Technology diffusion in hospitals: a log odds random effects regression model

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SUMMARY

This study identifies the factors that affect the diffusion of hospital innovations. We apply a log odds random effects regression model on hospital micro data. We introduce the concept of clustering innovations and the application of a log odds random effects regression model to describe the diffusion of technologies. We distinguish a number of determinants, such as service, physician, and environmental, financial and organizational characteristics of the 60 Dutch hospitals in our sample. On the basis of this data set on Dutch general hospitals over the period 1995–2002, we conclude that there is a relation between a number of determinants and the diffusion of innovations underlining conclusions from earlier research. Positive effects were found on the basis of the size of the hospitals, competition and a hospital's commitment to innovation. It appears that if a policy is developed to further diffuse innovations, the external effects of demand and market competition need to be examined, which would *de facto* lead to an efficient use of technology. For the individual hospital, instituting an innovations office appears to be the most prudent course of action. © 2013 The Authors. *International Journal of Health Planning and Management* published by John Wiley & Sons, Ltd.

KEY WORDS: diffusion; technology; hospitals; log odds regression model

INTRODUCTION

Even though an extensive body of literature exists on medical technology assessment, much less is known about the productivity consequences of new technologies and about the way technologies are diffused among hospitals. The tying together of productivity and technology diffusion is relevant because technology is often cited as a cause for increasing costs in developed countries. An assessment of the

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productivity—innovation diffusion relationship among hospitals—contributes to important policy recommendations on how to influence the diffusion of innovations in order to reduce costs and enhance quality of care. Because costs are involved in developing and introducing new medical technologies, insight as to which factors contribute to timely diffusion of these technologies is of great interest. The central question therefore is whether or not factors can be identified that are sensitive to policy measures.

In this paper, we intend to model and to measure the relationship between hospital characteristics and the probability of technological diffusion. Responding to the Greenhalgh *et al*. (2004) criticism that previous work in this area focused on a single unit within an organization or a single technology, we introduce the concept of clustering innovations to describe the diffusion of technologies. Because we have access to a rather unique panel data set (1995–2002) of more than 60 Dutch hospitals and 60 technological innovations, we can develop a detailed description of the diffusion process. In earlier studies, the productivity issue is discussed for a large number of innovations in the Dutch hospital industry (Blank, (2008); Blank and van Hulst, 2009).

In this research, we use a log odds random effects regression model to describe the diffusion of technologies. Log odds models are generally introduced when estimating probabilities or when a dependent variable is bounded. We also introduce an innovation index, as our dependent variable measuring the individual hospital's innovation "performance" relative to the industry's average. Because we are dealing with panel data, we apply a random effects model estimation technique (see, e.g., Greene, 2008: 831–835). The remainder of the paper unfolds as follows. In the Theory of diffusion section, we discuss a general theoretical background of the diffusion of innovations. In the Dutch hospital industry section, the institutional context of Dutch hospital industry is briefly discussed. In the Econometric model and estimation section, we present an econometric model for estimating the effects of various determinants on the innovation index, measuring the number of technologies relative to the industry's average. In the Data section, we describe the data followed by the Empirical results section where the outcomes of the econometric analyses are presented. In the Conclusions and policy recommendations section, we conclude the paper and present some possible policy recommendations.

THEORY OF DIFFUSION

The formal definition of technology diffusion is described as the process in which an innovation is communicated through certain channels over time among members of a social system. Technology diffusion is also necessary to economic growth particularly if it enhances productivity and quality of services/goods. In the field of medicine and health, the successful diffusion of technology and new knowledge may be a prerequisite to changes in practice patterns (Fitzgerald *et al*., 2002). The adoption of healthcare technology, particularly in information systems and in medical practice, is identified as a key ingredient to efficiency improvement (Hikmet *et al*., 2008). But the success of new practices via the diffusion of new technologies and/or knowledge requires several different interactions that may or may not be complete (Moser and Barrett, 2006). Despite advances in knowledge and technology,

questions still remain regarding the successful implementation of any innovation, and thus, there is a certain risk to changing practice patterns, which may or may not enhance productivity/efficiency.

