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Testing the Bed-Blocking Hypothesis: Does Higher Supply of Nursing and Care Homes Reduce Delayed Hospital Discharges?

CHE Research Paper 102

Testing the bed-blocking hypothesis: does higher supply of nursing and care homes reduce delayed hospital discharges?

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Abstract

Hospital bed blocking occurs when hospital patients are ready to be discharged to a nursing home but no place is available, so that hospital care acts as a more costly substitute for long-term care. We investigate the extent to which higher supply of nursing home beds or lower prices can reduce hospital bed blocking. We use new Local Authority level administrative data from England on hospital delayed discharges in 2010-13. The results suggest that delayed discharges do respond to the availability of care-home beds but the effect is modest: an increase in care-homes bed by 10% (250 additional beds per Local Authority) would reduce delayed discharges by about 4%-7%. We also find strong evidence of spillover effects across Local Authorities: higher availability of care-homes or fewer patients aged over 65 in nearby Local Authorities are associated with fewer delayed discharges.

Keywords: delayed discharges; long-term care; nursing and care homes; bed blocking; substitution.
JEL: I10, I18

Executive Summary

Bed-blocking occurs when hospital patients are ready to be discharged into long-term care but no place is available. Since hospital care is more costly than long term care, bed blocking leads to inefficiency.

Our study shows that the bed blocking is more common in Local Authorities where there is a smaller supply of long-term care beds and where prices for these beds are higher. We also find that there are spillover effects between Local Authorities: greater supply of beds in neighbouring Local Authorities will also reduce bed blocking in a Local Authority.

Acute care is largely provided in 164 NHS hospitals, free at the point of use for patients and ultimately paid for through general taxation. By contrast, long term care is provided in over 18,000 public or private care-homes and 60% of residents make at least some payment for this care, with means tested subsidies provided to poorer residents by their Local Authorities.

We investigate two research questions:

- does the supply (numbers and prices) of care-home beds in a Local Authority affect hospital discharge delays in the Local Authority?
- does the supply of care-homes in neighbouring Local Authorities affect delayed discharges ie are there spillovers between Local Authorities?

We use newly available data on delays for hospital patients in 147 Local Authorities in England between 2010 and 2012. The data distinguishes between delays due to the hospital, and delays due to social care, which is the responsibility of the Local Authority in the patient lives. We estimate panel data models which reduce the risk of omitted variable bias from unobserved factors (such as unmeasured morbidity) which are correlated with care home supply and with delayed discharges.

We find that:

- An increase in the number of care-home beds in a Local Authority by 250 (10%) reduces the number of hospital bed-days lost per month due to delayed discharges by 17 (6%)
- The number of delayed days is also reduced by an increase in care-home bed levels in neighbouring Local Authorities
- There are more delayed days in Local Authorities with higher prices for long term care
- An increase in the number of people aged 65+ by 1% increases the number of delays by 1.7%.

Policy implications:

- Although increases in the supply of long term care beds reduces delayed discharges, the effect is modest so that an increase in the supply will not significantly reduce overall costs across hospital and social care sectors
- Policies to reduce long term care prices may also reduce delayed discharges in addition to other effects.
- The spillover effects from one Local Authority to another of long term care beds supply and population size suggests the need for coordination of policies to reduce delayed discharge.

1. Introduction

As the population ages the number of individuals requiring long-term care is increasing (OECD, 2011). Several OECD countries report problems or growing concerns about waiting times for long-term care services (OECD, 2013, chapter 2). A key policy concern is what is known as hospital 'bed blocking': hospital patients who are ready to be discharged to a care home but are waiting in hospital for a care home bed. Since hospital care is generally more expensive than nursing or residential home care, bed blocking is a signal of allocative inefficiency.

This study investigates the extent to which higher supply of nursing and care home beds reduces delays in hospital discharges. Whether policymakers should encourage such increases in supply in order to reduce delayed discharges depends, inter alia, on the elasticity of the number of delayed discharges with respect to the availability of care-home beds. If the elasticity is high, then increases in care-home supply will have a significant positive externality on the hospital sector.

The rate at which hospital patients are discharged into a nursing home may depend not only on the supply of beds but also on their price and quality. Unlike health care, which is free or heavily subsidised in most of the OECD countries, there is very limited insurance for nursing home costs. Hence, higher prices may prolong search and make patients more reluctant to be transferred to a nursing home. Higher prices for nursing homes may therefore delay hospital discharges. If this is the case, then policy interventions that affect prices for nursing homes (such as encouraging competition (Forder and Allan (2014)) may also have effects in the hospital sector.

We also explore whether the supply of care-homes in a Local Authority affects delayed discharges in other Local Authorities. This is also important for policy. If spillover effects across Local Authorities are negligible, then policymakers will have to pay more attention to inequalities in care homes availability across Local Authorities since they will also imply variations in delayed discharges. But inequality in provision across Local Authorities may be of less concern if patients are willing to accept a bed in other Local Authorities. The presence of spillover effects may also raise coordination issues across Local Authorities by weakening incentives to expand care-homes capacity.

To answer our two research questions, we first provide a theoretical framework for understanding hospital delayed discharges. We then employ a new English panel data set on delayed discharges between 2010 and 2013 (Department of Health, 2011a). The data set provides two new measures of hospital delays for patients resident in a Local Authority: the number of delayed hospital *patients* at a monthly census point (averaged over the year) and the number of *days* waited in the previous month by all hospital patients medically ready for discharge, again averaged over the year. Moreover, the data distinguishes whether the cause of delayed discharge can be attributed to the hospital or to social care. We focus on delays due to social care.

We use two econometric approaches. First, to control for unobserved heterogeneity at Local Authority level, we use panel-data models which reduce the risk of omitted variable bias due to unobservables correlated with both hospital delays and availability of care homes. We exploit temporal and cross-section variation in the availability of care-homes and prices to identify their effect on hospital delayed discharges. Unobserved heterogeneity is likely to be important since Local Authorities differ in needs, geography, population size, policies, and controlling political party. To test for spillover effects across Local Authorities (our second research question), we use spatial-econometrics methods which allow for spatial dependence across geographical units (Anselin, 1988; Moscone and Tosetti, 2014).

We find that that delayed discharges do respond to the availability of care-home beds. The response is relatively modest: an increase in care-homes beds of 10% (250 additional beds per Local Authority) would reduce delayed discharges by 4%-7%. Although their estimated effects are less robustly estimated, higher prices also contribute to longer delayed discharges. We find that the number of elderly, over 65 years old, is a key driver of delays (with an elasticity of 1.0-1.5): having 6,000 (10%) additional elderly in an average Local Authority would increase delays by 10%-15%.

We also find spillover effects across Local Authorities with respect to both care home beds and elderly population. Higher availability of care-home beds in other Local Authorities reduces delayed discharges. Similarly, higher population in other Local Authorities increases delayed discharges. This suggests that patients are willing to cross Local Authority boundaries in order to secure a bed in a care-home.

Related literature

Although there is an extensive literature on substitution between informal care and formal long-term care (Van Houtven and Norton, 2004; Bolin, et al 2008; Bonsang, 2009; Gannon and Davin, 2010; Grabowski et al, 2012), there are relatively few studies on substitution between care homes (formal long-term care) and delayed hospital discharges (health care).[1]

Forder (2009) used small-area data on 8000 census areas in England and found that increasing spending on care homes by £1 reduces hospital expenditure by £0.35. Holmås et al. (2010) investigated the effect of fining owners of long-term care institutions who prolong length of stay at hospitals in Norway. Surprisingly, the study found that hospital length of stay is longer when the fines are used, which is interpreted as an example of monetary incentives crowding-out intrinsic motivation. Øien, Karlsson and Iversen (2012) investigated the effect of long-term financing system on the composition of long-term services at municipality level in Norway. Picone et al (2003) investigated the simultaneous determinants of hospital length of stay and discharge destination of US Medicare patients following hip fracture, stroke or heart attack. They showed that informal care (being married and number of children) and supply variables (available beds) affected the probability of being discharged home and to a nursing facility.

