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How do Hospitals Adopt Advanced Treatment Techniques? An assessment through the records of AMI patients in Japan*

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Abstract

For better clinical outcomes in hospitals, some advanced but costly techniques are often required. Facing these trade-offs of cost and quality, hospitals decide when and what techniques to apply. This paper investigates the spread of some advanced materials, mechanical devices, or procedures for acute myocardial infarction (AMI) through 11,120 patients' records in 92 hospitals in Japan. Since the daily cost of hospital services is fixed under a nationwide health insurance policy, we can assume almost uniform revenue constraints for treatment. The decisions of hospitals therefore are worth comparing. We measure the hospitals' propensities to adopt technologies and compare these with hospital-level mortality of AMI. In addition, we argue whether the spread of technical progress can be explained by geography (distance between the hospitals), or by governance under a hospital group. First, the results show that the propensities to adopt the advanced techniques vary greatly among hospitals, and these varieties explain hospital-level mortalities. Second, the physical distance between hospitals show a negative correlation to the spread of the same techniques. Finally, we observe similar decision patterns for hospitals under the same health care group.

Keywords: Health technology, Diffusion of innovations

JEL classification: I10, O33

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1. Introduction

Technological progress is an industry-wide phenomenon, but its effects on cost and quality have industry-level differences. In many manufacturing processes, technological inputs are gradually rewarded by a reduced per-unit cost of production. In health care services, on the other hand, some techniques continue to require higher per-unit costs to provide. Therefore, in health care, decisions for what technologies to use and when to adopt them are relatively crucial.

In cardiovascular care, for example, surgeries such as PCI (Percutaneous Coronary Intervention) or improved drugs like β-blockers, for example, have reduced mortality of AMI (Acute Myocardial Infarction) patients while they have increased costs of treatments (Heindenreich and McClellan, 2001). Overall, the technological progress is regarded as the primary factor for the soaring health care costs, making other presumable factors (aging societies, market imperfections, and malfunctions in insurance systems) almost negligible. (Newhouse, 1992).

A new technology is not worthwhile unless its costs pay for the improved clinical outcome such as a sharp reduction in mortality. Therefore, a reasonable way to decide whether the technology be adopted or not is to compare the increased costs of the technology and the benefit of improved health status. Many studies conclude that new technologies are, in general, worth their costs (Cutler and McClellan, 2001). But others point out that not all technologies improve the quality of health care. Even if a technology is applied to more and more patients repeatedly, the marginal cost stays almost the same while its marginal effectiveness declines.[1] Therefore such technologies become less and less cost-effective (Skinner, et al., 2006). Furthermore, some clinical effects depend heavily on a series of diagnoses and procedures by medical staffs, or on a facility of a hospital. Some comparative analyses between hospitals are required to control these differences.[2]

It is imperative, specifically, to examine what factors affect the adoption of

[1] This phenomenon is sometimes called the flat-of-the-curve effect, because in this case health care, where skilled-labor is intensive, is provided at the flat portion of the production function.

[2] Cutler and Huckman (2003) provide evidence on the impact of the diffusion of a new surgical procedure for coronary heart disease (PCI) on treatment productivity in New York State. The PCI is generally considered a potential substitute for the more expensive surgical procedure, coronary artery by-pass grafting (CABG). Given that lower unit costs are associated with PCI as compared to CABG it might be expected that total health care costs, or at least their rate of growth, would fall in this disease area. However as Cutler and Huckman (2003) show, while PCI does act as a substitute for CABG for many patients, less severely ill patients are now treated more with the new technology. The impact is therefore to increase overall health care costs even though there is a process of substitution at work.

technologies. As some studies reveal (Normand, et al., 1997, for example), hospitals have very different tendencies to apply some technologies to patients, resulting in diverse clinical and financial effects. For example, physicians may disagree as to which care is appropriate for a specific patient (McClellan and Brook, 1992). It means at least one of them is not choosing the appropriate care. Then it may urge physicians to an arms-race to apply some advanced methods (Baker and Phibbs, 2002). To address these invisible problems, we need to investigate the factors affecting the technology adoption.

This paper examines three material-intensive and/or human capital-intensive techniques for the care of AMI patients: IVUS (Intravascular Ultrasound), DES (Drug Eluting Stent) and IABP (Intra-Aortic Balloon Pumping). These are empirically proved to be the indicators of the advanced clinical and operational quality of hospitals.

The IVUS is a machine for more precise diagnosis of ischemic heart diseases. Where angiography shows a two-dimensional silhouette of the interior of the coronary arteries, the IVUS shows a cross-section of both the interior, and the layers of the artery wall itself. The primary benefit of the IVUS is that it offers a 360-degree view of the vessel wall from the inside, allowing a more complete and accurate assessment of a vessel than possible with angiography alone. The IVUS has better resolution than angiography, and can potentially provide specific information about the significance of calcifications and thrombi. Additionally, the IVUS has the power to differentiate the true luminal characteristics and size of a vessel from plaque (Singh et. al, 2015).

The DES is one kind of the tiny metal devices called stents, which are installed in arteries. The stents are usually metal mesh tubes inserted during PCI, a procedure that widens the blocked artery. The stents then prevent the artery from becoming blocked again (restenosis). Especially, the drug-eluting stents (DES) have a polymer coating over mesh that emits a drug gradually over time to help keep the blockage from recurring. In general, drug-eluting stents are preferred over bare-metal stents for most people. Not only are they more likely to keep the blockage from recurring than are bare-metal stents, but studies show the latest drug-eluting stents to be at least as safe as bare-metal stents (Zheng et. al, 2014).

The IABP is a polyethylene balloon mounted on a catheter, which is generally inserted into the aorta through the femoral artery in the leg. The balloon is guided into the descending aorta, approximately 2cm from the left subclavian artery. At the start of diastole, the balloon inflates, augmenting coronary perfusion. The primary goal of IABP treatment is to improve the ventricular performance of the failing heart by facilitating an increase in myocardial oxygen supply and a decrease in myocardial oxygen demand. The IABP may also have favorable effects on right ventricular (RV) function by complex mechanisms including accentuation of RV myocardial blood flow (Ahmad et.al, 2015).

We investigate how much the tendencies to adopt these technologies differ among hospitals, what factors affect such tendencies and whether the propensity to adopt is related to the quality of health care.

As for the determinants of technology adoption, the paper specifically focuses on, first, interaction among physicians/hospitals and, second, a governance of a health organization. It has been long recognized that human networks among physicians play an important role in technology diffusion (Coleman, et al., 1966). They may tend to rely on personal ties with colleagues, mentors and academic associations rather than on external information obtained from academic journals. This paper, based on the hypothesis that neighborhood facilitates are more likely to exchange ideas, and examines the clinical outcomes with each other.

Although geographic neighborhood is not the unique channel for exchanging information, it is a reasonable strategy to investigate technology diffusion through regional influences. Some studies show that health care costs and outcomes differ by region (Fisher, et al., 2003) and behind that exists differing propensity to adopt by region (Cutler, et.al., 2013). In addition, hospital managers, especially the headquarter officers of a group, can be highly conscious for the cost of technology. In the United States, Health Maintenance Organizations are found to exert important influences on the adoption of technologies (Li, et al., 2004). In Japan, however, managerial influences are not empirically clear. This paper examines whether hospitals belonging to a specific hospital group have different propensities to adopt technologies than other hospitals.

The remainder of the paper is organized as follows. The next section reviews the related literature. Section 3 describes the technologies to be analyzed and the data utilized. Section 4 presents the model and estimation results. Section 5 concludes.

2. Related Literature

Technology diffusion and productivity spillover have been a major topic in the growth, productivity, and industrial organization literatures for many decades.[3] There are numerous empirical studies analyzing the timing of adoption of new technologies in

[3] Unlike the invention, which often appears to occur as a single event or jump, the diffusion usually appears as a continuous and rather slow process. According to Hall (2004), diffusion is the cumulative or aggregate result of an individual's adoption. Each weighs the incremental benefits of adopting a new technology against the costs of change, often in an environment characterized by uncertainty (as to the future evolution of the technology and its benefits) and by limited information (about both the benefits and costs and even about the very existence of the technology).

several industries, and the studies on the health care industry are no exception. However, Serra-Sastre and McGuire (2009) point out that, health care industries show difference in its speed to adapt to new technologies, due to its non-market (public) features.

Culter and McClellan (1996) consider six factors that may influence technological diffusions in health care industry: (1) organizational factors within hospitals, (2) health insurance environments in which the cost of technology is reimbursed, (3) policies regulating technologies, (4) fears for malpractice claims from patients, (5) interactions between health care providers, and (6) characteristics of the population served by a hospital. They estimate the effects of these six factors on technology diffusion for treatments in heart attacks in U.S. hospitals. They find that insurance generosity, weak regulation on new technology, and interactions of providers are important factors for both technology adoption and the frequent use (adaption) of the technology.

Escarce (1996) examines the role of information and uncertainty on adaption in new medical technologies. The paper assumes that the informal discussion and interactions with colleagues are important source of information for physicians. These play some important roles to reduce the cost and uncertainty associated with adoption of a new surgical procedure. He examines the factors which influence the adoption of laparoscopic cholecystectomy in U.S. hospitals, and found that the some surgeons' adaptations in a hospital have a profound effect on the adoption by other surgeons in the same hospital.

Burke et al. (2007) examine the channel of the diffusion of new medical technologies more preciously. They find, regarding the local interactions among physicians, the high-status physicians (stars) exert greater influence than others in adaption and utilization of stents for medical treatments.

Baker (2001) investigates the relationship between managed care and adoption and diffusion of new medical technologies. He uses the market share of Health Maintenance Organization (HMO) as the proxy for degree of managed care and empirically examines the relationship between HMO share and diffusion of magnetic resonance imaging (MRI) equipment. He finds that the changes in financial and other incentives associated with managed care have a negative influence on technology adoption in health care.