Unfortunately, we do not have a standard theory on innovations diffusion's impact on productivity at our disposal. Stoneman (2001) marks that the contours of a theoretical framework for the diffusion of innovations are comparable with investment theory, and Baumol (2010) is also optimistic about an integrated theory on innovation but notes that estimating an empirical application is not straightforward. Typical aspects of innovations include the role of the diffusion of information and the high uncertainty about cost and benefits. Instead, in most of the literature, researchers applied some heuristic methods based on common sense. We present some relevant findings from the literature sketching out the standard framework of diffusion theory.

In some cases, a pro-innovation bias exists suggesting that all innovations can add to productivity or economic enhancements (i.e., increased profits or net revenues and decreased costs). However, if the innovations are different from local practices, even if it is shown to be effective, the new technology may not be adopted (Rogers, 2003).

Corroborating Rogers (2003), Easterly (2006) contends that decision-making of any change should emanate from those directly affected by an innovation. He further argues that deferring to decision-makers at the top, who may rely too much on theory, may not work at the local level because of social mores or common practice.

As with the case of any technological/ treatment innovations, the success of the diffusion rests on a determination of how good the science is (e.g., Burke *et al.*, 2007; Fitzgerald *et al.*, 2002). Burke *et al.* (2007) focused on the role of "star" physicians who were trained at and still work at highly reputable institutions. Even though these "star physicians" may be deemed credible in determining the scientific worthiness of new medical innovations, Burke *et al.* (2007) discovered that it was the strength of the local physician networks that was directly related to innovation diffusion.

Whereas these studies focus on the different physician types and their respective roles in the diffusion of technology, the role of the physician within an organization may also provide insights. Following the basic stages of technology diffusion as described by Rogers (2003) including knowledge, persuasion, decision, implementation and confirmation, the role physicians play in the hospital *vis-à-vis* the administration is relevant. If the technology being diffused is medically or scientifically determined, the advantage may go to the physician because of asymmetric information. If the technology is social or economic, the administrator may have the informational advantage. Therefore, identifying the change agents and their role within an organization would be instrumental in predicting innovation success. In line with this, Escare *et al.* (2001) addresses the informational and cost externalities that follow the adoption of a new procedure.

Size and scope of services are also important factors in forecasting whether or not an innovation will be successful. Larger organizations appear to innovate faster than smaller organizations. This may be due to the economies of scale and scope advantages of larger institutions (particularly hospitals) and the presence of slack in inputs that could be utilized directly with the innovation (Rogers, 2003; Blind and Jungmittag, 2004).

The markets in which organizations, in this case, hospitals, operate also may determine the diffusion of innovations. Schumpeter (1942) argues that some degree of market power is a precondition for technical and economic progress. This argument is applicable to hospital setting. Often considered to operate in a monopolist competition, diffusion of technological advances would be accomplished quickly because no single hospital administrator wishes to be viewed as providing lower quality especially if quality is defined in a structure or process manner, that is, having a wide array of medically sophisticated services (Donabedian, 2004). Conversely, focusing on the objective of structure or process quality could result in higher economic costs such as excess capacity, underutilization of inputs and dead weight loss.

Hence, if the market structure is endogenously determined, as suggested earlier, then the increase in competitors may or may not lead to increased research, development and innovation by individual firms. This is true if firms wish to free-ride on the knowledge generated by other entities that absorbed the costs. If the market structure is exogenous, there is an increase in research, development and possible innovation diffusion particularly among firms that are characterized as natural monopolies. The role of the market structure is, for instance, emphasized by Baker and Phibbs (2002). They conclude that the Health Maintenance Organization market share is associated with slower adoption of mid-level units for neonatal intensive care but not with adoption of the most advanced high-level units. A similar result was found for the diffusion of magnetic resonance imaging. Baker (2001) showed that increases in the Health Maintenance Organization market share are associated with slower diffusion of magnetic resonance imaging into hospitals between 1983 and 1993. The impact of managed care for a number of other technologies has been researched by Mas and Seinfeld (2008).

The type of payment mechanism is also relevant in the diffusion of technology. In the USA, positive operating margins derived from paying patients (i.e., insured) play an important role for hospitals meeting their respective objectives including technological advancements. Similarly, Chou *et al.* (2004) found that as insurance became more generous in Taiwan, more innovations were diffused among hospitals, thereby describing their interdependence (Weisbrod, 1991). Because of the tie between payment infusion and technology diffusion, forecasting innovation development and use would require an economically strong market with patients and insurers willing to pay for these added services. The role of a remuneration scheme is also being stressed by Selder (2005) who examined the incentives of healthcare providers to adopt new technologies. In the Dutch system, hospitals are reimbursed by the government for providing more technologically advanced services. Even though the payment mechanism in the Netherlands is different from the USA, the incentives are similar.

