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Does a hospital's quality depend on the quality of other hospitals? A spatial econometrics approach

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ABSTRACT

We examine whether a hospital's quality is affected by the quality provided by other hospitals in the same market. We first sketch a theoretical model with regulated prices and derive conditions on demand and cost functions which determine whether a hospital will increase its quality if its rivals increase their quality. We then apply spatial econometric methods to a sample of English hospitals in 2009–10 and a set of 16 quality measures including mortality rates, readmission, revision and redo rates, and three patient reported indicators, to examine the relationship between the quality of hospitals. We find that a hospital's quality is positively associated with the quality of its rivals for seven out of the sixteen quality measures. There are no statistically significant negative associations. In those cases where there is a significant positive association, an increase in rivals' quality by 10% increases a hospital's quality by 1.7% to 2.9%. The finding suggests that for some quality measures a policy which improves the quality in one hospital will have positive spillover effects on the quality in other hospitals.

1. Introduction

Quality is a key concern for patients and policymakers in health care markets. It is often argued that encouraging competition amongst health care providers will improve quality, especially when prices are fixed as higher quality is then the only way in which hospitals can attract more patients.[1] There is a large empirical literature on the relationship between quality and hospital competition (Gaynor and Town, 2011; Gravelle et al., 2012). The bulk of the literature has been about the US experience but some recent contributions are on the UK and other European countries. The evidence is mixed. Kessler and McClellan (2000) and Kessler and Geppert (2005) find a positive effect of competition on quality, and Gowrisankaran and Town (2003) a negative effect. Shen (2003) reports mixed results, and Shortell and Hughes (1988) and Mukamel et al. (2001) find no effect. Research on the English National Health Service (NHS) for the 1990s finds that competition was associated with lower quality (Propper et al., 2004, 2008) whereas studies of the more recent NHS experience find that more competition increased quality (Cooper et al., 2011; Gaynor et al., 2010; Bloom et al., 2011).

The usual way to test whether competition affects hospital quality is to examine the relationship between quality (often measured by hospital mortality) and measures of competition such as the Herfindahl index or the number of rival hospitals.[2] In this study we test whether a hospital's quality responds to the quality of its rivals. In industrial organisation terms, we test whether qualities are strategic complements, i.e. whether a provider responds to an increase in quality from rival providers by increasing quality. The traditional approach tests for an effect of competition on quality by estimating a reduced form relating quality to a measure of market structure. Our approach is to estimate a reaction function to test if a provider's decisions on quality depend on the quality decisions of rival providers. This is of interest for health care policy to improve quality, whether by changing the structure of the market in which hospitals operate, improving information available to patients,

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[1] Prospective payment systems under which hospitals are paid a fixed price dependent on the type of case are used in the US for Medicare and Medicaid patients, in 13 European countries including the UK, Australia, and in Korea, and New Zealand (Cyclus and Irwin, 2010; Paris et al., 2010).

[2] English studies have also been able to exploit changes in policy which encouraged hospitals to compete (e.g. Propper et al., 2008) or gave patients the right to choose from a larger set of hospitals (Cooper et al., 2011; Gaynor et al., 2010).

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giving them greater choice, or pay for performance schemes, since the effect of these policies will depend on the extent to which a hospital's own quality varies with the qualities of its rivals.

We first outline a theoretical model of hospital quality competition under regulated (fixed) prices. The model builds on the existing literature on quality competition with regulated prices (Ma and Burgess, 1993; Gaynor, 2006; Gravelle and Sivey, 2010; Brekke et al., 2011) which models quality competition within the simple Hotelling or Vickrey–Salop spatial frameworks. We derive conditions under which providers respond to an increase in rivals' quality by also increasing quality, so that qualities are strategic complements. We show that, if rivals' qualities do not affect the number of patients gained by a hospital when its quality increases, then qualities are complements (substitutes) if the marginal cost of treatment is increasing (decreasing) or the demand responsiveness increases (decreases) when rivals' quality is higher.

We then test whether qualities are strategic complements using cross-section data on English hospitals in 2009–10 and a set of 16 quality measures including mortality rates, readmission, revision and redo rates and indicators of patients' experience. Most previous work has used a single measure of quality (often mortality from acute myocardial infarction) on the assumption that different quality measures are highly correlated. We use 16 measures to see if the results are sensitive to the choice of quality measure. We take a spatial econometric approach: since hospitals and patients are geographically dispersed, patients must incur travel costs to receive treatment and so hospital location affects demand. Distance between hospitals hence also influences the extent to which decisions by one hospital affects decisions by other hospitals.

We follow the approach suggested by Mobley (2003) and Mobley et al. (2009) who examine whether prices are strategic substitutes, i.e. whether each provider responds to an increase in rivals' prices by reducing its own price. They estimate models in which the effect of rivals' prices depends on spatial proximity. We adapt their approach to examine competition on quality (as opposed to competition on price) and interpret the effect of the spatial quality lag as the slope of the hospital reaction function.

We find that the quality measures are poorly correlated and that the results from regression models vary across the measures. Quality responds positively to rivals' quality for seven out of the sixteen quality indicators and does not respond for the others. When an effect is detected (for overall mortality rates, in-hospital stroke mortality, knee replacement readmissions, stroke readmission within 28 days, and three indicators on patients' experience), an increase in rivals' quality by 10% increases quality by 1.7–2.9%.

Section 2 gives a brief description of the institutional setting. Section 3 provides the theoretical model. Section 4 describes the estimation methods and data. Section 5 presents the results, and Section 6 concludes.

2. Institutional setting

The British National Health Service (NHS) provides universal access to healthcare which is funded by taxation and free to patients at point of use.[3] Geographically defined local purchasers receive budgets from the central government to fund the health care for their populations. Most NHS hospital care is provided by public hospitals (Hospital Trusts) which are separate from the local purchasing body but subject to tight central financial and regulatory control by the Department of Health. Around half are Foundation Trusts, a status given only to hospitals which met certain financial and clinical requirements. Foundation Trusts have more discretion in using surpluses (they do not have to break even) and can borrow directly from the capital market. They have more discretion in staff remuneration (they do not have to follow national pay scales), they can invest in buildings and manage their own assets (Marini et al., 2008). About 20% of the hospitals have Teaching status, undertaking teaching and research, generally providing higher quality and more specialised care, and attracting more complex patients.

Government policy has sought to encourage hospitals to compete via quality. Hospitals receive a fixed price for each patient treated, with prices varying by diagnosis or treatment under a prospective price system similar to the US Diagnosis Related Groups (DRG) scheme but based on Healthcare Resource Groups (HRGs), the local version of DRGs. The HRG system, also known as 'Payment by Results' was initially introduced in 2003 for a subset of procedures and then gradually expanded to other types of admissions, including all types of elective admissions.[4] Money now follows the patient. Tariffs are based on national average costs of procedures (Street and Maynard, 2007) but with adjustments according to the Market Forces Factor (MFF) index which reflects exogenous geographical differences on input costs. From 2003 private sector providers have been able to enter the NHS market though they currently treat only a small proportion (2%) of NHS elective patients.

Policies to make demand more responsive to quality have been introduced. Since 2008 NHS patients have had the right to choose any qualified provider (NHS or private) for elective treatment. The Department of Health has promoted websites such as NHS Choices to provide patients with information about hospital performance on a wide range of quality measures.

There are also policies to directly influence quality. The Care Quality Commission (CQC) inspects hospitals through random audits. Hospitals that do not meet minimum national quality standards can be subject to warning notices requiring improvements, more frequent audits, sanctions or fines, prosecution, and suspension of service registration. There are also financial incentives for higher quality under the Commissioning for Quality and Innovation (CQUIN) scheme. NHS local purchasers are required to write contracts with local hospitals which link a set proportion of their revenue to quality indicators chosen by purchasers. 2009/10 (the period of our study) was the preparatory year for the CQUIN scheme during which 0.5% of NHS hospital revenue was linked to achievement of quality indicators (Fichera et al., 2013).

3. Theoretical model

Denote the quality of hospital i ($i = 1,.., N$) as q_i. The demand function of hospital i is

$$X_i = X(q_i, \mathbf{q}_{-i}; \boldsymbol{\delta}_i) \tag{1}$$

where $q_{-i} = (q_1, \ldots, q_j, \ldots, q_{i-1}, q_{i+1}, \ldots, q_N)$ is a vector of the qualities of rival providers. We assume that the demand function of provider i is increasing in its own quality q_i and decreasing in the quality of the rivals: $\partial X_i/\partial q_i > 0$, $\partial X_i/\partial q_j < 0$. Hospitals are demand substitutes: patients switch to a hospital if its quality is increased and away from it if a rival's quality is increased. Hospitals are imperfect substitutes because of travel costs and times, and switching costs. A marginal increase in quality q_i leads some but not all patients to switch from the other hospitals to hospital i.

The vector of parameters δ_i captures other factors affecting demand, such as the location of patients and other hospitals relative to hospital i, patient preferences over distance and quality, and central policies, for example geographical constraints on patients' choice sets.

[3] Around 15% of all elective (non-emergency) care is funded by private health insurance.

[4] Farrar et al. (2009) investigate the effect of the introduction of the HRG system using a difference-in-difference methodology. They find that the introduction of the new system leads to a reduction in length of stay and an increase in the proportion of day cases. No effect on clinical quality was observed.