3. The Area of Investigation and Data

The paper analyzes three advanced technologies applied to AMI patients. The three technologies include IVUS (Intravascular Ultrasound), DES (Drug Eluting Stent) and IABP (Intra-Aortic Balloon Pumping). These are new, costly, and operationally difficult technologies.

The IVUS, a machine for examination, list between $100,000 and $200,000 depending if they are integrated into a lab system or as a stand-alone cart-based system. The disposable IVUS catheters cost about $600-$1,000 each.[4] The operation of the machine needs one doctor for catheters operation, while one clinical technologist check the screenshots. The examination procedure is by far expensive and human-capital intensive compared to an angiography.

The DES costs 295,000 yen, while a bare-metal stent costs 184,000 yen (a nation-wide fixed price at the surveyed year of our data sets. The DES uses an intensive technology that allows drugs to dissolve very slowly in a body to keep the effects last for a long period. In addition, the DES has a shorter term of validity than a bare-metal stent. A hospital, therefore, needs an inventory management to estimate the frequency of use, not to waste these expensive materials.

The IABP requires an advanced expertise by doctors and medical technologists, compared with an artificial pump oxygenators with complex catheter operation.[5] These three technical inputs are discussed as the indicators of qualities or technologies of hospitals.

The sample is restricted to patients who suffer from AMI. The AMI patients should be admitted to hospitals as quickly as possible, usually to the nearest hospital. Therefore, both the patients' choice (of hospitals) and the selection of hospitals (to accept/reject patients) can be assumed minimal. In addition, one of the most important outcomes of AMI patient is the survival during the acute phase. Therefore, the quality of AMI care is evaluated by mortality in the past literature.

We estimate the propensity to adopt advanced technologies, and investigate the influential factors for their adoption. Specifically, we focus on the geographical proximity between hospitals and a governance over hospitals under the same management group. We also estimate the relationship between the propensity to adoption and the mortality rate.

Two of the authors (Kawabuchi and Igarashi) collect the DPC data (treatment records listed per episode of an in-hospital patient) of patients from hospitals upon their agreements over the ethical review. The DPC data has the total of 1,622,152 patients in 112 hospitals, and the samples of AMI patient are 11,663 in 108 hospitals during 2004-2010. The AMI samples are very small in number in 2004, 2005, 2010, so we use

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4 In Japan, each catheter costs between 111,000 yen and 175,000 yen, as a uniformly fixed price.

5 The IABP costs around 277800 yen (depending on the unit catheter cost) for the first day (36,800 yen per day afterwards). In the IABP, some subtle techniques and monitoring are required to medical staffs, which raise the costs more than the reference price. That may become one of the reasons that hospital may not likely to take the procedures.

the samples of 2006-2009 in our estimations. The basic estimation utilizes the data of 6,897 patients in 29 hospitals, for which data are available throughout from 2006 to 2009. We call the data set as the balanced panel of hospital data of AMI patients. The sample is restricted to the hospitals in the Kanto district (Tokyo, Kanagawa, Saitama, Chiba, Ibaragi, Tochigi, and Gunma Prefectures) to estimate the geo-statistical influences, data on 2,828 patients in 16 hospitals. We first use the entire balanced data to estimate the geo-statistical influences, but the calculations fail due to the presence of the very long distance between some hospitals. We therefore restrict the analysis to Kanto district where hospitals are located relatively close by. Regarding the effectiveness of management, we use the hospital records observed at least for two different years are included. In order to estimate the effectiveness of management in a robust way, we use as many of the AMI samples as possible. While, to account for the time series structure, we exclude the hospitals' records with only one-year sample. That keeps the sample consists of 11,120 patients in 92 hospitals.

The DPC data of hospitals contain rich information on patients such as their reasons or conditions as to hospitalization, as well as the outcomes (terminations) when they leave their hospitals (Before the DPC payment system launches, we only have the claim data, or the invoice of treatments. We then had no information over patients' physical conditions). [6]

Among the total of 92 hospitals we investigate, 69 hospitals belong to a hospital group. Each hospital in the group operates independently from the headquarter office. However, there are some occasions that the headquarter office provides a financial or managerial consultation to some affiliate hospitals. For example, when they are in need of physical investments like renewal or an establishment of medical units, headquarter acts cooperatively (with these hospitals) to raise funds (donations and subsidies).

As for personnel policy, each hospital hires physicians primarily by themselves. The headquarter office then offers some practical programs which assist physicians to train interns. In addition, the headquarter office holds the plenary meetings of the presidents to share the managerial concerns.

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[6] The health insurance payment system called Diagnosis Procedure Combination (DPC) based medical service payment system started in April 2003. The number of hospitals participating in the DPC-based payment system has increased from 82 in April 2003 to 1,585 in April 2014.In terms of the volume of beds, the number has increased from 66,497 to 492,206 during the period. The number of beds in 2014 accounts for about 55 per cent of the total number of beds (for acute care) in Japan. The hospitals have to submit DPC data of their patients to the Ministry of Health, Labor and Welfare. The DPC data files the information of patients such as diagnoses coded with the ICD-10 codes, procedures, comorbidities at admission, complications during the hospitalization, drugs and devices used, in-hospital mortality, length of stay and medical fee.

In April 2015, a joint procurement system has been launched for the group hospitals. The hospitals purchase drugs and medical materials jointly as far as they can in order to suppress total procurement costs by volume-purchasing.

The descriptive statistics in this section are concerned with the balanced panel of hospital data which contains data for the hospitals that have data for all the years. Table 1 shows the rates of adoption, expressed as the hospital-level ratio of AMI patients treated by each technique to all AMI patients, for three sets of techniques in question. The rate for IVUS is the highest at around a quarter. The adoption rates for DES and IABP are around 15%. The table also shows the mortality rate as 12.5%.

Figure 1 shows the three sets of information on adoption rates and the mortality rate by each hospital. The behavior over adoption varies greatly. The highest rates are 65% for IVUS, 50% for DES, and a little less than 30% for IABP, while the lowest rate is zero for all the three indicator of technologies. Note that these three sets of adoption rates may move together. A hospital which shows a high rate of adoption of one technique tends to adopt another technique also at a high rate. The hospital-level mortality rates exhibit a substantial variation, too. The highest rate is more than 30%, and the lowest is less than 5%.

Figure 2 shows the trends in technological adoption rates of each hospital over time. (We classify and count the records by each calendar year.) To our surprise, the overall rates of adoption decline rather than increase from 2006 to 2009 (Panel a). In 2008 a very sharp drop in the adoption rates is observed for IVUS and DES. Abstracting from the variation in the middle of the sample period, the declining trend is clear for the adoption of DES and IABP while the adoption rates of IVUS are steady (Panel b).

Figure 3 shows the adoption rates by region. The remarkable regional differences are observed for IVUS. The adoption rates of IVUS are high in the middle of Japan and are low at the both North and South of Japan. As for DES, the eastern districts tend to have higher adoption rates than western districts. In the case of IABP, The regional differences are not so salient. The figure also shows the mortality rates by region. They are low in the middle and high at the north and south ends of Japan. When calculating the correlation coefficient of the adoption rates and mortality rates for each hospital, for IVUS is -0.410, DES is 0.179, IABP is -0.243, and for each region, IVUS is -0.465, DES is -0.793, IABP is 0.157. Overall, propensities to adopt and mortality seem to be negatively correlated.

Table 2 shows the adoption rates and mortality for the hospitals which belong to a hospital group and those who do not. These group hospitals have significantly lower adoption rates for IVUS and DES. The adoption rates of IABP are comparable for two groups. The mortalities in the group hospitals are higher than those for non-group hospitals.

The basic statistics of explanatory variables are shown in Table 3. The average age is 69 and less than 30% of patients are female. A quarter of patients has diabetes mellitus and around a half has hypertension. The patients who have been previously suffered from myocardial infarction (old MI) and patients with stroke both account for around 2% of the sample. A fifth of the patients has heart failure and 8% of the patients developed shock. The patients with the Killip classes 2, 3 and 4 account for 11%, 4% and 7% of the sample, respectively.

4. The model and Estimation results

The model

Our analysis is based on the model in Skinner and Staiger (2009), in which medical outcome (survival) depends on the speed of technology diffusion. Here, the technology is modeled as the sum of many separate steps of innovations, each incurs cost to encourage the adoption. The hospital is assumed to maximize the present value of lives saved minus resource and learning costs. They find that the speed of diffusion for highly efficient and often low-cost innovations explain a large fraction of persistent variation in productivity of health care.

In this paper, model structure is as follows. The choice of technology is modeled as a logit regression. The explanatory variables include, among others, the unobserved heterogeneity about each hospital's propensity to adopt advanced technologies. The heterogeneity is modeled as a random effect. Other explanatory variables of interest are regional dummies and an indicator whether a hospital belongs to a hospital group. The mortality is analogously modeled. To control for the endogeneity of the adoption decisions and the mortality, the correlation between the random effects for technology choice and the random effects for mortality is incorporated in to the model.

For each hospital, the random effect is common to all the three indicators of technology. This is a common factor model in which, for each hospital, one random effect affects three technologies with different coefficients. In addition, each random effect is assumed to be time-variant. To alleviate some wild fluctuations over time, the random effects for different times are smoothed out using an autoregressive structure.

Let z_{ijkt} denote whether a technology *k* is applied to a patient *i* at a hospital *j* at time *t*. The variable follows the Bernoulli distribution with a parameter p_{ijkt}. For each technology *k*, a logit transformation of p_{ijkt} depends on a vector of general explanatory variables X_{ij}, random effect at each time c_{jt}, regional dummies $Region_{jk}$

and the hospital group dummy $Group_{jk}$. The random effect c_{jt} affects three technologies by different coefficients γ_k, one of which is normalized to 1 in order to facilitate the identification. In addition, γ_k for *k*=2 and 3 are restricted to be positive to prevent label switching.