Given the literature cited, innovation diffusion is not straight forward, and other factors enter in to the decision-making process. In order to shed some light on the diffusion process, we present an econometric model in which the aforementioned considerations are accounted for. We apply the model to Dutch hospital data to assess the factors affecting technology diffusion among hospitals operating in the Netherlands.

DUTCH HOSPITAL INDUSTRY

In the Netherlands, hospital capacity, such as the number of beds, the number of physicians, the number of wards and very expensive medical equipment, is regulated by the central government and fully reimbursed by the central government on a prospective basis. Budgets consist of a fixed component related to capacity and a variable component related to production. The fixed component is based on the so-called adherence, the number of beds and the number of associated physicians. The production-related component is based on regional agreements on the numbers of first-time visits, in-patient days, day-care patient days and the number of discharges.

To some extent, budgets are based on the severity of cases and on the types of specialty services supplied by the hospital. For each medical procedure, a price is fixed by the Central Tariffs Health Care, and this price is paid for by the insurance companies. Therefore, incentives exist to increase technological capability in order to treat more severely ill/injured patients. Hospitals also attract patients by supplying particular specialties implying that the inclusion of highly technical medical treatments, that is, technology diffusion, may be a way of expanding market share.

Similarly, capital is strongly regulated so that technology diffusion might also be affected by regulation. In this way, regulations in the Netherlands specify that capital can only be raised if hospitals are financially viable, thereby somewhat constraining the hospital administration's discretion on technology expansion. Other regulated aspects include the status of the hospital (academic/nonacademic), the capacity for trainees and the employment of physicians. The role of the physician *vis-à-vis* the hospital is relevant because it has been suggested by others, cited in the literature, that physicians may be crucial in identifying which technology is required for up-to-date medical practice. In the Netherlands, hospitals may have physicians on the payroll, self-employed physicians or a combination of both. The null hypothesis that we test is that there is no difference among hospitals based on their individual factors enumerated earlier and the propensity for diffusing technology.

ECONOMETRIC MODEL AND ESTIMATION

Because we adhere to Greenhalgh *et al.* (2004) and Spetz and Maiuro's (2004) suggestion for a more universal approach of technological diffusion, we begin by specifying an empirical model that investigates the relationship between an innovation index, which represents the number of innovations present at a hospital relative to the industry's average, and a set of determinants. Instead of investigating the presence of a particular innovation, we prefer to analyze the hospital's inclination to innovate. The central idea behind this approach, as advocated by Greenhalgh *et al.* (2004), is that the decision to introduce a new technology cannot be separated from the decision of the introduction of other technologies. According to Spetz and Maiuro (2004), the index should accurately reflect the degree of technology advancement across hospitals at a single point in time, and higher values of the index

should correspond to "more advanced," hospitals. The index also should be comparable over time, so that an increase in the value of the index reflects adoption of newly developed devices and processes. The innovation index applied here satisfies these conditions and is defined as the ratio of innovations present and the maximum attainable number of innovations. (For reasons of convenience, time and observation, suffixes are dropped from the equation) No weights were attached to the different innovations, because relevant data on, for instance, the cost of an innovation are lacking. We also applied a Saidin index, as suggested by Spetz and Baker (1999), but the outcomes of the analyses were not affected by using this index.

Our index can be represented as follows:

$$innov = \frac{1}{I} \sum_{i}^{I} innov_i$$

with *innov* as the innovation index, $innov_i$ where the innovation I is present ($1 = $ yes and $0 = $ no) and I as the maximum number of innovations attainable.

Because the innovation index takes values between 0 and 1, the model can be specified through a logistic transformation, guaranteeing that the dependent variable is bounded between 0 and 1:

$$innov = \frac{1}{1 + \exp - \left(\beta_0 + \sum_{k} \beta_k X_k \right)} \tag{1}$$

with X_k as the characteristic k and $\beta_0, \ldots, \beta_k$ as the parameters to be estimated.