Hospitals are prospectively financed by a third-party payer offering a per-treatment price p.[5] We assume that all the patients demanding treatment in a hospital are treated. The objective function of hospital i is[6]

$$\pi_i = pX_i(q_i, \mathbf{q}_{-i}; \boldsymbol{\delta}_i) - C_i(X_i(q_i, \mathbf{q}_{-i}), q_i; \gamma_i), \quad (2)$$

where the cost of supplying hospital treatments is given by the cost function $C(X_i, q_i; \gamma_i)$, with $C_X > 0$, $C_q > 0$. The marginal cost of quality is increasing $C_{qq} > 0$ but the marginal cost of treatment could be constant, increasing or decreasing. We place no restrictions on the effect of volume on the marginal cost of quality. There would be cost substitutability ($C_{Xq} > 0$), for example, if the average cost of treatment is constant with respect to output but increasing in quality ($C(X_i, q_i; \gamma_i) = c(q_i; \gamma_i)X_i$, with $c_q(q_i; \gamma_i) > 0$). Cost complementarity ($C_{Xq} < 0$) is also possible in the presence of learning by doing (with higher volumes reducing the marginal cost of quality). γ_i is a vector of parameters describing exogenous factors, such as input prices, which affect hospital i costs.

The hospitals simultaneously and independently choose qualities. Hospitals can invest in technology and information systems that improve diagnosis or treatment, introduce internal auditing, peer reviews and other clinical governance processes, and improve management and coordination of services to patients (Joint Commission, 2012). The assumption that quality of care can be chosen by hospitals (i.e. is not exogenous) is common to the extensive theoretical literature on hospital competition,[7] and, more broadly, on optimal incentive schemes for hospitals.[8] It is also consistent with the empirical evidence on hospital competition (noted in Section 1) that suggests that hospital quality is affected by competition.[9]

We assume that profit is strictly concave in q_i, which, see Eq. (6) below, imposes further restriction on demand and cost functions. Maximising profit with respect to q_i, the interior solution[10] satisfies

$$\frac{\partial X_i(q_i, \mathbf{q}_{-i}; \boldsymbol{\delta}_i)}{\partial q_i}\left(p - \frac{\partial C_i(X_i(q_i, \mathbf{q}_{-i}; \boldsymbol{\delta}_i), q_i; \gamma_i)}{\partial X_i}\right) = \frac{\partial C_i(X_i(q_i, \mathbf{q}_{-i}; \boldsymbol{\delta}_i), q_i; \boldsymbol{\delta}_i)}{\partial q_i}. \quad (3)$$

Solving Eq. (3) for q_i gives the reaction function for hospital i

$$q_i^R = q_i^R(\mathbf{q}_{-i}; \delta_i, \gamma_i). \quad (4)$$

We are interested in the effect of the rivals' qualities on hospital i quality. Using the implicit function theorem on Eq. (3), the slope of the reaction function is

$$\frac{\partial q_i^R}{\partial q_j} = \left(-\frac{\partial^2 \pi_i}{\partial q_i^2}\right)^{-1}\left[\left(p - \frac{\partial C_i}{\partial X_i}\right)\frac{\partial^2 X_i}{\partial q_i \partial q_j} - \left(\frac{\partial X_i}{\partial q_i}\frac{\partial^2 C_i}{\partial X_i^2} + \frac{\partial^2 C_i}{\partial q_i \partial X_i}\right)\frac{\partial X_i}{\partial q_j}\right] \quad (5)$$

where

$$\frac{\partial^2 \pi_i}{\partial q_i^2} = \left(p - \frac{\partial C_i}{\partial X_i}\right)\frac{\partial^2 X_i}{\partial q_i^2} - \frac{\partial X_i}{\partial q_i}\left(\frac{\partial^2 C_i}{\partial X_i \partial q_i} + \frac{\partial^2 C_i}{\partial X_i^2}\frac{\partial X_i}{\partial q_i}\right) < 0 \quad (6)$$

is the second order condition.

The reaction function of provider i depends on its demand and cost functions. Given Eq. (6), the sign of $\partial q_i^R/\partial q_j$ depends on the terms in the square brackets ($\partial^2\pi_i/\partial q_i \partial q_j$). To fix ideas, consider some special cases.

Case (i) The demand function is linear in qualities ($\partial^2 X_i/\partial q_i \partial q_j = 0$), and the marginal cost of treatment is constant and independent of quality ($\partial^2 C_i/\partial X_i^2 = 0$, $\partial^2 C_i/\partial q_i \partial X_i = 0$). Then, $\partial q_i^R/\partial q_j = 0$: the quality of provider i is independent of the quality of its' rivals.

Case (ii) The demand function is linear in qualities ($\partial^2 X_i/\partial q_i \partial q_j = 0$), as in (i), but the marginal cost of treatment is increasing with respect to quantity ($\partial C_i^2/\partial X_i^2 > 0$) and the marginal cost of quality is increasing with respect to quantity ($\partial^2 C_i/\partial X_i \partial q_i > 0$). Then $\partial q_i^R/\partial q_j > 0$ and qualities are strategic complements: an increase in a rival's quality leads to an increase in hospital i quality. The intuition is that an increase in quality by the rival reduces demand and therefore hospital i output at unchanged quality q_i, so that the marginal cost of treatment is reduced (because $\partial C_i^2/\partial X_i^2 > 0$), thereby increasing the profit margin ($p - \frac{\partial C_i}{\partial X_i}$), and the marginal cost of quality is reduced (because $\partial^2 C_i/\partial X_i \partial q_i > 0$).

Case (iii) Conversely, if the demand function is linear in quality ($\partial^2 X_i/\partial q_i \partial q_j = 0$), $\partial q_i^R/\partial q_j < 0$ if the marginal cost of treatment is decreasing in quantity ($\partial^2 C_i/\partial X_i^2 < 0$) and the marginal cost of quality is decreasing in quantity ($\partial^2 C_i/\partial X_i \partial q_i < 0$). In this case, qualities are strategic substitutes because an increase in the rival's quality, which reduces hospital i demand and output at given q_i, now increases the marginal cost of treatment and therefore reduces the profit margin from additional treatments and increases the marginal cost of quality.

Case (iv) As a final example, suppose that the marginal cost of treatment is constant and independent of quality so that $\partial^2 C_i/\partial X_i^2 = \partial^2 C_i/\partial X_i \partial q_i = 0$. Then, whether qualities are strategic complements or substitutes depends on the sign of $\partial^2 X_i/\partial q_i \partial q_j$. If an increase in rivals' quality increases (reduces) the responsiveness of demand to the provider's quality, then qualities are strategic complements (substitutes) and the provider increases (reduces) quality in response to rivals' quality.

The Nash equilibrium is derived by solving the N reaction functions $q_i^R = q_i^R(q_{-i}; \delta_i, \gamma_i)$ simultaneously to yield

$$q_i^E = q_i^E(\boldsymbol{\delta}, \boldsymbol{\gamma}), \qquad i = 1, \ldots, N \quad (7)$$

where $\delta = \delta_1, \ldots, \delta_N$ and $\gamma = \gamma_1, \ldots, \gamma_N$.

We estimate reaction functions. The rationale for doing so is that (i) it may be easier to do than to estimate the Nash equilibrium equations, and (ii) the properties of the reaction functions $q_i^R(q_{-i}; \delta_i, \gamma_i)$ are crucial to predicting the Nash equilibrium effects of parameter changes. To illustrate, suppose there are two hospitals in the market and there is a pro competitive policy change: for example making it easier for patients to switch from one hospital to another one or introducing patients' choice. Using δ to denote the policy, the effect on hospital quality, holding the quality of other hospitals constant, is

$$\frac{\partial q_i^R}{\partial \delta} = \left(-\frac{\partial^2 \pi_i}{\partial q_i^2}\right)^{-1}\left[\left(p - \frac{\partial C_i}{\partial X_i}\right)\frac{\partial^2 X_i}{\partial q_i \partial \delta} - \left(\frac{\partial X_i}{\partial q_i}\frac{\partial^2 C_i}{\partial X_i^2} + \frac{\partial^2 C_i}{\partial q_i \partial X_i}\right)\frac{\partial X_i}{\partial \delta}\right]. \quad (8)$$

[5] To simplify we assume that this price is sufficiently high that hospitals at least break even in equilibrium.

[6] We can also allow for hospital altruism by writing the hospital objective function as $u(\pi_i, q_i, X_i)$ with $u_q > 0$ or $u_X > 0$. This would not alter our general conclusion that the effect of the rivals' qualities on q_i depends on the properties of the cost and demand functions.

[7] See for example Brekke et al. (2011). See Gaynor (2006), Gaynor and Town (2011) and Brekke et al. (2014) for reviews.

[8] See, for example, the seminal papers by Ellis and McGuire (1986), Ma (1994), and Chalkley and Malcomson (1998a, 1998b). See Chalkley (2012) for a review.

[9] There is also an extensive empirical literature which shows that generally hospital quality responds to incentives, such as report cards (Dranove et al., 2003) and pay for performance (Sutton et al., 2012). See Christianson and Conrad (2011) for a recent review.

[10] To rule out corner solutions we assume $[\partial X_i(0, \mathbf{q}_{-i}; \boldsymbol{\delta}_i)/\partial q_i][p - \partial C_i(X_i(0, \mathbf{q}_{-i}; \boldsymbol{\delta}_i), 0; \gamma_i)/\partial X_i] > \partial C_i(X(0, \mathbf{q}_{-i}; \delta_i), 0; \gamma_i)/\partial q_i$.

