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

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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 higher cost 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 first provide a theoretical model of delayed discharges using queuing theory under stochastic but endogenous demand to characterise a market equilibrium with unregulated care home prices and positive waiting times. The model shows that in equilibrium the number of hospital patients waiting for a care home bed depends on the price of care home beds *and* their number. We use administrative data from England on hospital delayed discharges in 2010-11 and 2011-12. Cross-sectional analyses at Local Authority level suggest that the supply of long-term care beds and their prices affects hospital delayed discharges. In 2010-11 an increase in nursing-homes beds by 10% reduces delayed discharges by more than 6%. In 2011-12 an increase in nursing-homes prices by 10% increases delayed discharges by more than 7%. We also test for spillover effects across Local Authorities using spatial-econometrics. We find that smaller LTC supply (beds) or higher elderly population in neighbouring Local Authorities increases delayed discharges.

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

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1. Introduction

Due to the ageing of the population the number of individuals requiring long-term care is increasing (OECD, 2011). This is likely to require better coordination between the health and long-term care sectors. A key policy concern is what is known as hospital 'bed blocking' where hospital patients who are ready to be discharged to a nursing home are waiting in hospital for a nursing home bed. Since hospital care is generally more expensive than care provided by a nursing home, the failure to coordinate generates allocative inefficiency in hospital resources.

Several OECD countries report problems or growing concerns about waiting times for long-term care services (OECD, 2013, chapter 2). There is limited research (reviewed below) that examines substitution between the supply of nursing homes and delayed hospital discharges.[4] The main objective of this study is to estimate empirically the elasticity of the number of delayed discharges with respect to the availability of nursing-home beds using a new English data set. The rate at which hospital patients may be willing to move to a nursing home may depend not only on the bed availability but also on its price and its 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. Therefore, 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.

The study first provides a theoretical model of delayed discharges. Nursing home markets are characterised both by delays for a nursing home bed and by unregulated prices. This cannot be explained by standard economic models with deterministic demand and supply, rationing by waiting, and providers who do not face perfectly price elastic demand functions. In these circumstances a provider with a positive waiting time can always increase profit by raising price with their supply held constant. Their waiting time will fall to equate demand and supply and the provider will have higher revenue and unchanged costs. We therefore sketch a model where demand and supply are stochastic with demand dependent on price and expected waiting time and providers choosing the service rate. The model integrates queuing theory with economic theory. We derive a market equilibrium with positive expected waiting times which depend on the endogenous price and supply (service rate).

We then test empirically whether higher availability of nursing and care homes affects hospital delays. The study employs two newly available measures of hospital delays to patients resident in a Local Authority: the number of delayed hospital patients at a monthly census point and the total number of days waited in the previous month by all hospital patients medically ready for discharge. We have two years of this Local Authority level data.

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

The study employs several econometric approaches. First, we exploit cross-sectional variations at Local Authority level. This suggests that the supply of LTC beds and their prices are associated with hospital delayed discharges. In 2010-11 an increase in beds by 10% reduces delayed discharges by more than 6%. In 2011-12 an increase in price by 10% increases delayed discharges by more than 7%.

To control for unobserved heterogeneity at Local Authority level, we also specify a panel-data model. Our random-effects speciation provides results that are consistent with the cross-sectional ones. An increase in beds and a reduction in prices by 10% reduce delayed discharges by respectively 3% and 5%.

It seems plausible that the supply of LTC may spill over across Local Authorities. For example, a Local Authority with a high supply of nursing homes may reduce not only hospital delayed discharges in that authority but also in neighbouring ones. We test this hypothesis explicitly by employing a spatial-econometrics approach. We construct a matrix of distances across Local Authorities and a contiguity matrix. Employing a range of spatial-regression specifications, we find evidence of spillover effects. Lower LTC supply (beds) or higher elderly population in neighbouring Local Authorities increases delayed discharges.

In an initial attempt to allow for possible endogeneity we also estimate two stage least squares cross-section models. The instruments we have investigated so far are highly correlated with each other and we therefore only report some preliminary results using a single instrument (local house prices) for LTC prices. The IV results suggest that OLS estimates are underestimates of the effect of LTC prices.

Finally, we have started to experiment with data which gives the cause of delayed discharge and attributes it to the hospital or the local authority. We find that beds availability and prices have a larger effect on delays when these are measured as delays due to social care or lack of beds.

Related literature

There are only a few studies that investigate the interrelation between the availability of nursing homes (formal long-term care) and health care. This is in contrast to the extensive literature on the relation between informal and formal long-term care (Van Houtven and Norton, 2004; Bonsang, 2009; Bolin, et al 2008; Gannon and Davin, 2010; Grabowski et al, 2012).

Fernandez and Forder (2008) found that in England 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. 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. Holmas et al. (2010) investigate the effect of fining owners of long-term care institutions who prolong length of stay at hospitals in Norway. Surprisingly, the study finds that hospital length of stay is longer when the fines are used, which is interpreted as an examples of monetary incentives crowding-out intrinsic motivation. Øien, Karlsson and Iversen (2012) investigate 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 nursing facility.

The study that is closest to ours is Fernandez and Forder (2008). Like us, they also investigate the determinants of delayed discharges. We make several innovations. Our theoretical model integrates a queuing theory framework with an economic one to produce a queueing model with endogenous demand. We employ more refined measures both for hospital delays and for supply of nursing and care homes. To measure hospital delays in addition to patients delays at a point in time, we also employ the total number of delayed hospital days experienced in a given month. 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. Moreover, for one year we have data which are disaggregated by hospital and Local Authority, rather than at Local Authority only. On the methodological side, in addition to cross-sectional models, we exploit panel-data to control for unobserved heterogeneity at Local Authority level. We also employ a range of spatial-econometrics regressions to test for spillover effects across Local Authorities.