The study that is closest to ours is Fernandez and Forder (2008) who find that English Local Authorities with more home help hours, and nursing and residential care beds, had a lower rate of hospital delayed discharges and lower emergency readmission rates. Their study uses cross-section data and they use instrumental variables to attempt to resolve problems arising from endogeneity and omitted variables.

Our study makes several innovations. Our theoretical model integrates stochastic queuing theory with some simple economics to produce a model which can explain social market equilibria with positive waiting times for care home places. Our data set is more recent than in Fernandez and Forder (2008) and has more refined measures both for hospital delays and for supply of nursing and care homes. In addition to patients delayed at a point in time, we also investigate the total number of delayed hospital days experienced in a given month. We can also distinguish between total delays and delays due to social care. To measure supply of nursing and care homes, in addition to beds, we have direct measures of prices of nursing and care homes, and a measure of quality rating of nursing homes.

We exploit panel-data to control for endogeneity of care beds supply and prices and for unobserved heterogeneity at Local Authority level. We also employ a range of spatial-econometrics regressions

[1] See Norton (2000), Pestieau and Ponthière (2012) and Cremer, Pestiau and Ponthière (2012), Siciliani (2013) for comprehensive literature reviews.

to test for spillover effects across Local Authorities. Spatial-econometrics is increasingly used in health economics applications (see Moscone and Tosetti, 2014 for a more comprehensive review). For example, Moscone, Knapp and Tosetti (2007) use spatial panel methods to show that there is spatial interdependence in mental health expenditure across municipalities in England. Moscone and Tosetti (2010) investigated the effect of income on health care expenditure and found spatial correlation in health spending across the US states after controlling for unobserved effects. Using cross-sectional data from the US, Mobley (2003) find that hospital prices are strategic substitutes: a hospital with rivals who have higher prices will have a higher price. Gravelle, Santos and Siciliani (2013) investigate hospital qualities under fixed regulated prices in England and find that, for some quality measures, hospitals with rivals with higher quality also supply higher quality.

2. Institutional setting

Hospitals and nursing and care homes in England have different organisational arrangements and funding. Acute hospital care is predominantly provided by 164 public hospitals which are paid by a mix of prospective activity-based funding and block contracts with 151 local Primary Care Trusts which receive a tax funded budget from the Department of Health. National Health Service (NHS) patients do not pay for hospital care. By contrast, there are over 18,000 providers of social care (nursing and residential homes) (Laing and Buisson, 2010) which are a mix of for-profit, non-profit and public organisations. Most users (about 60%, Forder, 2007), pay for social care, with those on low incomes or with low wealth being subsidised by their Local Authority. Local Authorities also provide means tested personal social services, including home help services to those requiring care in their own home.

The coordination of health and long-term care for patients discharged from hospital is a long-standing concern (Baumann, et al 2007; Department of Health 2011b; House of Commons, 2003; National Audit Office, 2000) which culminated with the Community Care (Delayed Discharges) Act (2003) (Department of Health 2003). The Act requires Local Authorities and hospitals to collaborate around the discharge of patients from hospital. Local Authorities are required to reimburse hospitals for delayed discharges for which they are solely responsible.

3. A model of patients waiting for hospital discharge

We observe the number of patients waiting for hospital discharge at a census date. Assume that all patients with a delayed hospital discharge (ie medically ready for discharge but still in hospital) are waiting to find a place in a nursing home. We require a model which explains why patients are waiting rather than being immediately taken into a nursing home when medically ready for discharge. Models with deterministic demand and supply, as in Lindsay and Feigenbaum (1984) are not appropriate for markets in which providers can affect demand via their prices or quality choices. The spatial distribution of nursing homes and the fact that patients and relatives will face distance costs implies that nursing homes have some market power: their demand elasticity is not infinite with respect to price. In a deterministic model of waiting times it can never be profit maximising for a nursing home to have a waiting list. Since demand depends on price and waiting time, an increase in price with the number of nursing home residents held constant will reduce waiting time, thus increasing revenue and leaving costs unchanged.

To explain equilibria with positive waiting times we assume that demand and patient length of stay in a nursing home are uncertain: we use a stochastic queuing model with endogenous demand (balking). Suppose initially that there is a single nursing home with a single bed available for patients and that the number of patients who complete their treatment per instant of time follows a Poisson distribution with mean rate γ.[2] A proportion θ of these patients wish to enter a nursing home, so that the flow rate of demand for a nursing home place is also Poisson distributed with mean $\lambda = \gamma\theta$ (the arrival rate).

Patient lengths of stay in the nursing home are exponentially distributed with a mean of $1/\mu$, where μ is the "service" rate. We assume that the length of stay distribution is exogenous to the nursing home.[3] The expected waiting time (or delay) before a nursing home bed is available is $\bar{w}$ and it can be shown (Gross et al, 2008) that[4]

$$\bar{w} = 1/(\mu - \lambda) \quad (1)$$

Thus a bigger difference between the arrival rate (demand) and service rate (supply) increases delays for a place at a nursing home. By Little's Law (Little, 1961) the expected number of patients waiting for a nursing home place is

$$L = \bar{w}\lambda \quad (2)$$

We assume that patients do not observe the number waiting for the nursing home but do know the expected waiting time. Suppose that patient expected utility from a nursing home place after a delay of $\bar{w}$ is $v(y-p,q,\bar{w},x)$,[5] where y is income or wealth, p is the price of nursing home care, q is the quality of nursing home care, and x is a vector of patient characteristics. Utility from the alternative of discharge to the patient's home is $v^o(y,x)$. The proportion of patients θ who decide to opt for a nursing home place (ie for whom $v(y-p,q,\bar{w},x) - v^o(y,x) \geq 0$) will depend on their

[2] This is the number in the Local Authority which is our unit of analysis. Patients may be in several hospitals serving the Local Authority's patients.

[3] For example, suppose that patients exit a nursing home only on death and that nursing home quality does not affect mortality rates of nursing home patients.

[4] If the service rate is not strictly greater than the arrival rate then expected waiting time tends to infinity over time.

[5] For example with $v = u(y-p,q)e^{-rw}$ (similar to the Lindsay and Feigenbaum (1984) specification) and with Poisson arrival rate and exponential waiting home length of stay, expected utility from the nursing home is $u(y-p,q)(1+r\bar{w})^{-1}$ (see Gravelle and Schroyan (2014) for a derivation, and for further discussion of equilibrium queues with balking).

expectations about waiting times, since longer waits for a place will reduce their utility from a nursing home relative to their alternative destination. The proportion of patients who are medically ready to be discharged and who demand a nursing home place (θ) will therefore depend on nursing home price and quality, and on the joint distribution of income and other characteristics:

$$\theta = \theta(\bar{w}, p, q, F) \tag{3}$$

where F (somewhat loosely) denotes the joint distribution of y and x. The demand (arrival rate) for nursing homes is $\lambda = \gamma\theta$ and we expect, ceteris paribus, that higher prices and longer expected waiting times will reduce demand ie that $\lambda_p = \theta_p\gamma < 0$ and $\lambda_{\bar{w}} = \theta_{\bar{w}}\gamma < 0$.