Because the logistic specification is bounded by 0 and 1, the distribution of the error term does not meet the standard assumptions of ordinary least squares leading to biased and inconsistent estimates. This can simply be resolved by a log odds transformation. For details on this procedure, see, for instance, Kieschnick and McCullough (2003). Taking logarithms of the odds and adding an error term lead to the following linear model with a normally distributed error structure:

$$\ln \left(\frac{innov}{1 - innov} \right) = \beta_0 + \sum_{k} \beta_k X_k + \varepsilon \tag{2}$$

where β_k's are the coefficients that measure the impact of characteristic X_k on the innovation index, and ε is a normally distributed random error—with mean 0 and variance σ_ε—that captures the unmeasured and immeasurable effects on acquiring new technologies.

Because Equation (2) is a relationship between the log odds of technology diffusion and the characteristics of the hospitals, the interpretation of the estimates is not straightforward. Instead, we use the application of the marginal innovation index that can be derived from Equation (2) rather easily. The marginal innovation index reflects the change in the innovation index due to a unit change in one of the independent variables. From this analysis, we can interpret the relative importance of a change

in the independent variable leading to changes in the innovation index. The estimated marginal innovation index with respect to characteristic k for a hospital equals

$$MI_k = I \cdot \frac{\exp\left[\widehat{\beta}_0 + \sum_{k'}\widehat{\beta}_{k'}X_{k'}\right]}{\left[1 + \exp\left[\widehat{\beta}_0 + \sum_{k'}\widehat{\beta}_{k'}X_{k'}\right]\right]^2} \cdot \beta_k \tag{3}$$

Because the model is being applied to a set of panel data, the structure of the data should be taken into account. Because observations belonging to the same unit are not independent, the use of ordinary least squares would lead to inconsistent and inefficient estimates. Panel data techniques, such as a fixed effects and random effects, are therefore preferred. One of the drawbacks of fixed effects model is that it is incapable of estimating the effects of firm specific time invariant variables. Because in this analysis a number of variables are time invariant, a random effects approach is being applied. Examples of time (almost) invariant variables are the academic status of the hospital, the number of hospitals in the region, the number of hospital sites, physicians' involvement in hospital budgeting and the management structure.

DATA

General

Data for this study (covering the period 1995–2002) were obtained from the Ministry of Health, Welfare and Sport (collected by the Institute for Health Care Management) and from a separate survey among hospitals based on a questionnaire about innovations (collected by ECORYS and the Public Health Council). In the questionnaire, the hospitals were asked in which year a specific innovation was introduced at the hospital. On the basis of these data, we were able to calculate the innovation index. This survey contains information on 56 innovations from 66 general hospitals over the period 1995–2002. Observations on hospitals with missing or unreliable data were excluded from the data set. Various consistency checks were performed on the data to ensure that changes in average values and the distribution of values across time did not impose systematic bias. After the elimination of observations containing inaccurate or missing values in the data set, an unbalanced panel data set of 362 observations over the 8 years of study remained, about 70% of the total sample.

Because we have data on several variables over a complete set of hospitals, we are able to investigate how representative the sample is with respect to these variables, that is, whether a hospital is present or not present in the data set. On the basis of a logit analysis and applying a t-test, we concluded that the sample is representative with respect to the size, productivity and type of hospital (general, top clinical and university hospital). Given the tests we performed on our existing sample, we feel assured that our sample is representative (i.e., can be generalized) to the Dutch

hospital industry as a whole. Unfortunately, we are not able to check for selectivity with respect to the innovations, because in most cases, these data were lacking or unreliable. Because there are a substantial number of observations left in the data set, we do not regard this as a serious matter.

Innovations

Table 1 includes a complete list of technologies. The complete list consists of 56 items.

The proportion of innovations is the dependent variable, and it is obvious that the proportion of innovations increases in time. Because we would like to identify the characteristics that determine the relative performance (in terms of innovations) of individual hospitals, we control for this time effect by standardizing the number of observations by using year-by-year averages of the number of innovations. This standardized variable is called the innovation index. For example, in 1995, the number of innovations is rescaled with a factor 2 (the average number of innovations present in 1995) and in 2005 with a factor 4 (the average number of innovations present in 2002).

