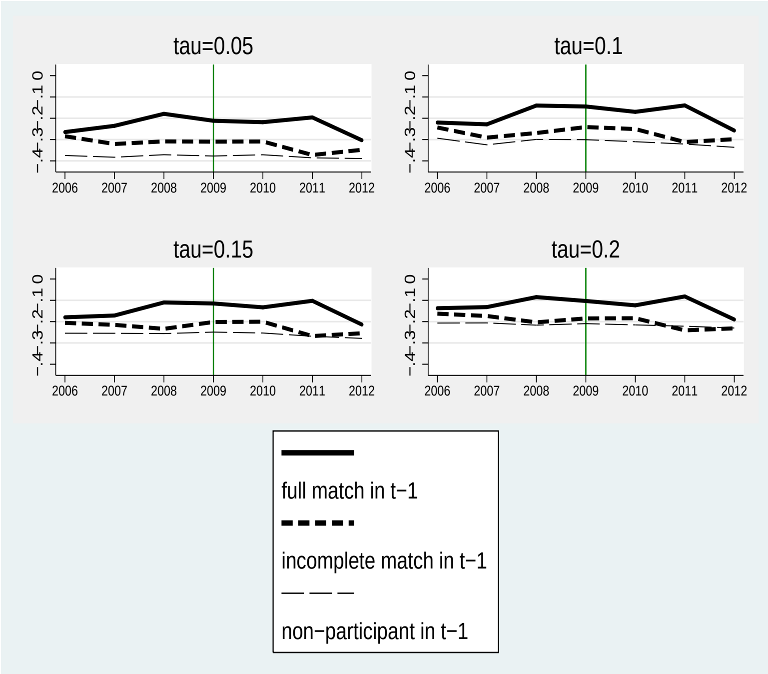

Figure 7: **Effect of full match in JRMP on change in output inefficiency**

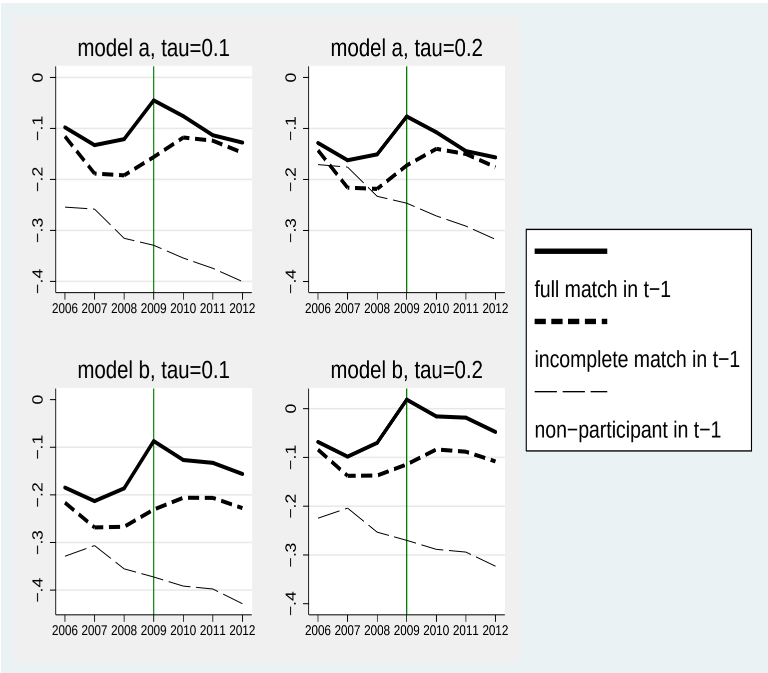

Figure 8: **Effect of full match in JRMP on change in cost inefficiency**

Notes: The results indicate estimates with Cobb-Douglass multi-output distance (cost) function. For each $t = 2006, ..., 2012$ the table demonstrates mean inefficiency change in subgroup g (with full match in $t-1$, incomplete match in $t-1$, or non-participants in JRMP in $t-1$), i.e. the values of $\bar{d}_{it} = \sum_{i_g=1}^{N_g}(e_{i_g,t} - e_{i_g,t-1})$. Models (a) and (b) denote respectively, models with inpatients and outpatients, and discharges and outpatients.