Thus the model for technology adoption is:

$$z_{ijkt} \sim Bern(p_{ijkt}) \tag{1}$$

$$logit(p_{ijkt}) = X_{ij} \cdot \beta_k + \gamma_k \cdot c_{jt} + \sum_{k=1}^{9} \delta_k \cdot Region_{jk} + \theta_k \cdot Group_{jk} \tag{2}$$

$$\gamma_1 = 1$$

$$\gamma_k \sim Normal(0, 0.1) \cdot I(0,), \ for \ k=2, \ 3. \tag{3}$$

The model for mortality is analogously:

$$death_{ijdt} \sim Bern(p_{ijdt}) \tag{4}$$

$$logit(p_{ijdt}) = X_{ij} \cdot \beta_d + \gamma_d \cdot d_{jt} + \sum_{d=1}^{9} \delta_d \cdot Region_{jd} + \theta_d \cdot Group_{jd} \tag{5}$$

The correlation between random effects, c_{jt} and d_{jt}, is modeled by specifying a multivariate normal distribution with mean μ_{jt} and a variance-covariance matrix τ_t. The prior distribution of τ_t is assumed to be an inverse Wishart distribution which covariance structure is diagonal to prevent estimated results are affected by the prior information between random effects, c_{jt} and d_{jt}:

$$b_{jt} \sim MVN(\mu_{jt}, \tau_t) \tag{6}$$

$$b_{jt} \equiv \begin{pmatrix} c_{jt} \\ d_{jt} \end{pmatrix}, \ \mu_{jt} \equiv \begin{pmatrix} \mu_{c_{jt}} \\ \mu_{d_{jt}} \end{pmatrix} \tag{7}$$

$$\tau_t \sim InvWish(R, 2), \text{ where R is a } 2 \times 2 \text{ matrix: } \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{8}$$

The random effects over time are assumed to follow the AR processes:

$$\mu_{c_{jt}} = \phi_{at} \cdot c_{j,t-1} + \varepsilon_{ajt} \tag{9}$$

$$\mu_{d_{jt}} = \phi_{dt} \cdot d_{j,t-1} + \varepsilon_{djt} \tag{10}$$

Other prior distributions are as follows. The vector of coefficients β_k follows an independent multivariate normal distribution, whose generic component is $\beta_{kl} \sim Normal(0, 0.1)$, subscript l represents the elements of β_k. The priors for $\delta_k, \theta_k, \delta_d, \theta_d, \phi_{at}$ and ϕ_{dt} are normal distributions, one of which is indexed as $\delta_k \sim Normal(0, 0.1)$.

The models are estimated by the Markov chain Monte Carlo (MCMC) method utilizing the WinBUGS software. The convergence is checked by the Gelman-Rubin statistics. The prior distributions are conventional diffuse priors.[7]

Results

(1) Balanced panel of hospitals

We estimate the model with the balanced panel of the hospital data, for those who provide the data throughout the surveyed years. The results are shown in Table 4. The hospitals' propensities to adopt advanced technologies vary substantially. Figure 4 plots the means of the estimated random effects for adoption together with their ranges from 2.5% to 97.5%. Using exponentiation, the value of a random effect represents how much more a hospital tends to adopt advanced technologies. More precisely, when c_{jt}, a hospital's random effect at time *t*, is included, the odds ratio, $\frac{p_1/(1-p_1)}{p_0/(1-p_0)}$, which is the ratio of two odds[8], will increase by a multiple $exp(c_{jt})$ compared with the case where c_{jt} is excluded. If the value is 2, for example, the odds ratio for the hospital is $\exp(2) \cong 7.4$ times the odds ratio without the hospital random effect ($c_{jt} = 0$). Hence, the value of 5 implies a very large (nearly 150 times) increase in the odds ratio. On the other hand, the value of -5 indicates a substantial (less than 0.01 times) decrease in the odds ratio.

During the surveyed years, the propensity to adopt does not exhibit any clear trend of each hospital (Figure 5). Although we observe a strange dip (a concentrated range of propensities) in 2008 just as in the raw data, the estimated trend is smoothed out thanks to the AR restriction.

The mortality rates also show the hospital-level heterogeneity and they are in upward trends, although we observe some irregular trend in 2008 (Figure 6). The scatterplot of propensity to adopt and mortality is drawn in Figure 7. There is a negative

[7] The sensitivity analysis using uniform priors failed, perhaps due to the heavy volume of the data.

[8] Here, p_1 denotes the probability to adopt advanced technologies with a hospital random effect, c_{jt}, while p_0 denotes the probability without a random effect. Odds are defines as $p_m/(1-p_m)$ for *m* = 0, 1. Recall that the logit function is just a logarithm of odds: $logit(p_m) \equiv \ln[p_m/(1-p_m)]$.

relationship, with correlation coefficients being between -0.26 and -0.43 (Table 5). This implies that the technology choice is not always be efficient. Therefore, a risk-taking choice of technology can only occasionally enhance the quality of health care.

As for the regional dummies, none of them are statistically significant in the association with the technology adoption in the IVUS and the IABP. In the estimation for the DES, however, the trend is observed that the DES is more likely to be in use in the east part of Japan than in the west (Figure 8). The 5% statistical significance is shown for Hokkaido, Tohoku and Tokai. The DES is an upgraded device of the BMS (bare-metal stent), which gives better clinical outcome even when other hospital-level or doctor-level conditions are unchanged. (This means that medical staffs do not need to acquire any new surgical skills for a new device.) This may explain why we view a quick spread of DES in use. In what follows, we employ a more direct measure of the network effect in a geo-statistical formulation, to check the robustness of the results.

(2) Geostatistical Modeling a la Banerjee, et al. (2015)

In the previous section, we measure the geographic influence by regional dummies. However, it is desirable to measure geographic proximity more directly. The distance between hospitals is one of frequently used measurements. We hypothesize that the nearer the hospitals are located, the closer their adoption propensities are.

Figure 9 plots the technology adoption rates of individual hospitals on a map. (In this section, we restrict our analysis to the hospitals located in the Kanto district due to the computational limits) The size of the circle is proportional to the adoption rate of each hospital. When the proximate hospitals have similar adoption rates, the circles in close distances are similar in sizes. We follow Banerjee, et al. (2015) in the modeling of the geographic influence on the propensity to adopt. Its main part is as follows:

$$z_{ijkt} \sim Bern(p_{ijkt}) \tag{11}$$

$$logit(p_{ijkt}) = X_{ijk}\beta_k + W_j, \tag{12}$$

where X_{ijk} includes c_{jt}, $Region_{jk}$ and $Group_{jk}$ to focus on the geo-statistical factor W_j.

W_j is a random effect which represents the geographical influences on the probability to adopt technologies for hospital *j*. The correlation between W_{j_m} and W_{j_n}, the random effects for hospital j_m and hospital j_n respectively, generates the correlation between p_{ij_mkt} and p_{ij_nkt}. The correlation between W_{j_m} and

W_{j_n} depends on the distances between hospital j_m and another hospital j_n. To implement this idea,W_j's are stacked to form a matrix W which follows a multivariate normal distribution with mean zero and a variance-covariance matrix H. The (*m*, *n*) element of *H*, $H[j_m, j_n]$, is the correlation between W_{j_m} and W_{j_n}. Let $H[j_m, j_n]$ depends negatively on the square of the distance $d[j_m, j_n]^2$ between the hospitals. As the distances between hospitals become closer, the more correlated are the propensities to adopt technologies. The precise specifications are listed below. The key parameter is φ. If φ is estimated to be positive, the negative correlations between the distance and hospitals' propensities are confirmed. Here, the model is specified as follows:

$$W \sim MVN(0, H) \tag{13}$$

$$H[j_m, j_n] = \frac{1}{tau_W} \times \exp(-\varphi \times d[j_m, j_n]^2) \tag{14}$$

$$\varphi \sim gamma(0.1, 0.1) \tag{15}$$

$$tau_W \sim gamma(0.1, 0.1) \tag{16}$$

The data on 2,828 patients who are hospitalized in the 16 hospitals in the Kanto district are used. (We here need to split the data into compartments, to implement our estimation within the limit of computation.) The Kanto district (plane), among other regions, could represent our geo-statistical analysis in the most noiseless way. There are relatively few mountainous barriers (ups-and-downs) in the traffic between hospitals. In addition, the transportation is densely connected. The distance between hospitals is naturally a good proxy of "remoteness". We use all the hospitals located in the Kanto district. Unfortunately, not all the hospitals provide the data throughout from 2006 to 2009. The missing values are imputed by assigning diffuse prior distributions to explanatory variables for each patient. In the estimation, the numbers are drawn from the prior distributions, and applied as values for the explanatory variables.

When we observe no convergence, the initial values are taken from the estimation results of the balanced panel, for example, we use -0.393 –this value is the estimation results of the balanced panel- to the initial value of the coefficients of "sex". Then we apply the MCMC algorithm near the convergence region.

The estimate of the geo-statistical parameter φ is plotted in Figure 10, where it converges into zero. The median of the estimated φ is 0.2603 (Table 6). We translate this estimate into the correlation of propensities between two hospitals, taking each hypothetical distance in the horizontal axis. In Figure 11, we plot the distance between two hospitals ($d[j_m, j_n]$ in equation (14)) on the horizontal axis. On the vertical axis, we plot the correlation ($H[j_m, j_n]$ in equation (14)) between the geo-statistical random effects, W_{j_m} and W_{j_n}. Recall that $H[j_m, j_n]$ represents the correlation between two hospitals' $logit(p_{ijkt})$. The figure indicates that when the hospitals are located very closely, the correlation $H[j_m, j_n]$ is around 0.4, but as the distance expands, the correlation rapidly diminishes to zero at 1.5 kilometers. Since our sample hospitals are located far more than 1.5 kilometer, the geo-statistical correlations in our sample happen to be virtually zero.