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 who get prospective activity-based funding from 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. There are over 18,000 providers of social care (nursing and residential homes) (Laing and Buisson, 2010) who 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.

The coordination of health and long-term care for patients discharged from hospital is a long-standing concern (Baumann, et al 2007; House of Commons, 2003; National Audit Office, 2000) which has culminated with the Community Care (Delayed Discharges) Act (2003). The Act requires local authorities and hospitals to collaborate around the discharge of patients from hospital. Councils are liable for reimbursing hospitals for delayed discharges for which they are solely responsible.

2. 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 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. The fact that nursing home prices are not regulated implies that a deterministic queuing model (eg Lindsay and Feigenbaum, 1984) is not appropriate. 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. 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 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 λ^o.[5] A proportion π 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 $\lambda = \pi\lambda^o$ (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.[6] 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

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

As intuitively expected, 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

$$L = \bar{w}\lambda \tag{2}$$

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 $v(y - p, q, \bar{w}, x)$,[7] 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 vector of patient characteristics. Utility from the alternative of discharge to the patient's home is $v^o(y,x)$. The proportion of patients π 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 expectations about waiting times, since

[5] 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.

[6] 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.

[7] 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 (2013) for a derivation, and for further discussion of equilibrium queues with balking).

longer waits for a place will reduce their utility from a nursing home relative to their alternative destination. π will therefore depend on nursing home price and quality, and on the joint distribution of income and other characteristics:

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

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

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

$$\lambda - \pi(\bar{w}, p, q, F)\lambda^o = \lambda - \pi\left((\mu-\lambda)^{-1}, p, q, F\right)\lambda^o = 0 \tag{4}$$

an implicit equation which we can solve for

$$\lambda^a = \lambda^a(\mu, \lambda^o p, q, F) \tag{5}$$

which is the arrival rate of patients (demand for the nursing home) as function of variables which are exogenous to each patient. The expected number of patients waiting for discharge to a nursing home is (from Little's Law)

$$L^a = \bar{w}^a\lambda^a = L^a(\mu, \lambda^o, p, q, F) \tag{6}$$

More generally, with a nursing home with k beds, Poisson arrivals and exponential length of stay, the average waiting time is

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

where $G_k < 0$, $G_\mu < 0$, and $G_\lambda > 0$.[8] Substituting this expression for the expected waiting time into $\pi(\bar{w}, p, q, F)$ we can again solve the implicit function $\lambda - \pi(\bar{w}^b, p, q, F)\lambda^o = 0$ for the arrival rate $\lambda^b(k, \mu, \lambda^o p, q, F)$ 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 to the nursing home is

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

We can generalise the model to allow for a monopolistically competitive nursing home sector. Suppose that there are N identical nursing homes available to the Local Authority's patients in hospital. In equilibrium each nursing home will choose the same price and number of beds. We assume that patients do not observe the number waiting for any nursing home but do know the expected waiting time.[9] Patients will be indifferent about which nursing home they choose since the expected waiting time, price and quality are the same in all nursing homes. Patients will therefore be distributed equally across the N nursing homes

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

[9] With nursing homes drawing patients from several hospitals any individual patient will find it difficult to observe the actual number waiting at any instant.

and so the arrival rate (demand) for each home is $\lambda/N = \pi\lambda^o/N$. Substituting λ/N for λ in the previous derivations we get the expected number of patients waiting as

$$L^c = \bar{w}^c \lambda^c / N = L^c(k, \mu, \lambda^o, N, p, q, F) \tag{9}$$

where, for example $\bar{w}^c = G(k, \mu, \lambda N^{-1})\left(k\mu - \lambda N^{-1}\right)^{-1}$

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

The number waiting L is decreasing in nursing home prices: an 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 increase in supply (via an increase in the number of nursing homes N or the number of beds per home k) is ambiguous. The reason is that 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. (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.)

We can also extend the model to take account of the fact that nursing homes do not have identical prices, quality, and waiting times. Suppose that patients (or their relatives) search amongst the set of nursing homes to find an expected utility maximising (net of search costs) combination of price, quality and expected waiting time for a place. Having chosen a nursing home h with price p_h, expected waiting time $\bar{w}_h$, quality q_h, the patient waits for a bed in the chosen home to become vacant. Let the equilibrium proportion of patients choosing nursing home h be π_h. This will depend on the characteristics of nursing home h and its rivals and on the distribution of patient characteristics: $\pi_h = \pi_h^d(\bar{w}_h^d, p_h, q_h, \bar{w}_{-h}^d, p_{-h}, q_{-h}, F)$ where k_{-h} etc denote the beds, length of stay, prices, and qualities in other nursing homes. The expected arrival rate at home h is $\pi_h\lambda^o$ and the expected waiting time in home h is $\bar{w}_h^d = G(k_h, \mu, \pi_h\lambda^o)\left(k_h\mu - \pi_h\lambda^o\right)^{-1}$. Then the expected number of patients waiting for nursing home h is

$$\begin{aligned} L_h^d &= \bar{w}_h^d \lambda_h = \bar{w}_h^d \pi_h \lambda^o = \bar{w}_h^d \pi_h^d(\bar{w}_h^b, p_h, q_h, \bar{w}_{-h}^b, p_{-h}, q_{-h}, F)\lambda^o \\ &= L_h^d(k_h, \mu, p_h, q_h, k_{-h}, p_{-h}, q_{-h}, \lambda^o, F) \end{aligned} \tag{10}$$

[10] The comparative static properties depend 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).

