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Hospital coordination and integration with social care in England: The effect on post-operative length of stay☆,☆☆

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ABSTRACT

In spite of significant policy interest in improving the integration of health and social care services, little is known about the economics of coordination across the two sectors. We specify a Markov queuing model and use data collected from administrative records to estimate the link between two proxy indicators of across-sector complexity of discharge arrangements and post-operative length of stay in hospital for older people undergoing hip replacements. The results suggest that the number of local authorities involved in care planning and commissioning of social care services for discharges from a given hospital is significantly positively correlated with longer post-operative lengths of stay. A particularly strong effect is found between variability through time in the number of authorities involved in discharges from a given hospital and lengths of stay. The results suggest that improving information systems and joint assessment processes used during the discharge of patients with social care needs is likely to achieve significant efficiency gains in the health care system as a whole.

1. Introduction

Like many health care systems, the National Health Service (NHS) in England faces considerable financial and resource challenges. There is concern that the current policy of protecting the level of real government expenditure on the NHS relies on achieving efficiency savings of at least 3% a year. These are substantial efficiency goals, given that over the 15 years prior to 2010, NHS productivity growth, upon which these efficiency gains are based, averaged less than 0.5% per annum. Indeed, one set of commentators estimated that NHS productivity fell by almost 1% in 2012/13 and 2013/14, thus suggesting that a reliance on efficiency savings to release resources to meet growing service demand promises a bleak future (Health Foundation, 2015). Hospitals in particular are feeling the constraints, with 66% returning financial deficits over the financial year 2015/16 and 51% estimated to be in financial deficit in 2016/17 despite central government relief. A major policy initiative associated with these efficiency savings is centered around an increase in the integration of care across the health care and social care systems.

A key aim of the drive towards integration has been to improve the management of hospital case throughput. As a result, the identification of patients ready to be discharged and facing a delay because of a lack of available support facilities on discharge has become a major concern. The UK National Accounts Committee estimates that the total number of hospital bed days attributable to delays in the discharge process, which are recorded through a monthly census, is approximately 2.7 million per year, resulting in a cost of £820 million to the NHS (House of Commons Committee of Public Accounts, 2016). It is suggested that current estimated delays represent an underestimate of the true figure, as they are

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based on time from clinical assessment, and as hospital capacity is stretched these assessments are themselves subject to delay.

As Fig. 1 shows, a significant proportion of delayed discharges in the NHS over the analysis period were linked to a lack of support outside of the hospital. Since 2014, the delays for those awaiting care outside hospital has increased further, and now account for approximately 45% of all acute and non-acute delayed discharges.

In an attempt to address this particular issue, the UK government introduced the Better Care Fund (BCF) in 2015, a funding mechanism for incentivizing improved coordination of care commissioning across the health and social care sectors. Under the BCF, NHS resources have been earmarked for supporting better integration between the NHS and Local Authorities (LAs) social services departments, the latter being responsible for supporting large numbers of high-need patients following their hospital discharge. Current levels of expenditure associated with the BCF are £3.8 billion (for the year 2016). While this is a significant amount, almost £2 billion is in fact not new resource, but a transfer from the NHS budget to the LA's budget. Moreover, this funding aimed at improving the integration and coordination of health and social care is being introduced at a time when the social services expenditure on adult services, managed by LAs, has fallen by 10% in real terms since 2010.

Delayed discharge amongst the elderly is seen as a particularly crucial and complex issue, with over 85% of delayed discharges incurred by those aged 65 and older (National Audit Commission, 2016). NHS England, the body responsible for managing the health care system in England, recommends the implementation of 22 processes to optimise the transition from hospital to the social care system. These emphasise system-level processes for care coordination, including regular meetings between local health and social care service managers, the agreement of roles and responsibilities of care sector providers in the local economy, ongoing monitoring of existing pressures, and the pooling of resources to reduce organisational divisions. At a more practical level, it is recommended that joint local protocols and assessment forms, secure communication methods, up-to-date directories of services and single points of access and named contacts are developed. The UK Public Accounts Committee (PAC) has highlighted that despite a "good understanding of good practice in discharging older patients from hospital", the take-up of key processes for patient information sharing and coordination between hospitals and LAs is not widespread (National Audit Commission, 2016). For example, less than 50% of hospitals have developed joint or shared patient assessments between health and social service providers (op. cite., p14–p15).

While there is a relatively substantial literature on the economics of long-term care (see Fernandez et al., 2011; Grabowski et al., 2012; Norton, 2000; Pestieau and Ponthiere, 2012; Siciliani, 2013 for reviews), there is less formal analysis addressing the impact of delayed hospital discharges. Picone et al. (2003) study the interaction between length of stay and discharge destination for Medicare patients. In the UK, Forder (2009) looks at the substitution between expenditure on care homes and hospital expenditure, and Fernandez and Forder (2008) find a lower rate of delayed discharges and lower emergency readmission rates in geographic areas where there is more home care and nursing and residential care beds. Gaughin et al. (2015) found that delayed discharges in England were reduced by the availability of care home beds. In all cases however, the quantified substitution effects were relatively small.

To provide some further institutional background, the 192 NHS hospitals in England are paid fixed DRG-type prices for the provision of care for a given population covered by one of the 202 Health Care Commissioning Groups (CCGs), who receive their budget from public finances raised through taxation. Discharged patients requiring social care receive this through the 152 English LAs who provide adult social care through community-based and institutional care in nursing and residential homes, funded by a combination of local and central taxation and user charges at the point of use. Concerns over delayed discharges led to the Community Care (Delayed Discharges) Act (HM Government, 2003) and further funding support, as noted above, within the Health and Social Care Act (HM Government, 2012).

Both Acts oblige LAs and hospitals to coordinate patient discharges from hospital. Hospital patients are only formally discharged from hospital once their condition is stable and they can be safely transferred out of the hospital. Until then, a hospital doctor remains responsible for their care. Once deemed medically fit, NHS patients are only to be discharged once they have an assessment of the support needed to be discharged safely, they are given a written care plan setting out the support required to meet the assessed needs, and assurances are taken that the support in the care plan has been put in place and it is safe for the patient to be discharged. As shown in Fig. 1, delays with patients' discharge assessments and the lack of care outside of hospital account for approximately one fifth and two thirds of all delays in a given year. Discharge policies vary across hospitals, and define amongst other things how patients, carers and professionals are involved in the discharge planning. In England, social care provision is means-tested and this process usually involves a financial assessment of the charges that might be levied from patients for social care services. Approximately 60% of social care users in England pay for services using their own resources, while those on low income are subsidised (Fernandez et al., 2011). LAs are responsible for commissioning any necessary care, and must reimburse hospitals for delayed discharges that they are wholly responsible for.