(3) The Hospital Group Effects with the Full data Set.

We estimate the effects of the hospital group using the full data set containing 92 hospitals with 11,120 patients. [9]

Table 7 shows the results of the hospital group dummies. The median propensities are significantly negative for IVUS and DES. Whereas the propensity for mortality is not significant, with a tendency to be positive. This means that the group hospitals adopt less advanced technologies, which might be associated with their higher mortalities. As an inference, there is a possibility that the group hospitals maintained the same outcome (insignificant relevance with mortality) with less cost (less adoption of costly technology). These results imply that the governance affects the diffusion of technologies, and could also affect the efficiency of health care through a careful choice of technology.

5. Conclusion

In health care services, new medicines and surgeries tested repeatedly through clinical trials have a great potential to improve the quality of health care. However, at the same time, the application of new technology to each treatment raise its costs sharply. Therefore, for a provider, the return of a new technology should be worth its costs, especially when the reference price (the financial reward to a provider) is fixed under social security system. We therefore investigate the decisive factors for adopting new technologies. Our analysis aims to clarify how the technologies diffuse and how clinically effective they are.

[9] Since not all the hospitals provide data that covers from 2006 to 2009, the missing values are imputed by assigning diffuse prior distributions to explanatory variables for each patient. For example, "sex" is missing in a patient, we apply Bernoulli distribution to prior of "sex".

This paper investigates the extent and nature of technology diffusion in health care. Some advanced technologies in cardiovascular care, IVUS, DES and IABP, are examined to indicate the technical level for treatments in AMI. We measure the hospitals' propensity to adopt new technologies and compare these with mortalities to determine the efficiency of technology. In addition, we test whether the technology diffusion is mediated by the network effect, and whether the governance of the providers has a strong influence on technology adoption.

Our results show that the propensities to adopt techniques vary greatly among hospitals. Specifically, the hospitals with higher propensities tend to have lower mortalities. This relationship is, however, modest. Therefore, more deliberate choice of technology may enhance the quality of health care.

As for the regional differences in the decisions over adoption, we indicate that the correlation of decisions decays by distance. We employ a geo-statistical model to test the network effect via proximity (physical distance between hospitals). We find that the decisions about the adoption depends negatively on the distance between hospitals.

Finally, we investigate the role of governance (by headquarter of the hospital group) on the technology adoption and the quality of health care. The hospitals affiliated with the hospital group have lower propensities to adopt as well as higher mortalities. These observations can be associated with the governance through our series of observation. But the random effect for mortality is not strongly significant. Arguably, the group hospitals achieved the same outcome with less cost. These results imply that management does affect the diffusion of technologies and, possibly, affect the efficiency of health care through a careful choice of technology.

References

Ahmad, Y., Sen, S., Shun-Shin, M. J., Ouyang, J., Finegold, J. A., Al-Lamee, R. K., ... & Francis, D. P. (2015). Intra-aortic Balloon Pump Therapy for Acute Myocardial Infarction A Meta-analysis. *JAMA International Medicine.* 2015 Mar 30. doi: 10.1001/jamainternmed.2015.0569. [Epub ahead of print]

Baker, Laurence C. (2001) Managed care and technology adoption in health care: Evidence from magnetic resonance imaging. *Journal of Health Economics*, Volume 20, Issue 3, 395–421

Baker, Laurence C. and Ciaran S. Phibbs. (2002) Managed Care, Technology Adoption and Health Care: The Adoption Of Neonatal Intensive Care. *Rand Journal of Economics,* v33 (3), 524-548.

Banerjee, Sudipt, Bradley Carlin and Alan Gelfand. (2015) *Hierarchical Modeling and Analysis for Spatial Data.* Second edition. CRC Press.

Burke M, Fournier G, Prasad K. (2007) The diffusion of a medical innovation: Is success in the stars? *Southern Economic Journal,* 73(3), 588–603.

Coleman, James, Elihu Katz and Herbert Menzel. (1966) *Medical Innovation: A Diffusion Study*. Bobbs-Merrill Co.

Cutler, David M. and Mark McClellan. (1996) The Determinants of Technological Change in Heart Attack Treatment. NBER Working Papers 5751

Cutler, David, and Mark McClellan. (2001) Is Technological Change in Medicine Worth It? *Health Affairs,* 20 (September/October): 11–29.

Cutler, David M., and Robert S. Huckman. (2003) "Technological development and medical productivity: the diffusion of angioplasty in New York state." *Journal of Health Economics*, 22.2: 187-217.

Cutler, David, Jonathan Skinner, Ariel Dora Stern and David Wennberg. (2013) Physician Beliefs and Patient Preferences: A New Look at Regional Variation in Health

Care Spending. *NBER Working Paper* 19320.

Escarce José J. (1996) Externalities in hospitals and physician adoption of a new surgical technology: An exploratory analysis. *Journal of Health Economics,* 15, 715-734

Fisher, Elliott S., David E. Wennberg, Terese A. Stukel, Daniel J. Gottlieb, Francis Lee Lucas, et al. (2003) The implications of regional variations in Medicare spending. Parts 1 & 2. *Annals of Internal Medicine,* 138, pp.288-98.

Hall, Bronwyn H. "Innovation and diffusion." In *Handbook on Innovation*. Oxford U. 2004.

Heidenreich, Paul, and Mark McClellan. (2001) Trends in Heart Attack Treatment and Outcomes, 1975-1995 -- Literature Review and Synthesis. In David M. Cutler and Ernst R. Berndt, editors. *Medical Care Output and Productivity*. University of Chicago Press.

Li, Rui, Jodi Simon, Thomas Bodenheimer, Robin Gilles, Lawrence Casalino, Julie Schmittdiel and Stephen Shortell. (2004) Organizational Factors Affecting the Adoption of Diabetes Care Management Processes in Physician Organizations. *Diabetes Care,* Vol.27, No.10, pp.2312-2316.

McClellan, Mark, and Robert Brook. (1992) Appropriateness of medical care: A comparison of methods to set standards. *Medical Care,* 30: 565-586, July 1992.

Newhouse, Joseph. (1992) Medical Care Costs: How Much Welfare Loss? *Journal of Economic Perspectives,* 6(3):3-21.

Normand, Sharon-Lise, Mark Glickman and Constantine Gatsonis. (1997) Statistical Methods for Profiling Providers of Medical Care: Issues and Applications. *Journal of the American Statistical Association,* Vol. 92, No. 439 (Sep., 1997), pp. 803-814.

Serra-Sastre Victoria and Alistair McGuire. (2009) Diffusion of Health Technologies: Evidence from the Pharmaceutical Sector. in Coast-Font Joan, Chirstophe Courbage and Alistair McGuire, ed,, *The Economics of New Health Technologies: Incentives, Organization and Financing*, Oxford University Press.

Singh, V., Patel, J., Patel, N., Patel, N., Arora, S., Patel, N., ... & Badheka, A. (2015). Effect of Intravascular Ultrasound Guided Percutaneous Coronary Interventions on In-hospital Outcomes. *Journal of the American College of Cardiology*, 65(10_S). doi:10.1016/S0735-1097(15)61686-2.

Skinner, Jonathan and Douglas Staiger. (2009) Technology Diffusion and Productivity Growth in Health Care. *NBER Working Paper* No.14865.

Skinner, Jonathan, Douglas Staiger, and Elliott Fisher (2006) Is Technological Change in Medicine Always Worth It? The Case of Acute Myocardial Infarction. *Health Affairs*, 25(2): w34-w47.

Zheng, F., Xing, S., Gong, Z., & Xing, Q. (2014). Five-year Outcomes for First Generation Drug-eluting Stents versus Bare-metal Stents in Patients with ST-segment Elevation Myocardial Infarction: A Meta-analysis of Randomised Controlled Trials. *Heart, Lung and Circulation*, 23(6), 542-548.

Table 1: Summary Statistics(Balanced Panel)

Variable	Obs	Mean	Std. Dev.	Min	Max
IVUS	6,767	0.256	0.436	0	1
DES	6,767	0.161	0.368	0	1
IABP	6,770	0.131	0.337	0	1
Mortality	6,770	0.125	0.331	0	1

Table 2: Adoption and Mortality of Group Hospitals

	IVUS	DES	IABP	Mortality
Group Hospitals	0.236	0.158	0.115	0.144
Non-Group Hospitals	0.41	0.264	0.097	0.087

Numbers of Group Hospital: 69

Numbers of Non-Group Hospitals: 23

Table 3: Summary Statistics of variables used in estimations(Balanced Panel)

Variable	Obs	Mean	Std. Dev.	Min	Max
age	6,770	69.039	12.861	0	102
sex	6,770	0.283	0.451	0	1
diabetes mellitus	6,770	0.256	0.437	0	1
hypertension	6,770	0.54	0.498	0	1
hypertensive heart c	6,770	0.006	0.08	0	1
hyperlipidemia	6,770	0.454	0.498	0	1
old MI	6,770	0.017	0.129	0	1
acute renal failure	6,770	0.009	0.094	0	1
chronic renal failure	6,770	0.028	0.164	0	1
cerebral hemorrage	6,770	0.001	0.024	0	1
stroke	6,770	0.022	0.147	0	1
transient ischemic a	6,770	0.001	0.027	0	1
heart failure	6,770	0.207	0.405	0	1
copd	6,770	0.003	0.051	0	1
LBBB	6,770	0	0	0	0
atrial fibrillation	6,770	0.041	0.198	0	1
shock	6,770	0.08	0.271	0	1
killip class 2	6,770	0.112	0.315	0	1
killip class 3	6,770	0.035	0.183	0	1
killip class 4	6,770	0.069	0.253	0	1
Hospital group	6,770	0.957	0.203	0	1
Hokkaido	6,770	0.08	0.271	0	1
Tohoku	6,770	0.058	0.234	0	1
Kanto	6,770	0.242	0.428	0	1
Tokai	6,770	0.185	0.388	0	1
Shinetsu	6,770	0.086	0.281	0	1
Kinki	6,770	0.095	0.294	0	1
Chugoku	6,770	0.081	0.273	0	1
Shikoku	6,770	0.06	0.237	0	1
Kyushu	6,770	0.113	0.317	0	1