The expected number of hospital patients waiting for a long term care bed in the Local Authority is

$$L^d = \sum_h L_h^d\left(k_h, \mu, p_h, q_h, k_{-h}, p_{-h}, q_{-h}, \lambda^o, F\right) = L^d(\mathbf{k}, \mathbf{p}, \mathbf{q}, \mu, \lambda^o, F) \qquad (11)$$

This model is highly stylised in that it assumes that the choice of nursing home and hence the wait for a long term care bed takes place after the patient is medically to be discharged. This ignores the possibility that the patient or their relatives can search, choose a long term care provider and start waiting before they are ready to be discharged. Allowing for this would considerably complicate the model and is unlikely to alter its main implication that both prices and supply of long term care beds will influence the equilibrium waiting time for a long term care bed and hence the number of hospital patients waiting for beds. Introducing search by patients could however change the direction of the effect of prices and supply on the numbers waiting. For example, patients and their families may be willing to spend longer searching in markets with higher prices or with more care homes.

3. Econometric models

We do not have data on choice of nursing home to enable us to estimate patient choice models to estimate L^d. Instead we use LA level data and so estimate a simplified version of (11) as

$$L^e = L^e(\bar{k}, N, \bar{p}, \bar{q}, \bar{\mathbf{x}}, n) \qquad (12)$$

using information on LA level means of nursing home beds per home, number of homes, average prices, average quality, average patient characteristics, and the population (n) of the LA.

OLS

We employ several econometric models to investigate the determinants of delayed discharges. In our simplest specification, data are cross-sectional and aggregated at Local Authority (LA) level. Our linear regression model for each of the two years is:

$$y_i = \alpha + \beta_1 s_i + \beta_2 x_i + u_i \qquad (13)$$

where y_i is a measure of hospitals' delayed discharges for patients resident in Local Authority i (either the number of delayed patients or number of days spent in hospital by delayed patients); s_i is a vector of variables measuring the supply of nursing and care homes in LA i, such as beds availability, prices and quality ratings; and x_i is a vector of control variables for local needs, such as number of elderly population and standardised mortality rates. All variables are in logs.

Panel data

We have data for two years and to control for possible unobserved heterogeneity at LA level, we estimate panel-data models

$$y_{it} = \alpha_t + \alpha_i + \beta_1 s_{it} + \beta_2 x_{it} + u_{it} \qquad (14)$$

where y_{it} is delayed discharges in LA i in year t. α_i is a vector of fixed (or random) effects at LA level and α_t is a time dummy. We therefore test whether LAs that experienced a larger increase in beds or reduction in prices over time were characterised by a larger reductions in delayed discharges.

Spatial spillover effects

It is plausible that the availability of LTC supply in a given Local Authority may affect delayed discharges not only in the same LA but also in neighbouring ones. To test whether LTC supply spills over across different Local Authority boundaries, we estimate spatial econometric models. We specify a linear spatial lag model as:

$$y_i = \alpha + \rho \sum_j \omega_{ij}\, y_i + \beta_1\, s_i + \lambda \sum_j \omega_{ij}\, s_i + \beta_2\, x_i + \psi \sum_j \omega_{ij}\, u_i + e_i \qquad (15)$$

where $\omega_{ij} \geq 0$ is a distance weight specified in more detail below. We can write the model in matrix form as

$$y = \alpha + \rho\, W y + s\, \beta_1 + W s\, \lambda + \beta_2\, x + \psi\, W u + e. \qquad (16)$$

The coefficient ρ on the spatial lag dependent variable determines whether higher delays in nearby LAs induce a higher delay in a given LA. This could arise as the result of unobserved demand factors that increase delays both in the LA considered and the neighbouring ones. Allowing for a spatial lag in this context therefore helps to control for omitted variable bias. The coefficient ψ on the spatial error term indicates if there is a spatially dependent relationship between the error term in neighbouring Local Authorities and delays in a given LA. 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. The coefficients λ on the vector of spatially-lagged regressors whether higher LTC supply and lower demand in nearby LAs reduce delayed discharges in a given LA (ie whether there are spillovers).

We use a row-standardised inverse distance matrix. Define d_{ij} as the distance between LA i and LA j. The weights are given by:

$$\omega_{ij} = 0 \qquad \text{if} \quad i=j$$

$$\omega_{ij} = (d_{ij}^{-1})/(\textstyle\sum_j d_{ij}^{-1}) \qquad \text{if} \quad i \neq j$$

The inverse distance specification gives a lower weight to the delayed discharges of LAs that are more distant from LA i. This row-standardisation permits us to interpret Wy as a weighted average delayed discharges across LAs, where the weights are inversely related to the distance between LAs. Similarly, we can interpret Ws as the weighted average LTC supply and Wx as the average population or demand shifter. We estimate (15) by maximum likelihood, which is consistent and efficient in the presence of the spatial lag term, while OLS is biased and inconsistent (Anselin, 1988). We use four specifications of spatial models. The Spatially Lagged Xs (SLX) model, applies the distance matrix to one or more independent variables. In this case, as in other specifications, we apply the weights matrix to the population variable and the beds variable to create two additional variables measuring local spill-over effects. All Spatial specifications include these variables. The Spatial Durbin Model (SDM) adds a variable which applies the weights matrix to the dependent variable. That is the impact of delays in neighbouring Local Authorities upon delays in the home Authority. This can help to control for unobservables that affect both a Local Authority and its neighbours. The Spatial Durbin Error Model (SDEM) instead applies the weights matrix to the error term. Finally, the Generalised Spatial Model (GSM) applies the weights matrix to both the dependent variable and error term, in addition to the key regressors.