We can compute the arrival rate of patients (demand for the nursing home) as a function of variables which are exogenous to each patient as[6]

$$\lambda^a = \lambda^a(p, q, \mu, \gamma, F) \tag{4}$$

The expected number of patients waiting for discharge to a nursing home is

$$L^a = \bar{w}^a\lambda^a = L^a(\mu, \gamma, p, q, F) \tag{5}$$

The single profit maximising care home chooses price and quality to maximise expected profit

$$\pi = \left(p - c(q)\right)\lambda^a(p, q, \mu, \gamma, F) \tag{6}$$

so that the equilibrium price $p(\mu, \gamma, F)$ and quality $q(\mu, \gamma, F)$ are also functions of the exogenous factors entering patient preferences and the cost function.[7]

We can generalise the model to allow for a nursing home to have $k > 1$ beds and for there to be more than one nursing home.[8] For example, with a nursing home with k beds, Poisson arrivals and exponential length of stay, the average waiting time is

$$\bar{w}^b = G(k, \mu, \lambda)\frac{1}{k\mu - \lambda} \tag{7}$$

[6] Substituting from (1) for $\bar{w}$ in (3) and using the definition $\lambda = \pi\lambda^o$ gives

$$\lambda - \theta(\bar{w}, p, q, F)\gamma = \lambda - \theta\left((\mu - \lambda)^{-1}, p, q, F\right)\gamma = 0$$

an implicit equation which we can solve for λ^a

[7] If the queueing model was deterministic with demand function $D(p,q,w)$ and output x, then waiting time $w(p,q,x)$ is determined by $D(p,q,w) - x = 0$ for $w > 0$ and $D(p,q,0) - x \le 0$ for $w = 0$, with $w_p < 0$, $w_q > 0$ if $w > 0$. Then it can never be profit maximising to have a positive queue: if $w > 0$ the care home can raise price, keeping output constant and letting the waiting time fall, thereby increasing profit since revenue is increased and costs unchanged. With a stochastic queueing model the expected waiting time is always positive. Suppose that quality is fixed, then $\pi_p = (p - c)\lambda_p^a + \lambda^a$ and with $\lambda_p^a < 0$ the care home will never want to set such a high price that $\lambda^a = 0$ (and in any case as λ^a tends to 0 the expected waiting time tends to $1/\mu$, not zero). Thus non-stochastic waiting time models cannot explain the existence of positive queues ie of people waiting to be discharged.

[8] Details available from authors.

where $G_k < 0$, $G_\mu < 0$, and $G_\lambda > 0$.[9] Substituting this expression for the expected waiting time into $\theta(\bar{w}, p, q, F)$ we can again solve for the arrival rate $\lambda^b(k, \mu, \gamma, p, q, F)$ as a function of variables exogenous to patients. Since Little's Law holds for general queuing systems, the number of patients waiting to be discharged is

$$L^b = \bar{w}^b \lambda^b = L^b\left(k, \mu, \gamma, p, q, F\right) \tag{8}$$

The expected number waiting in hospital for discharge to a nursing home will depend, inter alia, on the size of the local population and its morbidity which determine λ^o. With greater local morbidity the survival of patients in nursing homes may also be smaller, so that μ is greater and length of stay in nursing home shorter, thereby reducing the number waiting. Hence the effect of greater population morbidity on the number waiting for a nursing home bed is ambiguous.

The number waiting L is decreasing in nursing home prices: a ceteris paribus increase in p reduces the proportion of patients who opt for nursing homes (λ) and this in turn reduces the expected wait $\bar{w}$. Thus both parts of $L = \bar{w}\lambda$ are reduced by an increase in p.[10]

The effect of an increase in supply (an increase in the number of beds k) is ambiguous. The reason is that an increase in supply reduces the expected waiting time $\bar{w}$ but leads to an increase in demand for nursing home places λ. Whether the number waiting increases or falls depends on whether the demand for nursing home places is elastic or inelastic with respect to expected waiting time. If demand is inelastic, then it will fall.[11] There is no evidence on the effect of waiting times on the demand for nursing home places but most studies of the effect of hospital waiting times report that demand for hospital care is inelastic with respect to hospital waiting times (Gravelle et al, 2002; Gravelle et al, 2003; Martin and Smith, 1999; Martin et al, 2007).

[9] $G\left(k, \mu, \lambda\right) = \frac{(k\rho)^k}{k!}\left((1-\rho)\sum_{j=0}^{j=k-1}\frac{(k\rho)^j}{j!} + \frac{(k\rho)^k}{k!}\right)^{-1}$ where $\rho = \lambda/\mu$.

[10] The comparative static properties depend on the stability of the system (exogenous increases in demand increase the waiting time which reduces demand – we require that the net effect is an increase in demand so that the system is stable).

[11] There is an obvious analogy between the number waiting $\bar{w}\lambda$ in this market and total expenditure (price time quantity demanded) in conventional markets.

4. Econometric models

We use Local Authority level data and estimate a version of (7) as

$$L = L(k, \overline{p}, \overline{q}, n, \overline{\mathbf{x}}) \qquad (9)$$

using information on number of care-home beds (k), average care-home prices $(\overline{p})$, average care-home quality rating $(\overline{q})$, the population (n) of the Local Authority, and average socio-economic and other characteristics of the population $(\overline{\mathbf{x}})$. We employ two main econometric models to investigate the determinants of delayed discharges.

Panel data

Our first regression model is:

$$y_{it} = \alpha_t + \delta_i + \beta_1 s_{it} + \beta_2 x_{it} + u_{it} \qquad (10)$$

where y_{it} a measure of delayed discharges for hospital patients resident in Local Authority i in year t (either the number of delayed patients or number of bed days lost to delays), s_{it} is a vector of variables measuring the supply of nursing and care homes in Local Authority i, such as beds availability, prices and quality ratings; and x_{it} is a vector of control variables for local needs, such as number of elderly population and rate of deaths among people aged 65 and over. All variables are in logs. δ_i is a Local Authority effect which controls for unobserved heterogeneity at Local Authority level and α_t is the year effect. We estimate (9) by random effects with robust standard errors and clustering on Local Authorities. To test whether the random effects model is consistent we use a test based on Mundlak (1978), adding the mean of the time varying variables to (9) and estimate it by random effects (Wooldridge, 2010). If the means are jointly insignificant then the random effects specification is consistent and we can use random effects to test whether Local Authorities that experience a larger increase in beds or reduction in prices over time are characterised by a larger reductions in delayed discharges.[12]

Spatial effects

It is plausible that the availability of care-home supply in a given Local Authority may affect delayed discharges not only in the same Local Authority but also in neighbouring ones. To test whether the availability of care-homes supply spills over across different Local Authority boundaries, we estimate spatial econometric models

$$y_{it} = \alpha_t + \delta_i + \theta\textstyle\sum_j \omega_{ij}\, y_{it} + \beta_1 s_{it} + \gamma\sum_j \omega_{ij}\, s_{it} + \beta_2 x_{it} + \psi \sum_j \omega_{ij}\, u_{it} + e_{it} \qquad (11)$$

where y_{it}, s_{it} and x_{it} are specified as in (9). $\omega_{ij} \geq 0$ is a distance (spatial) weight specified in more detail below.

The coefficients γ associated with the vector of spatially-lagged regressors test whether higher supply of care-homes and lower demand in nearby Local Authorities reduces delayed discharges in a given Local Authority, ie whether there are spillovers across Local Authorities.

The coefficient θ on the spatial lag dependent variable allows for higher delays in nearby Local Authorities to be associated with more delayed discharge in a given Local Authority. This could arise

[12] Some variables, such as quality rating for care homes, or income deprivation are available only for one year, and can therefore be introduced as time-invariant in the Random Effects specifications (see results section for more details).

as the result of unobserved demand factors that increase delays both in the Local Authority considered and the neighbouring ones. Allowing for a spatial lag therefore helps to control for omitted variable bias. The coefficient ψ on the spatial error term allows for a spatially dependent relationship between the error term in neighbouring Local Authorities and delays in a given Local Authority. This could arise from omitted variable bias where the value of that missing variable in a nearby Local Authority affects the number of delays in a given Authority.