*Sex: Female=0, Male=1
*Variables from diabetes mellitus to Shock is Comorbidities at admission
*Killip Class: Severity classificationof cardiac dysfunction in AMI
  Killip Class1: No signs of heart failure
  Killip Class2: Mild to moderate heart failure
  Killip Class3: Pulmonary edema, severe heart failure
  Killip Class4: Cardiogenic shock (cyanosis, impaired consciousness)
*Hospital group : 1 when the patient was admitted to hospital of Hospital group
*Region:
  Hokkaido: Hokkaido
  Tohoku: Aomori, Akita, Iwate, Yamagata, Miyagi,
  Kanto: Gunma, Tochigi, Ibaraki, Saitama, Tokyo, Kanagawa, Chiba,Yamanashi
  Tokai: Aichi, Gifu, Mie, Shizuoka
  Shinetsu: Nagano, Niigata, Toyama, Ishikawa, Fukui
  Kinki: Osaka, Kyoto, Wakayama, Nara, Hyougo, Shiga
  Chugoku: Tottori, Okayama, Hiroshima, Shimane, Yamaguchi
  Shikoku: Tokushima, Ehime, Kagawa, Kouchi
  Kyushu: Fukuoka, Saga, Nagasaki, Kumamoto, Ohita, Kumamoto, Miyazaki, Kagoshima, Okinawa

Table 4: Basic Estimation Results								
	Variable	mean	sd	2.50%	5.00%	median	95.00%	97.50%
IVUS								
	constant	−0.302	1.322	−2.41	−2.177	−0.467	2.103	2.95
	age	−0.002	1.00E−03	−0.004	−0.003	−0.002	0.00E+00	0.00E+00
	sex	−0.393	0.084	−0.558	−0.531	−0.393	−0.255	−0.229
	diabetes mellitus	0.241	0.087	0.071	0.098	0.241	0.383	0.411
	hypertension	0.427	0.084	0.262	0.289	0.428	0.567	0.594
	hypertensive heart disease	1.095	0.448	0.199	0.351	1.099	1.822	1.958
	hyperlipidemia	0.725	0.086	0.557	0.584	0.725	0.867	0.896
	old MI	−0.056	0.282	−0.614	−0.522	−0.055	0.404	0.489
	acute renal failure	−0.653	0.404	−1.471	−1.332	−0.645	−0.004	0.114
	chronic renal failure	−0.258	0.248	−0.751	−0.671	−0.254	0.147	0.221
	cerebral hemorrage	−2.423	2.12	−7.145	−6.272	−2.189	0.632	1.076
	stroke	−0.312	0.254	−0.814	−0.734	−0.311	0.102	0.18
	transient ischemic attack	0.464	1.017	−1.616	−1.242	0.487	2.088	2.409
	heart failure	0.126	0.097	−0.065	−0.034	0.126	0.287	0.317
	copd	0.421	0.597	−0.747	−0.562	0.423	1.4	1.592
	LBBB	−0.003	3.174	−6.251	−5.233	0.004	5.194	6.194
	atrial fibrillation	−0.079	0.19	−0.454	−0.393	−0.077	0.233	0.292
	shock	0.366	0.133	0.105	0.146	0.366	0.585	0.628
	killip class 2	−0.03	0.13	−0.286	−0.244	−0.03	0.185	0.225
	killip class 3	−0.433	0.2	−0.827	−0.762	−0.432	−0.104	−0.041
	killip class 4	−0.716	0.167	−1.046	−0.992	−0.714	−0.443	−0.391
	Hokkaido	1.348	1.237	−0.986	−0.628	1.325	3.456	3.871
	Tohoku	1.096	1.27	−1.335	−0.971	1.102	3.235	3.623
	Kanto	0.496	1.204	−1.891	−1.491	0.514	2.483	2.828
	Tokai	−0.875	1.25	−3.494	−3.122	−0.824	1.128	1.574
	Shinetsu	1.344	1.239	−1.462	−0.768	1.442	3.187	3.486
	Kinki	−0.682	1.317	−3.185	−2.842	−0.669	1.495	1.935
	Chugoku	−1.766	1.33	−4.415	−4.023	−1.721	0.375	0.756
	Shikoku	−3.261	2.267	−7.921	−7.093	−3.192	0.336	0.996
	Kyushu	0.333	1.287	−2.222	−1.814	0.342	2.44	2.839
	Hospital group	−4.38	1.006	−6.643	−6.318	−4.305	−2.896	−2.701
DES								
	constant	−2.386	1.38	−4.955	−4.531	−2.451	−0.085	0.3
	age	0	0.001	−0.002	−0.001	0	0.001	0.001
	sex	−0.219	0.09	−0.395	−0.367	−0.219	−0.07	−0.041
	diabetes mellitus	0.369	0.093	0.187	0.216	0.37	0.521	0.552
	hypertension	0.421	0.092	0.242	0.27	0.42	0.572	0.6
	hypertensive heart disease	1.204	0.485	0.231	0.394	1.209	1.991	2.133
	hyperlipidemia	0.597	0.093	0.417	0.446	0.596	0.749	0.779
	old MI	0.599	0.286	0.027	0.123	0.603	1.062	1.151
	acute renal failure	−0.785	0.522	−1.882	−1.679	−0.76	0.03	0.167
	chronic renal failure	−0.22	0.272	−0.766	−0.677	−0.216	0.22	0.304
	cerebral hemorrage	−2.764	2.051	−7.364	−6.483	−2.542	0.199	0.637
	stroke	−0.068	0.255	−0.577	−0.493	−0.065	0.349	0.425
	transient ischemic attack	0.638	0.993	−1.41	−1.036	0.67	2.214	2.52
	heart failure	−0.152	0.109	−0.366	−0.331	−0.153	0.026	0.059
	copd	−1.706	1.095	−4.176	−3.685	−1.594	−0.111	0.126
	LBBB	−0.013	3.154	−6.213	−5.184	−0.011	5.168	6.152
	atrial fibrillation	0.05	0.203	−0.356	−0.289	0.052	0.379	0.441
	shock	0.123	0.144	−0.161	−0.115	0.124	0.359	0.403
	killip class 2	0.262	0.138	−0.009	0.035	0.263	0.489	0.533
	killip class 3	0.033	0.216	−0.395	−0.325	0.036	0.383	0.45
	killip class 4	−0.154	0.181	−0.512	−0.454	−0.153	0.139	0.194
	Hokkaido	2.897	1.308	0.369	0.811	2.881	5.143	5.549
	Tohoku	2.428	1.34	−0.154	0.268	2.42	4.693	5.162
	Kanto	−0.171	1.233	−2.554	−2.212	−0.154	1.852	2.223
	Tokai	−2.344	1.315	−4.926	−4.557	−2.33	−0.165	0.186
	Shinetsu	0.573	1.259	−1.96	−1.527	0.6	2.593	3.018
	Kinki	−0.925	1.342	−3.638	−3.177	−0.927	1.323	1.76
	Chugoku	−1.82	1.418	−4.761	−4.242	−1.786	0.446	0.846
	Shikoku	−2.654	2.44	−7.619	−6.773	−2.593	1.254	1.96
	Kyushu	0.011	1.421	−2.798	−2.331	0.035	2.286	2.696
	Hospital group	−3.311	1.132	−5.851	−5.39	−3.215	−1.624	−1.396