Two stage least squares

LTC prices or beds may be endogenous either due to reverse causality (higher hospital delays triggering higher LTC supply) or omitted variable (higher demand increasing both hospital delays and higher LTC supply). In an initial investigation we have estimated cross section two stage least squares models. Our initial set of candidate instruments (local house prices, local pay, and index of local input prices (Market Forces Factor) were highly correlated and seem to be most correlated with LTC prices. We therefore report here on results obtained using the house price index as an instrument for LTC prices.

Generalised linear models

Because of the skewness of the dependent variables we use the log of patients delayed and days delayed as the dependent variables. In some case the raw dependent has a value of zero. We therefore estimate generalised linear models using the log link so that the model is

$$\ln(\mathrm{E}y_i) = \alpha + \beta_1 s_i + \beta_2 x_i \qquad (17)$$

and we experiment with the error distribution.

4. Data

Dependent variables

Our key dependent variables are from the "Acute and Non-Acute Delayed Transfers of Care" dataset (DH 2011). The dataset records delays in the transfer of patients from hospital care to social care in England. We use two dependent variables: i) the number of "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; ii) the number of "days of delay" during the month experienced by all patients with delayed discharges, not just those waiting at census date. This is the number of bed-days lost due to delays of discharge into social care during the month. As both variables are heavily skewed we take their logs.

We have data for two years: 2010-11 and 2011-12 (both measured from August to July). For 2010-11 data are reported at Local Authority level. The Local Authority is the council with responsibility for adult social care where the patient resides.[11]

We also have data for one year 2011-12 which provides a breakdown of the reasons for the delayed discharge, including if the patient was waiting for a home care bed, and if the LA or hospital was responsible for the delay. These dependent variables are highly correlated with the total number of delayed patients and total days of delay but we report some initial experiments using them as dependent variables.

[11] The Isle of Wight is 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.

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 long-term beds, the average price, and the average quality rating.

The Care Quality Commission (CQC) data on every residential or nursing home in the UK. were aggregated to LA level by mapping the postcode of each provider to a Local Authority. Only providers with a 'primary client' of 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 are registered. The CQC data are measured on May 2011 and May 2012.

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 and June 2011. We use care homes with a primary client of patients aged 65 and over and each provider is mapped to a Local Authority through its postcode. The Laing and Buisson dataset provides eight price categories. It is assumed that the average price of care in any given provider is the average of all its prices. The rating of each institution, used as a proxy for quality, is its 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 were only available up to 2010 and so are used only in cross-section analysis for 2010-11.

Control variables

Population within Local Authority of people aged 65 and over is a control for demand. We use data from the Office for National Statistics (ONS) population estimates for mid 2010 and mid 2011. The data are provided at lower super output area level and aggregated to Local Authority level. Standardised Mortality Rate (SMR) is also as a control for demand to measure health in in each Local Authority. These data are also taken from the ONS for 2010 and 2011.

5. Results

Summary statistics

Table 1 provides descriptive statistics variables at Local Authority level. On average, 28 patients are ready to be transferred on midnight of each sampled day in each Local Authority. In an average calendar month, 771 bed days are lost due to patients not being discharged when ready in each Local Authority. These variables exhibit a wide range of variation. They are also heavily skewed, with more providers at the lower end of the distribution.

The average population aged 65 and over in a Local Authority is around 58,000, with around 2,400 residential or nursing home beds spread among 69 providers mainly caring for patients in this age group. The average price for a week of care is £540, though in some Authorities it reaches over £1,000. The average rating of a care home is relatively stable at 3 (Good). The number of hours of homecare provided by a Local Authority in a week is on average around 1,600 hours.

OLS

Table 2 reports the results from the OLS regressions separately for 2010-11 and 2011-12. In 2010-11, an increase in the elderly population by 1% increases the number of delayed patients and days of delay by about 1.7%. An increase in beds of nursing and care homes reduces delayed patients and days of delay by respectively 0.6% and 0.55%. An increase in price of nursing and care homes by 1% increases delayed patients and days of delay by respectively 0.5% and 0.44% though only the first is significant at 10% level which the second is statistically insignificant. The results are consistent with the idea that availability of beds for nursing homes are a key determinant of delayed discharges. The positive effect of prices may arise because patients spend longer searching in markets with higher average prices.

Higher mortality rates (a proxy of need) are positively associated with delays in 2010-11. Higher quality rating is positively associated with delays: higher quality may make patients more willing to opt for a nursing home and therefore also contribute to further delays in hospital while waiting for a place.

The results for 2011-12 exhibit generally smaller effects. Although the effect of elderly population is confirmed (though with a smaller elasticity of 1), the number of beds for nursing and care homes ceases to be significant. In contrast, the coefficient associated with price is larger: an increase in price by 1% now increases delays by about 0.8%. We also estimated models using only beds or only prices as the supply side measures and find that their coefficients are somewhat larger in absolute value and highly statistically significant.