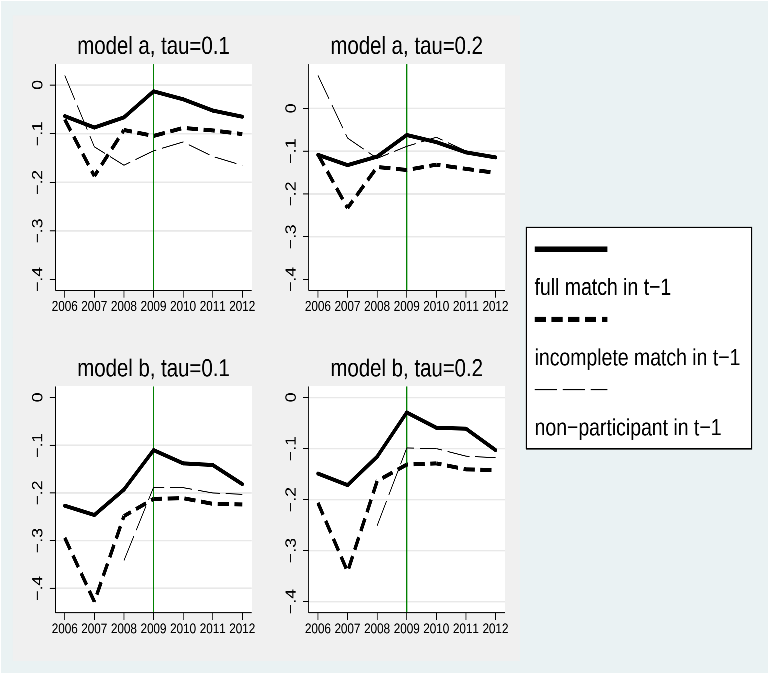

Figure 9: **Effect of JRMP on change in output inefficiency of PPS hospitals**

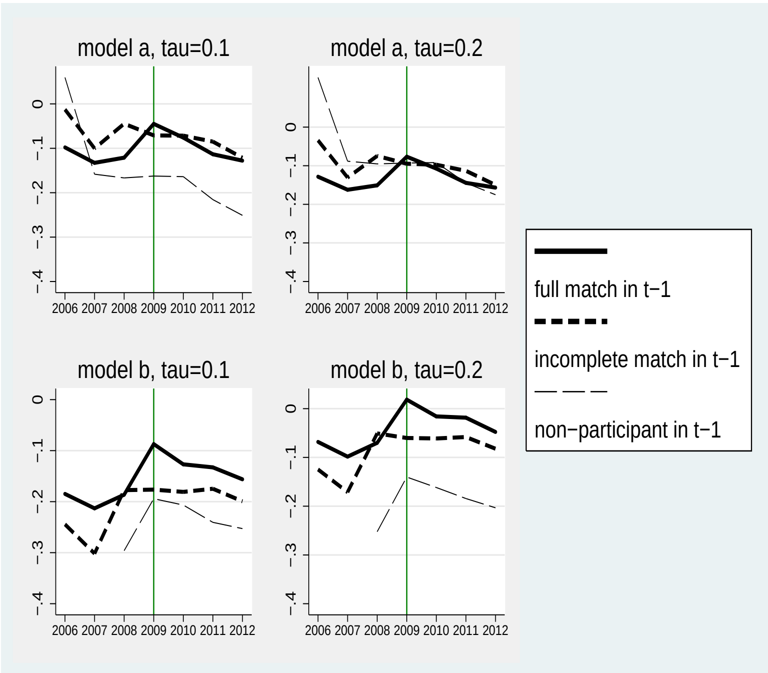

Figure 10: **Effect of JRMP on change in cost inefficiency of PPS hospitals**

Notes: The results indicate estimates with Cobb-Douglass multi-output distance (cost) function. For each $t = 2006, ..., 2012$ the table demonstrates mean inefficiency change in subgroup g of PPS hospitals (with full match in $t-1$, incomplete match in $t-1$, or non-participants in JRMP in $t-1$), i.e. the values of $\bar{d}_{it} = \sum_{i_g=1}^{N_g}(e_{i_g,t} - e_{i_g,t-1})$. Models (a) and (b) denote respectively, models with inpatients and outpatients, and discharges and outpatients.