In the NHS, inefficiencies in the discharge process associated with problems of coordination between health and social care have been discussed in terms of "delayed transfers of care", or DTOCs. Their quantification, however, has proved challenging and is the subject of much debate. An important criticism of DTOC indicators is that they rely on a subjective assessment that a patient is "ready to be discharged", and this assessment reflects differences in clinical and discharge practices across hospitals and between professionals. Whether a patient is seen as ready to be discharged can also reflect other factors, most importantly the quantity and quality of health and social care services available post-discharge, which creates a potential endogeneity problem in models examining the interrelationship between the measurement of DTOCs and hospital and social care exchanges. The indicators also potentially reflect the financial position of a hospital trust, as hospital staff responsible for the coding of the variable have a financial incentive to attribute DTOCs to shortfalls in social care to extract financial compensation from local authorities. Finally, individual-level data about DTOCs have only been available for the NHS since 2013/14 and are characterised by extremely high levels of missing data.

Against this background, our study examines whether issues of coordination between hospitals and LAs determine post-operative lengths of stay for elderly individuals who have undergone a procedure (hip-replacement) and who require care post-discharge. We explicitly consider the hypothesis that as the number of LAs that a single hospital site deals with increases, that hospital's patients will face longer discharge processes and greater post-operative lengths of stay. Specifically, we test whether the post-operative length of stay for patients who have undergone hip surgery is longer for those patients discharged from hospitals who deal with a greater number of LAs or where the hospital faces a greater variability in the number of LAs they discharge to. These hypotheses are motivated by the expectation that hospitals find it difficult to develop efficient joint arrangements with LA social care departments when having to discharge their patients to many and/or varying numbers of local authorities. We expect the coordination of assessment and service commissioning functions, in particular, will be more complex and difficult as they rely on close relationships between

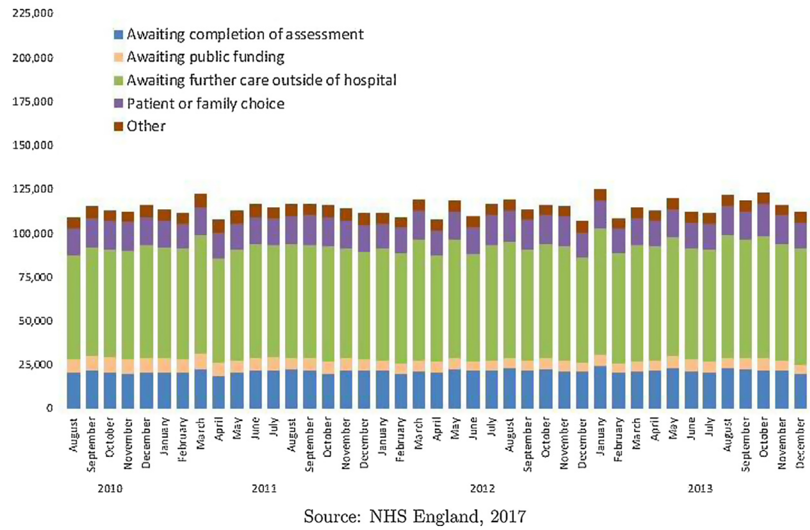

Fig. 1. Number of Delayed Days during the reporting period, Acute and Non-Acute, for NHS Organisations in England by reason for delay. *Source*: NHS England, 2017.

health and social care front line workers and on a good understanding of the local supply of care services for supporting individuals post-discharge. The number of and variation in the LAs a single hospital deals with therefore proxy the increasing uncertainty and complexity arising from coordination of hospital and social care provision.

We outline a queuing model to build our hypotheses about the relationship between numbers and variation in local authorities and post-operative lengths of stay. This queuing model and our empirical strategies are outlined in Section 2. Section 3 provides discussion of the data, while Section 4 presents the results. This is followed by a set of conclusions in Section 5.

2. Model and empirical specification

We outline a queuing model to motivate our contention that increases in the number of LAs and in the variation in the number of LAs being dealt with by a single hospital lead to longer time to discharge. We provide our motivation by drawing on Gaughin et al. (2015) who proposed a model of time from hospital discharge to nursing home as a Markov queuing model, defined in queueing terms as M/M/1.[1] That is, a Markov model where patients ready to be discharged followed a Poisson distribution with a given mean rate or discharge time to a single server for each discharged patient. In our case, we are dealing with a similar but slightly more general and complex problem characterised as an M/G/1 queuing system.

The time to discharge is our focus of interest. We retain a Poisson arrival rate of potentially dischargeable patients (the M arrival stream). Each LA provides a variety of community and institutional care packages, where these social care packages are the bundles of specific services to be produced and delivered to each individual upon discharge. The LA servicing "rate" relates to a process which includes the assessment and identification of the needs of individual patients, the design of the appropriate care package, the commissioning of the care and the actual delivery of the services. This process varies across individuals within each LA and is therefore better represented by an (unknown) distribution, (defined as G). The service rate is therefore stochastic, and of unknown distribution, to better represent the different care service times. This generalises the queuing model for hospital discharge to LA care as an M/G/1 system to reflect that queuing depends on both the arrival rate of potentially dischargeable patients and the LA throughput ("servicing") of any given patient which is subject to variation around an average service time, as represented by the (unknown) distribution (G). Note also that the number of LAs ("servers" in queuing literature terms) for any given potentially dischargeable patient is 1. While any given hospital simultaneously discharges to a number of different LAs ("servers"), each patient awaiting discharge has to go to the particular LA in which that patient resides. That is, there is only 1 LA allocated to each potentially dischargeable patient.

We can use this formulation of queuing to show that, as the servicing times of any LA are independent across individual patients and represented by an unknown distribution (G), times to discharge increase as hospitals deal with greater numbers of LAs. We can also show that time to discharge increases as the variation in LA servicing times grow at the individual LA level, and that variation in the number of LAs any given hospital transacts with is also likely to increase discharge times. We use these findings to aid specification of our empirical model.

To do so, let us define generally the mean care service provision rate as $E(\mu)$ and the variance in this service provision rate within the LA as σ^2, as drawn from this unknown distribution (G). The rate of servicing required to be provided by the given LA in any given time period is then $\rho = \lambda E(\mu)$. This is essentially the average utilisation rate of any given LAs capacity to process patients through needs-assessment to the appropriate care service package and secure and deliver that care.

Defining the average number of potential patients waiting to be discharged as $E(L^q)$ then the average time to discharge for these patients $E(W)$ is given as:

$$E(W) = E(L^q)E(\mu) + \rho E(R) \qquad (1)$$

where the first term is the mean time required to service those due to be discharged to LAs (which includes the patients needs assessment, the design of the package, the commissioning of the care and the actual delivery of the service) and the second term is the time to complete the discharge process of those already in the process of being discharged to the LA system, with $E(R)$ defining the remaining (residual) servicing time of those individuals.

[1] This is conventional notation for a queuing model based on the arrival stream (M), the service times (M) and the number of servers; M/M/1 denotes Poisson arrivals, exponential service times and a single server).