Hospital and environmental characteristics

From the determinants cited in earlier works and available data, we have constructed a list of explanatory variables. We distinguish the variables based on service; physician; and environmental, financial and organizational characteristics:

- number of admissions as an indicator of demand,
- case mix of admitted patients capturing incentives for more technological services,
- proportion of self-employed physicians is specified for the physician input,
- proportion of trainee physicians indicates teaching,
- number of physicians per admission indicates time resources available to a physician,
- academic hospital indicates whether academic hospitals may adopt technologies than nonteaching hospitals,
- number of hospitals in region designates market and the degree of a monopolistic competition market,
- financial surplus as the ability to afford technological diffusion,
- number of hospital sites relates to the spatial dispersion of (a group of) buildings of a hospital organization,
- physician involvement in hospital budgeting linking the administration and medical activities within a hospital,
- a more decentralized management structure may be less likely to innovate, particularly if some sectors are satisfied with current practices and may be wary of the cost of innovation and
- an existence of a hospital innovation office clearly indicates a hospital's overall commitment to innovation.

Larger hospitals may be able to introduce and to use new technologies on a wider scale more quickly than small hospitals. However, the introduction of new technologies may be frustrated by bureaucratic procedures in larger hospitals, or the

Table 1. List of innovations

Multidisciplinary diagnostic and treatment	Technical quality	Nurse consulting hour
Pelvis policlinic	Laparoscopic gallbladder removal	COPD nurse
Diabetes foot policlinic	Laparoscopic intestine neoplasm section	CVA consultant
Mamma policlinic	Laparoscopic kidney removal	Decubitus nurse
Constipation and wee-wee policlinic (children)	Use of seal equipment at intestine surgery	Diabetes nurse
Mother child unit	MRI instead of muelografics	cardiac nurse
Proctologic policlinic	Shaver blades at endonasal surgery	Mamma care nurse
Vascular or risk policlinic	Stroke care unit	MS nurse
Cardiac policlinic	Thermo therapy gynecology	Stoma nurse
Pain policlinic	TVT devices	Wound consultant
Sleep disorder policlinic	Preoperative nutrition	Rheumatic consultant
Lung revalidation	Decubitus prevention	Oncology consultant
Down policlinic	Preoperative screening by anaesthesiology	Function differentiation
Protocol of reference by general practitioner	(Postoperative) pain registration	
Chain care	Logistics	ICT
Stroke service	Cataract line	Electronic data at consultation room and the ward
Total hip (reduction of hospital stay duration)	Joint care for orthopedics	Process support ICT
Total knee (reduction of hospital stay duration)	One stop visit (MRI, varicose vein and hernia)	
Integrated psychogeriatric care	Filtering of patients (elective, emergency/focused care)	
Integrated diabetes care		
Integrated COPD care		
Transmural care for oncology patients	Hospital transferred care	
Transmural care for palliative care	Home monitoring of pregnancy	
Cooperation with general practitioner	Self-measurement thrombosis care	
Transmural care	Night home dialysis	

COPD, chronic obstructive pulmonary disease; CVA, cerebral vascular accident; TVT, tension-free vaginal tape; MRI, magnetic resonance imaging; MS, multiple sclerose; ICT, information and communication technology.

diffusion of new technologies may also be slowed down by information lags between doctors and management. Similar explanations hold for the case mix of patients. Some new technologies can be applied to various patient types or various treatments that will increase the intensity of use over a wide array of patients' needs. On the contrary, some new technologies can only be applied to a limited number of patient types or treatments, for instance, treatments with a low complexity. In this

case, the introduction of new technologies to hospitals with low case mix may be more profitable. Case mix is measured here as the weighted sum of discharges per specialty. The weights are established on the average length of stay per specialty (over all hospitals).

Burke *et al*. (2007) and Fitzgerald *et al*. (2002) both present arguments about the relevance the role of physicians play in technology diffusion. Physicians are therefore driving forces in promoting the introduction of new technologies because they may have professional and economic grounds for promoting new technologies. New technologies may also increase their own productivity and increase their ability to increase their income.

Opposition to new technology may arise from some physicians' aversion to learning new medical skills and to the adaptation of new organizational procedures. Characteristics such as age and experience of physicians, method of payments (wages or fee per patient) and work load are included in our model of physician-based determinants. We also include the proportion of trainees in the total number of physicians as a measure of teaching intensity.