Mean output inefficiency is stable (or slightly decreases in case of $\tau = 0.2$) in the whole group of local public hospitals. The values of output and cost inefficiency are larger in absolute terms for the whole group of local public hospitals, if compared to JRMP hospitals or PPS hospitals. Similarly to the findings of parametric and nonparametric frontier analysis studies with local public hospital database (Besstremyannaya (2013)), our panel data quantile regression estimates show that cost efficiency decreases for all local public hospitals and PPS hospitals.

Output and cost inefficiency decreases both for PPS and FFS hospitals (values of inefficiency change are below zero), as well as for JRMP and non-JRMP hospitals. However, the absolute value of inefficiency fall is smaller for PPS hospitals if compared to FFS (Figures 3– 4) and for JRMP hospitals if compared to JRMP non-participant hospitals (Figures 5– 6). The fall in efficiency for JRMP hospitals decreases in 2008-2010 and starts increasing since 2011, which may be attributed to the introduction of regional caps in the 2010 matching process.

As regards hospitals with full match within JRMP program, their efficiency decrease is smaller if compared to hospitals with incomplete match or JRMP - non-participants. Note that for full match hospitals the smallest value of inefficiency drop is noted in 2009. Starting 2010 (i.e. based on 2009 matching results) inefficiency of full match hospitals decreases faster than in the previous years. Most likely, this reflects the fact that hospitals lowered their vacancy levels as early in 2009, anticipating the announced change in the program design. So the full match in 2009 does not reflect the actual demand of hospitals in trainees. As regards hospitals with incomplete match, their inefficiency drop rate starts decreasing since 2011, reflecting the results of the matching process in 2010 – the year of the regional cap introduction (Figures 7– 8).

Inefficiency changes of PPS hospitals, which had full or incomplete match within JRMP have similar time profiles to all hospitals, which faced full/incomplete match ((Figures 9– 10). The changes in the PPS payment schedule of 2012 do not have any effect on time profile of technical or cost efficiency. The findings about peaks in inefficiency corresponds to the results of Kamada and Kojima (2012) and Kamada and Kojima (2010) about the ineffectiveness of regional caps within existing JRMP mechanism.

Additionally, an introduction of a regional cap has resulted in an increase in the share of hospitals with full match, and lower efficiency gains owing to participation in JRMP and full match. Note that the number of unfilled vacancies increased in Hokkaido, Shikoku and Kyushu - most economically deprived regions, which experience the highest lack of doctors in local public hospitals.

Table 2: **Output and cost efficiency of Japanese local public hospitals by geographic zone,** $\tau = 0.2$