IABP								
	constant	−2.152	1.088	−4.415	−4.064	−2.149	−0.355	−0.003
	age	−0.001	0.001	−0.002	−0.001	−0.001	0	0.001
	sex	−0.42	0.094	−0.604	−0.574	−0.419	−0.267	−0.238
	diabetes mellitus	0.338	0.089	0.163	0.192	0.339	0.484	0.511
	hypertension	−0.11	0.087	−0.282	−0.254	−0.11	0.033	0.06
	hypertensive heart disease	−0.497	0.574	−1.722	−1.502	−0.462	0.382	0.533
	hyperlipidemia	−0.153	0.09	−0.33	−0.301	−0.153	−0.006	0.023
	old MI	0.452	0.269	−0.093	−0.002	0.456	0.885	0.964
	acute renal failure	1.047	0.299	0.455	0.55	1.05	1.533	1.628
	chronic renal failure	0.327	0.214	−0.098	−0.03	0.33	0.674	0.738
	cerebral hemorrage	0.591	1.383	−2.394	−1.829	0.683	2.695	3.045
	stroke	−0.044	0.268	−0.587	−0.496	−0.038	0.385	0.462
	transient ischemic attack	−3.004	2.03	−7.512	−6.659	−2.801	−0.049	0.388
	heart failure	0.691	0.088	0.516	0.545	0.691	0.834	0.863
	copd	−0.68	0.838	−2.505	−2.147	−0.617	0.581	0.791
	LBBB	0.013	3.168	−6.203	−5.207	0.014	5.245	6.224
	atrial fibrillation	0.131	0.19	−0.252	−0.188	0.135	0.436	0.494
	shock	2.145	0.106	1.939	1.972	2.144	2.319	2.354
	killip class 2	0.268	0.132	0.006	0.048	0.27	0.483	0.522
	killip class 3	1.005	0.176	0.655	0.712	1.007	1.29	1.345
	killip class 4	1.306	0.135	1.041	1.084	1.306	1.527	1.568
	Hokkaido	−0.958	1.068	−3.035	−2.734	−0.96	0.903	1.253
	Tohoku	−0.117	1.065	−2.185	−1.887	−0.115	1.742	2.081
	Kanto	0.217	1.058	−1.835	−1.546	0.223	2.075	2.405
	Tokai	0.026	1.059	−2.025	−1.735	0.033	1.886	2.217
	Shinetsu	−0.533	1.068	−2.621	−2.316	−0.529	1.333	1.677
	Kinki	−0.395	1.062	−2.466	−2.161	−0.393	1.467	1.797
	Chugoku	0.395	1.061	−1.654	−1.366	0.399	2.262	2.587
	Shikoku	−0.34	1.071	−2.435	−2.12	−0.342	1.522	1.86
	Kyushu	−0.65	1.063	−2.717	−2.42	−0.652	1.211	1.542
	Hospital group	−0.223	0.288	−0.778	−0.695	−0.222	0.258	0.348
Mortality								
	constant	−3.154	1.268	−5.515	−5.215	−3.168	−0.927	−0.482
	age	0.038	0.004	0.029	0.031	0.037	0.044	0.046
	sex	0.339	0.103	0.137	0.169	0.339	0.507	0.54
	diabetes mellitus	−0.678	0.133	−0.941	−0.899	−0.677	−0.461	−0.419
	hypertension	−1.802	0.124	−2.048	−2.008	−1.801	−1.599	−1.56
	hypertensive heart disease	−2.23	1.085	−4.664	−4.167	−2.123	−0.654	−0.417
	hyperlipidemia	−2.368	0.178	−2.725	−2.665	−2.364	−2.08	−2.028
	old MI	−0.19	0.331	−0.856	−0.745	−0.183	0.342	0.443
	acute renal failure	1.067	0.331	0.419	0.522	1.067	1.612	1.713
	chronic renal failure	0.275	0.223	−0.17	−0.097	0.277	0.637	0.705
	cerebral hemorrage	−1.376	2.422	−6.65	−5.689	−1.148	2.175	2.65
	stroke	0.22	0.283	−0.347	−0.252	0.225	0.677	0.762
	transient ischemic attack	−2.262	2.237	−7.125	−6.242	−2.079	1.098	1.648
	heart failure	−0.356	0.121	−0.594	−0.556	−0.356	−0.157	−0.119
	copd	−0.572	0.796	−2.219	−1.934	−0.54	0.677	0.897
	LBBB	0.012	3.158	−6.152	−5.152	0.002	5.209	6.235
	atrial fibrillation	−1.149	0.252	−1.654	−1.57	−1.144	−0.741	−0.668
	shock	0.771	0.144	0.488	0.533	0.771	1.007	1.053
	killip class 2	−0.403	0.211	−0.822	−0.753	−0.4	−0.061	0.001
	killip class 3	0.971	0.239	0.498	0.573	0.973	1.36	1.434
	killip class 4	2.179	0.171	1.845	1.896	2.177	2.46	2.516
	Hokkaido	0.467	1.123	−1.719	−1.365	0.457	2.324	2.696
	Tohoku	−1.409	1.141	−3.71	−3.327	−1.397	0.455	0.825
	Kanto	−0.232	1.011	−2.224	−1.907	−0.221	1.409	1.677
	Tokai	0.192	1.043	−1.876	−1.555	0.178	1.887	2.227
	Shinetsu	−0.265	1.098	−2.371	−2.05	−0.271	1.533	1.918
	Kinki	−0.151	1.125	−2.365	−2.005	−0.139	1.671	1.996
	Chugoku	−0.316	1.16	−2.633	−2.241	−0.306	1.588	1.92
	Shikoku	−0.242	1.204	−2.59	−2.213	−0.234	1.735	2.099
	Kyushu	−0.886	1.169	−3.23	−2.815	−0.883	1.061	1.415
	Hospital group	0.343	1.202	−2.044	−1.65	0.327	2.328	2.657

Table 5: Correlation between Adoption Propensity and Mortalit

	Correlation Coefficient
2006	−0.354
2007	−0.434
2008	−0.261
2009	−0.259

Table 6: Estimate of the Geostatistical Effect

node	mean	sd	2.50%	5.00%	median	95.00%	97.50%
phi	1.827	4.036	0.003	0.004	0.26	8.956	13.38

Table 7 Propensity to adopt technology and Mortality (Group Hospitals)

Variable	mean	sd	2.50%	5.00%	median	95.00%	97.50%
IVUS	−2.122	0.6518	−3.348	−3.157	−2.143	−0.976	−0.6961
DES	−1.793	0.4832	−2.726	−2.573	−1.807	−0.9446	−0.7491
IABP	0.1341	0.1236	−0.1054	−0.06803	0.1336	0.3382	0.377
Mortality	0.5207	0.2965	−0.05814	0.03274	0.5237	1.009	1.105

Figure 1: Adoption and Mortality Rate by Hospital

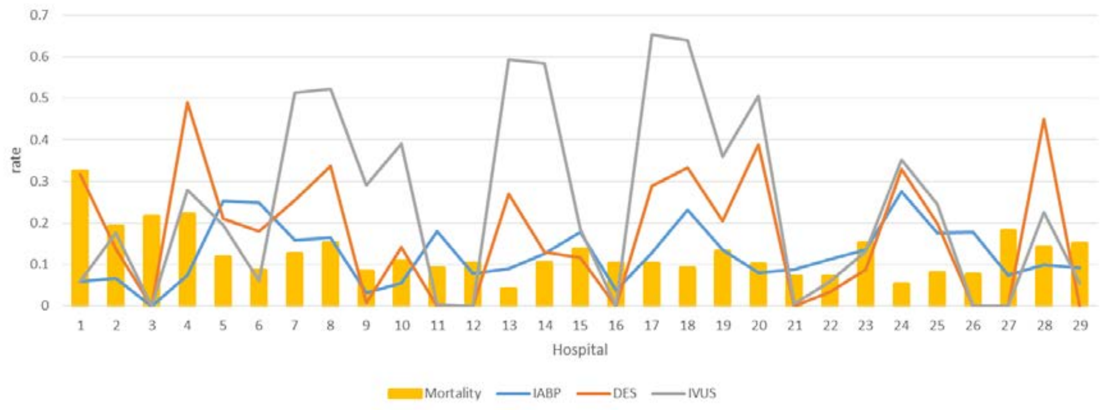
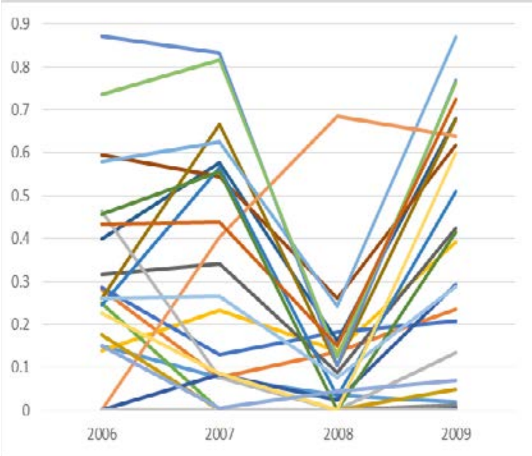


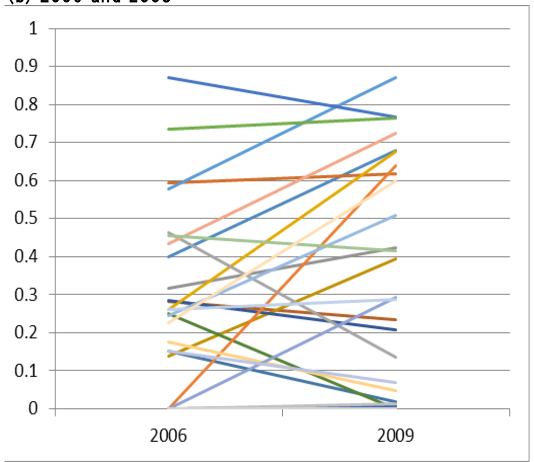
Figure 2: Change in Adoption Rates for Each Year