We want to show that the expected time of potentially dischargeable patients to discharge, $E(W)$, depends on both the mean service provision rate, $E(\mu)$, and the variance in this provision rate, σ^2. Use of Little's Law (Little, 1961) allows us to define the numbers waiting to be discharged in terms of the "arrival" rate of potentially dischargeable patients and the average wait for discharge:

$$E(L^q) = \lambda E(W) \tag{2}$$

Combining (1) and (2) gives:

$$E(W) = \frac{\rho E(R)}{1-\rho} \tag{3}$$

which is commonly referred to as the Pollaczek–Khinchin mean value formula (see Grimmett and Stirzaker, 1982). It can also be shown (Grimmett and Stirzaker, 1982) that $E(R)$ can be written as:

$$E(R) = \frac{E(\mu^2)}{2E(\mu)} = \frac{\sigma_\mu^2 + E(\mu)^2}{2E(\mu)} = \frac{1}{2}(cv_\mu^2 + 1)E(\mu) \tag{4}$$

So (3) becomes:

$$E(W) = \frac{\rho \frac{1}{2}(cv_\mu^2 + 1)E(\mu)}{1-\rho} \tag{5}$$

where cv_μ^2 is the square of the coefficient of variation relating to the unknown LA care service provision rate distribution (G).

From (3)–(5) it can be seen that the mean time to discharge of potentially dischargeable patients depends on any given LA's mean service processing and delivery time and the variation around their mean service processing and delivery time. In other words, if a hospital is facing 2 LAs and therefore two (M/G/1) queuing systems, where both LAs have the same arrival rate of potential patients waiting to be discharged and average social care processing and service rates, if one LA has a higher variance in this processing and service rate their patients will experience a higher mean queue size and delay to discharge.

Noting that $\rho = \lambda E(\mu)$ we can re-write (5) as:

$$E(W) = \frac{\lambda E(\mu^2)}{2(1-\rho)} \tag{6}$$

and expressing $E(\mu^2)$ in terms of cv_μ^2 the expected time to discharge can be written as:

$$E(W) = \frac{\rho(1 + cv_\mu^2)}{2E(\mu)(1-\rho)} \tag{7}$$

This clearly shows that, holding all other parameters of the queuing model constant, the mean time to discharge increases linearly in cv_μ^2 at a rate $\frac{\rho}{2E(\mu)(1-\rho)}$. In other words, the impact of cv_μ^2 on lengthening discharge time is magnified as ρ, the LA processing and care package delivery rate, increases.

The types of social care provided by the LA and the demand across individuals for any given type of care are of course liable to differ, as captured by G. This, coupled with the fact that any given potentially dischargeable hospital patient must be served by their LA of residence means that the time and resource costs of processing discharges will vary by LA and individual patient. While different hospitals will behave differently, the clear implication is that increasing the transactions across LAs will tend to lead to increasing discharge times. We now give some rationale for this assumption.

Any given hospital needs to coordinate patient discharges with a number of LAs. From a single hospital's perspective, the overall average time to discharge, $E(W^H)$, across all its potentially dischargeable patients will be a mixture distribution, defined as a weighted sum of the underlying independent distributions defining the discharge times to each LA this hospital is transacting with; that is, a weighted sum of each of the $E(W)$ defined above. As such, the average discharge time at the hospital level will be defined as:

$$E(W^H) = \sum_{i=1}^{N} w_i E(W_i) \tag{8}$$

where the w_i are (non-random) weights ($w_i \geq 0$ and $\sum w_i = 1$) attached to each of the underlying (single LA) discharge time distributions and the $E(W_i)$ are the average discharge times of the patients from each hospital being discharged to a given LA i. It seems reasonable to assume that the w_i reflect the proportion of patients being discharged by a single hospital to any given LA. Depending on the processing and servicing times any given hospital experiences with any individual LA, it may be that a hospital's discharge time increases or decreases as the number of LAs it coordinates with increases. This gives rise to a testable proposition that hospital discharge times are, as we might expect, a function of the number of LAs any single hospital deals with. We pursue this empirically below by testing whether discharge times increase with the variation in the number of LAs a hospital transacts with.

The variance of the mixture distribution, $\sigma^2{}_{W^H}$, defining the average discharge time for each individual hospital is:

$$\sigma^2{}_{W^H} = \sum_{i=1}^{N} w_i((E(W_i) - E(W^H))^2 + \sigma_i^2) \tag{9}$$

Eq. (9) incorporates both the dispersion of mean discharge times of the individual LAs expected discharge time relative to the overall (mixture) mean discharge time and the individual variation around each, given each LAs expected discharge time that a hospital transacts with. Feldmann and Whitt (1998) show that mixture distributions derived from underlying M/G/1 models can be modelled in approximation as a hyperexponential distribution. Such distributions have a number of properties, including the fact that their coefficients of variation are always greater than 1.[2] We would expect given (9) above and the observation that mixture models based on an M/G/1 queue can be associated with coefficients of variation greater than 1, that hospitals transacting across increasing number of LAs will face increasing variation in expected discharge times.

In other words, our heuristic model of the discharge process implies that the time to discharge within any given hospital will be a function of the number of LAs a single hospital transacts with. Based on the reasonable assumption that processing and coordination times will increase as the number of LAs a given hospital transacts with increases and as the variation in the number of LAs a hospital transacts with fluctuates over time, then we might expect the discharge time for that hospital's potentially dischargeable patients to increase also.

Assuming time to discharge to be a random process, the discharge queueing model can be specified as a count process with transition probabilities attached to each state. We can then examine explicitly the implied transition intensities associated with hospital discharge, as defined by the Markov process underlying the queuing model.[3] Focusing on the discharge probabilities we can

[2] Feldman and Whitt (1998) are explicitly concerned with long-tailed distributions, which we can presume will apply to a degree in our case. Certainly as delayed discharges grow the tail of the distribution will grow. In fact the coefficient of variation will equal 1 in such distributions but only for the trivial case where the service rates are always equal across LAs.

[3] Focus on transition probabilities and hazards also adds more information in the modelling of the data through incorporation of time to the event (time to discharge in our case) which a simple Poisson regression, for example, does not. Moreover, the Poisson model, with a split at each unique discharge time, is in fact equivalent to a Cox model, but such a Poisson specification eats degrees of freedom (Royston and

specify an empirical model based on either a single discharge risk or a set of competing risks of discharge. Single discharge destinations seem reasonable if we assume that at any point in time individuals face either discharge or remaining in hospital, with the latter encompassing death within hospital. Empirically, we test whether the probability of discharge decreases, implying the time to discharge increases, with the number of LAs a hospital contracts with and with the variation in the number of LAs a hospital coordinates with over time. Specifying a single discharge hazard will capture this decreasing hospital-LA discharge effect. If on the other hand, it is believed that all hospital discharges are affected by decreasing probabilities of discharge as a hospital negotiates with increasing numbers of LAs, but that different discharge destinations affect the underlying discharge probabilities of an individual being discharged at any point in time differently, then a competing risk model would seem more appropriate.

For the single discharge destination model we adopt a flexible parametric survival model approach, based on the set of Royston–Parmar estimators (Royston, 2002). These parametric models are useful as they allow flexibility in the specification of the underlying hazard function, (and consequently the survival function), through smoothing a baseline cumulative hazard function across a number of linear splines. Specifically, they are not restricted to a single distributional assumption and do not rely on non-proportionality to be imposed. Moreover, they easily incorporate covariates into the specification. These estimators are therefore a more flexible form of specification than the commonly used (but more restrictive) Cox proportional hazards model. Royston and Parmar (2002) outline the generalisability of the approach through transformation of the survival function by a link function $g(\cdot)$ such that

$$g\{S(t:z)\} = g(S_0(t)\}\beta\prime z$$

where $S_0(t) = S(t;0)$ is the baseline survival function and β are parameters to be estimated for a set of covariates z. The approach is to model the logarithm of the baseline cumulative hazard function associated with $S(t;z)$, as a cubic spline function of log time (Royston, 2002). Cubic spline functions are used to generalise the shape of the survival function. Natural cubic splines may be approximated by linear splines through imposing boundary knots and a number of internal knots to define the linear splines. Spline complexity is determined by the number of degrees of freedom (df), which determines the maximum number of internal knots[4]. Actual fitting of the splines can be achieved parsimoniously through comparison of the Akaike information criterion (AIC) (Akaike, 1998) and the Bayes information criterion (BIC) (Schwarz, 1978).