Relaxing constraints on patient choice sets will increase the number of patients that a hospital will gain when it increases its quality, since more patients have the opportunity to choose it. Thus demand will become more responsive to quality: $\partial^2 X_i/\partial q_i \partial\delta > 0$. If price exceeds marginal cost, the first term in the square brackets in Eq. (8) is positive. Although demand becomes more responsive to quality, the effect of the policy on demand for a particular hospital ($\partial X_i/\partial\delta$) is ambiguous: it depends on the relative quality of the hospitals and the geographical distribution of patients and hospitals. Thus, even in an apparently straightforward example of a pro-competitive policy, the direct effect on hospital i quality holding the quality of other providers constant ($\partial q_i^R/\partial\delta$) is unclear.

The effect on the Nash equilibrium quality of hospital i in this example with two hospitals is

$$\frac{\partial q_i^E}{\partial\delta} = \left[\frac{\partial q_i^R}{\partial\delta} + \frac{\partial q_i^R}{\partial q_j}\frac{\partial q_j^R}{\partial\delta}\right]\Delta^{-1} \tag{9}$$

where

$$\Delta = 1 - \frac{\partial q_i^R}{\partial q_j}\frac{\partial q_j^R}{\partial q_i} > 0 \tag{10}$$

and where the sign of Δ follows from the requirement that the equilibrium be stable (Dixit, 1986).

We see from Eq. (9) that whilst it is not necessary for quality to be a strategic complement for either hospital for the pro-competitive policy to increase quality for both hospitals, in general the magnitude of the pro-competitive effect will depend on the slopes of the hospital reaction functions with respect to rival quality. With identical hospitals

$$\frac{\partial q_i^E}{\partial\delta} = \frac{\partial q_i^R}{\partial\delta}\left(1 - \frac{\partial q_i^R}{\partial q_j}\right)^{-1} \tag{11}$$

and the direct effect of policy $\partial q_i^R/\partial\delta$ is amplified by interdependencies in hospital demand functions. The amplification is increasing in the cross effect $\partial q_i^R/\partial q_j$ and so is bigger when quality is a strategic complement than when it is a strategic substitute.

Note that the assumptions required for competition policy (as captured by δ) to increase equilibrium quality are different from those for qualities to be strategic complements. For example, if the marginal cost of treatment is increasing in quality or quantity, and competition policy increases aggregate demand for the provider ($\partial X_i/\partial\delta > 0$), then the effect of δ on quality is indeterminate. The competition policy increases the sensitivity of demand to quality, which tends to increase quality, but it also reduces the price-marginal cost markup, which tends to reduce quality. With the plausible assumption that $\partial X_i/\partial q_j < 0$, the same assumptions about the cost function imply that qualities are strategic complements. If a rival provider increases quality, then the reduction in demand for provider i leads to a reduction in its marginal cost and an increase in its price-marginal cost markup, leading provider i to increase its quality.

4. Methods

4.1. Estimation

To test if qualities are strategic complements, strategic substitutes or independent, we estimate the reaction function

$$q_i^R = f_i(\mathbf{q}_{-i}, \mathbf{z_i}, \ \varepsilon_i) \tag{12}$$

where the vector $\mathbf{z_i}$ captures observed parameters from $\boldsymbol{\delta}_i$, γ_i which shift hospital i demand and cost functions and ε_i summarises factors we do not observe. We specify a linear spatial lag model as

$$q_i = \alpha + \rho\sum\nolimits_j w_{ij} q_j + \mathbf{z_i}\beta' + \varepsilon_i \tag{13}$$

where $w_{ij} \geq 0$ is a distance weight specified in more detail below and $w_{ii} = 0$.

We can write the model in matrix form

$$\mathbf{q} = \boldsymbol{\alpha} + \rho\mathbf{W}\mathbf{q} + \mathbf{z}\beta' + \varepsilon. \tag{14}$$

The coefficient ρ on the quality spatial lag variable $\mathbf{Wq}$ determines the sign of the slope of the reaction function. Notice that this specification, as in Mobley (2003) and Mobley et al. (2009), assumes that strategic complementarity ($\rho > 0$) or substitutability ($\rho < 0$) holds between all pairs of hospitals.

We use a row-standardised inverse distance matrix with a 30 min travel time threshold. This is the same travel time threshold as in Propper et al. (2004, 2008) but we also report the results from other thresholds. Define d_{ij} as the distance between hospital i and j, and d_{ij}^{30} as the distance corresponding to 30 minutes travel time between hospital i and j. The weights are given by:

$$\begin{aligned} w_{ij} &= 0 \qquad \text{if} \ \ i = j, \\ &= \frac{d_{ij}^{-1}}{\sum_j d_{ij}^{-1}} \quad \text{if} \ \ d_{ij} \leq d_{ij}^{30} \text{ and } i \neq j, \\ &= 0 \qquad \text{if} \ \ d_{ij} > d_{ij}^{30} \text{ and } i \neq j \end{aligned} \tag{15}$$

The inverse distance specification gives a lower weight to the quality of rivals that are more distant from hospital i. This row-standardisation permits us to interpret $\mathbf{Wq}$ as a weighted average of the quality of rivals, where the weights are inversely related to the distance between the providers. The quality of a rival is included only if the rival is within a catchment area of 30 minutes travel time.

We estimate Eq. (14) by maximum likelihood, which is consistent and efficient in the presence of the spatial lag term, whilst OLS is biased and inconsistent (Anselin, 1988).

The spatial lag model (14) is often presented in a reduced form as (e.g. Le Gallo et al., 2003; Mobley, 2003; Mobley et al., 2009):

$$(\mathbf{I} - \rho\mathbf{W})\mathbf{q} = \boldsymbol{\alpha} + \mathbf{z}\beta' + \varepsilon, \tag{16}$$

which can be rearranged as

$$\mathbf{q} = (\mathbf{I} - \rho\mathbf{W})^{-1}\alpha + (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{z}\beta + (\mathbf{I} - \rho\mathbf{W})^{-1}\varepsilon, \tag{17}$$

or

$$q_i = \alpha\sum_j a_{ij} + \sum_k \beta_k\left(\sum_j a_{ij} z_{jk}\right) + \sum_j a_{ij}\varepsilon_j \tag{18}$$

where a_{ij} is the element in the ith row, jth column of $(\mathbf{I} - \rho\mathbf{W})^{-1}$.

The error process $(\mathbf{I} - \rho\mathbf{W})^{-1}\varepsilon$ means that a random shock for a specific provider not only affects the quality of that provider, but also has an impact on the quality of other hospitals through the spatial multiplier effect (Le Gallo et al., 2003). These effects are propagated to all hospitals, so that ε_j and z_{jk} will affect q_i even if hospital i ignores the quality of hospital j when choosing q_i.[11]

The conventional approach is to solve the simultaneous conditions (3), or equivalently (4), for the equilibrium qualities $q_i^E =$

[11] Hospital i will not be affected by ε_j only if hospital j is not one of direct rivals (i.e. q_j does not affect its demand), and hospital j is not a second order rival of i (hospital j is not a rival of a hospital which is a rival of hospital i), nor a third, fourth,.... order rival.

$q_i^E(\boldsymbol{\delta}, \boldsymbol{\gamma})$ where, in general, the quality in hospital i depends on the demand and cost functions of all hospitals. To produce an estimatable specification it is assumed that the equilibrium quality for a hospital depends on a local subset of the demand and cost conditions for all hospitals: $q_i^E = g(\mathbf{z}_i, \varepsilon_i)$. The $\mathbf{z}_i$, as in the spatial specification, includes measures of competitive structure such as the number of rivals within some radius or Herfindahl indices. Although the same measures of market structure may appear in $\mathbf{z}_i$ in the conventional and spatial specifications, they play different roles. In conventional specifications the interest is in testing for an effect of competition by examining the coefficients on the market structure variables in $\mathbf{z}_i$. In the spatial specification the market structure measures in $\mathbf{z}_i$ are covariates: the main interest is in the sign of spatial lag to test whether rival's qualities are strategic complements or substitutes.

4.2. Data

4.2.1. Quality measures

The literature on hospital competition and quality has used a very limited set of quality measures, most often using hospital mortality for admissions for acute myocardial infarction (AMI) as the measure of hospital quality. AMI admissions are generally emergencies, where patients exercise a very limited amount of choice. The justifications for using AMI mortality as a quality measure in competition studies are that it may be easier to measure the quality of elective care and that it reduces endogeneity problems arising when competition measures, such as the Herfindahl, are based on patient flows. In this paper we use measures of market structure which are not determined by patient flows and we use a mix of measures of quality for both elective and emergency admissions. We examine the correlations amongst them and whether the results on the effect of rivals' quality on hospital quality are sensitive to the quality measure.

We use 16 measures of hospital quality from Dr Foster[12] for the financial year 2009/10 for 147 hospitals (NHS Hospital Trusts). Details on these measures are in the Appendix A. Six of the quality measures are based on standardised mortality rates, seven on standardised readmission, revisions and redo rates, and three are derived from surveys of patients' experiences. The mortality, readmission, revision, and redo measures allow for the case mix of the hospital. Five of the measures are for emergency admissions, five are for electives, and six are for both.

4.2.2. Spatial lags

For each hospital we define a catchment area of 30 min car drive. On this definition of the catchment area about one third of all hospitals are monopolists, i.e. they do not have any other provider within a 30 min car drive. Another third have one or two rivals. 16% have three to five rivals, 12% have six to nine rivals, and only 7% have more than nine rivals (up to a maximum of 14). We initially exclude monopoly hospitals from our analyses. This reduces the sample of hospitals from 147 to 99 observations. Summary statistics for the smaller sample are provided in Table 1. We check the sensitivity of our results to the definition of the catchment area by estimating models using catchment areas of 60 min and 98 min car drive time. With a catchment area of 60 min 142 hospitals have at least one rival and with a catchment area of 98 min all hospitals in England have at least one rival in the catchment area.