(1) IVUS

(a) All Years

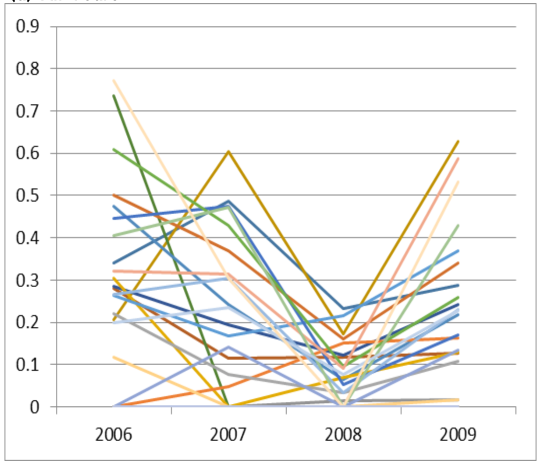


(b) 2006 and 2008

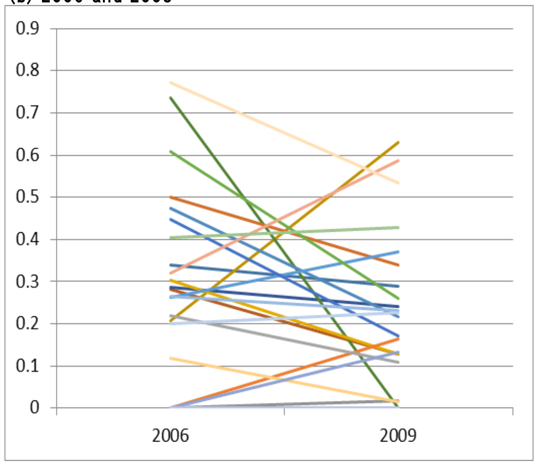


(2) DES

(a) All Years

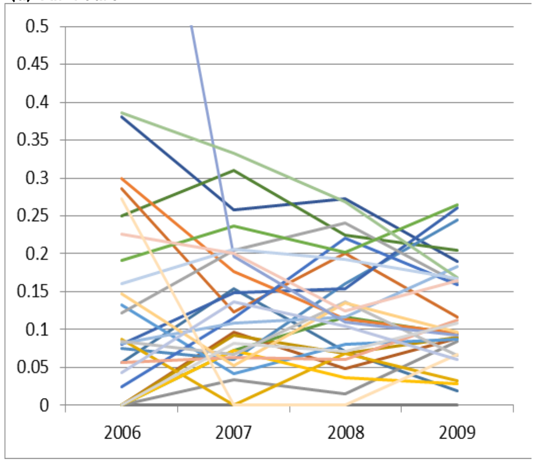


(b) 2006 and 2008

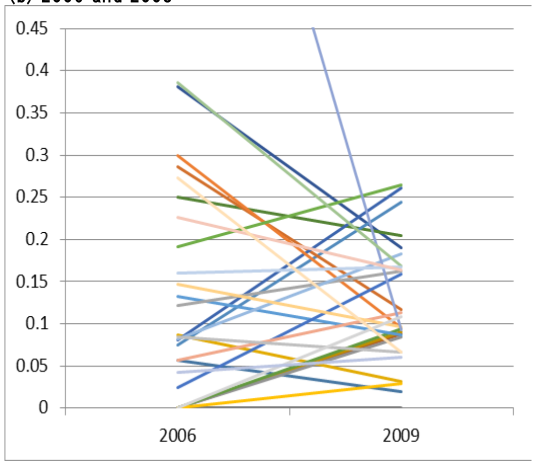


(3) IABP

(a) All Years



(b) 2006 and 2008



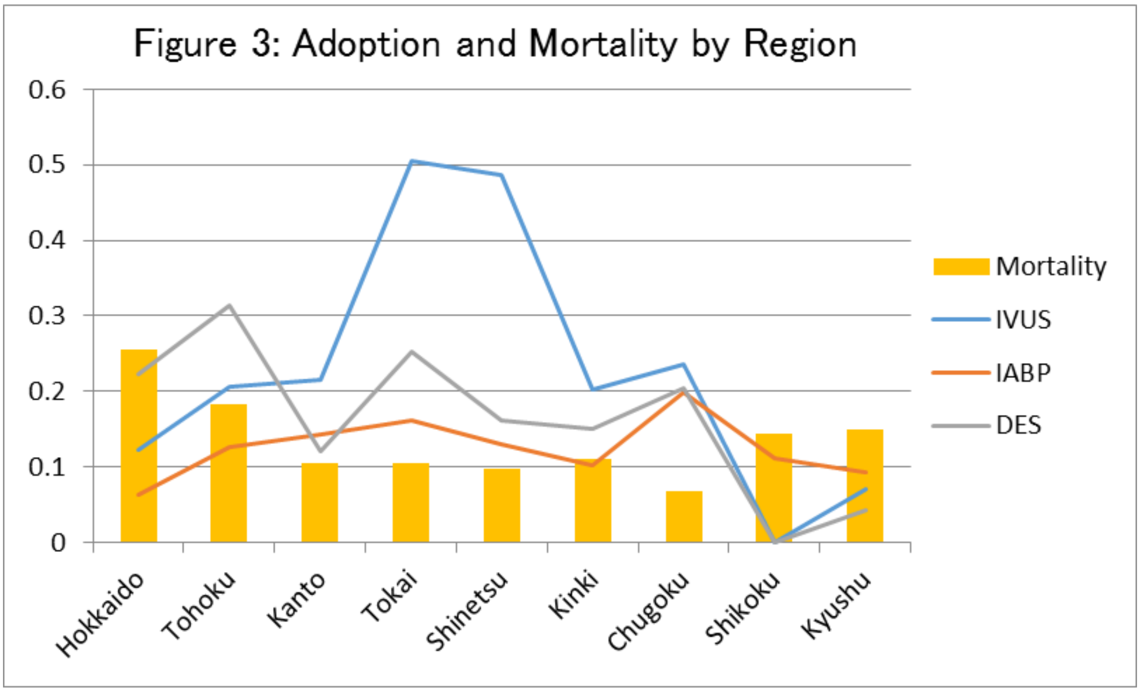


Figure 3: Adoption and Mortality by Region
0.6
0.5
0.4
0.3
0.2
0.1
0
Hokkaido
Tohoku
Kanto
Tokai
Shinetsu
Kinki
Chugoku
Shikoku
Kyushu
Mortality
IVUS
IABP
DES

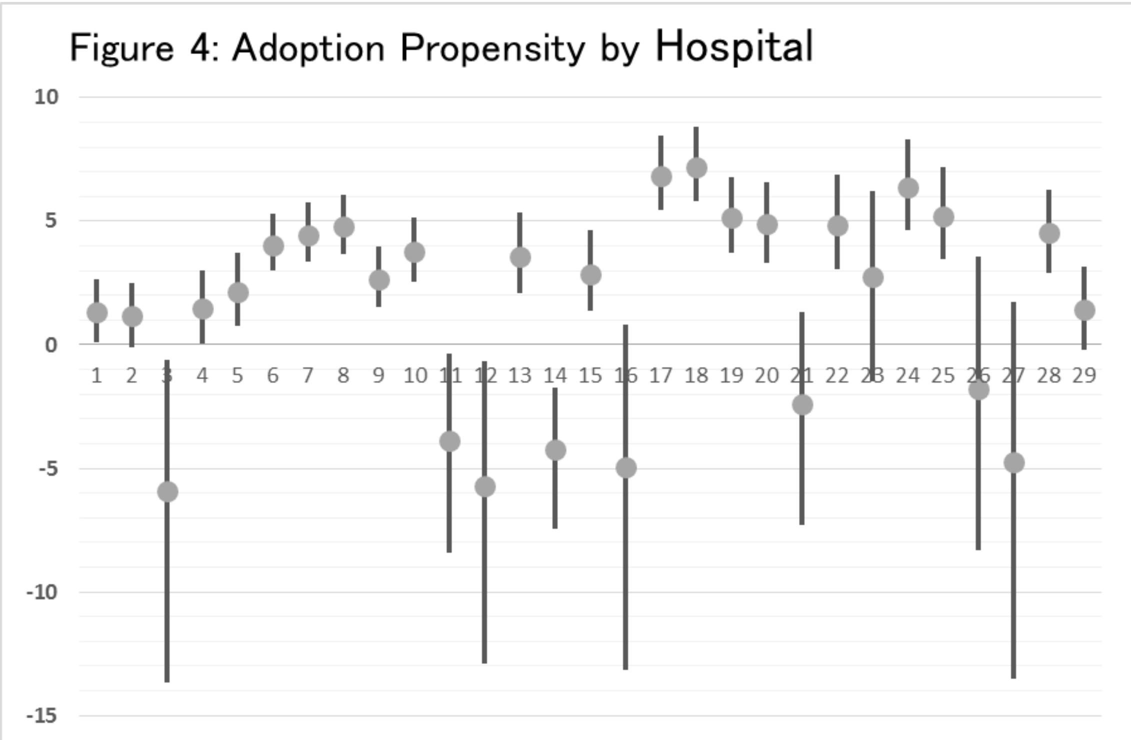


Figure 4: Adoption Propensity by Hospital
10
5
0
-5
-10
-15
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29