We use four specifications of spatial models. The Spatially Lagged Xs (SLX) model applies spatial weights to one or more independent variables. In this case, we apply a weight matrix to the population variable and the beds variable to create two additional variables measuring local spill-over effects. This is estimated as a standard fixed or random effect panel model augmented with spatially lagged covariates.

The spatially autoregressive model (SAR) adds a variable derived by applying the weight matrix to the dependent variable. No spatially-lagged regressor is included in this specification. The Spatial Durbin Model (SDM) combines a spatially lagged dependent variable and spatially lagged independent variables. Finally, the Spatial Durbin Error Model (SDEM) instead applies the weight matrix to the error term, as well as to explanatory variables.

We estimate (10) by maximum likelihood, which is consistent and efficient in the presence of the spatial lag term, while OLS is biased and inconsistent (Anselin, 1988). This cross-sectional approach has been extended to a panel framework (see Baltagi et al, 2009; Elhorst, 2010; and Moscone and Tosetti, 2014).

As customary in the spatial literature, we use a row-standardised inverse distance matrix. Define d_{ij} as the distance between Local Authority i and Local Authority j. The weights are given by:

$$\begin{aligned} \omega_{ij} &= 0 && \text{if } i=j \\ &= (d_{ij}^{-1})/(\textstyle\sum_j d_{ij}^{-1}) && \text{if } i\neq j \end{aligned}$$

The inverse distance specification gives a lower weight to the delayed discharges of Local Authorities that are more distant from Local Authority i. This row-standardisation permits us to interpret Wy as a weighted average delayed discharges across Local Authorities, where the weights are inversely related to the distance between Local Authorities' centroids. Similarly, we can interpret Ws as the weighted average LTC supply and Wx as the average population or demand shifter.

5. Data

Dependent variables

Our key dependent variables are from the "Acute and Non-Acute Delayed Transfers of Care" dataset (Department of Health, 2011a). The dataset records delays in the transfer of patients from hospital care to social care in England by each of 147 Local Authorities. The relevant Local Authority is the council with responsibility for adult social care where the patient resides.[13] We use two types of dependent variables: (i) "delayed patients" measured as the number of patients who are ready to be discharged from hospital into social care but have not been discharged at midnight on the last Thursday of each month, averaged over the year; (ii) "days of delay" during the month experienced by all patients with delayed discharges, not just those waiting at census date, averaged over the year. We have data for four years, from January 2010 to December 2013.

As both dependent variables are heavily skewed and sometimes have a value of zero, we apply the inverse hyperbolic sine transformation $y = f(z) = \ln\left(z + (z^2+1)^{\frac{1}{2}}\right)$ where z is the raw variable (Burbidge et al, 1988). If $z = 0$, then $y = 1$ and $y \approx \ln z + \ln 2$, $dy/dz \approx 1/z$ for $z > 0$, so that the coefficients on logged explanatories can be interpreted as elasticities.

The data distinguish between delays due to the hospital, to social care (which is the responsibility of the Local Authority in which the patient lives) and delays due to both. In our preferred specifications we use delays due to social care as the dependent variables. We also estimate models including all delays as a robustness check.

Long-term care

We capture supply conditions for long-term care in nursing and care homes by measuring, for each Local Authority, the number of care-home beds, the average price charged by care- homes, and the average quality rating of care-homes.

The Care Quality Commission (CQC) data on every care (residential or nursing) home in England were aggregated to Local Authority level by mapping the postcode of each provider to a Local Authority. Only providers whose 'primary client' is people aged 65 and over are included. A provider's 'primary client' is the category of patients for which the largest proportion of its beds is registered. The CQC data are measured for May of each year.

The average price per week and average rating of care-homes in each Local Authority is taken from the Laing and Buisson dataset of care homes for July 2010, June 2011, June 2012 and June 2013. We again use care-homes whose primary client group is patients aged 65 and over. Each provider is mapped to a Local Authority through its postcode. The Laing and Buisson dataset has eight price categories and we use the unweighted average. The rating of each institution, used as a proxy for quality, is its CQC star rating of Poor, Adequate, Good and Excellent. This is converted to a numerical range of 1-4 where 1 = Poor and 4 = Excellent. The data is only available up to 2010 and so we use the 2010 values for subsequent years 2011-2013.

[13] The Isle of Wight and City of London are excluded. The two unitary authorities of East and West Cheshire are combined into the county of Cheshire due to some of the delays data being provided only for this older configuration of the county. Similarly, the two unitary authorities of Bedford and Central Bedfordshire are combined into a single unit.

Control variables

We control for variations in demand using the population within each Local Authority who are aged 65 and over. We use data from the Office for National Statistics (ONS) mid-year population estimates for 2010 to 2012 (Office of National Statistics, 2011). Disaggregated population figures by Local Authority for mid-2013 are not available. We therefore run most of the analysis with 3 years of data (2010, 2011 and 2012) and then conduct sensitivity analysis with 4 years of data by using population in 2012 as a proxy for 2013. We measure the number of deaths among people aged 65 and over per 100,000 people aged 65 and over for the same time period to control for variations in population health.

The number of people of all ages receiving homecare per 100,000 is included as a control as a substitute for long-term care. This data is from the Health and Social Care Information Centre (HSCIC) releases of Personal Social services: Expenditure and Unit Costs. Each dataset covers a financial year from the 1st April to the 31st March for 2009-10 to 2012-13 inclusive. Finally, the rate of people aged 65 and over receiving social security benefits is used as a control for deprivation in a Local Authority. These data are taken from the Index of Multiple Deprivation. As with CQC quality rating, we have data only for 2010 and assume that values for later years are unchanged.

6. Results

Descriptive statistics

Table 1 provides descriptive statistics at Local Authority level. On average, 28 patients are delayed at midnight of the monthly census day in each Local Authority. The delays of 8.6 patients are attributed to social care (ie to the Local Authority where the patient resides). In an average calendar month in each Local Authority, 776 bed days are lost due to patients not being discharged when ready, of which 237 days are the responsibility of the Local Authority. These variables have wide variation and are heavily right skewed, with most Local Authorities at the lower end of the distribution.

The average Local Authority has a population aged 65 and over of 60,000 and has 2,500 residential or nursing home beds mainly caring for patients in this age group. The average Local Authority price for a week of care is £550, though in some Authorities it reaches over £1,000. The average rating of care homes is 3 (Good) and there is little variation in this variable across Local Authorities. The average number of deaths per 100,000 is 4,421. The average proportion of individuals on income benefits is 20%.

Regression results

Table 2 reports the results for models in which the dependent variable is the logarithm of number of patients delayed due to *social care* (ie where the responsibility for the delay has been attributed to social care as opposed to hospital care). Five random effects specifications are provided, all using robust standard errors and with clustering within Local Authorities. All models in Tables 2 to 8 pass the Mundlak (1979) test for consistency of the random effects specification.

Column (1) of Table 2 provides the results from a standard RE model without spatial factors. It suggests that an increase in the elderly population by 1% increases the number of delayed patients by about 1.5%. An increase in beds of nursing and care homes by 1% reduces delayed patients by 0.52%. An increase in price of nursing and care homes by 1% increases delays by 1%.