For the alternative competing risks model of hospital discharge, we consider an individual who has had surgery and denote the duration of hospital stay after surgery by t and consider three mutually exclusive discharge destinations: discharge to usual place of residence (incorporating any community-based social care), discharge to nursing home or discharge to residential home. Let $\delta_r = 1$ be discharged to destination r, and 0 otherwise. We model the instantaneous probability, $\lambda(t)$, that an individual will be discharged at time t given that they have survived in hospital until time t, to destination r as:

$$\lambda_r(t) = \lim_{\delta t \to |0} \frac{Pr(t < T \leqslant t + \delta_r = 1 | T \geqslant t)}{\delta t}$$

We model these competing risks using an estimation method proposed by Wei (1989) and Lin (1994) which defines marginal probabilities.

We also empirically test the implications of our conceptual model by fitting a Poisson regression. We do so as a robustness check, given that more information is provided through the time to discharge specification, but to ensure the basic empirical results still hold in a simpler specification. Note, however, that as the Poisson specification models counts of days in hospital, while the time to discharge models are based on probabilities of discharge, we expect parameters to be of opposite sign in the two specifications.

3. Data

We use data on hospital discharge collected on an administrative database by the NHS Health Care and Social Care Information Centre (HCSIC) for the years 2002 to 2013 for patients who have undergone elective hip surgery. Hip surgery is a useful marker condition used to examine health and social care quality for frail and older patients (Boulton et al., 2016). We concentrate on patients over 75 years of age as they are at most risk of needing LA social care following hospital discharge. We further restrict our sample to patients from larger hospitals, with admissions greater than 150 per year, to purge small numbers and as this is where delayed discharges are assumed to be most problematic. After dropping cases seemingly aged greater than 115 years or who had missing confounding variable data this provides complete data on 171,979 elderly patients aged 75 and above during this period.

Given the limitations discussed above of DTOC indicators in the NHS, our empirical model examines variations in post-operative length of stay, a measure which combines the time that a patient takes to recover from the intervention (in our case a hip operation) and the subsequent period of time that the patient spends in hospital until he/she is discharged. Variations in post-operative length of stay reflect therefore both differences between patients' needs and differences in the time it takes to organise the discharge of the patient once he/she has recuperated enough from the intervention. In the empirical model, we control for patient need by focusing on a homogenous intervention (hip operations) for specific age groups, and by including indicators of age, gender, comorbidity, number of diagnoses and count of procedures and specific indicators of complexity (whether the patient suffered a fractured hip, presence of an open wound, urinary tract infection and pulmonary embolism) and of socioeconomic deprivation of the patient's place of residence. We also control for the type of hip replacement carried out (cemented or uncemented) and for potential systematic differences in patient needs between hospitals (e.g. due to targeting effects) through hospital trust and treatment centre fixed effects, and by focusing on hospitals with more than 150 admissions per year.

Our dependent variable returns, for any individual, the probability (hazard) of being discharged at any point in time after having an operation, conditioned on still being in hospital up to that point in time. We account for confounding influences to allow us to test our hypothesis that, in accordance with the queueing model outlined above, hospital discharge time is a function of the number of LAs an individual hospital transacts with. We use counts of the number of LAs any one hospital discharges hip patients to during

Lambert, 2011). Both the Poisson and the Cox models assume proportional hazards, hence our preference for the more general Royston–Parmar models.

[4] Defining $x = ln(t)$ we can define the survival function through a function $s(x)$, based on the log of time, which is approximated by a spline. Defining the boundary knots as k_{min}, k_{max}, if m internal knots are defined within these boundaries, such that $k_1 < \cdots < k_m$ with $k_1 > k_{min}$ and $k_m < k_{max}$ then the natural cubic spline can be written as $s(x) = \gamma_0 + \gamma_1 x + \gamma_2 \upsilon_1(x) + \cdots + \gamma_{m+1} \upsilon_1(x)$ where the jth function of υ is defined for $j = 1, \ldots, m$ as $v_j(x) = (x - k_j)^3_+ - \lambda_j (x - k_{\min})^3_+ - (1 - \lambda)(x - k_{\max})^3_+$ and $\lambda_j = \frac{k_{\max} - k_j}{k_{\max} - k_{\min}}$ and $(x - \alpha)^3_+ = \max\{0, (x - \alpha)^3\}$.

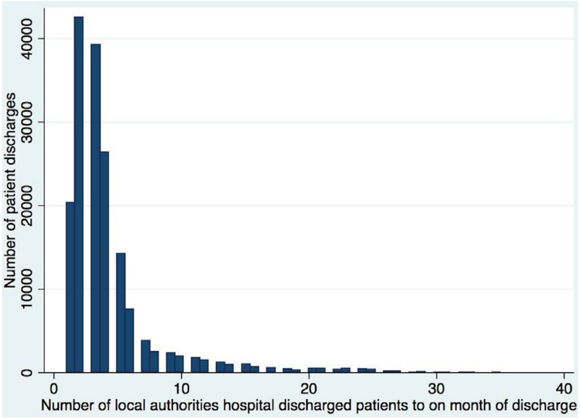

Fig. 2. Distribution across the patients in the sample of the number of local authorities that the hospital site discharged patients to on the month the patient was discharged.

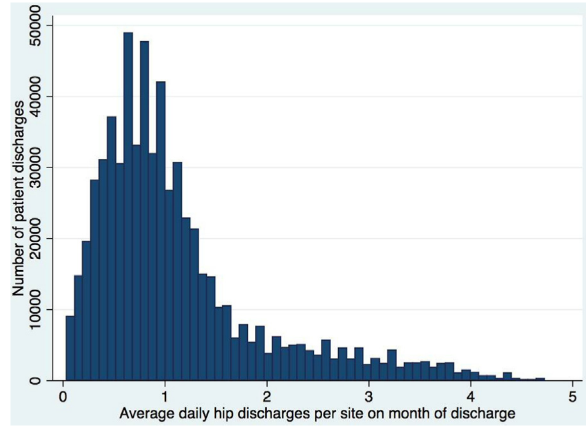

Fig. 3. Average daily hip discharges per month per site.