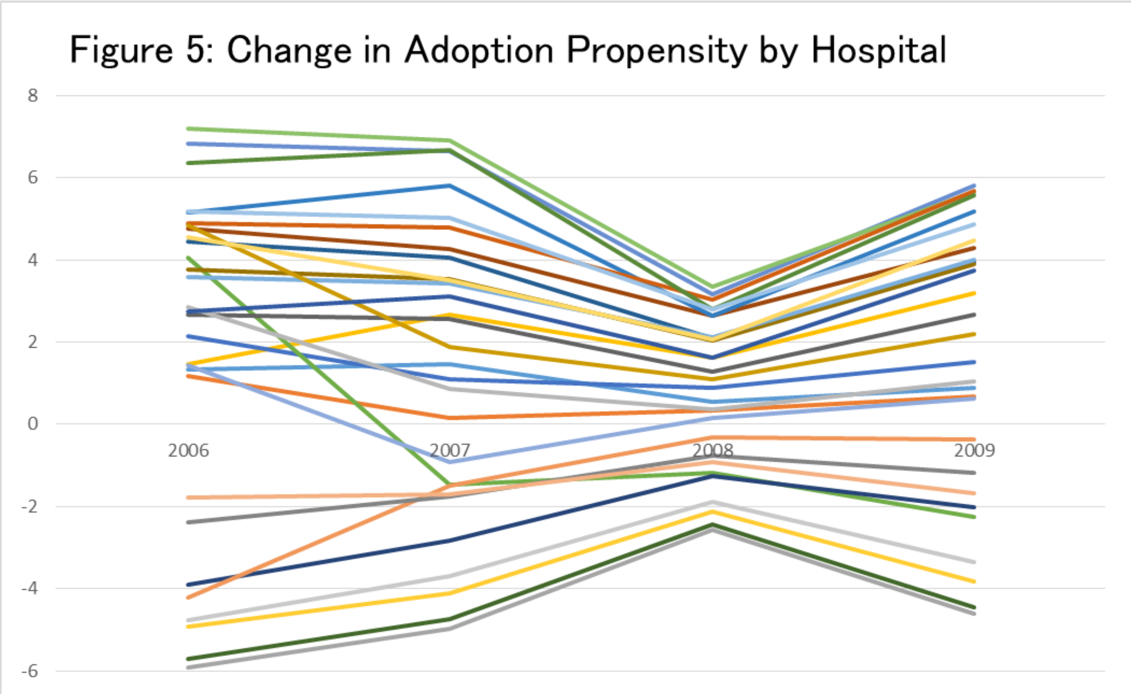


Figure 5: Change in Adoption Propensity by Hospital

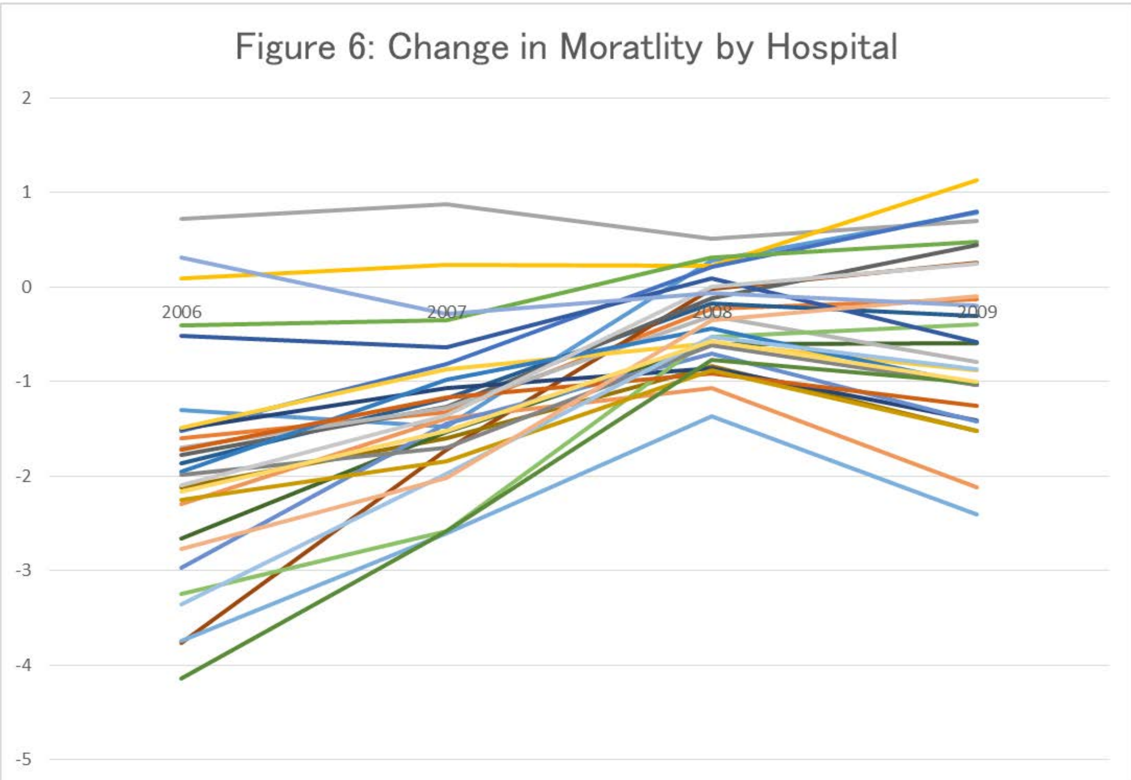


Figure 6: Change in Moratlity by Hospital

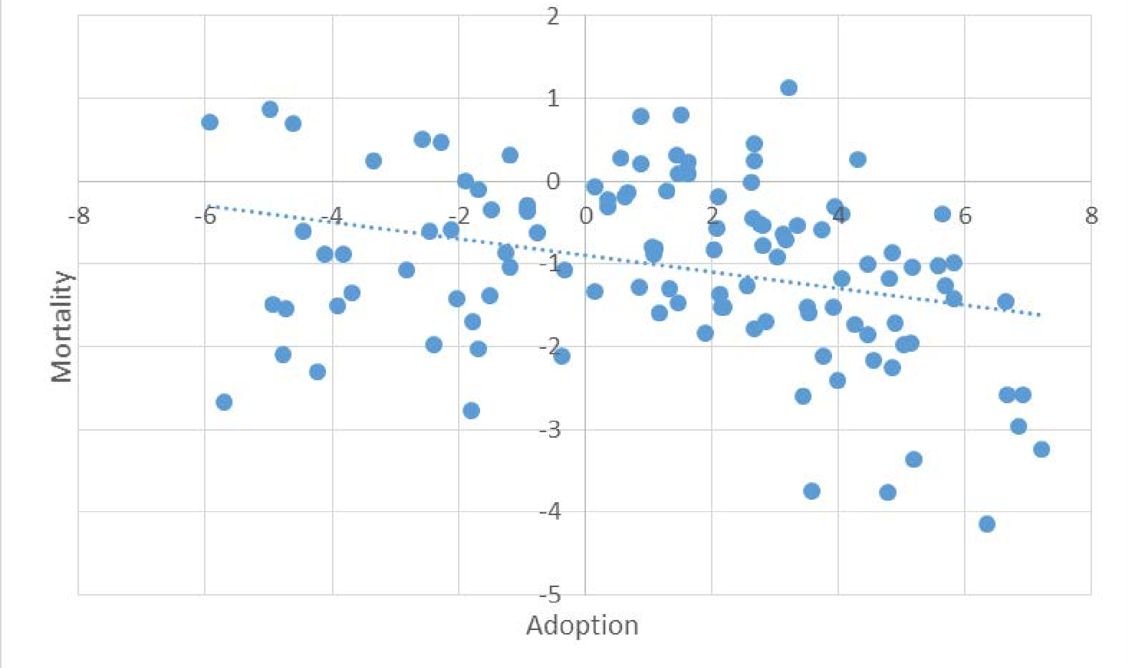


Figure 7 Adoption Propensity vs. Mortality

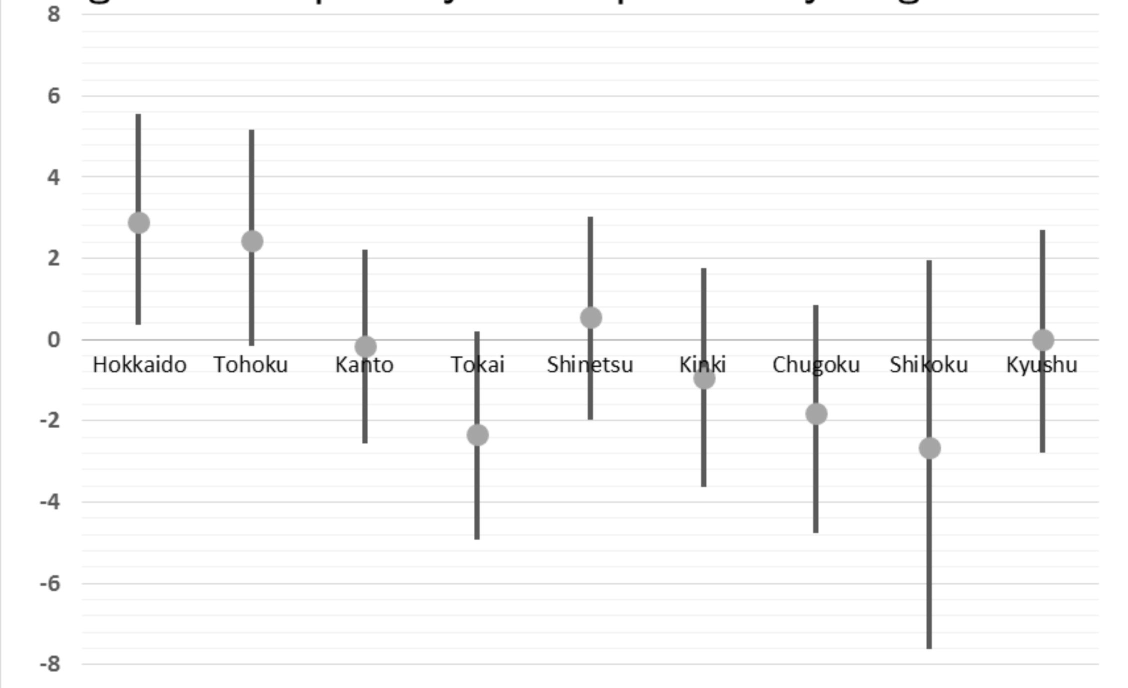
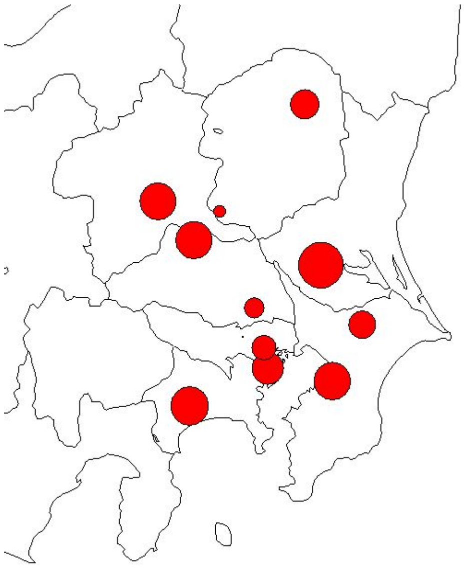


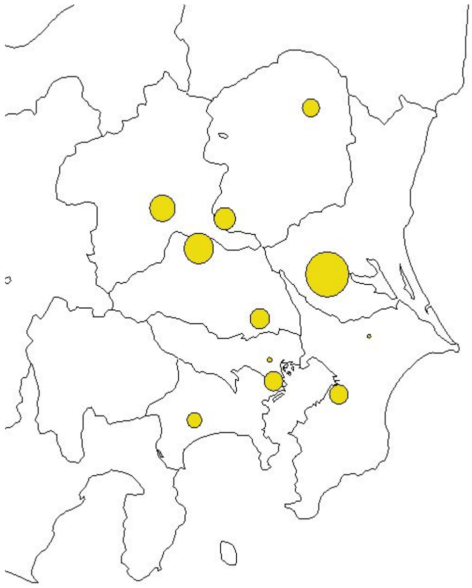
Figure 8: Propensity to Adopt DES by Region

Figure 9 Adoption Rate for the Kanto district

(1) IVUS



(2) DES



(3) IABP