		all		JRMP		
zone	**year** (t)	$\bar{te}_{it}$	$\bar{ce}_{it}$	vacancies	$\bar{te}_{it}$	$\bar{ce}_{it}$
Hokkaido	2005	-0.197	-0.058	1.67	-0.120	-0.096
	2006	-0.254	-0.115	2.00	-0.227	-0.162
	2007	-0.260	-0.157	0.88	-0.209	-0.194
	2008	-0.286	-0.197	0.80	-0.319	-0.251
	2009	-0.280	-0.223	1.56	-0.181	-0.173
	2010	-0.291	-0.291	1.13	-0.175	-0.201
	2011	-0.309	-0.337	0.29	-0.148	-0.178
Tohoku	2005	-0.158	-0.120	1.46	-0.074	-0.058
	2006	-0.217	-0.183	1.30	-0.121	-0.099
	2007	-0.174	-0.154	1.68	-0.126	-0.116
	2008	-0.173	-0.184	2.12	-0.173	-0.173
	2009	-0.168	-0.202	1.96	-0.192	-0.190
	2010	-0.165	-0.232	1.61	-0.163	-0.168
	2011	-0.166	-0.254	2.36	-0.198	-0.210
Kanto	2005	-0.190	-0.259	0.72	-0.126	-0.178
	2006	-0.238	-0.320	0.72	-0.175	-0.233
	2007	-0.241	-0.322	0.71	-0.246	-0.304
	2008	-0.286	-0.397	1.13	-0.241	-0.310
	2009	-0.279	-0.390	1.45	-0.221	-0.283
	2010	-0.261	-0.376	1.47	-0.200	-0.268
	2011	-0.277	-0.418	1.61	-0.211	-0.297
Chubu	2005	-0.104	-0.118	2.11	-0.094	-0.084
	2006	-0.135	-0.157	1.75	-0.127	-0.129
	2007	-0.187	-0.230	1.92	-0.225	-0.247
	2008	-0.200	-0.250	2.70	-0.209	-0.221
	2009	-0.198	-0.245	2.53	-0.213	-0.219
	2010	-0.178	-0.255	1.53	-0.184	-0.192
	2011	-0.193	-0.286	1.43	-0.196	-0.212
Kinki	2005	-0.165	-0.158	1.33	-0.104	-0.114
	2006	-0.240	-0.257	0.98	-0.166	-0.181
	2007	-0.223	-0.243	1.38	-0.197	-0.216
	2008	-0.279	-0.309	2.20	-0.243	-0.268
	2009	-0.285	-0.303	2.42	-0.248	-0.233
	2010	-0.279	-0.310	1.04	-0.234	-0.225
	2011	-0.284	-0.323	0.98	-0.245	-0.252
Chugoku	2005	-0.084	-0.038	1.43	-0.072	-0.045
	2006	-0.087	-0.052	1.33	-0.103	-0.091
	2007	-0.125	-0.098	1.50	-0.134	-0.117
	2008	-0.148	-0.180	2.33	-0.210	-0.201
	2009	-0.129	-0.175	2.40	-0.190	-0.185
	2010	-0.129	-0.188	1.92	-0.194	-0.207
	2011	-0.129	-0.228	1.60	-0.182	-0.243

Table 2: **Output and cost efficiency of Japanese local public hospitals by geographic zone, $\tau = 0.2$**

zone	**year (t)**	**all** $\bar{te}_{it}$	$\bar{ce}_{it}$	**JRMP** vacancies	$\bar{te}_{it}$	$\bar{ce}_{it}$
Shikoku	2005	-0.108	-0.073	2.25	-0.109	-0.095
	2006	-0.147	-0.113	1.63	-0.215	-0.218
	2007	-0.155	-0.123	1.25	-0.230	-0.238
	2008	-0.173	-0.182	1.00	-0.268	-0.327
	2009	-0.219	-0.243	2.75	-0.297	-0.299
	2010	-0.196	-0.226	3.57	-0.222	-0.257
	2011	-0.190	-0.256	2.00	-0.221	-0.240
Kyushu	2005	-0.145	-0.078	1.00	-0.121	-0.068
	2006	-0.178	-0.094	1.35	-0.155	-0.093
	2007	-0.179	-0.116	1.26	-0.154	-0.105
	2008	-0.223	-0.174	3.00	-0.214	-0.142
	2009	-0.219	-0.196	3.39	-0.230	-0.166
	2010	-0.219	-0.234	3.13	-0.241	-0.199
	2011	-0.219	-0.198	2.93	-0.255	-0.236

Notes: The results indicate estimates with Cobb-Douglass multi-output distance (cost) function and models with inpatients and outpatients. For each $t = 2005-2012$ the table demonstrates mean inefficiency in each zone, i.e. the values of $\bar{e}_{it} = \sum_{i=1}^{N} e_{it}$. Vacancies indicates the mean number of unfilled vacancies, according to matching process in year $t-1$.

5.2 Forecasting

As introduction of regional cap was targeted at bridging the gap in trainee employment between six large prefectures (Tokyo, Kanagawa, Aichi, Kyoto, Osaka, Fukuoka) and the rest of the country, we analyze the percentage changes in the forecast values of output y_{Mit} under full match in year $t-1$ and the actual value are positive for these two groups of prefectures. The results demonstrate that as regards exclusively acute care local public hospitals (model b), regional cap has led to deterioration of output in the six large prefectures. The mean percentage change of output is positive in the 6 prefectures in 2010-2012, reflecting that full match of trainees would have increased hospital production. At the same time, the mean percentage change of output is negative in the remaining prefectures, showing that employing additional trainees would in fact have lowered the output (Table 3).