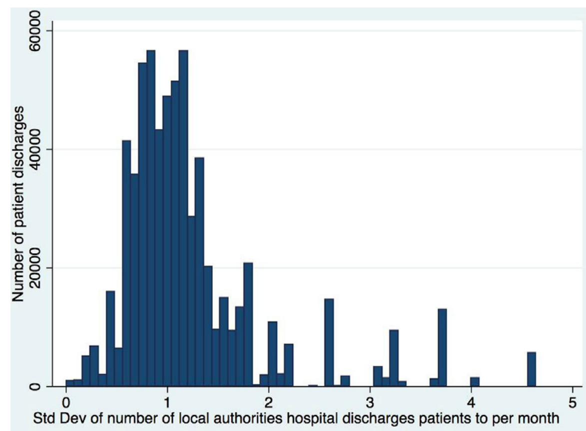

Fig. 4. Distribution of Std Dev of number of local authorities per site per month.

each month as a proxy for this coordination cost.[5] We also explicitly test whether the variability in the number of LAs that a hospital coordinates their discharge processes with is associated with time to discharge. We do so by defining a proxy variable based on the variation (standard deviation) in the number of LAs any one hospital discharges to (and therefore coordinates with) over the period of observation in the data, averaged over a month.

The probability of discharge is conditioned on a set of confounding factors that systematically determine hospital discharge. As well as the set of patient characteristics mentioned above, a number of hospital characteristics (teaching status, whether a Foundation Trust; as the latter have more autonomous management), and variables indicating day of discharge, total number of hip operations performed at each hospital per annum, the average waiting time for hip surgery at each site, the average number of hip replacement discharges per month at each hospital site and the average yearly occupancy rate of the hospital trust were included in the models.

Table 1 gives descriptive details of these data. The mean age of our population is 80 (noting we are only interested in individuals 75 and above) and most are female. The level of comorbidities, on average, is low while most individuals come from a relatively non-deprived background.[6] As noted, we are particularly interested in the number of LAs a single hospital deals with in any given period and the variation in this number of LAs over any given period. On average, hospitals deal with approximately 4 LAs per month in discharging hip patients, although with considerable variation. Fig. 2 reports the distribution of average number of LAs any single hospital site deals with in a given month for our sample of patients. As can be readily seen, this is very skewed, with the vast majority of patients being discharged from hospitals dealing with less than 10 LAs on a given month, but a few from hospitals dealing with considerably more LAs.

To give some context, we also show in Fig. 3 the average daily number of hip related discharges per hospital site for our sample of discharged patients. The figure shows a significant right skew in the distribution, with the large majority of discharges in the sample taking place in hospitals dealing with fewer than 2 discharges per day (averaged on a given month). Finally, Fig. 4 reports on the variation (standard deviation) in the number of LAs a given hospital site deals with per month over the whole time-period covered by the data. The figure indicates considerable variation in the levels of volatility in the number of LAs that hospitals discharge patients to, with the vast majority of discharges in the data taking place in hospitals sites with less than 2 standard deviations in the number of LAs over the period observed in the data. Overall, 368 hospital sites and 165 hospital trusts are included in the analysis.

4. Results

Table 2 presents the main estimates from our empirical analysis based on the Royston–Parmar and competing risks specifications given above. The Royston–Parmar models were run with different numbers of splines applied and tested through the use of the AIC and BIC information criteria. In the event, the coefficient values did not change by much over a range of spline values. Therefore, in trading off parsimony with number of splines, we selected the smallest number of splines which thereafter only minimally affected the AIC and BIC values. This suggested 4 splines.[7]

For the Royston–Parmar models we provided 3 sets of estimates, including and excluding hospital trust and LA fixed effects, for the

[5] Month was chosen as the appropriate unit of time for counting local authorities involved in discharge processes, as daily or even weekly counts did not allow the variation in local authority numbers to be assessed adequately.

[6] The deprivation score is base on an index of deprivation calculated at a small area level covering over 32,000 geographical areas within England, and across seven domains; income, employment, health deprivation and disability, education, barriers to housing, crime and living environment. The area of greatest deprivation is ranked 1 and area of least deprivation 32,482. Individuals are assigned, anonymously by postcode to the relevant area and consequently deprivation ranking.

[7] The results were not affected when the specifications were run with 2, 3 or 5 splines.

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Minimum	Maximum
Age at discharge	80.062	4.109	75	103
Gender: female	0.667	0.471	0	1
Charlson: commorbidity index	1.368	2.229	0	6
Count of diagnoses	3.670	2.349	1	20
Count of procedures	2.475	1.087	1	24
Hip replacement cemented	0.464	0.294	0	1
Hip replacement uncemented	0.219	0.226	0	1
Hip fracture	0.179	0.383	0	1
Open wound	0.006	0.077	0	1
Urinary tract infection	1.135	0.812	0.032	4.724
Pulmonary embolism	0.0003	0.018	0	1
Local deprivation index	0.119	0.093	0	0.96
Foundation trust	0.558	0.497	0	1
Hospital is treatment centre	0.039	0.194	0	1
Number of LAs patients are discharged to per site per month	4.178	3.921	1	35
Volatility LAs: Std Dev of number of LAs per site per month	1.205	0.693	0	4.637
Total yearly number of hip discharges at site	399.586	279.304	1	1355
Occupancy rate hospital trust	84.303	5.826	42.323	98.401
Monthly average waiting time for hip operations (days)	133.021	65.843	1	660
Average daily discharges per site	0.048	0.010	0.032	4.724
LA care home beds (per population 65 plus)	1.135	0.010	0.008	0.082
Discharge day: Sunday	0.017	0.130	0	1
Discharge day: Monday	0.170	0.375	0	1
Discharge day: Tuesday	0.194	0.396	0	1
Discharge day: Wednesday	0.194	0.396	0	1
Discharge day: Thursday	0.197	0.398	0	1
Discharge day: Friday	0.177	0.381	0	1
Number of observations: 171,979				

Table 2
Main results.