Environmental factors that may affect technology diffusion include teaching status of the hospital and the market competition of other hospitals in the region. We include teaching status because the introduction of new technologies typically occurs at academic hospitals. This is consistent with the culture of teaching hospitals that invite rather than distrust innovations (Burke *et al*., 2007). Competition may affect the ability to innovate in two ways. When competition is driven by quality factors, such as improved surgery procedures or improved diagnostic techniques, the introduction of new technologies may benefit from these market pressures. If competition is driven by reducing service prices, the effects of new technology are ambiguous.

It is obvious that an important determinant explaining diffusion is the ability to finance the investment in new technologies. Actual surpluses or profits may indicate the financial abilities of a hospital.

The introduction of new technologies is related to the organizational decision structure, information dissemination and cultural aspects of the organization. Because no reference to the effect of these types of variables was found in the literature, we add to the knowledge base of how these organizational aspects can affect the probability of technological innovation. Specific variables used to measure these aspects include the number of hospital sites, the involvement of physicians in the financial planning and control cycle of the hospital, the existence of a decentralized management structure and the presence of a specialized innovation office. The number of hospital sites refers to the spatial dispersion of buildings of a hospital organization. Different sites may hinder the diffusion of innovations due to a lack of communication and interaction or even rivalry among employees of the different sites. It is also more difficult to share new technologies among different sites, that is, the scale argument.

Physicians represented in the financial decision-making process may be more sensitive to the claims of their colleagues regarding the benefits of the new technology. However, it may also be argued that physicians with financial responsibilities may be more aware of other organizational considerations such as cost control or medical effectiveness thereby turning down their colleagues' claims.

Bureaucratic procedures with respect to large-scale expensive investments or reforms may slow down introduction, whereas small-scale investments may be adopted from a more decentralized organization.

The presence of a hospital innovation office indicates the perceived relevance of innovations by the management because it acquires and bundles information on new technologies. Therefore, any information lag is reduced by the existence of such an office.

The involvement of physicians in the financial planning and control cycle of the hospital, the existence of a decentralized management structure and the presence of a specialized innovation office were part of the special questionnaire and measured as dichotomous variables (0 = not present; 1 = present).

Statistical descriptives

The descriptive statistics of the variables are summarized in Table 2. In the case of dichotomous variables (value is 0 or 1), the mean can be considered as the proportion that satisfies the value equals 1.

EMPIRICAL RESULTS

In Table 3, we show the estimates of the log odds regression model based on random effects estimation. The estimation has been carried out with the software package TSP, version 5.1.

The scaled R^2 equals 0.14, implying that only a small portion of the variation in the standardized number of observations is explained by the variables included. In order to test for any misspecification, we also tested the possibility of nonlinear

Table 2. Descriptives

Variable	Mean	Standard deviation	Minimum	Maximum
Proportion of innovations (standardized)	0.36	0.18	0.02	1.00
Number of patients (×1000)	21.76	9.94	5.08	50.74
Case mix of patients	1.01	0.07	0.83	1.73
Proportion of physicians on the payroll	0.39	0.25	0.00	1.00
Proportion of trainee physicians	0.23	0.23	0..00	1.76
Number of physicians per admissions	5.26	2.35	2.13	18.40
Academic hospital (yes/no)	0.18	0.39	0.00	1.00
Number of hospitals in region	4.42	2.37	1.00	9.00
Financial surplus	0.00	0.02	−0.12	0.11
Number of hospital sites	1.54	0.72	1.00	4.00
Physician involvement in hospital budgeting	0.95	0.21	0.00	1.00
Decentralized management structure	0.66	0.47	0.00	1.00
Hospital innovation office	0.55	0.50	0.00	1.00