Panel data

Table 3 reports the results when employing a random effects specification. For both measures of delayed discharges, the Hausman test suggests that the random effects specification is consistent (chi-square statistics are 8.10, $p = 0.23$ and 9.07, $p = 0.17$). Table 4 also provides the results when data are pooled across the two years. The results from the random effects specification are broadly consistent with those from the cross sections. An increase in beds by 1% or a reduction in prices by 1% reduces the number of delayed patients respectively by 0.3% and 0.6%. Only a price effect is detected for days of delay: an increase in price by 1% increases the number of delayed days by 0.6%. The elasticity with respect to beds is -0.2 but not statistically significant.

Spatial econometrics

Tables 4.A-4.D display the results from the spatial regressions. The results are generally in line with the cross-sectional ones but also provide some evidence of spillover effect. When delayed patients are used as dependent variable in 2010-11, we find that lower beds availability or higher population increases delayed discharges. The coefficients are slightly smaller than those from OLS (the elasticity with respect to beds is -0.55 instead of -0.60; the elasticity with respect to population is 1.58 rather than 1.68). Lower beds and higher population from neighbouring LAs have also an effect on delayed discharges. The elasticities are equal to -2.5 and 3.5. The magnitude of the effects may be explained because the coefficients pick up the effects of variations in population and beds in all other Local Authorities weighted by distance. The presence of spillover effects is robust across different specifications (ie when we allow for spatially-lagged dependent variable and for spatial dependence in the error term). The lagged dependent variable can potentially control for omitted variables at local level (affecting a given LA and its neighbours). It is generally not statistically significant.

There is evidence of spillover effects for 2010-11 also when days of delays is used as dependent variable though this is mainly for population (the coefficient on beds is high and the p-value is close but above the 10% significance level). We do not find evidence of spillover effects for 2011-12. The coefficients for beds and price have the same sign as in 2010-11 but smaller in magnitude. Spatially-lagged prices are generally not significant and have been excluded from the final specification.

Instrumental variables

Tables 5.A-5.B have models in which the price of LTC is instrumented with an index of house prices (HPI). In the first stage regressions the HPI is significantly positively associated with prices charged by care homes. Table 5.A compares the results from OLS with IV regression when delayed patients are used as the dependent variable. The coefficient on price doubles in absolute value when instrumented and the coefficient on beds reduces. There are similar but weaker effects of instrumenting when days of delay is used as dependent variable in Table 5B.

We obtain similar results when price is instrumented using the Market Forces Factor (an index of input prices and other costs) or the median LA pay as instruments. Since HPI is highly correlated with these alternative instruments, we are not able to include all of them in our IV regressions.

While we have several potential instruments for price, we do not have at present a plausible instrument which is a good predictor of long term care beds. In these preliminary results therefore we have assumed that the LTC beds are exogenous so as to present results with the same explanatories as other models. Models which do not include the beds variable yield similar results on the price variable. In future work we will explore possible instruments for long term care beds.

Type of delay

Tables 6.A-6.B report preliminary results when we use as dependent variable measures of delay broken down by “reason for delay”. We focus on delays due to “social care” and delays due to “lack of beds”. Because some LAs have no patients delayed because of lack of beds or no delays due to social care we use a GLM specification with a log link which allows interpreting coefficients as elasticities. The modified Park tests strongly support the use of a gamma distribution. The link test (where the dependent variable is regressed on the square of its predicted value) supports the use of a log link, except for the model for days of delay where responsibility lies with the Local Authority.

When the more disaggregated measures of delay are used, the coefficients of the supply variables are considerably larger and are generally highly statistically significant. The elasticity of the supply of beds in modelling the number of patients delayed increases from -0.3 to -0.9 and -0.7 and becomes highly statistically significant. Similarly, price elasticity increases from 0.9 to 2.1 and 2.3. Similar changes can be seen when days of delay are modelled. These results plausibly suggest that it is those delays caused by a lack of beds or some other factor controlled by the Local Authority, which are most affected by the characteristics of long term care supply.

6. Conclusions

We have reported some preliminary investigations of the relationship between supply conditions in the long term care market and hospital bed blocking. Our key findings are that the number of nursing and care homes beds is associated with delayed discharge from hospital. The effect can be large with for example an increase in nursing-homes beds by 10% reducing delayed discharges by more than 6% in one year. We find that prices also matter and higher price for nursing and care homes are associated with increased delays both in our cross-sectional and panel-data specifications. The reason may be that patients may search for longer when prices are higher. There is also evidence of endogeneity in that the effect of LTC prices is greater when price is instrumented. Finally, we find some evidence of spillover effects across Local Authorities.

Future work. In future work we will expand the set of socio-economic and health related explanatory variables. For, example, we will examine if the number of 65+ hospital patients from an LA is a better measure of exposure that the total LA population aged 65+. We will look for additional instrumental variables to allow us to instrument both beds and prices and to perform over-identification tests. One possibility is to use data on LA decisions on planning applications since many smaller nursing and care homes are converted from normal dwellings and planning permission is required for this.

We will also include measures of the variability of prices and quality and beds within Local Authorities to test if greater dispersion increases delayed discharge by increasing search time. Our spatial regressions will be enriched by employing a contiguity-spatial matrix in addition to one based on inverse distance, and by estimating spatial panel models.