	R-P estimates; >74 Trust and LA FEs			R-P estimates; >74 Trust FEs			R-P estimates; >74 LA FEs			Competing Risks; >74 No Trust or LA FEs		
	Coeff.	OR	*Z*	Coeff.	OR	*Z*	Coeff.	OR	*Z*	Coeff.	OR	*Z*
Age at discharge	−0.119***	0.888	(−91.17)	−0.119***	0.888	(−89.82)	−0.117***	0.890	(−91.61)	−0.0584***	0.943	(−95.26)
Gender: female	−0.370***	0.691	(−36.86)	−0.369***	0.691	(−36.63)	−0.361***	0.697	(−36.31)	−0.156***	0.856	(−29.40)
Charlson index	−0.0131***	0.987	(−5.56)	−0.0131***	0.987	(−5.57)	−0.0111***	0.989	(−4.77)	−0.00556***	0.994	(−4.39)
Count of diagnoses	−0.165***	0.848	(−63.01)	−0.164***	0.849	(−62.57)	−0.152***	0.859	(−60.24)	−0.0670***	0.935	(−53.39)
Count of procedures	−0.316***	0.729	(−62.60)	−0.316***	0.729	(−62.25)	−0.315***	0.730	(−64.15)	−0.130***	0.878	(−58.29)
Cemented	−0.627***	0.534	(−33.40)	−0.627***	0.534	(−33.43)	−0.505***	0.603	(−29.71)	−0.169***	0.845	(−19.23)
Uncemented	0.182***	1.200	(6.27)	0.178***	1.195	(6.16)	0.0611**	1.063	(2.54)	0.00816	1.008	(0.64)
Hip fracture	−0.613***	0.542	(−7.74)	−0.612***	0.542	(−7.73)	−0.599***	0.549	(−7.67)	−0.277***	0.758	(−6.21)
Open wound	−1.794***	0.166	(−28.44)	−1.794***	0.166	(−28.32)	−1.818***	0.162	(−29.11)	−0.567***	0.567	(−24.95)
UTI	−1.070***	0.343	(−25.65)	−1.067***	0.344	(−25.55)	−1.070***	0.343	(−25.92)	−0.388***	0.678	(−20.95)
Embolism	−0.913***	0.401	(−3.33)	−0.895***	0.409	(−3.26)	−0.867***	0.420	(−3.18)	−0.301**	0.740	(−2.55)
Local deprivation	−0.710***	0.492	(−12.84)	−0.726***	0.484	(−13.84)	−0.690***	0.502	(−12.68)	−0.483***	0.617	(−18.63)
Foundation trust	0.769***	2.158	(5.32)	0.975***	2.650	(10.57)	0.137***	1.147	(10.83)	0.0307***	1.031	(6.12)
Treatment centre	0.194***	1.214	(4.61)	0.193***	1.213	(4.70)	0.310***	1.363	(10.42)	0.138***	1.148	(9.14)
LAs per month	−0.0102***	0.990	(−2.73)	−0.0100***	0.990	(−2.71)	−0.0378***	0.963	(−12.98)	−0.0196***	0.981	(−13.95)
Volatility LAs	−0.196***	0.822	(−6.35)	−0.192***	0.825	(−6.34)	−0.132***	0.876	(−8.29)	−0.0415***	0.959	(−5.94)
Nb hips per year	0.00152***	1.002	(22.66)	0.00152***	1.002	(22.68)	0.000191***	1.000	(3.66)	0.0000301	1.000	(1.10)
Occupancy rate	0.00276**	1.003	(2.18)	0.00279**	1.003	(2.20)	0.00212**	1.002	(2.19)	0.00152***	1.002	(3.46)
Waiting time site	−0.00969***	0.990	(−90.81)	−0.00973***	0.990	(−89.16)	−0.00997***	0.990	(−98.33)	−0.00404***	0.996	(−99.18)
Average daily disch	0.128***	1.136	(7.21)	0.128***	1.136	(7.22)	0.185***	1.203	(10.73)	0.0934***	1.098	(9.75)
Sunday	−0.377***	0.686	(−9.32)	−0.379***	0.685	(−9.37)	−0.371***	0.690	(−9.25)	−0.158***	0.854	(−7.24)
Monday	−0.304***	0.738	(−13.22)	−0.302***	0.739	(−13.17)	−0.288***	0.750	(−12.63)	−0.0973***	0.907	(−7.28)
Tuesday	−0.403***	0.668	(−17.76)	−0.403***	0.669	(−17.75)	−0.388***	0.678	(−17.27)	−0.111***	0.895	(−8.47)
Wednesday	−0.386***	0.680	(−17.04)	−0.384***	0.681	(−16.95)	−0.347***	0.707	(−15.48)	−0.0944***	0.910	(−7.17)
Thursday	−0.346***	0.707	(−15.38)	−0.347***	0.707	(−15.41)	−0.331***	0.718	(−14.84)	−0.106***	0.899	(−8.04)
Friday	−0.201***	0.818	(−8.83)	−0.200***	0.819	(−8.81)	−0.194***	0.823	(−8.61)	−0.0491***	0.952	(−3.67)
Constant	12.58***		(23.12)	12.58***		(66.96)	12.16***		(24.02)			
(*N*)		171,979			171,979			171,979			171,979	

t statistics in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

population over 75 year old. We specify fixed effects at the hospital trust level (rather than at the hospital site level) in order to control for general (but unobservable) trust management characteristics, while still capturing hospital site level discharge processes through our proxies; the number of LAs dealt with and the volatility measure. Discharges are managed at the site, not trust level, so our proxies capture the correct level of aggregation for discharge practice.[8]

Across all specifications the main coefficients of interest, on the variable giving the number of LAs any individual hospital discharged individuals to ("LAs per month") and on the variable giving the variation in the number of LAs a hospital dealt with on average each month within our period of observation ("Volatility LAs"), remain similar in magnitude, negative and highly statistically significant. The exponentiated coefficients on the Royston–Parmar models return odds ratios, which not surprisingly are significant across all the specifications.[9] The competing risks model returns results which support those of the Royston–Parmar model. The results indicate that as the number of LAs increased the likelihood of being discharged on a given day, conditioned on a given post-operative length of stay being reached, decreases. Similarly, as the volatility (proxied by the standard deviation) in the number of LAs an individual hospital coordinates with increases, the likelihood of being discharged decreases.[10]

Our preferred specification, reported in the first column of Table 2, includes fixed effects on both hospital trust and LAs to capture unobserved heterogeneity. In this specification the coefficient of −0.0102 returns an odds of being discharged of 0.990. Increasing variability in the number of LAs being dealt with, is associated with a coefficient of −0.196 and an odds ratio of 0.822. In other words, as the variation in the number of LAs dealt with by a given hospital increases by 1 standard deviation, the likelihood of discharge for an elderly patient having a hip procedure falls by 0.178.

The other results returned from our core specifications are also meaningful and statistically significant with the likelihood of post-operative discharge falling with increased patient need and complexity (age at discharge, number of co-morbidities, number of diagnoses and procedures, presence of an open wound, urinary tract infection and pulmonary embolism), and with the index of deprivation of the area the patient has been admitted from. We also find that the probability of discharge is lower if the patient is female. The size of the social deprivation effect might respond to a combination of demand and supply-side factors. Socioeconomic deprivation has been associated with multimorbidity that included mental health disorders, and with greater prevalence of limiting long term illness, in particular in urban areas (Barnett et al., 2001, 2012). The indicator might therefore control for unaccounted-for need-related factors. In addition, more deprived areas might be faced with relatively more severe supply side constraints. We test this within our robustness checks in Table 3, and find that the large negative relationship between economic deprivation and the probability of discharge remains even when residential care supply indicators are included in the model.

In terms of the hospital characteristics, Trust Foundation hospitals, which have more autonomous management practices than other hospitals, and treatment centres, which specialise on common elective surgery and diagnostic procedures, are associated with higher likelihood of post-operative discharge, as are hospitals that had a higher yearly volume of hip patients and higher average daily number of discharges in the month of discharge. Taken together, these results suggest that larger hospitals have better discharge practices, a finding that seems intuitive and possibly reflects higher staff to patients ratios and better information management systems in such institutions. A hospital site with greater occupancy rates had larger discharge probabilities, all else equal, possibly reflecting capacity constraints. Having controlled for volume of cases and occupancy rates, lower probabilities of discharge are associated with higher waiting times for admission.