Table 3. Random effects estimates

	Estimate	T-value	Lower bound	Upper bound
Number of patients (×1000)	0.031	2.795	0.009	0.053
Case mix of patients	−0.015	−0.023	−1.343	1.312
Proportion of self-employed physicians	−0.406	−1.369	−0.986	0.175
Proportion of trainee physicians	−0.367	−0.922	−1.147	0.413
Number of physicians per admissions	0.051	1.137	−0.037	0.139
Academic hospital	−0.164	−0.687	−0.631	0.303
Number of hospitals in region	0.0981	2.103	0.007	0.190
Financial surplus	1.5796	0.951	−1.677	4.836
Number of hospital sites	−0.048	−0.280	−0.382	0.287
Physician involvement in hospital budgeting	−0.237	−0.440	−1.291	0.817
Decentralized management structure	−0.220	−0.876	−0.713	0.272
Hospital innovation office	0.477	1.974	0.004	0.951
R^2	0.13			

behavior by applying a Ramsey 2 test. The corresponding F-test of no influence of higher-order terms could not be rejected. Specifically, the findings presented in Table 3 show a number of characteristics affecting the diffusion of technologies. Although one may think of many other relevant explanatory variables, the low explanatory power may also indicate the large stochastic element in the diffusion of innovations and may result in the rather pessimistic conclusion that not many instruments can be implemented to influence the diffusion process.

The numbers of patients, the number of hospitals in the region and the presence of a hospital innovation office have a significant positive effect on innovations (at 5% significance level). It appears that the size of the hospital, the extent of competition and the management's affinity to innovations contribute to a fast introduction of new technologies.

The case mix of patients, the proportion of self-employed physicians, the proportion of physician trainees, the number of physicians per admission, the academic status of the hospital, the financial viability, the number of sites, the role of physicians in management and the management structure show no consistent effects on innovations. The hypothesis of these corresponding effects equaling 0 could not be rejected.

The absence of a positive effect of the academic status of a hospital may be regarded as a striking outcome. However, because of the financing system and the large (cross) subsidies for teaching and research purposes, one can also easily argue that academic hospitals also lack some financial incentive for adopting new technologies and are also less sensitive to market conditions, especially in the case of administrative innovations.

Another striking result is that, aside from the innovation office, organizational and managerial characteristics do not seem to play a positive role in the adoption of innovations.

While the interpretations of the magnitude of the parameters are not very straightforward, marginal effects of the independent variables on the innovation index

(standardized proportion of technologies) are also calculated (see Equation (3)). The marginal effects represent the change in the proportion of innovations due to a change of one unit in a characteristic. It shows that 10 000 extra admissions correspond to a 0.03 higher index of innovations. The number of hospitals in a region increases the innovation index by 0.009. The expected effect of the presence of a hospital innovation office equals 0.043. Generally, the effects are thus modest, indicating that we cannot unambiguously fail to accept the null hypothesis.

CONCLUSIONS AND POLICY RECOMMENDATIONS

In response to the Greenhalgh *et al.* (2004) criticism that previous work in the diffusion of technologies' literature focused on a single unit within an organization or a single technology, we introduce the concept of clustering innovations and the application of a log odds random effects regression model to describe the diffusion of technologies. In explaining the diffusion process, we distinguish a number of determinants, such as service; physician; and environmental, financial and organizational characteristics of the 60 Dutch hospitals in our sample.

Generally, there is a relation between a number of determinants and the diffusion of innovations corroborating the earlier conclusion reached by Greenhalgh *et al.* (2004). Positive effects were found for the size of the hospitals (number of admissions), competition (number of hospitals in region) and a hospital's commitment to innovation (presence of innovation office). However, the explained variance by these determinants is limited, indicating that either we have not been able to identify the relevant determinants or we need to conclude that the diffusion of innovations has a strong stochastic nature. However limited, it appears that if a policy is developed to further diffuse innovations, the external effects of demand and market competition need to be examined, which would *de facto* lead to an efficient use of technology. For the individual hospital, instituting an innovations office appears to be the most prudent course of action.

Despite the fact that we have included a substantial number of innovations, it is obvious that we have only taken into account a sample of all possible innovations. In future research, the list of innovations could be expanded. Because no data were available on the magnitude or the significance of the innovations, we were forced to aggregate the innovations as unweighted. If data are available on, for instance, the cost or the number of patients that are affected by the innovation, different innovations could be aggregated weighted by their respective costs or number of patients. Extensive data collection is necessary in this case. Given that we have addressed the issue raised by Greenhalgh *et al.* (2004), our approach is very well suited for including intangible innovations, particularly, organizational changes that are difficult to empirically test within models applied to new hospital infrastructures.

CONFLICT OF INTEREST

The authors have no competing interests.

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