4.2.3. Controls

In addition to the spatial lag measuring the quality of rivals within the 30 min drive time catchment area, we control for the number of hospitals within a 30 min car drive catchment area (there are on average 4 rivals). The number of hospitals within the catchment area is one of the measures of market structure used in conventional studies of competition and quality. By including it in the model we test if it adds anything to the explanation of hospital quality once we account for the quality of rivals.

We use population density within 15 km from the hospital (which approximately corresponds to a 30 min car drive) as an additional control since the demand for a hospital, and hence its incentives for quality will depend in part on the number of potential patients in its catchment area.

We construct three dummy variables indicating if the hospital is a teaching hospital, a Foundation Trust, or located in London. Table 1 shows that 20% are teaching hospitals, 52% are Foundation Trusts and 24% are located in London.

We also have a measure of overall hospital activity (the total number of inpatient spells), and the MFF index of labour costs faced by each hospital. On average a hospital has 92,000 inpatient spells. The MFF has an average of 1.03 and varies between 0.9 and 1.2.

Table 1
Descriptive statistics.

		Mean	SD	Min	Max
Quality measures	Type				
Overall mortality rate	B	98.28	9.50	71.85	117.93
Mortality from high risk conditions	M	98.46	10.09	73.02	120.59
Mortality from low risk conditions	B	90.29	27.79	31.30	150.92
Deaths after surgery	B	98.31	25.50	26.33	157.36
Deaths resulting from hip fracture	M	99.96	24.29	43.54	167.87
In-hospital stroke mortality	M	100.91	13.07	76.10	166.07
Hip replacement readmissions	L	109.09	24.24	55.29	175.31
Knee replacement readmissions	L	102.60	36.46	0.00	219.41
Stroke readmission within 28 days	M	105.91	18.98	60.44	158.08
Hip revisions and manipulations within 1 year	L	1.09	0.63	0.00	3.51
Knee revisions and manipulations within 1 year	L	0.55	0.78	0.00	7.14
Hip fracture – operation given within 2 days	M	67.47	11.51	42.83	94.31
Redo rates for prostate resection	L	4.13	1.99	0.00	9.23
Clean Hospital room/ward	B	85.95	2.95	79.00	93.70
Involved in decisions	B	69.68	3.31	60.00	77.40
Trust in doctors	B	88.16	2.27	81.50	92.90
Controls					
Number of rivals within 30 min car drive		3.99	3.50	1.00	14.00
Teaching hospital		0.20	0.40	0.00	1.00
Foundation Trust		0.52	0.50	0.00	1.00
Total number of inpatient spells (in thousands)		91.73	42.09	28.59	216.77
Staff MFF		1.03	0.10	0.91	1.20
Population density within 15 km		2217	2046	264.16	7256
London Trust		0.24	0.43	0.00	1.00

Note. B: measures quality of both elective and emergency admissions. M: measures quality of emergency admissions. L: measures quality of elective admissions. Summary statistics for 99 hospitals with at least 1 rival with 30 min drive time.

5. Results

5.1. Correlation amongst quality measures

Previous studies on the effect of competition on quality have used a small sub-set of quality indicators. This may be appropriate if quality indicators are highly correlated within the hospital. Tables 2A and 2B show that this is generally not the case within our sample. The different quality measures are not highly correlated and often not correlated at all. This suggests that focusing on any single quality measure may lead to a partial picture of the relation between the quality of each hospital and its rivals. This also motivates our regression analysis where we estimate a separate regression for each indicator.

[12] http://myhospitalguide.drfosterhealth.co.uk/.

Table 2A
Correlations amongst mortality and readmission variables.

	Overall mortality rate	Mortality from high risk conditions	Mortality from low risk conditions	Deaths after surgery	Deaths from hip fracture	In hospital stroke mortality	Hip replacement readmissions	Knee replacement readmissions	Stroke readmissions	Hip revisions & manipulations within 1 year	Knee revisions & manipulations within 1 year	Hip fracture operation within 2 days
Mortality from high risk conditions	**0.8**	1										
Mortality from low risk conditions	**0.35**	**0.25**	1									
Deaths after surgery	**0.29**	**0.25**	**0.22**	1								
Deaths from hip fracture	**0.33**	**0.37**	0.19	0.2	1							
In-hospital stroke mortality	**0.32**	**0.49**	0.14	0.02	0.16	1						
Hip replacement readmissions	0.02	0.04	−0.07	−0.08	−0.04	0.03	1					
Knee replacement readmissions	−0.02	0.02	0.11	−0.12	−0.06	−0.04	**0.32**	1				
Stroke readmission	−0.03	−0.03	−0.12	−0.02	0.16	0.04	0.07	0.09	1			
Hip revisions & manipulations within 1 year	0.01	−0.09	−0.05	−0.09	−0.02	−0.05	0.01	0.11	0.04	1		
Knee revisions and manipulations within 1 year	−0.09	−0.16	−0.18	−0.11	−0.05	0.06	0.02	−0.06	0.06	**0.38**	1	
Hip fracture operation within 2 days	−0.05	−0.09	0.03	−0.07	−0.05	−0.03	0.02	−0.02	0.01	0.09	0.02	1
Redo rates for prostate resection	−0.13	−0.07	−0.04	−0.16	−0.08	0.02	−0.05	−0.01	0.08	−0.06	0.01	0.11

Note: absolute value of correlation of at least 0.21 required for significance at 1%. N = 146.

5.1.1. Correlation amongst mortality rates

Table 2A reports correlation matrix for the six mortality indicators. The overall mortality rates are highly correlated with mortality from high-risk conditions (0.8) since are a large component of overall mortality rates, but correlations are in the range 0.29–0.35 with other mortality indicators. Mortality rates from high-risk conditions have correlations in the range 0.25–0.49 with mortality rates other than overall mortality. Mortality rates from low-risk conditions have a low correlation with any other measure (in the range 0.14–0.35). The correlation between death after surgery and any other measure is in the range 0.02–0.29. Deaths resulting from hip fracture have a correlation of 0.37 with mortality rates of high risk conditions (again due to some extent to the first being included in the second), of 0.33 with overall mortality and between 0.16 and 0.2 with any other mortality indicator. In-hospital stroke mortality rates have a correlation of 0.49 with mortality rates of high risk conditions (again due to some extent to the first being included in the second), of 0.32 with overall mortality rates and between 0.02 and 0.16 with the other mortality indicators.

5.1.2. Correlation amongst readmission rates, revision rates and redo rates

Table 2A also shows that hip readmissions have a correlation of 0.32 with knee readmissions and of only 0.07 with stroke readmissions. There is very low correlation with the other measures (in the range −0.05 to 0.02). Note that, perhaps surprisingly, there is no correlation between hip readmissions and hip revisions (0.01), and between hip readmissions and the proportion of operations within 2 days following a hip fracture (0.02). Knee readmissions have a correlation of 0.32 with hip readmissions and only 0.09 with stroke readmission. There is very low correlation with other measures (in the range −0.06 to 0.11). As for hip replacements and revisions, there is no correlation between knee readmissions and knee revisions (−0.06). Stroke readmissions have a low correlation with all other measures (0.01 to 0.09). Hip and knee revisions have a correlation of 0.38 but there is low correlation with any other measure (in the range −0.06 to 0.11). Redo rates for prostate resection have low correlation with any other measure (in the range −0.06 to 0.11). The proportion of hip fracture patients with an operation within two days has a low correlation with all other measure (in the range −0.02 to 0.11). Note that this last indicator is a positive quality measure whilst the others are negative.

5.1.3. Correlation between readmission and mortality rates

The correlation between readmission and mortality rates is generally low and varies between −0.18 (knee revisions and mortality from low risk conditions) and 0.16 (death from hip fracture and stroke readmissions). Note that there is no correlation between stroke readmission rates and stroke in-hospital mortality rates (0.04).

5.1.4. Correlation between patients' experience and other quality indicators

Table 2B reports on the correlations of patient experience with other indicators. The three indicators of patients' experience have correlations between 0.46 and 0.76. Since patient experience measures quality positively and mortality or the readmissions measure it negatively, one would expect a negative correlation between patient experience and the other quality measures. The correlation ranges between 0.02 and −0.24.[13]

[13] The correlations between the three patients' experience variables tend to be higher compared to those between indicators based on mortality or readmission rates. An alternative approach would be to construct an aggregate patient experience indicator, perhaps by principal component analysis. However, this approach would make the interpretation of the coefficients in the regression analysis more difficult. To keep the presentation more transparent we prefer to investigate each indicator separately.

Table 2B
Correlations amongst satisfaction, mortality, and readmissions.

	Mortality from high risk conditions	Deaths from hip fracture	Hip replacement readmissions	Stroke readmission	Clean Hospital room/ward	Involved in decisions
Deaths resulting from hip fracture	**0.37**	1				
Hip replacement readmissions	0.04	−0.04	1			
Stroke readmission	−0.03	0.17	0.07	1		
Clean Hospital room/ward	0.02	0.03	−0.1	−0.17	1	
Involved in decisions	−0.14	−0.04	−0.18	**−0.24**	**0.5**	1
Trust in doctors	−0.15	−0.06	−0.04	**−0.22**	**0.46**	**0.76**

Note: absolute correlation of 0.21 required for significance at 1%. N = 146.