The equilibrium queuing model also requires further work in two respects. The first is to introduce the possibility that patients and their families may spend time searching for a care home place and this may affect discharge delays. The second is to examine supply decisions by nursing homes. For example, we could consider a two stage game played by nursing home. In the second stage homes choose price and number of beds taking the number of competing homes as given. At the prior, first stage, firms take decisions about whether to enter a market and entry and exit occur until rents are eliminated in each market. In equilibrium in market j, the number of beds per home k_j, the price p_j, and the number of homes N_j would depend on exogenous factors affecting costs and demand shifters. This extension could inform our choice of instruments for care home prices and beds.

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Table 1. Descriptive statistics. Local Authorities 2010/11-2011/12

	N	mean	sd	min	max
Delayed patients	148	28.24972	28.00348	1.75	164.25
Days of delay	148	771.3305	820.1933	40.08	5528.67
Beds in nursing and care homes	148	2400.52	2240.811	233	11711
Average price in nursing and care homes	148	539.9836	111.2142	384	1081
Average quality rating nursing and care homes	148	3.060258	.1912676	2.6	3.7
Population over 65 years	148	58329.6	51362.15	7947	264931
Standardised Mortality Rates (SMR)	148	101.5338	11.68835	59	135
Hours of Homecare (per week)	148	1578.801	1262.253	185	6950

Table 2. Delayed discharges: cross-section, OLS

	Delayed Patients				Days of Delay			
	2010-11		2011-12		2010-11		2011-12	
Population 65+	1.681***	(0.000)	1.090***	(0.000)	1.709***	(0.000)	1.060***	(0.000)
Nursing-homes Beds	-0.599***	(0.001)	-0.239	(0.235)	-0.547***	(0.008)	-0.160	(0.452)
Standardised mortality rate	0.945**	(0.040)	0.361	(0.563)	0.917*	(0.085)	0.229	(0.719)
Nursing-homes Price	0.494*	(0.091)	0.807**	(0.040)	0.437	(0.191)	0.749*	(0.055)
Nursing-homes Rating	-1.390*	(0.060)	-1.284	(0.143)	-1.780**	(0.050)	-1.531	(0.105)
Homecare (Hrs)/Week	0.0403	(0.782)	0.226	(0.131)	0.0128	(0.932)	0.207	(0.173)
Constant	-16.74***	(0.000)	-13.89**	(0.011)	-13.09***	(0.007)	-9.466*	(0.094)
Observations	148		148		148		148	
R^2	0.710		0.643		0.683		0.641	

All variables are in logs.

Table 3. Delayed discharges: panel data

	Patients Delayed				Days of Delay			
	Pooled		Random Effects		Pooled		Random Effects	
Population 65+	1.454***	(0.000)	1.338***	(0.000)	1.468***	(0.000)	1.293***	(0.000)
Nursing-homes Beds	-0.471***	(0.000)	-0.313**	(0.019)	-0.418***	(0.004)	-0.211	(0.129)
SMR	0.736*	(0.059)	0.756*	(0.063)	0.679	(0.121)	0.995**	(0.022)
Nursing-homes Price	0.491**	(0.048)	0.560*	(0.053)	0.398	(0.139)	0.600*	(0.058)
Nursing homes Rating	0.130	(0.207)	0.0534	(0.597)	0.106	(0.321)	0.0464	(0.653)
Year 2011-12	-0.0841	(0.177)	-0.0972***	(0.002)	0.0169	(0.803)	-0.00163	(0.959)
Constant	-16.46***	(0.000)	-16.37***	(0.000)	-12.80***	(0.001)	-14.74***	(0.000)
Observations	296		296		296		296	
Hausman			8.10	0.2306			9.07	0.1721
R^2	0.666				0.648			

All variables are in logs.

Tables 4A-4D. Spatial regressions

Table 4.A: Patients Delayed 2010-11

	SLX		SDM		SDEM		GSM	
	coef	p	Coef	p	coef	p	coef	p
Population 65+	1.578***	(0.000)	1.574***	(0.000)	1.581***	(0.000)	1.581***	(0.000)
Nursing-homes Beds	-0.553***	(0.002)	-0.549***	(0.002)	-0.555***	(0.001)	-0.555***	(0.002)
SMR	1.154**	(0.011)	1.153***	(0.009)	1.174***	(0.008)	1.174**	(0.015)
Nursing-homes Price	0.413	(0.300)	0.416	(0.285)	0.400	(0.314)	0.400	(0.281)
Nursing-homes Rating	-0.824	(0.270)	-0.824	(0.254)	-0.803	(0.260)	-0.803	(0.255)
Homecare	0.0755	(0.590)	0.0763	(0.579)	0.0769	(0.578)	0.0769	(0.566)
Spatially-lagged population 65+	3.533***	(0.004)	3.406**	(0.025)	3.558***	(0.004)	3.558*	(0.051)
Spatially-lagged nursing-homes beds	-2.514**	(0.018)	-2.449**	(0.034)	-2.546**	(0.017)	-2.547**	(0.049)
Constant	-36.51***	(0.000)	-35.79***	(0.000)	-36.58***	(0.000)	-36.59***	(0.001)
Rho (Lagged Dependent)			0.0569	(0.890)			-0.000241	(1.000)
Sigma			0.468***	(0.000)	0.468***	(0.000)	0.468***	(0.000)
Lambda (Lagged Error)					0.113	(0.819)	0.113	(0.859)
Observations	148		148		148		148	
R^2	0.728							