Column (2) includes spatially-lagged beds and population (SLX model) and shows spillover effects across Local Authorities. An increase in the elderly population by 1% across other Local Authorities increases delays by 4.6%. An increase in 1% in beds across other Local Authorities reduces delays by 2.8%. Similar effects of spatially lagged beds and population are found in the SDEM and SDM models. We do not report results from models with spatially-lagged prices since, like the own price variable, they are generally insignificant. The SAR and SDM models both show that delays are correlated across Local Authorities, conditional on the explanatories. The SDM model, for example, implies that an increase in delays in other nearby Local Authorities by 1% increases delays by 0.3%, suggesting that there are unobserved local factors influencing delays.

Table 3 reports results from models when delays are measured in days. The key elasticities are broadly in the same range. An increase in the elderly population by 1% increases the number of bed-days lost due to delays by about 1.7%-2% across the different specifications. An increase in beds at nursing and care homes by 1% reduces days of delay by 0.6%-0.7%. An increase in price of nursing and care homes by 1% increases delays by 1.1%-1.5%. Again, there is evidence of spatial spillovers across Local Authorities. An increase in 1% in beds across other Local Authorities reduces delays by 3.1%-4%.

Sensitivity analyses

If social beds and prices have an effect it should be only on delays attributed to social care and thus we would expect a weaker association of beds and prices with a measure of all delays which also includes delays due to the hospital. Tables 4 and 5 are analogous to Tables 2 and 3 but measure total delays, ie delays that have been attributed to social care, hospital care or both. We find that the results are qualitatively similar in terms of sign but statistical significance tends to be lower: beds are significant at 10% level only in two specifications, and prices are never significant.

The models presented in Tables 2-5 are from a panel of three years (2010, 2011, 2012). We have data for an additional year (2013), except for the population of 65 or over. We re-run our key models (in Tables 2 and 3) with 4 years of data, using population in 2012 as to measure population in 2013. The results are in Tables 6 and 7 and are similar to those in Tables 2 and 3, though the additional year of data improves the precision of our estimates. The beds variable is always significant at 5% level.

We also augment the analysis with additional controls. In Table 8 we report results from models after adding mortality rates for the elderly (as a proxy of health needs), the number of recipients of care at their own home per 100,000 population, and a measure of income deprivation. We also interact income deprivation with care-homes prices: subsidies from Local Authorities to care home residents are means tested. Hence, when the population is poorer, more of the patients will be eligible for subsidy and so we expect that prices will have less effect on delayed discharges. The results are in Table 8. The effects of care-home beds and prices are qualitatively similar to Tables 2 and 3 but less precisely estimated. In Local Authorities with more homecare provision delays are smaller though the effect is statistically insignificant. We also find that as expected, the interaction of income deprivation and price has a negative effect on delays, though again the effect is insignificant. None of the additional controls is significant.

In Table 9 we have results from models in which we have added the standard deviation of care home prices within the Local Authority. We argue that patients (or their relatives) will spend longer searching for a care home bed the greater the dispersion of prices, as well as the higher the average price. But, given that care home beds for poor patients are more likely to be subsidised, we expect that the dispersion of prices will have a smaller effect on delay in Local Authorities with a higher proportion of the population receiving means tested social security payments. The coefficients on the standard deviation of prices and its interaction with the income benefit rate have the signs we expect but are statistically significant only for the standard deviation and then only in two of the four models reported. Moreover, only one of the models passes the Mundlak test, suggesting that the random effects models are inconsistent.

Quantitative effect

Our preferred models in Table 2 yield an elasticity of the number of patients delayed with respect to beds supply of –0.4 to –0.5. Thus an increase in care home beds of 10% (from 2500 to 2750 in an average Local Authority) would reduce the number of patients delayed each month by 4%-5%. Given a monthly average number of 8.6 delayed patients this corresponds to a reduction of less than one patient per month (0.34-0.43 patients) in an average Local Authority. In terms of delays measured in hospital bed days, a 10% increase in home-care beds would reduce delayed bed days by 5.8-7.2%, which, given an average of 238 delayed bed days in a month, corresponds to a reduction of 14-17 days per month in an average Local Authority. The quantitative effect appears therefore to be relatively modest.

7. Conclusions

Coordination between the health and long-term care sectors is critical to address concerns about hospital bed blocking. This study has investigated the extent to which expanding the supply of nursing and care home beds can reduce delayed discharges.

The results suggest that delayed discharges in hospitals do respond to the availability of care-home beds but that the response is relatively modest: an increase in care-home beds of 10% (250 additional beds per Local Authority) would reduce delayed discharges by 4%-7%. Given a monthly average number of 8.6 delayed patients and 238 delayed bed days in a month, a 10% increase in care-home beds leads to a reduction of less than one delayed patient per month and a reduction of 14-17 days of delay per month.

Although less robustly estimated, we find some evidence of positive effect of care-home prices on delayed discharges. These may arise because patients spend longer searching in markets with higher average prices. Policies aimed at encouraging competition across care homes and at reducing prices may therefore bring further reductions of hospital delays.

Unsurprisingly, the number of elderly, over 65 years old, is a key driver of delays (with an elasticity of 1.0-1.5): 6,000 (10%) additional elderly in an average Local Authority would increase delays by 10%-15%. Given the ageing of the population, this suggests that bed-blocking will increase in the future.

We find spillover effects across Local Authorities with respect to both care-home beds and elderly population. Higher availability of care-homes in other Local Authorities reduces delayed discharges. Similarly, higher population in other Local Authorities increases delayed discharges. This suggests that patients are willing to cross boundaries in order to secure a bed in a care-home.

A key implication is that policies aimed at specific Local Authorities need to take account of these spillovers which could otherwise lead to free riding and ‘races to the bottom’ in the absence of coordination. For example, a Local Authority would have a weaker incentive to encourage an expansion of care-homes capacity if some of the benefits in terms of reductions in delayed discharge accrue to neighbouring Local Authorities or if the needs of the elderly population of a Local Authority can be satisfied by neighbouring capacity. The presence of such spillover effects, with patients in one Local Authority willing to accept beds in nearby Local Authorities, implies that inequalities in care homes availability across Local Authorities may be of less concern than the total supply of care home beds.

Table 1: Descriptive statistics. Local Authorities 2010-2012

	Mean	SD (overall)	SD (between)	SD (within)	Min	Max
Delayed patients (all patients)	28.24	27.65	26.92	6.59	1.08	149.42
Days of delay (all patients)	775.8	806.8	784.7	194.9	36.3	4910.6
Delayed Patients due to social care	8.61	11.37	10.86	3.46	0	100.83
Days of delay due to social care	237.4	331.4	317.8	96.7	0	2908
Care-homes beds	2499	2326	2319	238	233	12431
Care-homes prices	550.71	123.13	121.90	19.18	384.37	1181.25
Care-homes rating	3.1	0.2	0.2	0	2.7	3.7
Population over 65	59512	52263	52342	2047	7723	277127
Homecare recipients/100,000	1548	770	716	287	0	5932
Deaths /100,000	4421	414	399	114	3313	5747
Income benefit rate/100	0.2089	0.0786	0.0788	0	0.0726	0.5198

Data are for 147 Local Authorities. Mean, min, max over three years. Delayed patients: number waiting for discharge on monthly census date. Days of delay: total days of delay experienced by all delayed patients during a month. Delayed patients and delayed days are averages of monthly data over the year.