5.2. Regression results

We use Moran I's statistic to test departures from spatial randomness. Table 3 reports significant positive spatial correlation for nine of the 16 quality measures (overall mortality, mortality from high risk conditions, deaths after surgery, in-hospital stroke mortality, knee replacement readmissions, stroke readmission within 28 days, clean hospital room/ward, involved in decisions, and trust in doctors). In no case there is significant negative spatial correlation.

Table 4 reports the results from spatial regression models for mortality rates. The first column suggests that teaching hospitals have 8.4% lower overall mortality rates and an increase in rivals' quality by 10% increases quality by 2.8%. For mortality from high risk conditions teaching hospitals also have higher quality and hospital activity increases the mortality rates. However, rivals' quality is not statistically significant. The third and fourth columns are for the mortality from low-risk conditions, and deaths after surgery. None of the covariates or the quality of other hospitals significantly affects these two measures of mortality. The fifth column suggests that hospitals with a Foundation Trust status have 9.3% lower mortality rates following hip fracture. Finally, for stroke mortality, an increase in rivals' quality by 10% increases quality by 1.8%.

Table 5 has the results for hip and knee readmissions. Hip replacement readmissions are lower for providers in areas with higher costs (proxied by the MFF) and with higher population densities. Knee readmission rates are 23% lower in teaching hospitals and an increase in rivals' quality by 10% increases quality by 2.3%. Similarly, stroke readmission rates are smaller in teaching hospitals and are smaller if rivals have smaller stroke readmission rates. Teaching hospitals also have lower hip revision rates (by 34%). None of the covariates or the quality of rivals are significant in columns 5 and 6 (knee revisions and operation within two days for hip fracture patients). In column 7 higher costs, volume and population density are associated with higher redo rates for prostate resection.

Table 3
Moran's I statistics for quality measures.

Quality measures:	Moran's I	p-value
Overall mortality rate	0.340	0.000
Mortality from high risk conditions	0.294	0.001
Mortality from low risk conditions	−0.029	0.429
Deaths after surgery	0.160	0.034
Deaths resulting from hip fracture	0.018	0.378
In-hospital stroke mortality	0.180	0.020
Hip replacement readmissions	0.013	0.403
Knee replacement readmissions	0.205	0.011
Stroke readmission within 28 days	0.204	0.012
Hip revisions and manipulations within 1 year	−0.004	0.546
Knee revisions and manipulations within 1 year	−0.011	0.548
Hip fracture — Operation given within 2 days	0.001	0.449
Redo rates for prostate resection	0.125	0.077
Clean hospital room/ward	0.365	0.000
Involved in decisions	0.311	0.000
Trust in doctors	0.321	0.000

Note: The expected value for Moran's I statistic if there is no spatial correlation is $E(I) = -1/(N-1) = -0.010$. The reported p-value is based on an empirical distribution using 10,000 permutations.

In Table 6 column 1 suggests that patients in Foundation Trust hospitals are more satisfied about cleanliness and that an increase in rivals' quality by 10% increases the quality by 1.8%. In column 2 patients in teaching hospitals and Foundation Trusts have higher satisfaction with their involvement in decisions and an increase in rivals' quality by 10% increases the quality by 2.5%. Finally, in column 3 patients have greater trust in doctors in teaching hospitals and an increase in rivals' quality by 10% increases quality by 2.9%.

On the whole, the results suggest that teaching hospitals perform better: quality is significantly better for seven of the 16 quality measures and no worse for the others. This is in line with expectation since teaching hospitals tend to attract better qualified doctors. Although teaching hospitals treat more severely ill patients, this is taken into account by the casemix standardisation of the quality measures. Foundation hospitals have lower hip mortality rates and better patients' satisfaction in two of the three dimensions. Hospitals who apply for Foundation status have to satisfy a number of financial and clinical requirements and this may explain their higher quality. For two quality indicators (mortality from high-risk conditions and prostate redo rates), larger hospitals as proxied by larger total inpatient spells have worse quality. Large hospitals may suffer from congestion effects struggling to cope with large volumes of patients. Higher personnel costs, as proxied by staff MFF, is associated with lower quality for three measures (two readmission rates and one patient satisfaction). Although hospitals are compensated for higher costs, the compensation is partial and therefore hospitals with higher MFF will have stronger incentives to cut costs, which in turn may make more difficult to maintain high quality standards. Hospitals in London have generally similar quality to other hospitals (except that London hospitals have higher hip-replacement readmissions).

Our focus is on whether a hospital's quality is correlated with the quality of its rivals. We find a positive correlation (a positive spatial lag coefficient) for seven of the quality measures (overall and stroke mortality, knee and stroke readmission, and for the three patient satisfaction measures). The positive coefficient indicates that qualities are strategic complements. The overall mortality rates are also used as a key performance indicator by regulators. Hospitals may compare themselves against nearby hospitals on this measure.

The positive spatial lag for all three patient satisfaction measures may be because patient satisfaction has a greater effect on demand than other measures. Unlike the other quality measures the three measures of patients' subjective experience are not casemix adjusted to allow for patient characteristics. These characteristics may vary across areas and also affect patients' reporting behaviour. We do however include control variables which are likely to be correlated with patient characteristics. For example, the MFF variable is based on input prices and is thus related to the income and education levels of the population. Population density will also capture differences between patients in rural and urban areas, and the London indicator also captures population density, education and income to a certain extent.[14]

[14] When we allow for further socioeconomic variables (within hospitals catchment areas) the impact of the rivals quality is almost unchanged (results reported in Table A1).

Table 4
Spatial models of hospital competition and risk adjusted mortality rates.

	Overall mortality rate	Mortality from high risk conditions	Mortality from low risk conditions	Deaths after surgery	Deaths from hip fracture	In-hospital stroke mortality
Number rivals within 30 min	0.962	0.870	−0.860	−0.851	−0.388	0.633
	(1.542)	(1.201)	(−0.379)	(−0.440)	(−0.202)	(0.616)
Teaching hospital	−8.430***	−5.782**	4.248	−1.728	−8.102	−2.736
	(−3.471)	(−2.047)	(0.477)	(−0.227)	(−1.081)	(−0.679)
Foundation Trust	−2.174	−0.970	1.957	−3.852	−9.307*	−0.161
	(−1.254)	(−0.481)	(0.310)	(−0.711)	(−1.731)	(−0.057)
Total inpatient spells (1000)	0.0189	0.0463*	−0.0139	0.0144	−0.0179	0.00880
	(0.878)	(1.851)	(−0.178)	(0.214)	(−0.271)	(0.246)
Staff MFF	−22.85	−26.12	9.959	−15.92	−44.87	−5.235
	(−1.596)	(−1.562)	(0.194)	(−0.363)	(−1.031)	(−0.227)
Population density within 15 km	−0.00242	−0.00214	0.000447	0.00186	0.00136	0.00139
	(−1.582)	(−1.207)	(0.080)	(0.391)	(0.289)	(0.553)
London Trust	4.013	3.688	−2.535	−21.01	−2.334	−6.480
	(0.739)	(0.585)	(−0.128)	(−1.236)	(−0.139)	(−0.721)
Constant	96.59***	107.0***	86.39	115.2**	150.5***	83.91***
	(5.115)	(4.960)	(1.581)	(2.421)	(3.178)	(3.222)
ρ (Spatial quality lag)	0.276***	0.164	−0.0438	0.0511	0.0276	0.179*
	(2.895)	(1.635)	(−0.386)	(0.463)	(0.244)	(1.645)
Sigma^2	57.09***	77.01***	757.1***	550.7***	542.8***	154.4***
	(6.956)	(7.007)	(7.033)	(7.033)	(7.035)	(6.996)
Observations	99	99	99	99	99	99
BIC	730.267	757.972	983.297	951.798	950.305	827.043

t-statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A conventional measure of competition (the number of rivals within 30 min car drive) is not significant in any of the models. As we noted in Section 3, the conditions required for qualities to be strategic complements (i.e. having a positively sloped reaction function) are different from those required for competition to affect quality. We also estimated the models in Tables 4–6 omitting the number of rivals and obtained similar results on the effect of the rivals' quality (available on request).

5.3. Sensitivity analysis

We replicated the analyses with the catchment area set to 60 min and to 98 min travel time. Larger catchment areas imply that the number of competitors is also larger and reduces the number of hospitals with no rivals. With a catchment area of 60 min 142 hospitals have at least one competitor in the catchment area. With a catchment area defined by 98 min travel time all hospitals in England have at least one rival in the catchment area.

Tables 7 and 8 report spatial lags from models with samples based on the 60 and 98 min drive time catchment areas and with the same specifications as those reported in Tables 4 to 6. The results from Tables 7 and 8 are generally weaker compared to those with a smaller catchment area. The spatial quality lag is significant for overall mortality, knee replacement readmissions and patients' involvement with a 60 min drive time catchment area. With a 98 min drive time catchment area the spatial lag is significant only for the overall mortality and trust in doctors.

Table 5
Spatial models of hospital competition and risk-adjusted readmission, revision and redo rates.