Table 3: **Percentage change in output under potential full match and actual match in Japanese prefectures**

	model a				**model b**			
year	**6 large**		**others**		**6 large**		**others**	
2005	-0.27	(1.86)	-0.22	(6.21)	-3.76	(8.52)	-2.36	(14.56)
2006	-0.32	(3.41)	1.36	(5.32)	-2.73	(8.14)	-1.27	(10.62)
2007	2.31	(12.69)	6.42	(24.74)	-1.37	(6.65)	7.39	(43.05)
2008	1.68	(5.98)	5.36	(14.43)	-3.59	(9.25)	2.37	(22.15)
2009	1.89	(5.37)	4.14	(9.90)	-3.31	(9.15)	-2.18	(13.19)
2010	1.33	(5.67)	3.03	(8.23)	0.15	(5.91)	-1.61	(10.57)
2011	1.58	(9.19)	3.20	(6.60)	0.64	(7.88)	-2.43	(11.40)
2012	1.94	(10.29)	3.29	(7.79)	0.56	(8.76)	-3.58	(9.26)

Notes: The results indicate estimates with Cobb-Douglass multi-output distance function. "6 large" denotes Tokyo, Kanagawa, Aichi, Kyoto, Osaka, and Fukuoka; "others" indicates the remaining 41 prefecture. For each $t = 2005, ..., 2012$ the table demonstrates mean percentage change in output in subgroup g of hospitals with incomplete match in year $t-1$ (in 6 large prefectures or in the remaining prefectures), i.e. the values of $\bar{y}_{Mit} = 100 \cdot \sum_{i_g=1}^{N_g} (\hat{y}_{Mj} - y_{Mj})/y_{Mj}$, where $\hat{y}_{Mit}$ is estimated using the algorithm described in subsection 3.5.3. Standard deviation in parentheses. Models (a) and (b) denote respectively, models with inpatients and outpatients, and discharges and outpatients. The number of observations in models a (b) is 46-58 (29-37) in 6 large prefectures and 128-161 (50-61) in the remaining prefectures.

6 Conclusion

The paper employs quantile regression approach to estimate technical and cost efficiency of evaluates of Japanese local public hospitals, as well as to measure the effect of Japan residency matching program (JRMP) and inpatient prospective payment system (PPS) on efficiency time profile. Efficiency is estimated using panel data fixed effect quantile regression models with two endogenous treatment variables. We exploit nationwide longitudinal databases on hospital participation in the two reforms and on financial performance of local public hospitals. The results demonstrate that more efficient hospitals opt for each of the reforms, and participation further improves efficiency dynamics. The introduction of regional caps in JRMP resulted in efficiency losses, while a step towards best-practice rate setting in inpatient PPS did not have an effect on efficiency changes.

References

Abadie, A., Herr, J. L., Imbens, G. W., and Drukker, D. M. (2004). NNMATCH: Stata module to compute nearest-neighbor bias-corrected estimators. *Statistical Software Components.*

Abadie, A. and Imbens, G. (2002). Simple and bias-corrected matching estimators for average treatment effects.

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.

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.

Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *The American Economic Review*, pages 941–973.

Battese, G. and Corra, G. (1977). Estimation of a production frontier model: with application to the pastoral zone off eastern australia. *Australian Journal of Agricultural Economics*, 21(3):169–179.

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.

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.

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.

Biørn, E., Hagen, T. P., Iversen, T., and Magnussen, J. (2003). The effect of activity-based financing on hospital efficiency: a panel data analysis of DEA efficiency scores 1992–2000. *Health Care Management Science*, 6(4):271–283.

Busse, R., Geissler, A., Quentin, W., and Wiley, M. (2011). *Diagnosis-Related Groups in Europe: Moving towards transparency, efficiency and quality in hospitals.* McGraw-Hill International.

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.

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

Chalkley, M. and Malcomson, J. (2000). Government purchasing of health services. In *Handbook of Health Economics*, pages 847–890. Elsevier.

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.

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.

Crump, R. K., Hotz, V. J., Imbens, G. W., and Mitnik, O. A. (2009). Dealing with limited overlap in estimation of average treatment effects. *Biometrika*, 96(1):187–199.