Table 2: Patients delayed due to social care, 2010-12

	RE		SLX		SDEM		SAR		SDM	
	coef	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**
Care-homes beds	-0.520**	(0.021)	-0.408*	(0.085)	-0.413*	(0.076)	-0.501**	(0.020)	-0.404*	(0.080)
Care-homes prices	1.010***	(0.006)	0.756	(0.110)	0.726	(0.123)	0.894**	(0.013)	0.681	(0.143)
Care-homes rating	-1.910*	(0.098)	-1.289	(0.260)	-1.261	(0.266)	-1.502	(0.175)	-1.186	(0.293)
Population over 65	1.553***	(0.000)	1.406***	(0.000)	1.413***	(0.000)	1.507***	(0.000)	1.399***	(0.000)
Year 2011	-0.113**	(0.023)	-0.0466	(0.423)	-0.0462	(0.514)	-0.0686	(0.162)	-0.0288	(0.614)
Year 2012	-0.266***	(0.000)	-0.0336	(0.763)	-0.0286	(0.812)	-0.155**	(0.014)	-0.00347	(0.975)
Spatially-lagged beds			-2.825***	(0.005)	-2.878***	(0.004)			-2.306**	(0.025)
Spatially-lagged population			4.681***	(0.003)	4.748***	(0.003)			3.689**	(0.025)
Spatially-lagged error					0.248	(0.136)				
Spatially-lagged delays							0.521***	(0.000)	0.318**	(0.030)
Constant	-14.56***	(0.000)	-41.92***	(0.000)	-42.11***	(0.000)	-15.13***	(0.000)	-35.52***	(0.001)
Mundlak test	5.82	0.2133	4.68	0.5849	4.73	0.5783	4.97	0.2902	4.39	0.6245

N = 3x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors.

Spatial models: SLX (Spatially Lagged Xs), SDEM (Spatial Durbin Error Model), SAR (Spatial Autoregressive Model), SDM (Spatial Durbin Model).

Table 3: Days of delay due to social care, 2010-12

	RE		**SLX**		**SDEM**		**SAR**		**SDM**	
	coef	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**
Care-homes beds	-0.726**	(0.011)	-0.586*	(0.054)	-0.589**	(0.048)	-0.688**	(0.013)	-0.579*	(0.053)
Care-homes prices	1.467***	(0.002)	1.199**	(0.048)	1.144*	(0.059)	1.264***	(0.008)	1.086*	(0.071)
Care-homes rating	-3.090*	(0.056)	-2.174	(0.187)	-2.126	(0.195)	-2.508	(0.111)	-2.022	(0.215)
Population over 65	1.980***	(0.000)	1.781***	(0.000)	1.786***	(0.000)	1.904***	(0.000)	1.768***	(0.000)
Year 2011	-0.0219	(0.743)	0.0647	(0.430)	0.0676	(0.530)	-0.0261	(0.690)	0.0481	(0.561)
Year 2012	-0.177**	(0.029)	0.136	(0.387)	0.141	(0.420)	-0.120	(0.133)	0.115	(0.463)
Spatially-lagged beds			-3.919**	(0.016)	-3.999**	(0.015)			-3.172*	(0.060)
Spatially-lagged population			6.714**	(0.012)	6.803**	(0.011)			5.328*	(0.056)
Spatially-lagged error					0.315**	(0.027)				
Spatially-lagged delays							0.547***	(0.000)	0.331**	(0.020)
Constant	-16.08***	(0.000)	-56.88***	(0.001)	-56.99***	(0.001)	-17.85***	(0.000)	-48.78***	(0.008)
Mundlak test	7.2	0.1257	5.31	0.5044	5.59	0.4703	6.07	0.1938	5.16	0.523

N = 3x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors.

Spatial models: SLX (Spatially Lagged Xs), SDEM (Spatial Durbin Error Model), SAR (Spatial Autoregressive Model), SDM (Spatial Durbin Model).

Table 4: Patients delayed (all), 2010-12

	RE		SLX		SDEM		SAR		SDM	
	coef	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**
Care-homes beds	-0.343**	(0.026)	-0.264	(0.120)	-0.259	(0.122)	-0.350**	(0.024)	-0.252	(0.131)
Care-homes prices	0.340	(0.169)	0.138	(0.639)	0.121	(0.679)	0.407	(0.101)	0.0974	(0.740)
Care-homes rating	-1.281*	(0.094)	-0.997	(0.207)	-0.971	(0.218)	-1.023	(0.180)	-0.926	(0.238)
Population over 65	1.389***	(0.000)	1.300***	(0.000)	1.296***	(0.000)	1.368***	(0.000)	1.286***	(0.000)
Year 2011	-0.0610*	(0.096)	-0.0225	(0.566)	-0.0369	(0.685)	-0.0440	(0.239)	-0.00650	(0.870)
Year 2012	-0.132***	(0.003)	-0.00397	(0.958)	-0.0188	(0.883)	-0.0933**	(0.046)	0.0157	(0.838)
Spatially-lagged beds			-1.470**	(0.026)	-1.534**	(0.024)			-1.036	(0.127)
Spatially-lagged population			2.260**	(0.027)	2.342**	(0.025)			1.151	(0.280)
Spatially-lagged error					0.630***	(0.000)				
Spatially-lagged delays							0.510***	(0.000)	0.520***	(0.000)
Constant	-10.00***	(0.000)	-21.93***	(0.001)	-22.23***	(0.001)	-11.92***	(0.000)	-14.62**	(0.035)
Mundlak test	5.09	0.278	4.06	0.6679	3.79	0.7056	4.47	0.3466	3.54	0.7355

N = 3x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable (patients delayed due to hospital and/or social care) and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. Spatial models: SLX (Spatially Lagged Xs), SDEM (Spatial Durbin Error Model), SAR (Spatial Autoregressive Model), SDM (Spatial Durbin Model).

Table 5: Days of delay (all), 2010-12

	RE		SLX		SDEM		SAR		SDM	
	coef	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**
Care-homes beds	-0.314*	(0.065)	-0.266	(0.161)	-0.262	(0.163)	-0.338**	(0.048)	-0.257	(0.169)
Care-homes prices	0.322	(0.186)	0.240	(0.431)	0.211	(0.486)	0.417*	(0.088)	0.174	(0.565)
Care-homes rating	-1.622*	(0.062)	-1.271	(0.150)	-1.227	(0.163)	-1.279	(0.134)	-1.149	(0.187)
Population over 65	1.398***	(0.000)	1.325***	(0.000)	1.322***	(0.000)	1.386***	(0.000)	1.313***	(0.000)
Year 2011	0.000458	(0.990)	0.0314	(0.417)	0.0299	(0.737)	-0.0118	(0.740)	0.0219	(0.564)
Year 2012	-0.0139	(0.756)	0.0997	(0.188)	0.0922	(0.451)	-0.0371	(0.385)	0.0654	(0.388)
Spatially-lagged beds			-1.447**	(0.041)	-1.515**	(0.034)			-1.049	(0.140)
Spatially-lagged population			2.525**	(0.020)	2.611**	(0.018)			1.349	(0.227)
Spatially-lagged error					0.619***	(0.000)				
Spatially-lagged delays							0.561***	(0.000)	0.553***	(0.000)
Constant	-6.614***	(0.000)	-22.28***	(0.002)	-22.54***	(0.002)	-10.72***	(0.000)	-15.76**	(0.029)
Mundlak test	4.63	0.3278	3.53	0.7393	3.42	0.7549	4.12	0.3897	3.14	0.7914

N = 3x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable (days of delay due to hospital and/or social care) and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. Spatial models: SLX (Spatially Lagged Xs), SDEM (Spatial Durbin Error Model), SAR (Spatial Autoregressive Model), SDM (Spatial Durbin Model).