Table 4.B: Patients Delayed 2011-12

	SLX		SDM		SDEM		GSM	
	coef	p	Coef	p	coef	p	coef	p
Population 65+	1.057***	(0.000)	1.057***	(0.000)	1.059***	(0.000)	1.056***	(0.000)
Nursing-homes Beds	-0.206	(0.341)	-0.204	(0.329)	-0.206	(0.326)	-0.204	(0.319)
SMR	0.614	(0.345)	0.624	(0.323)	0.619	(0.330)	0.622	(0.337)
Nursing-homes Price	0.760	(0.114)	0.758	(0.104)	0.754	(0.115)	0.762*	(0.071)
Nursing-homes Rating	-1.004	(0.271)	-0.990	(0.255)	-0.993	(0.257)	-0.995	(0.214)
Homecare	0.223	(0.159)	0.222	(0.146)	0.223	(0.146)	0.223	(0.176)
Spatially-lagged population 65+	2.297	(0.134)	2.160	(0.219)	2.306	(0.118)	2.129	(0.269)
Spatially-lagged nursing-homes beds	-1.732	(0.174)	-1.664	(0.213)	-1.744	(0.157)	-1.643	(0.250)
Constant	-26.63**	(0.013)	-25.93**	(0.024)	-26.64***	(0.010)	-25.79**	(0.023)
Rho (Lagged Dependant)			0.0759	(0.858)			0.0896	(0.881)
Sigma			0.529***	(0.000)	0.529***	(0.000)	0.529***	(0.000)
Lambda (Lagged Error)					0.0365	(0.943)	-0.0267	(0.970)
Observations	148		148		148		148	
R^2	0.649							

Table 4.C: Days of Delay 2010-11

	SLX		SDM		SDEM		GSM	
	coef	p	coef	p	coef	p	coef	p
Population 65+	1.629***	(0.000)	1.615***	(0.000)	1.645***	(0.000)	1.643***	(0.000)
Nursing-homes Beds	-0.595***	(0.007)	-0.584***	(0.007)	-0.609***	(0.004)	-0.608***	(0.003)
SMR	1.119**	(0.032)	1.117**	(0.027)	1.201**	(0.018)	1.199**	(0.027)
Nursing-homes Price	0.697	(0.143)	0.707	(0.128)	0.657	(0.165)	0.658	(0.109)
Nursing-homes Rating	-1.182	(0.185)	-1.171	(0.172)	-1.063	(0.207)	-1.065	(0.179)
Homecare	0.102	(0.485)	0.104	(0.467)	0.108	(0.456)	0.108	(0.473)
Spatially-lagged population 65+	3.297**	(0.019)	2.900*	(0.067)	3.418**	(0.017)	3.386*	(0.070)
Spatially-lagged nursing-homes beds	-1.844	(0.135)	-1.683	(0.181)	-1.979	(0.118)	-1.964	(0.146)
Constant	-37.47***	(0.000)	-35.57***	(0.000)	-38.13***	(0.000)	-37.97***	(0.000)
Rho (Lagged Dependant)			0.192	(0.606)			0.0147	(0.978)
Sigma			0.525***	(0.000)	0.523***	(0.000)	0.523***	(0.000)
Lambda (Lagged Error)					0.366	(0.347)	0.359	(0.471)
Observations	148		148		148		148	
R^2	0.706							

Table 4.D: Days of Delay 2011-12

	SLX		SDM		SDEM		GSM	
	coef	p	coef	p	coef	p	coef	p
Population 65+	1.023***	(0.001)	1.023***	(0.000)	1.039***	(0.000)	1.031***	(0.001)
Nursing-homes Beds	-0.163	(0.496)	-0.159	(0.493)	-0.170	(0.462)	-0.164	(0.445)
SMR	0.461	(0.480)	0.502	(0.428)	0.520	(0.419)	0.522	(0.446)
Nursing-homes Price	0.830*	(0.091)	0.814*	(0.087)	0.767	(0.126)	0.784*	(0.080)
Nursing-homes Rating	-1.200	(0.212)	-1.129	(0.217)	-1.069	(0.253)	-1.077	(0.210)
Homecare	0.237	(0.134)	0.236	(0.125)	0.235	(0.127)	0.236	(0.172)
Spatially-lagged population 65+	2.298	(0.166)	1.878	(0.290)	2.439	(0.142)	2.075	(0.293)
Spatially-lagged nursing-homes beds	-1.525	(0.262)	-1.367	(0.315)	-1.687	(0.220)	-1.502	(0.314)
Constant	-24.48**	(0.029)	-22.93**	(0.041)	-24.90**	(0.023)	-23.61**	(0.035)
Rho (Lagged Dependant)			0.263	(0.490)			0.190	(0.729)
Sigma			0.553***	(0.000)	0.553***	(0.000)	0.553***	(0.000)
Lambda (Lagged Error)					0.276	(0.540)	0.157	(0.808)
Observations	148		148		148		148	
R^2	0.648							

All variables are in logs.