Although not reported here due to space constraints, our results confirm that the splines are parsimonious with our underlying time to discharge data. The log of the transform variable used to impose these linear restrictions is also significant and the value (0.139) indicates that a Cox proportional hazards model is not a good fit to the baseline hazard.[11]

Table 3 reports a number of robustness checks, including the results of the competing risks and Poisson models. We report the results of the various time to discharge models, before turning to the Poisson. We are aware that, given data restrictions, we cannot fully control for supply-side effects. However, we do have data on LA care home bed supply per older population for a sub-sample of our period of analysis (2011–2013). The specification including LA care home beds retains hospital trust and LA fixed effects. Results are given in the first column of Table 3, where it can be seen that although the sample size is considerably reduced, the two coefficients of interest ("LAs per month" and "Volatility LAs") remain negative and the latter retains statistical significance at the 10% level. Indeed, all the variables retain coefficients of similar sign and magnitude to those reported in Table 2. The additional variable, picking up the influence of supply-side effects ("Care home beds") is positive and significant, showing that higher local care home bed supply, as expected, increases the likelihood of post-operative discharge. The second and third columns in Table 3 report the influence of the number of discharges a hospital deals with by sorting our sample into hospitals dealing with small numbers of discharges, less than 1 discharge per day (Table 3 column 2) and hospitals dealing with greater numbers of discharges (more than 1 discharge per day; column 3). In both cases, hospital trust and LA fixed effects are retained. In line with our theoretical model, the larger the number of LAs a hospital deals with the greater is the negative impact on post-operative discharge probabilities.

Table 3 also shows that for hospitals dealing with a low discharge load, the sign on our coefficient of interest ("LAs per month") is in fact switched, becoming positive although insignificant. For the hospitals with larger discharge load, again in keeping with our hypothesis, the coefficient is both negative and significant. The coefficient picking up variability in the numbers of LAs a hospital deals with is everywhere negative, but not always significant. When restricting the specification to the very elderly (over 85 years of age) the coefficients are again negatively signed but not statistically significant, probably due to the drop in sample size. All other variables retain their signs and magnitude in the robustness checks.

The Poisson regression results, noting that the signs on the coefficients are reversed as a result of this specification, support the findings of our time to discharge models. Overall, the extensive robustness checks therefore support our hypotheses, just as our main specifications did, that both the number of LAs a hospital deals with and increasing the variability in the number of LAs a hospital deals with decrease the likelihood of conditional discharge.

[8] Hospital trusts may be spread across a number of sites. The discharge process is generally located at the site level. The ratio of hospital sites to hospital trusts in the data is 2.2.

[9] The odds ratios reported should be interpreted as the relative change in the average probability of discharge at any point in time across our sample associated with a one unit change in the indicator.

[10] The calculated odds from the competing risks model is similar in magnitude to those returned by the Royston–Parmar models.

[11] Royston and Parmar (2002) generalise cumulative hazard function, in the form $ln[-lnS(t)] = ln[-lnS_0(t)] + x\beta$ to $g_\theta[S(t)] = g_\theta[S(t) + x\beta]$ where g_θ is a monotonic increasing function depending on the parameter θ. They go on to show, that under specific transformation as θ tends to 0 the Cox proportional hazards specification is returned. Crudely, as $\ln\theta$ is positive and significant this implies θ is not equal to 0, which would imply non-proportionality. Full table of results are available on request.

Table 3
Robustness checks.

	R-P; >74s old Trust and LA FEs LA supply Coeff	R-P; >74 old Trust and LA FEs > 1 disch./day Coeff	R-P; >74 old Trust and LA FEs 1 disch./day Coeff	R-P; >74 old Trust and LA FEs 1 LA on average Coeff	R-P estimates; >84 Trust and LA FEs Coeff	Poisson; >74 old Trust and LA FEs Coeff
Age at discharge	-.1218938***	−.1163814***	−.1220025***	−.1187058***	−.1308936***	.0250368***
Gender: female	−.4392929***	−.3568836***	−.3912961***	−.3701347***	−.2281225***	.0559684***
Charlson index	−.0104011***	−.0127453***	−.0140218***	−.0130237***	−.014825**	.0017836***
Count of diagnoses	−.2316296***	−.1566623***	−.1809499***	−.1645738***	−.1588302***	.0412998***
Count of procedures	−.34082***	−.3000509***	−.330245***	−.315797***	−.2980287***	.075726***
Cemented	−.4917967***	−.4922013***	−.7617732***	−.6294831***	−.5856112***	.1157933***
Uncemented	−.2152165***	.3461172***	−.113955**	.1832461***	.1815869**	−.0778965***
Hip fracture	−.7473417***	−.5296144***	−.7127235***	−.6208864***	−.5206531***	.0751578***
Open wound	−1.59379***	−1.816316***	−1.782245***	−1.793271***	−1.420153***	.398495***
UTI	−1.088297***	−.9934323***	−1.198288***	−1.067298***	−1.046215***	.2175001***
Embolism	−.6821642	−.6503281*	−1.434372***	−.9097058***	−2.274523***	.1263756***
Local deprivation	−.6374804***	−.5553851***	−.935306***	−.7111279***	−.7096423***	.1676499***
Foundation trust	1.087609***	.8156675***	.9682986***	.7660883***	.6250194	−.1706784***
Treatment centre	.6177007***	.3457711***	.5244533***	.1919757***	.2545066**	−.0421134***
LAs per month	−.0100534	−.004471	−.0089363*	−.0099782***	−.0215416**	.0022511***
Volatility LAs	−.1121397	−.2330639***	−.1136309	−.207738***	−.0255451	.0397061***
Nb hips per year	.0003911***	.0022303***	.0014188***	.0014989***	.0011038***	−.0003586***
Occupancy rate	−.0002593	.002792	.0013493	.0025823**	−.0010878	−.0005668**
Waiting time site	−.0018218***	−.0091715***	−.010159***	−.00972***	−.0085163***	.0019574***
Average daily disch	.0685154**	.1055246***	.1280968***	.1274907***	.1281471***	−.0220346***
LA care home beds	30.66764***					
Sunday	−.2909044***	−.4572312***	−.1920133***	−.3746129***	−.5435577***	.0820822***
Monday	−.3145687***	−.3311697***	−.2492664***	−.3039912***	−.3997607***	.0658482***
Tuesday	−.3862319***	−.4090366***	−.3650405***	−.402208***	−.4132085***	.076655***
Wednesday	−.468752***	−.4014352***	−.345495***	−.3845735***	−.3279173***	.0752159***
Thursday	−.4588319***	−.361774***	−.3052667***	−.3463889***	−.2830897***	.0756808***
Friday	−.2576886***	−.1983473***	−.184181***	−.2004396***	−.183419***	.0420064***
Constant	.1059066***	.1367946***	.1131574***	.1307605***	.2426472***	
(*N*)	55,172	98,647	73,332	171,613	26,429	171,979

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

5. Conclusions

Given the emphasis on increasing efficiency through improving the integration of health and social care in the recent reforms of the NHS in England, there has been remarkably little attention to this topic in the economics literature. There are a small number of studies that attempt to quantify the degree of substitution that exists across health and social care provision. The general finding being that, while there is a degree of substitution across these forms of care, it is small in magnitude. There has been little exploration, however, of the mechanisms that may support or hinder integration and lead to different levels of substitutability.