Table 6: Patients delayed due to social care, 2010-13

	RE		SLX		SDEM		SAR		SDM	
	coef	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**
Care-homes beds	-0.691***	(0.002)	-0.547**	(0.019)	-0.549**	(0.017)	-0.665***	(0.002)	-0.540**	(0.019)
Care-homes prices	0.675**	(0.043)	0.407	(0.333)	0.391	(0.352)	0.593*	(0.074)	0.362	(0.389)
Care-homes rating	-1.494	(0.163)	-0.940	(0.378)	-0.923	(0.383)	-1.152	(0.264)	-0.863	(0.412)
Population over 65	1.734***	(0.000)	1.563***	(0.000)	1.565***	(0.000)	1.682***	(0.000)	1.552***	(0.000)
Year 2011	-0.0977**	(0.049)	-0.0263	(0.641)	-0.0269	(0.702)	-0.0574	(0.239)	-0.0115	(0.837)
Year 2012	-0.235***	(0.000)	0.0137	(0.897)	0.0159	(0.891)	-0.133**	(0.035)	0.0377	(0.718)
Year 2013	-0.299***	(0.000)	-0.0404	(0.738)	-0.0347	(0.794)	-0.171**	(0.024)	-0.000895	(0.994)
Spatially-lagged beds			-3.000***	(0.002)	-3.034***	(0.001)			-2.503***	(0.009)
Spatially-lagged population			4.838***	(0.001)	4.883***	(0.001)			3.913**	(0.011)
Spatially-lagged error					0.255	(0.106)				
Spatially-lagged delays							0.488***	(0.000)	0.292**	(0.037)
Constant	-13.60***	(0.000)	-41.16***	(0.000)	-41.31***	(0.000)	-14.23***	(0.000)	-35.38***	(0.001)
Mundlak test	8.26	0.0827	6.16	0.4055	7.45	0.1139	6.23	0.3985	5.9	0.435

N = 4x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable (patients delayed due to social care) and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors. Spatial models: SLX (Spatially Lagged Xs), SDEM (Spatial Durbin Error Model), SAR (Spatial Autoregressive Model), SDM (Spatial Durbin Model).

Table 7: Days of delay due to social care, 2010-13

	RE		**SLX**		**SDEM**		**SAR**		**SDM**	
	coef	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**
Care-homes beds	-0.892***	(0.002)	-0.700**	(0.021)	-0.700**	(0.019)	-0.846***	(0.002)	-0.691**	(0.021)
Care-homes prices	1.054**	(0.015)	0.715	(0.177)	0.694	(0.192)	0.913**	(0.035)	0.655	(0.219)
Care-homes rating	-2.631*	(0.078)	-1.810	(0.237)	-1.790	(0.239)	-2.168	(0.136)	-1.711	(0.258)
Population over 65	2.143***	(0.000)	1.907***	(0.000)	1.908***	(0.000)	2.064***	(0.000)	1.892***	(0.000)
Year 2011	-0.00454	(0.946)	0.0934	(0.240)	0.0943	(0.336)	-0.01000	(0.879)	0.0778	(0.337)
Year 2012	-0.141*	(0.076)	0.204	(0.171)	0.203	(0.208)	-0.0930	(0.241)	0.182	(0.227)
Year 2013	-0.171*	(0.053)	0.187	(0.257)	0.190	(0.287)	-0.117	(0.181)	0.167	(0.310)
Spatially-lagged beds			-4.222***	(0.006)	-4.250***	(0.006)			-3.587**	(0.025)
Spatially-lagged population			6.933***	(0.005)	6.963***	(0.005)			5.788**	(0.028)
Spatially-lagged error					0.248	(0.121)				
Spatially-lagged delays							0.495***	(0.000)	0.269*	(0.068)
Constant	-14.53***	(0.000)	-54.88***	(0.001)	-54.89***	(0.001)	-16.30***	(0.000)	-48.46***	(0.005)
Mundlak test	9.55	0.0488	7.37	0.2877	8.57	0.0729	7.63	0.2668	7.32	0.2925

N = 4x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors.

Spatial models: SLX (Spatially Lagged Xs), SDEM (Spatial Durbin Error Model), SAR (Spatial Autoregressive Model), SDM (Spatial Durbin Model).

Table 8: Augmented models of delayed discharge, 2010-12

	Delays due social care (SLX)				All Patients delayed (SLX)			
	Patients delayed		Days of delay		Patients delayed		Days of delay	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Care-homes beds	-0.453*	(0.071)	-0.676**	(0.044)	-0.352*	(0.066)	-0.347*	(0.100)
Care-homes prices	1.332**	(0.023)	1.875**	(0.013)	0.520	(0.137)	0.562	(0.122)
Care-homes rating	-0.539	(0.626)	-1.257	(0.454)	-0.527	(0.505)	-0.811	(0.363)
Population over 65	1.585***	(0.000)	2.030***	(0.000)	1.469***	(0.000)	1.482***	(0.000)
Income benefit rate/100	6.271	(0.197)	9.113	(0.133)	1.802	(0.588)	3.856	(0.229)
Income benefit-Price interaction	-0.875	(0.243)	-1.312	(0.159)	-0.228	(0.663)	-0.555	(0.269)
Recipients of homecare/100,000	-0.0205	(0.532)	-0.0126	(0.794)	-0.0343	(0.186)	-0.0288	(0.308)
Death rate/100,000	0.207	(0.776)	0.525	(0.599)	0.768	(0.152)	0.647	(0.259)
Year 2011	-0.0679	(0.314)	0.0529	(0.594)	-0.0135	(0.773)	0.0408	(0.378)
Year 2012	-0.0816	(0.504)	0.0970	(0.581)	-0.00869	(0.913)	0.102	(0.206)
Spatially-lagged population	5.112***	(0.001)	7.254***	(0.004)	2.509**	(0.010)	2.799***	(0.007)
Spatially-lagged beds	-2.788***	(0.005)	-3.946**	(0.015)	-1.485**	(0.023)	-1.522**	(0.030)
Constant	-44.12***	(0.001)	-59.12***	(0.006)	-31.77***	(0.001)	-27.17***	(0.004)
Mundlak test	13.35	0.2048	14.31	0.1593	11.19	0.343	7.8	0.6485

N = 3x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors.

Spatial models: SLX (Spatially Lagged Xs), SDEM (Spatial Durbin Error Model), SAR (Spatial Autoregressive Model), SDM (Spatial Durbin Model).

Table 9: Augmented models of delayed discharge with standard deviation of prices, 2010-2012

	Delays due to social care (SLX)				**All patients delayed (SLX)**			
	Patients delayed		**Days of delay**		**Patients delayed**		**Days of delay**	
Care-homes beds	-0.415*	(0.091)	-0.764**	(0.021)	-0.411**	(0.028)	-0.420**	(0.042)
Care-homes prices	1.719***	(0.001)	2.157***	(0.001)	0.418	(0.254)	0.643*	(0.085)
Care-homes rating	-0.748	(0.485)	-1.150	(0.469)	-0.444	(0.558)	-0.719	(0.400)
Population over 65	1.554***	(0.000)	2.132***	(0.000)	1.527***	(0.000)	1.565***	(0.000)
Income benefit rate/100	9.439**	(0.041)	13.51**	(0.012)	2.252	(0.504)	4.818	(0.135)
Recipients of homecare/100,000	-0.00936	(0.765)	-0.00404	(0.932)	-0.0225	(0.361)	-0.0178	(0.520)
Death rate/100,000	0.151	(0.830)	0.698	(0.467)	0.838	(0.103)	0.753	(0.184)
SD care-homes price 65+	0.0858	(0.421)	0.266*	(0.075)	0.121*	(0.069)	0.0985	(0.189)
Income benefit-Price interaction	-1.340	(0.101)	-1.979**	(0.028)	-0.0937	(0.870)	-0.613	(0.284)
Income benefit-SD price interaction	-0.0304	(0.925)	-0.0134	(0.965)	-0.264	(0.186)	-0.113	(0.571)
Year 2011	-0.0952	(0.133)	0.0178	(0.850)	-0.0277	(0.547)	0.0205	(0.661)
Year 2012	-0.136	(0.251)	0.0358	(0.839)	-0.0201	(0.799)	0.0692	(0.384)
Spatially-lagged population	5.111***	(0.001)	7.121***	(0.005)	2.531***	(0.009)	2.708***	(0.008)
Spatially-lagged beds	-2.574***	(0.009)	-3.561**	(0.024)	-1.427**	(0.028)	-1.323*	(0.055)
Constant	-42.65***	(0.001)	-58.44***	(0.006)	-32.57***	(0.000)	-28.47***	(0.002)
Mundlak	26.46***	(0.009)	30.86***	(0.002)	14.42	(0.275)	13.56	(0.330)

N = 3x147 LAs. *p<0.1, **p<0.05, ***p<0.01

Log models: dependent variable and explanatories are in logs. All models are estimated with random effects and cluster robust standard errors.