	Hip replacement readmissions	Knee replacement readmissions	Stroke readmission within 28 days	Hip revisions and manipulations within 1 year	Knee revisions and manipulations within 1 year	Hip fracture — Operation given within 2 days	Redo rates for prostate resection
Number rivals within 30 min	2.295	2.939	−0.383	0.0347	−0.0904	0.0826	−0.181
	(1.215)	(1.048)	(−0.264)	(0.692)	(−1.548)	(0.090)	(−1.256)
Teaching hospital	4.088	−23.41**	−10.00*	−0.336*	−0.137	0.220	0.267
	(0.555)	(−2.133)	(−1.783)	(−1.706)	(−0.601)	(0.061)	(0.477)
Foundation Trust	−4.279	0.451	−2.431	0.0279	0.139	3.025	0.309
	(−0.806)	(0.058)	(−0.604)	(0.201)	(0.856)	(1.186)	(0.773)
Total inpatient spells (1000)	0.0137	0.136	−0.0228	0.000649	−0.00125	−0.0292	0.00965*
	(0.211)	(1.396)	(−0.456)	(0.376)	(−0.619)	(−0.918)	(1.947)
Staff MFF	−120.7***	−30.52	19.25	0.822	0.838	26.11	10.08***
	(−2.786)	(−0.482)	(0.585)	(0.721)	(0.635)	(1.261)	(3.066)
Population density within 15 km	−0.00845*	−0.00256	0.00455	−0.0000263	0.000221	0.000251	0.000586*
	(−1.832)	(−0.372)	(1.286)	(−0.215)	(1.545)	(0.112)	(1.656)
London Trust	39.90**	12.02	−11.66	0.0316	0.159	−3.427	−1.827
	(2.430)	(0.488)	(−0.930)	(0.072)	(0.311)	(−0.429)	(−1.461)
Constant	237.7***	93.60	68.00**	0.163	−0.295	44.05**	−7.406**
	(4.857)	(1.391)	(1.998)	(0.139)	(−0.215)	(1.969)	(−2.202)
ρ (Spatial quality lag)	−0.0415	0.225**	0.167*	−0.00910	−0.194	−0.0357	−0.0143
	(−0.377)	(2.310)	(1.646)	(−0.080)	(−1.397)	(−0.331)	(−0.127)
Sigma2	521.5***	1157.7***	304.2***	0.368***	0.502***	123.6***	3.023***
	(7.034)	(6.983)	(7.006)	(7.036)	(6.967)	(7.034)	(7.035)
Observations	99	99	99	99	99	99	99
BIC	946.377	1027.201	893.993	227.872	260.092	803.867	436.426

t-statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6
Spatial models of hospital competition and patient experience.

	Clean hospital room/ward	Involved in decisions	Trust in the doctors
Number rivals within 30 min	0.0245	0.0849	0.202
	(0.122)	(0.374)	(1.383)
Teaching hospital	1.126	2.322***	1.988***
	(1.446)	(2.601)	(3.491)
Foundation Trust	1.181**	1.096*	0.399
	(2.110)	(1.735)	(0.983)
Total inpatient spells (1000)	0.00532	0.00139	−0.000366
	(0.771)	(0.177)	(−0.073)
Staff MFF	−3.750	−5.856	−6.670**
	(−0.794)	(−1.125)	(−1.962)
Population density within 15 km	−0.000113	−0.000230	−0.000294
	(−0.230)	(−0.413)	(−0.817)
London Trust	−1.026	0.0368	0.237
	(−0.590)	(0.019)	(0.187)
Constant	73.50***	57.66***	69.02***
	(6.679)	(6.092)	(6.843)
ρ (Spatial quality lag)	0.179*	0.245**	0.285***
	(1.814)	(2.499)	(2.924)
Sigma2	5.854***	7.567***	3.122***
	(7.003)	(6.972)	(6.946)
Observations	99	99	99
BIC	503.052	529.558	442.783

t-statistics in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We suspect that a catchment area of 60 or 98 minutes is too large. Since England is densely populated and competition amongst hospitals is mainly local, a travel time of more than an hour may include hospitals which do not compete. The average number of providers within a catchment area of 60 min is about eight which is more than double the number with a 30 min catchment area. If hospitals which are more than 30 min drive time apart are not competing, using a spatial quality lag calculated including such hospitals will tend to reduce the estimated effect of the spatial lag. This dilution will be exacerbated because with row standardised inverse distance weights, including more rivals will reduce the weight on the quality of nearby genuine rivals. In short, increasing the catchment area beyond 30 min drive time may produce a less relevant spatial measure of the quality of rivals.

We also estimated models with our preferred catchment area of 30 min drive time but, instead of dropping monopoly hospitals with no rivals within 30 min, we included them with a spatial lag of zero and added a monopoly dummy to the regression.[15] The results are in Table 9. These models with 147 hospitals have significant positive spatial lags for overall mortality rates, deaths after surgery, patients' involvement, and trust in doctors. The results are thus broadly consistent with those in Tables 4–6 though less precise, presumably because the spatial lag variable has less variation with 48 observations having a value of zero.

We have also run our preferred specification with a catchment area of 30 min drive time but included beds as an additional weight when computing the distance matrix. Intuitively, we would expect that, other things equal, having rivals with more capacity would increase the effect of a change in their quality on a hospital's demand and hence on its quality. The results are reported in Table 10 and are very similar to those in Tables 4–6, suggesting that allowing for rivals' capacity makes little difference.

We also estimated models without the number of rivals and with the number of rivals weighted by distance. Results are similar to those in Tables 4–6.[16]

Since our results are from cross-sectional observational data, there is always a risk of omitted variable bias, which in this context is also known as the reflection problem (Manski, 1993). Spatial dependence in quality may arise because there is interdependence of decisions or because there are unmeasured factors, affecting quality choices, that are common to a region or a catchment area. Our analysis controls for a number of hospital characteristics and most quality measures are risk-adjusted (except for patient-reported ones). But there may remain some unmeasured factors. For example, more skilled doctors (who produce better patient outcomes) are more likely to have more choice of hospital to work in and to choose to live in areas with better amenities and higher quality of life. Or individuals living in certain areas may be characterised by poor dietary habits and lifestyle (not captured by risk adjustment) leading to worse health outcomes.

As an additional robustness check, to reduce the risk of omitted variable bias, we added more controls. Table A1 in Appendix A reports estimates of the spatial quality lag when we include as additional controls seven indices of socio-economic deprivation (for Income, Employment, Health and Disability, Education Skills and Training, Barriers to Housing and Other Services, Crime, and Living Environment).[17] In Table A1 each deprivation index is separately added to the baseline model. The results show that the coefficient of the spatial quality lag is highly robust to the inclusion of these additional covariates. However, we cannot rule out the possibility that the spatial lag is due to informational spillovers: if hospital A is physically close to hospital B, then it may be more likely that hospital A will know about a technology used by hospital B and adopt the new technique used at hospital B.

Our theoretical model suggests that the spatial lag would be greater, other things equal, when demand is more responsive to quality. Hence we might expect that the spatial lag would be greater for quality of elective conditions (such a hip replacements) than for quality of emergency conditions (such as hip fractures) where patients exercise less choice and are more likely to be treated in the nearest hospital.[18]

Six of our quality measures are not specifically measures of elective or emergency care (overall mortality, deaths after surgery, mortality from high risk conditions, and the three patient experience measures). For the ten condition-specific measures, three have positive and statistically significant spatial lags. The largest of these is for knee replacement readmissions – an elective quality measure – and the other two are for stroke which is an emergency condition. Of the remaining seven spatial lags which are not significantly different from zero, two are for emergency conditions and five for elective conditions. These mixed results suggest that comparison of the magnitude of the spatial lags from elective and emergency conditions is not a robust method of

[15] The inclusion of 48 monopoly hospitals in the sample of 147 hospitals potentially affects estimates of both the effect of the spatial lag and of the effect of the number of rivals. For monopolists (who have no rival within 30 km) the spatial lag is set to zero. Only four of the 16 quality measures have an observed minimum of zero across hospitals and so the spatial lag, being a weighted average of the quality of a subsample of hospitals, is also always greater than zero for all observations for these 12 quality measures. Moreover for these 12 quality measures, zero is at least 3 standard deviations (and usually more) away from than the mean. For the other four quality measures the coefficients of variation are 0.7, 1.7, 2.0, and 2.8. Thus setting the value of the spatial lag for monopolists to zero leads to a high proportion of observations (48 out of 147) having a spatial lag which is a considerable distance in SD units from the other observations. If the original regression line between own quality and the spatial lag estimated for the sample of 99 non-monopolists has a positive slope, adding the monopolists to the sample will reduce the slope of the regression line between own quality and the spatial lag of quality unless the average quality of the monopolists lies below the intercept of the regression line estimated on the sample excluding the monopolists. Given the large difference between the zero spatial lag of the monopolists and the average spatial lag of non-monopolists this seems unlikely. We also estimated the models for the full sample of 147 hospitals with the spatial lag measured for rivals within 30 km without a monopoly dummy, for the two quality regressions with the most significant spatial lags (overall mortality, trust in doctors). In both cases (results available on request) the spatial lag becomes very small and insignificant and the coefficient on the number of rivals is also smaller and has smaller lower t statistic.

[16] See Tables 7–9 of Gravelle et al. (2013).

[17] These variables are measured at small area level from census data, known as Lower Super Output Areas – LSOAs – (each area covering on average a population of 1500 individuals) and then attached to the hospital if the centroid of the LSOA falls within the catchment area of the hospital. The data on socio-economic deprivation was obtain from the Neighbourhood Statistics (http://www.neighbourhood.statistics.gov.uk/).

[18] Since the spatial lags are weighted averages of quality and the dependent variable is quality, the coefficient on the spatial lag (rho) is dimensionless and can be compared across different quality measures.

Table 7
Spatial quality lag from models with 60 min car-drive time catchment area.