Tables 5A-5B. Instrumental Variables Regressions (2SLS)

Table 5.A: Patients Delayed, IV for Price

	OLS 2010		IV 2010		OLS 2011		IV 2011	
	coef	p	coef	p	coef	p	coef	p
LA Ln Beds 65+	-0.599***	(0.001)	-0.493***	(0.003)	-0.239	(0.235)	-0.129	(0.541)
LA Ln Av Price	0.494*	(0.091)	1.252***	(0.005)	0.807**	(0.040)	1.631**	(0.014)
LA Ln Pop 65+	1.681***	(0.000)	1.625***	(0.000)	1.090***	(0.000)	1.044***	(0.000)
LA Ln SMR	0.945**	(0.040)	1.515***	(0.004)	0.361	(0.563)	1.163	(0.167)
LA Ln Av Rating	-1.390*	(0.060)	-1.878**	(0.013)	-1.284	(0.143)	-1.790*	(0.060)
LA Ln Homecare (Hrs)/Week 65+	0.0403	(0.782)	0.0115	(0.937)	0.226	(0.131)	0.188	(0.226)
Constant	-16.74***	(0.000)	-23.54***	(0.000)	-13.89**	(0.011)	-22.26***	(0.005)
Observations	148		148		148		148	
R^2	0.710		0.696		0.643		0.630	
IV (house prices, t test)			2.68	(0.000)			5.66	(0.000)

Table 5.B: Days of Delay, IV for Price

	OLS 2010		IV 2010		OLS 2011		IV 2011	
	coef	p	coef	p	coef	p	coef	P
LA Ln Beds 65+	-0.547***	(0.008)	-0.503**	(0.022)	-0.160	(0.452)	-0.112	(0.636)
LA Ln Av Price	0.437	(0.191)	0.754	(0.132)	0.749*	(0.055)	1.105*	(0.096)
LA Ln Pop 65+	1.709***	(0.000)	1.685***	(0.000)	1.060***	(0.000)	1.040***	(0.000)
LA Ln SMR	0.917*	(0.085)	1.156**	(0.034)	0.229	(0.719)	0.576	(0.464)
LA Ln Av Rating	-1.780**	(0.050)	-1.984**	(0.033)	-1.531	(0.105)	-1.749*	(0.082)
LA Ln Homecare (Hrs)/Week 65+	0.0128	(0.932)	0.000726	(0.996)	0.207	(0.173)	0.190	(0.218)
Constant	-13.09***	(0.007)	-15.94***	(0.003)	-9.466*	(0.094)	-13.08*	(0.079)
Observations	148		148		148		148	
R^2	0.683		0.681		0.641		0.638	
IV (house prices, t test)			2.68	(0.000)			5.66	(0.000)

All variables are in logs.

Tables 6A-6B. GLM Regressions

Table 6.A: Patients Delayed 2011-12, GLM with Log Link and Gamma Distribution

	All Delays		Delays due to Social Care		Delays due to a lack of beds	
	coef	p	coef	p	coef	p
LA Ln Beds 65+	-0.272	(0.107)	-0.850***	(0.005)	-0.697***	(0.005)
LA Ln Av Price	0.915**	(0.015)	2.058***	(0.000)	2.270***	(0.000)
LA Ln Pop 65+	1.148***	(0.000)	2.023***	(0.000)	1.828***	(0.000)
LA Ln SMR	0.834	(0.115)	1.997**	(0.028)	1.079	(0.165)
LA Ln Av Rating	-1.118	(0.110)	-2.161	(0.107)	-2.110*	(0.051)
LA Ln Homecare (Hrs)/Week 65+	0.188	(0.185)	0.0597	(0.763)	0.00340	(0.986)
Constant	-16.91***	(0.001)	-33.74***	(0.000)	-29.81***	(0.000)
Observations	148		148		148	
Linktest (t stat)	0.341	(0.733)	-1.783	(0.075)	-1.412	(0.158)
Park Test Gaussian (Chi^2 stat)	30.29	(0.000)	130.7	(0.000)	163.1	(0.000)
Park Test Poisson (Chi^2 stat)	6.552	(0.011)	28.23	(0.000)	36.17	(0.000)
Park Test Gamma (Chi^2 stat)	0.148	(0.701)	0.651	(0.420)	0.551	(0.458)
Park Test Inverse Gaussian (Chi^2 stat)	11.07	(0.001)	47.98	(0.000)	56.23	(0.000)
Link	Log		Log		Log	
Family	Gamma		Gamma		Gamma	

Table 6.B: Days of Delay 2011-12, GLM with Log Link and Gamma Distribution

	All Delays		Delays due to Social Care		Delays due to a lack of beds	
	coef	p	coef	p	coef	p
LA Ln Beds 65+	-0.188	(0.312)	-0.770**	(0.021)	-0.591**	(0.027)
LA Ln Av Price	0.918**	(0.024)	1.887***	(0.001)	2.151***	(0.000)
LA Ln Pop 65+	1.103***	(0.000)	1.938***	(0.000)	1.728***	(0.000)
LA Ln SMR	0.710	(0.218)	1.412	(0.138)	0.710	(0.393)
LA Ln Av Rating	-1.347*	(0.080)	-2.381	(0.113)	-2.092*	(0.080)
LA Ln Homecare (Hrs)/Week 65+	0.189	(0.229)	0.125	(0.574)	0.0308	(0.879)
Constant	-12.94**	(0.021)	-26.53***	(0.002)	-23.92***	(0.001)
Observations	148		148		148	
Linktest (t stat)	0.0931	(0.927)	-2.652	(0.008)	-1.552	(0.121)
Park Test Gaussian (Chi^2 stat)	33.08	(0.000)	115.4	(0.000)	149.8	(0.000)
Park Test Poisson (Chi^2 stat)	8.558	(0.003)	25.58	(0.000)	33.13	(0.000)
Park Test Gamma (Chi^2 stat)	0.00984	(0.921)	0.392	(0.532)	0.529	(0.467)
Park Test Inverse Gaussian (Chi^2 stat)	7.436	(0.006)	39.81	(0.000)	51.99	(0.000)
Link	Log		Log		Log	
Family	Gamma		Gamma		Gamma	

All variables are in logs.