An obvious means of integrating care is to improve the coordination of hospital discharge procedures, both through greater availability of adult social care, for example increasing home helps, nursing and residential home beds, and through improved coordination in the design and commissioning of this care. The importance of coordinating needs assessment and care planning processes effectively is most acute at the points of transition between care systems, such as when patients with social care needs are being discharged from hospital. If patients are better managed with respect to their social care support, quicker discharge ought therefore to improve hospital throughput.

This paper provides evidence that coordination problems between hospital providers and LA social care departments, as measured by the impact of hospitals transacting with increasing numbers of and variation in LAs in discharging elderly patients, do impose a real cost on the NHS. The analysis confirms that coordination and contracting issues between hospitals and LAs are a major concern, as noted in the Public Accounts Committee report (2016/17) on delayed discharges. Our results suggest modest impacts on post-operative length of stay as the number of LAs that hospital sites deal with increases, but a larger impact as the variation in LAs dealt with increases.

Our empirical analysis allows us to quantify the impact on hospital use of the number of, and variability in, hospital-LA relationships by using our results to predict their impact on post-operative lengths of stay, holding other factors in the model constant. Taking the impact of increasing numbers of LAs dealt with first, within our sample of elderly patient discharged after elective hip procedures, hospital sites are observed to deal with 4 LAs per month on average. Using our preferred model (reported in the first column within Table 3 and incorporating hospital trust and local authority fixed effects), our estimates would suggest that a doubling in the average number of LAs that each hospital deals with (i.e. from 4 to 8), would only lead to a 1% increase in post-operative length of stay. The small magnitude of this effect implies that, for a given level of volatility, hospitals are able to adapt their discharge processes over the long-run to accommodate increasing numbers of partner LAs. This finding is in line with the modest reduction in discharge times achieved as the supply of care home beds increases within a given locality reported by Gaughin et al. (2015).

The impact on post-operative length of stay that the increasing variation in LAs dealt with by a hospital is significantly larger. This is important given that, as shown in Fig. 4 which considers elderly hip patients alone, this variation may be considerable. Assuming first, that there is no variation in the number of LAs that a hospital deals with over the study period, (i.e. setting the indicator of standard deviation in the number of local authorities to zero) the model predicts (holding all other variables at their observed levels) an average of 8.21 days of post-operative stay across the study sample. This “no variation baseline” post-operative length of stay can then be compared with the post-operative stay predicted using the average observed level of variation in the number of LAs faced by hospital sites in our sample. Continuing to hold all other variables in the model constant, the average observed level of variability in the number of LAs dealt with by each hospital in the sample is associated with a predicted average post-operative length of stay of 8.64 days. That is, approximately an additional half day (0.43 days) in the discharge process for each patient relative to the "no variation baseline" level. We can extrapolate this effect to quantify the aggregate impact of variability in LA destination following discharge on the wider NHS population. Applying the 0.43 extra days (the 8.64 minus 8.21 days) to the total 4.4 million per year hospital admissions of over 75 year olds in England, would result in an additional 1.9 million hospital days per year. A crude monetary value of these additional hospital days can be approximated using the average excess bed-day cost for elective hip fracture patients with a single operative procedure, given by NHS Reference Costs as £226.66 per patient in 2016/17. Per patient, the impact of the observed variability in LAs dealt with, through the impact of longer post-operative stay would therefore be on average an additional £111 per discharge, which aggregated across the total NHS admissions for over 75s would correspond to £430 million per year. This estimated additional 0.43 days in post-operative length of stay represents an average effect for all patients in the sample, including those that do not require any professional support post-discharge. It is of course likely that significantly longer delays will occur for the more frail patients requiring significant levels of formal social care support post-discharge.

One means of attempting to quantify the impact on hospital sites subject to the greatest variations in the number of local authorities they discharge patients to is to assume a level of 2 standard deviations above the mean variation. Other factors being held constant, this level of variation results in an additional 0.84 days added to post-operative stay relative to the "no variation baseline" stay. That is, almost double the effect size. Our results suggest then, that hospitals appear to find it increasingly challenging to put in place effective joint arrangements as they deal with greater variation in the number of local authorities with which they coordinate discharges through time. We presume this reflects the increased costs associated with setting-up appropriate and stable coordination systems and generally establishing strong inter-organizational relationships, which have been recognized as critical for achieving effective care coordination (Bolland and Wilson, 1994).

While an obvious conclusion might be reached that to achieve the necessary efficiency savings NHS hospitals should be incentivised to deal with small number of LAs, such a policy would require a significant reorganization of the geographical boundaries of health and social care organizations in England, or unrealistic changes in the admission (as this dictates the LA the patient is discharged to) and discharge policies regarding the patient's destination post-discharge. Moreover, our results emphasise the impact of variability and thus suggest that a more productive strategy might concentrate on the streamlining of discharge procedures and processes, for instance through investment in information sharing systems covering patients care needs and the availability of social care supply at the national level. The development of national databases providing a "live" picture of care provider availability seems particularly important given the distribution of factors associated with delayed hospital days reported in Fig. 1. Our results also beg the question of whether hospital payment structures in England should reflect the complexity of local discharge arrangements, and specifically whether compensation should be provided to hospitals facing greater challenges in the coordination of needs assessments, care planning and service commissioning across health and social care.

The full efficiency consequences of changes in post-operative length of stay are unclear, however. For example, it is unlikely that reductions would lead to hospital cost savings given existing waiting lists, and further research is required to understand the full cost implications for community health and social care services of alternative discharge arrangements and associated throughput decisions. Earlier discharges would require additional primary care and LA resources. Whilst current UK policy initiatives are considering the resource consequences of these issues, the overall welfare effects of different discharge arrangements remain undefined.

There are three specific limitations worth considering when drawing policy implications from our analysis. First, we recognise that post-operative lengths of stay do not specifically measure delays in the discharge process, although we could expect post-operative stays and delayed discharges to be strongly correlated. At present, it is difficult to quantify the degree of correlation or even rely on the existing individual-level indicators of delayed transfers of care in NHS hospitals because of the high levels of missing data, problems with the reliability of the coding process and the limited time period for which they are available. Currently, therefore, post-operative lengths of stay represent a more reliable indicator for examining delayed discharges, but we recognise they are a proxy. The second important feature of the analysis is the fact that our analysis focusses on hip procedures. Although hip fractures are commonly used as a marker condition for examining health and social care quality for frail and older patients, it is clear that our estimates do not represent the average effect across the whole population of older NHS acute care patients. Future analyses should explore the impact of hospital site-local authority variability for different health conditions, and in particular for non-elective procedures which are likely to involve greater complexity in the design and implementation of post-discharge support plans. Finally, it is worth reflecting on the nature of our indicators of coordination complexity across health and social care organisations during the hospital discharge process. Our results highlight the importance of such complexities by using as proxies the number and variability in the number of local authorities involved in the discharges from hospital sites. Although our theoretical model provides a rationale for the use of these indicators, and a clear set of hypotheses to be tested empirically, further attention should be paid to the measurement of coordination failures, and the relative importance of specific problems in needs assessment, care planning and/or service commissioning. The fact that we find significant effects attributed to the variables that we have used to proxy these complexities provides support to the importance of these issues in defining hospital and LA discharge relations.

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