Mortality rates	Spatial lag (t)	Readmission/revisions/redo rates	Spatial lag (t)	Patient experience	Spatial lag (t)
Overall mortality rate	0.324** (2.419)	Hip replacement readmissions	−0.108 (−0.656)	Clean hospital room/ward	0.0881 (0.595)
Mortality from high risk conditions	0.0736 (0.458)	Knee replacement readmissions	0.248* (1.755)	Involved in decisions	0.281** (2.307)
Mortality from low risk conditions	0.0210 (0.142)	Stroke readmission within 28 days	0.157 (1.105)	Trust in doctors	0.206 (1.611)
Deaths after surgery	0.163 (1.123)	Hip revisions and manipulations within 1 year	0.119 (0.734)		
Deaths resulting from hip fracture	0.0911 (0.584)	Knee revisions and manipulations within 1 year	−0.265 (−1.232)		
In-hospital stroke mortality	0.0372 (0.244)	Hip fracture — operation given within 2 days	0.0699 (0.498)		
		Redo rates for prostate resection	−0.125 (−0.848)		

Models include the same covariates as those in Tables 4 to 6. Observations: 142. t-statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8
Spatial quality lag from models with 98 min car-drive time catchment area.

Mortality rates	Spatial lag (t)	Readmission/revisions/redo rates	Spatial lag (t)	Patient experience	Spatial lag (t)
Overall mortality rate	0.396** (2.100)	Hip replacement readmissions	0.178 (0.776)	Clean hospital room/ward	0.119 (0.499)
Mortality from high risk conditions	0.243 (1.120)	Knee replacement readmissions	0.195 (0.885)	Involved in decisions	0.275 (1.408)
Mortality from low risk conditions	−0.0157 (−0.063)	Stroke readmission within 28 days	0.278 (1.347)	Trust in doctors	0.328* (1.732)
Deaths after surgery	0.304 (1.521)	Hip revisions and manipulations within 1 year	0.308 (1.367)		
Deaths resulting from hip fracture	−0.0594 (−0.215)	Knee revisions and manipulations within 1 year	−0.409 (−1.208)		
In-hospital stroke mortality	0.219 (0.899)	Hip fracture — operation given within 2 days	0.0956 (0.491)		
		Redo rates for prostate resection	−0.195 (−0.731)		

Models include same covariates as those in Tables 4 to 6. Observations: 147. t-statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

testing the underlying theory. Moreover, some of the empirical literature on hospital competition discussed in Section 1 reports that competition affects quality as measured by mortality for AMI, an emergency condition, suggesting that there could be spatial lags amongst quality for emergency conditions.

5.4. Falsification test

We also undertook falsification tests. If demand for a hospital speciality depends on the quality of that speciality, rather than on the quality of other specialities in the hospital, then there should be no spatial

Table 9
Spatial quality lag with monopolists (30 min car-drive time catchment area).

Mortality rates	Spatial lag (t)	Readmission/revisions/redo rates	Spatial lag (t)	Patient experience	Spatial lag (t)
Overall mortality rate	0.287*** (3.004)	Hip replacement readmissions	−0.00705 (−0.063)	Clean hospital room/ward	0.192** (2.059)
Mortality from high risk conditions	0.198** (1.986)	Knee replacement readmissions	0.230** (2.419)	Involved in decisions	0.232** (2.434)
Mortality from low risk conditions	−0.0417 (−0.378)	Stroke readmission within 28 days	0.140 (1.374)	Trust in doctors	0.269*** (2.756)
Deaths after surgery	0.0617 (0.563)	Hip revisions and manipulations within 1 year	−0.0296 (−0.267)		
Deaths resulting from hip fracture	0.0451 (0.414)	Knee revisions and manipulations within 1 year	−0.241* (−1.848)		
In-hospital stroke mortality	0.169 (1.487)	Hip fracture — Operation given within 2 days	−0.0513 (−0.475)		
		Redo rates for prostate resection	−0.0125 (−0.106)		

Models include the same covariates as those in Tables 4 to 6 plus indicator for hospitals with no rivals within 30 min drive time. Observations: 147. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10
Spatial quality lag ρ with bed weights (30 min car drive time catchment area).

Mortality rates	Spatial lag (t)	Readmission/revisions/redo rates	Spatial lag (t)	Patient experience	Spatial lag (t)
Overall mortality rate	0.280*** (3.025)	Hip replacement readmissions	−0.0549 (−0.503)	Clean hospital room/ward	0.190* (1.935)
Mortality from high risk conditions	0.183* (1.856)	Knee replacement readmissions	0.217** (2.208)	Involved in decisions	0.254*** (2.649)
Mortality from low risk conditions	−0.0269 (−0.237)	Stroke readmission within 28 days	0.144 (1.407)	Trust in doctors	0.295*** (3.083)
Deaths after surgery	0.0408 (0.366)	Hip revisions and manipulations within 1 year	−0.0171 (−0.149)		
Deaths resulting from hip fracture	0.0374 (0.335)	Knee revisions and manipulations within 1 year	−0.193 (−1.376)		
In-hospital stroke mortality	0.179 (1.624)	Hip fracture — Operation given within 2 days	0.00836 (0.080)		
		Redo rates for prostate resection	−0.0329 (−0.283)		

Models include the same covariates as those in Tables 4 to 6. Observations: 99. t—statistics in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

correlation between the quality of, say, the orthopaedics department in a hospital and the quality of cardiology departments in rival hospitals. However, if there are unobserved region-specific factors, such as population morbidity, affecting all types of quality, then we would observe significant coefficients on the spatial lag of cardiology quality in a model of orthopaedic quality.

Table 11 reports the estimates of the spatial lag from models in which the dependent variables shown in the top row of the table are regressed on the usual covariates and spatial lags of a different type of quality as indicated in the first column. Since we detect a significant own spatial lag for overall mortality rates, we regress overall mortality on spatial lags of quality variables that also have a significant own spatial lag, i.e. two of the patients' satisfaction variables (patient self-reported involvement and trust in doctors), and two of the readmission variables (knee and stroke). We do not run regression of overall mortality against other mortality variables, since by construction they are included in overall mortality. The results are reported in the first column of Table 11. We also examine the relationship between mortality rates of different clinical conditions, for example regressing deaths resulting from hip fracture against the spatial lag of in-hospital stroke mortality (last column in Table 11). Similarly we examine the relationship between readmissions for different clinical conditions, for example regressing hip or knee readmissions on the spatial lag of stroke readmissions. We also test whether hip and knee readmissions and mortality from low risk conditions respond to the spatial lag of patient satisfaction measures (second, third and fourth column of Table 11).

With one exception, the spatial lag is never significant in these models. The exception is for the regression of hip replacement readmissions against the spatial lag of knee replacement readmissions, though this is only statistically significant at 10% level. Since this can be plausibly explained by both procedures being performed within the same speciality, we suggest that the falsification tests do not reject a causal interpretation of the spatial lag in Tables 4–6.

6. Conclusions

We have investigated the effect of the quality of rivals on a hospital's quality using a spatial-econometrics framework. Our theoretical model implies that the quality of a provider responds to the quality of its rivals when the marginal cost of treatment is increasing and/or the responsiveness of demand to quality increases in rivals' quality. Our empirical analysis using recent English data suggests that this is the case for seven of the 16 quality indicators, where quality is significantly a strategic complement. We do not find any cases where rivals' qualities are negatively correlated with provider quality.

Table 11
Falsification tests: spatial quality lag.

Spatial lag variable	Dependent variable: Overall mortality rate	Hip replacement readmissions	Knee replacement readmissions	Mortality from low risk conditions	Deaths resulting from hip fracture
Hip replacement readmissions	0.000222 (0.004)		0.388 (1.656)		
Knee replacement readmissions	−0.0421 (−1.373)	0.149* (1.699)			
Stroke readmission within 28 days	0.0606 (0.963)	0.0126 (0.069)	0.126 (0.449)		
Involved in decisions	0.0207 (0.053)	−1.592 (−1.444)	−0.556 (−0.324)	−0.883 (−0.659)	
Trust in doctors	−0.152 (−0.249)	−1.554 (−0.888) −1.554	−3.091 (−1.149)	−3.448 (−1.652)	
In-hospital stroke mortality					0.135 (0.453)

Models include the same covariates as those in Tables 4 to 6. 99 observations. The cells contain the coefficient on the spatial lag (and t statistic) from models in which the dependent variable is indicated in the column heading and the quality variable used for the spatial lag is indicated in the horizontal row.

Patient's satisfaction measures on cleanliness, doctors' trust and patient's involvement show the most consistent positive association with rivals' quality. Two of six mortality rates (overall mortality and in-hospital stroke mortality) and two readmission measures (knee and stroke) respond to rivals' quality. When an effect is detected our preferred models, with hospital markets defined by catchment areas of 30 min drive time, suggest that an increase in rivals' quality by 10% increases a hospital's quality by 1.7%–2.9%. The results are generally robust to the use of larger catchment areas (60 min or 98 min drive time). Our results are broadly in line with the model of hospital prices in Mobley et al. (2009) where the estimated spatial lags implied that a 10% reduction in the rivals' price reduces prices by a hospital's price by 2.3%–2.8%.