Spatial models: SLX (Spatially Lagged Xs)

References

Anselin L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers, Dordrecht.

Baltagi B, Egger P, and Pfaffermayr M. (2009). A generalized spatial panel data model with random effects. *CPR Working Papers No. 113*. Syracuse, NY: Center for Policy Research Maxwell School, Syracuse University.

Baumann M, Evans S, Perkins M, Curtis L, Netten A, Fernandez J and Huxley P. (2007). Organisation and features of hospital, intermediate care and social services in English sites with low rates of delayed discharge. *Health and Social Care in the Community*. 15, 4, 295-305.

Bolin K, Lindgren B and Lundborg P. (2008). Informal and formal care among single-living elderly in Europe. *Health Economics*. 17(3), 393–409.

Bonsang E. (2009). Does informal care from children to their elderly parents substitute for formal care in Europe? *Journal of Health Economics*. 28, 143-154.

Burbidge J, Magee L and Robb A. (1988). Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, 83, 401, 123-127.

Cremer H, Pestieau P and Ponthiere G. (2012). The economics of long-term care: a survey, *Nordic Economic Policy Review*, number 2/2012, 107-148.

Department of Health (2003). *The Community Care (Delayed Discharges Etc) Act 2003: Guidance for Implementation*, accessed on 13 November 2012.

Department of Health (2011a). *Monthly delayed transfer of care SitReps: Definitions and Guidance*, accessed on 7.8.2012.

Department of Health (2011b). *NHS Support for Social Care 2010/11-2012/13*. London.

Elhorst P. (2010). Spatial panel data models. In Fisher M, Getis A, (eds) *Handbook of Applied Spatial Analysis: Software Tools Methods and Applications*. Springer.

Fernandez J and Forder J. (2008). Consequences of local variations in social care on the performance of the acute health care sector. *Applied Economics*. 40(12), 1503-1518.

Forder J. (2007). Self-funded social care for older people: an analysis of eligibility variations and future projections, *PSSRU Discussion Paper 2505*, University of Kent.

Forder J. (2009). Long-term care and hospital utilisation by older people: An analysis of substitution rates. *Health Economics.* 18, 1322-1338.

Forder J and Allan S. (2014). *The impact of competition on quality and prices in the English care homes market*, 34, 73-83.

Gannon B and Davin B. (2010). Use of formal and informal care services among older people in Ireland and France. *European Journal of Health Economics*, 11, 499-511.

Grabowski D, Norton E and Van Houtven C. (2012). Informal care. In: Jones A. (Ed.), *The Elgar Companion in Health Economics*, Second edition, Edward Elgar Publishing, Cheltenham, 307-317.

Gravelle H, Dusheiko M and Sutton M. (2002). The demand for elective surgery in a public system: Time and money prices in the UK National Health Service, *Journal of Health Economics*, 21 (3): 423-449.

Gravelle H, Santos R, Siciliani L. (2013). Does a hospital's quality depend on the quality of other hospitals? A spatial econometrics approach to investigating hospital quality competition. Centre for Health Economics, University of York, CHE Research Paper 82.

Gravelle H, Schroyan F. (2014). *Optimal provider payments with rationing by waiting*, mimeo.

Gravelle H, Smith PC, Xavier A. 2003. Performance signals in the public sector: the case of health care. *Oxford Economic Papers*, 55, 81-103.

Gross D, Shortle J, Thompson J, Harris C. (2008). *Fundamentals of Queueing Theory*. Fourth Edition, Wiley.

Holmås TH, Kjerstad E, Lurås H, Straume OR. (2010). Does monetary punishment crowd out pro-social behaviour? A natural experiment on hospital length of stay. *Journal of Economic Behavior & Organization*, 75, 261-267.

House of Commons, Committee of Public Accounts (2003). *Ensuring the Effective Discharge of Older Patients from NHS Acute Hospitals: Thirty-Third Report of Session 2002–2003*. *HC* 459 Stationery Office, London.

Laing and Buisson. (2010). *Care homes complete dataset*, Laing and Buisson.

Lindsay C and Feigenbaum B. (1984). Rationing by waiting lists. *American Economic Review*, 74, 404-417.

Little J. (1961) A proof of the queueing formula $L = \lambda W$. *Operations Research*, 9, 383-387.

Martin S, Rice N, Jacobs R and Smith P. (2007). The market for elective surgery: Joint estimation of supply and demand, *Journal of Health Economics*, 26: 263.285.

Martin S and Smith P. (1999). Rationing by waiting lists: an empirical investigation, *Journal of Public Economics*, 71: 141.164.

Mobley LR. 2003. Estimating hospital market pricing: an equilibrium approach using spatial econometrics, *Regional Science and Urban Economics*, 33(4), 489–516.

Moscone F and Tosetti E. (2014) Spatial econometrics: theory and applications in health economics, *Encyclopedia of Health Economics*, 329-334.

Moscone F, Knapp M and Tosetti E. (2007), Mental health expenditure in England: a spatial panel approach, *Journal of Health Economics*, 26, 842-864.

Moscone F and Tosetti E. (2010), Health expenditure and income in the US, *Health Economics*, 19, 1385-1403.

Mundlak, Y. (1978), On the pooling of time series and cross section data. *Econometrica*, 46, 69-85.

National Audit Office (2000). *Inpatient Admissions and Bed Management in NHS Acute Hospitals*. London: Stationery Office.

Norton E. (2000). Long-term Care. In AJ Culyer and JP Newhouse (eds) *Handbook of Health Economics*, volume 1, chapter 17, Elsevier Science.

OECD (2011). Help wanted? Providing and paying for long-term care, *OECD Policy Studies*, OECD publishing.

OECD (2013). *A good life in old age? Monitoring and improving quality in long-term care*, OECD Health Policy Studies, OECD publishing.

Øien H, Karlsson M and Iversen T. (2012) The impact of financing incentives on the composition of long-term care in Norway, *Applied Economic Perspectives and Policy.* 34, 258-274.

Office of National Statistics (2011), accessed on 7 August 2012:
http://www.ons.gov.uk/ons/publications/re-reference-tables.html?edition=tcm%3A77-231847

Pestieau P, Ponthiere G. (2012). Long-term care insurance puzzle, in *Financing long-term care in Europe* (edited by J. Costa-Font and C. Courbage), Palgrave, McMillan.

Picone G, Wilson RM and Chou S-Y. (2003). Analysis of hospital length of stay and discharge destination using hazard functions with unmeasured heterogeneity. *Health Economics*. 12, 1021-1034.

Siciliani L. (2013). The Economics of Long Term Care, *The B.E. Journal of Economic Analysis and Policy*.

Wooldridge J. (2010), *Econometric Analysis of Cross Section and Panel Data*, MIT Press.

Van Houtven CH and Norton EC. (2004). Informal care and health care use of older adults. *Journal of Health Economics.* 23(6), 1159-1180.