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

France, F. H. R. (2003). Case mix use in 25 countries: a migration success but international comparisons failure. *International journal of medical informatics*, 70(2):215–219.

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.

Greene, W. (2012). *Econometric Analysis, 7th ed.* Pearson Education.

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.

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

Heckman, J. J. and Vytlacil, E. J. (2007). Econometric evaluation of social programs, part i: Causal models, structural models and econometric policy evaluation. *Handbook of Econometrics*, 6:4779–4874.

Hodgkin, D. and McGuire, T. (1994). Payment level and hospital response to prospective payments. *Journal of Health Economics*, 13(1):1–29.

Hollingsworth, B., Dawson, P., and Maniadakis, N. (1999). Efficiency measurement of health care: a review of non-parametric methods and applications. *Health Care Management Science*, 2(3):161–172.

Hollingsworth, B. and Street, A. (2006). The market for efficiency analysis of health care organisations. *Health Economics*, 15(10):1055–1059.

Holmstrom, B. and Milgrom, P. (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics and Organization*, 7:24.

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

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics*, 86(1):4–29.

Imbens, G. W. and Wooldridge, J. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1):5–86.

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).

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.

Kamada, Y. and Kojima, F. (2012). Stability and strategy-proofness for matching with constraints: A problem in the Japanese medical match and its solution. *American Economic Review*, 102(3):366–370.

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

Knox, K., Blankmeyer, E., and Stutzman, J. (2007). Technical efficiency in Texas nursing facilities: a stohcastic 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. (2005). *Quantile regression*. Number 38. Cambridge university press.

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

Koutsomanoli-Filippaki, A. and Mamatzakis, E. (2011). Efficiency under quantile regression: What is the relationaship 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.

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.

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

Meeusen, W. and van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18(2):435–444.

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 (2012a). Heisei 24nendo sinryouhoushuu kaitei-niokeru DPC seido (DPC/PDPS)-no taiyou-nitsuite (gaiyou) (An outline of DPC/PDPS system within the 2012 revision of fee schedule, Mar 28).

Ministry of Health, Labor and Welfare (2012b). Heisei 24nendo sinryouhoushuu kaitei-niokeru DPC seido (DPC/PDPS)-no taiyou-nitsuite (hosoku jikou) (Supplementary information on DPC/PDPS system within the 2012 revision of fee schedule, Apr 25).

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

Motohashi, H. (2009). Productivity of medical services: TFP (total factor productivity) and DEA (data envelopment analysis) of Japanese hospitals. ESRI Discussion Paper Series 210, Economic and Social Research Institute Cabinet Office.

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.

Nishioka, K. (2010). DPC-no kongo-no yukue. (Future development of DPCs). *ournal of Japan Hospital Association*, 6:18–45.

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.

Okuyama, T. (2008). An action of the DPC Support Tool project team in hospital of Sagamihara. *Journal of Japan Hospital Association*, 4:18–23.

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

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55.

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.

Saito, J. (2007). DPC-to kyuuseiki byouin-no iryou (DPC and health care at acute hospitals). *Journal of Japan Hospital Association,*, 4:12–26.

Sato, M. (2007). DPC dounyu-niokeru shinryou jouhou kanri. (Medical data management due to introduction of DPCs). *Journal of Japan Hospital Association*, 6:52–71.

Suwabe, A. (2004). Our efforts on DPC in Iwate Medical University hospital. *Rinsho Byouri*, 52:1011–1014.

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.

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.

Yasunaga, H., Ide, H., Imamura, T., and Ohe, K. (2005a). Impacts of the Japanese diagnosis procedure combination based payment system on cardiovascular medicine-related costs. *International Heart Journal*, 46:855–866.

Yasunaga, H., Ide, H., Imamura, T., and Ohe, K. (2005b). A proposal for reforms in the prospective payment system on DPC. *Hospital Administration*, 42(2):15–27.

Yasunaga, H., Ide, H., Imamura, T., and Ohe, K. (2006). Influence of Japan's new diagnosis procedure combination-based payment system on the surgical sector: does it really shorten the hospital stay? *Surgery Today*, 36(7):577–585.