The results suggest that providers may respond more to variations in rivals' quality for those quality dimensions that are more easily observable to patients (like cleanliness and patient's involvement) and less to clinical ones. Our theoretical framework suggests that this result may be rationalised by the plausible assumption that demand is more responsive to patient experience quality measures than to clinical ones, so that providers have a stronger incentive to respond when patients of rivals have a better experience in their hospitals. This effect may be reinforced in the presence of social networks where patients share information on hospital experience with individuals living in the same neighbourhood (Moscone et al., 2012) or if the marginal cost of improving patient experiences is lower than the marginal cost of clinical quality. Our results are also relevant for the assessment of policies, other than those affecting competition amongst hospitals, which aim at improving quality, for example via guidelines, since they suggest that there will be beneficial spillovers as quality improvement in one provider will lead to quality improvements by its rivals.

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Appendix A. Quality measures

The quality measures (accessed 14 May 2012) are from:

http://www.drfosterhealth.co.uk/quality-reports

http://www.drfosterhealth.co.uk/patient-experience

Mortality rates

Mortality data provided by Dr Foster are risk adjusted. A logistic regression is used to estimate the expected in-hospital mortality. Each measure is adjusted for differences in casemix: sex, age on admission, admission method, socio-economic deprivation, primary diagnosis, comorbidities, number of previous emergency admissions, financial year of discharge, palliative care, month of admission, ethnicity and source of admission.

The overall standardised mortality rates cover all in-hospital deaths, i.e. all spells whose method of discharge was death. Stroke and hip fracture mortality rates are for spells whose primary diagnostic code was acute cerebrovascular disease (ICD10: G46, I60-I64, I66) or fracture neck of femur (ICD10: S720-S722). Standardised deaths after surgery refer to surgical patients who had a secondary diagnosis such as internal bleeding, pneumonia or a blood clot and subsequently died.

High risk conditions include mortality from spells whose primary diagnosis is one of five groups: Acute myocardial infarction (ICD10: I21, I22), Acute cerebrovascular disease (ICD10: G46, I60-I64, I66), Pneumonia (ICD10: A202, A212, A310, A420, A430, A481, A78, B012, B052, B250, B583, B59, B671, J12-J16, J170-J173, J178, J18, J850, J851), Congestive heart failure–nonhypertensive (ICD10: I50) and Fracture of neck of femur–hip (ICD10: S720-S722). Low risk conditions include all in-hospital mortalities from all conditions with a death rate lower than 0.5%. This includes more than 100 diagnosis groups.

Readmission rates are for hospital readmissions within 28 days from discharge for patients admitted for stroke, knee and hip replacement. Stroke, knee and hip replacement standardised readmission ratios are the ratio of observed number of spells with emergency readmissions within 28 days of discharge with a knee replacement procedure (procedure/OPCS code O18, W40-W42, W5[234][1389](+Z844-6), W580-2(+Z846)), a hip replacement procedure (W37-W39, W93-W95) or an acute cerebrovascular disease diagnostic (ICD10: G46, I60-I64, I66), to the expected number of readmissions for each procedure. The expected number is estimated using a logistic regression that adjusts for the same factors as in the standardisation for in-hospital mortality. The readmission rate attributed to a given hospital is for all patients who were treated in that hospital and readmitted within 28 days in that same hospital or any other hospital.

Revisions

The knee or hip revisions and manipulations within 1 year are the proportion of joint replacements with a revision procedure within 365 days of the initial (index) procedure, over the total number of joint replacements carried out at the trust over a three year period.

Redo rates

Redo rates for prostate resection are the rates of endoscopy resection of outlet of male bladder procedure (OPCS code: M65) spells where a second operation was performed within three years. The denominator includes all transurethral resection of the prostate procedures discharged between April 2004 and March 2007.

Hip fracture operations within two days is the percentage of patients with a fracture neck of femur primary diagnoses (ICD10: S720-S722) that received a related procedure (W code) within two days.

Patients' experience

Patients' experience measures are derived from the 2009 NHS Inpatient Survey for the Care Quality Commission which is administered to a random sample of patients in all acute trusts. The variables relate to three questions to patients: 1) “In your opinion how clean was the hospital room or ward?” (Clean hospital room/ward). The patient could give one of five possible answers: very clean, fairly clean, not very clean, not at all clean. Dr Foster measures the proportion of patients who found the hospital or room very clean or clean. 2) “Were you involved as much as you wanted to be in decisions about your care and treatment?” (Involved in decisions). The patient could answer: yes, definitely; yes, to some extent; no. Dr Foster measures the proportion of patients who answered yes. 3) “Did you have confidence and Trust in doctors treating you?” (Trust in doctors). The patient could answer: yes, always; yes, sometimes; and no. Dr Foster measures the percentage of patients who answered yes.

Table A1
Spatial lags from model with additional controls for socio-economic factors.

Dependent variable	Baseline	Additional deprivation measure included							
		Overall depriv.	Income depriv.	Empl. depriv.	Health depriv.	Educat. depriv.	Barriers depriv	Crime depriv	Living depriv.
Mortality rates									
Overall mortality rate	0.276***	0.274***	0.266***	0.276***	0.277***	0.239**	0.263***	0.271***	0.274***
	(2.895)	(2.885)	(2.794)	(2.907)	(2.911)	(2.461)	(2.733)	(2.850)	(2.862)
Mortality from high risk conditions	0.164	0.148	0.138	0.159	0.160	0.121	0.148	0.155	0.165
	(1.635)	(1.473)	(1.370)	(1.578)	(1.595)	(1.178)	(1.467)	(1.529)	(1.642)
Mortality from low risk conditions	−0.0438	−0.0388	−0.0409	−0.0406	−0.0377	−0.0441	−0.0656	−0.0444	−0.0618
	(−0.386)	(−0.342)	(−0.362)	(−0.357)	(−0.331)	(−0.389)	(−0.579)	(−0.391)	(−0.538)
Deaths after surgery	0.0511	0.0372	0.0405	0.0540	0.0602	−0.0897	0.0426	0.0239	0.0517
	(0.463)	(0.340)	(0.369)	(0.492)	(0.550)	(−0.806)	(0.383)	(0.215)	(0.468)
Deaths resulting from hip fracture	0.0276	−0.0133	−0.0305	−0.0137	−0.0262	−0.00561	0.0373	0.00600	0.00756
	(0.244)	(−0.114)	(−0.263)	(−0.118)	(−0.229)	(−0.048)	(0.331)	(0.053)	(0.067)
In-hospital stroke mortality	0.179*	0.165	0.141	0.176	0.178	0.169	0.0911	0.179	0.179
	(1.645)	(1.507)	(1.268)	(1.616)	(1.637)	(1.536)	(0.785)	(1.642)	(1.643)
Readmission/revisions/redo rates									
Hip replacement readmissions	−0.0415	−0.0585	−0.0599	−0.0465	−0.0461	−0.0516	−0.0517	−0.0477	−0.0410
	(−0.377)	(−0.529)	(−0.543)	(−0.422)	(−0.416)	(−0.469)	(−0.466)	(−0.434)	(−0.372)
Knee replacement readmissions	0.225**	0.212**	0.220**	0.204**	0.210**	0.213**	0.215**	0.223**	0.229**
	(2.310)	(2.123)	(2.225)	(2.033)	(2.088)	(2.174)	(2.212)	(2.290)	(2.353)
Stroke readmission within 28 days	0.167*	0.133	0.135	0.142	0.120	0.137	0.166	0.152	0.164
	(1.646)	(1.284)	(1.301)	(1.376)	(1.142)	(1.325)	(1.643)	(1.509)	(1.620)
Hip revisions and manipulations within 1 year	−0.00910	0.368***	0.367***	0.365***	0.365***	0.360***	0.353***	0.367***	0.356***
	(−0.080)	(7.035)	(7.036)	(7.035)	(7.035)	(7.034)	(7.036)	(7.036)	(7.034)
Knee revisions and manipulations within 1 year	−0.194	−0.194	−0.196	−0.194	−0.195	−0.194	−0.229*	−0.201	−0.204
	(−1.397)	(−1.397)	(−1.411)	(−1.395)	(−1.403)	(−1.396)	(−1.649)	(−1.447)	(−1.462)
Hip fracture — operation given within 2 days	−0.0357	−0.0560	−0.0366	−0.0400	−0.0497	−0.0352	−0.0296	−0.0467	−0.127
	(−0.331)	(−0.521)	(−0.340)	(−0.371)	(−0.461)	(−0.329)	(−0.274)	(−0.440)	(−1.146)
Redo rates for prostate resection	−0.0143	−0.00307	−0.00363	−0.0278	−0.0334	0.00840	−0.0355	0.00583	−0.0431
	(−0.127)	(−0.027)	(−0.032)	(−0.249)	(−0.300)	(0.074)	(−0.313)	(0.052)	(−0.375)
Patients' experience									
Clean hospital room/ward	0.179*	0.192*	0.186*	0.190*	0.182*	0.191*	0.155	0.173*	0.181*
	(1.814)	(1.953)	(1.888)	(1.956)	(1.853)	(1.936)	(1.553)	(1.745)	(1.833)
Involved in decisions	0.245**	0.234**	0.228**	0.245**	0.245**	0.215**	0.210**	0.237**	0.234**
	(2.499)	(2.375)	(2.303)	(2.499)	(2.498)	(2.141)	(2.089)	(2.419)	(2.360)
Trust in doctors	0.285***	0.281***	0.281***	0.286***	0.286***	0.278***	0.266***	0.274***	0.286***
	(2.924)	(2.875)	(2.871)	(2.933)	(2.942)	(2.814)	(2.639)	(2.811)	(2.937)

Cells contain coefficient (and t statistic) on spatial lag of dependent variable from model a measure of deprivation added to the covariates in the corresponding baseline model of Tables 4 to 6.

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