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Private ownership and hospital efficiency

Santiago Palacio-Ciro, Luigi Siciliani, Peter Sivey

CHE Research Paper 204

Private Ownership and Hospital Efficiency

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This study uses anonymised administrative data from Hospital Episode Statistics accessed through the NHS England Secure Data Environment/York Data Safe Haven.
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Ethics approval
The analysis was conducted under the relevant data access approvals and data-sharing agreements. As the study involved secondary analysis of anonymised routinely collected data, separate ethical approval was not required.

Conflicts of interest
No conflicts of interest were reported by the authors.

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Abstract

Health systems across countries combine public and private providers that often compete for publicly funded patients. Economic theory predicts that private providers may face stronger incentives to operate more efficiently. We test this hypothesis by estimating the causal effect of hospital ownership on length of stay (LOS), a common indicator of hospital efficiency. To account for unobserved patient heterogeneity, we instrument hospital ownership with differential distance to the nearest public and private provider. Estimation is conducted using a two-part model within a two-stage residual inclusion framework. In the first part, we use a probit model to estimate the probability of an overnight stay. In the second part, we use a negative binomial model for inpatient LOS. This specification allows us to distinguish differences in provider behaviour in overnight admission decisions from differences in the management of inpatient stays. We analyse administrative data on 596,852 publicly funded admissions for planned surgical procedures in orthopaedics, general surgery, and gynaecology in England between April 2023 and March 2024. The instrumental variable estimates indicate that private providers have lower inpatient LOS by approximately 0.58 days. By contrast, we find no significant effect of hospital ownership on the probability of an overnight stay. Private providers also exhibit lower 30-day emergency readmissions, by 0.37 percentage points under the instrumental variable approach. Separating day-case and inpatient processes is therefore important for understanding how ownership shapes provider behaviour across related margins of care. Our findings suggest that private-sector participation in elective care could improve efficiency without compromising quality.

Keywords: Hospital ownership, length of stay, efficiency, quality, two-part model, 2SRI.

1. Introduction

The configuration of the hospital sector across countries is characterised by the coexistence of public and private providers, which often compete for publicly funded patients (Anderson et al., 2025; Maresso et al., 2023; Molander, 2025). However, the degree of public-private mix varies markedly across health systems. In OECD countries such as Colombia, Germany, and Japan, hospital ownership is predominantly private, whereas in Denmark, Sweden, and the UK it is largely public, with fewer than 20% of hospitals privately owned. The public-private mix is more balanced in Australia, France, and Italy (Dixit & Sambasivan, 2018; Katori, 2024; Montagu, 2021; World Bank & IFC, 2019). The involvement of the private sector has increased over time. In England, initial expansions of private provision in publicly-funded elective care followed pro-competitive reforms introduced in the mid-2000s which were aimed at improving efficiency. More recently, the National Health Service (NHS) has increasingly relied on private providers to meet elective care backlogs (Fletcher et al., 2024). Private providers accounted for 5.6% of NHS-funded elective activity prior to COVID-19, rising to 7.5% in 2022/23 (Nuffield Trust, 2024).

As private sector participation expands, it becomes increasingly important to understand how hospital ownership affects provider behaviour. A central argument advanced in favour of private sector involvement is efficiency. Length of stay (LOS) has been commonly used as a proxy for efficiency and viewed as a mechanism for cost containment, given its direct link to treatment costs, bed capacity, and patient outcomes (for example, Cooper et al., 2018; Gutacker & Street, 2018; Kruse et al., 2018; Kulinskaya et al., 2005; Martin & Smith, 1996; Takaku & Yamaoka, 2019). Although healthcare providers in England operate under the same payment scheme, ownership types face different incentives to translate cost reductions into organisational gains. In theory, private providers have stronger incentives to pursue strategies to contain costs (Bjorvatn, 2018; Brekke et al., 2012; Duggan, 2000; Glaeser & Shleifer, 2001; Sloan et al., 2001), since they can retain any surplus made when fixed prices exceed costs. Public providers, by contrast, face softer budget constraints. To maximise profits, private providers may pursue greater efficiency through higher day-case rates and shorter inpatient stays. Nonetheless, such behaviours could also reflect cream-skimming (Ellis, 1998). Moreover, if cost-cutting practices such as LOS reductions are predominantly observed in one provider type, this may raise quality concerns, underscoring the need to assess whether efficiency gains come at the expense of patient outcomes.

In this study, we use administrative data to investigate how public and private providers in England differ in their management of hospital LOS. The study uses a large sample of publicly funded elective admissions in orthopaedics, general surgery, and gynaecology between April 2023 and March 2024, treated across public and private hospital sites. We distinguish day cases from overnight stays in order to understand how hospital ownership affects provider behaviour across the two margins of LOS. These margins are shaped by distinct reimbursement incentives under the NHS payment system, which financially favours same-day discharge (NHS England, 2025b). These incentives, alongside clinical guidelines promoting day cases (e.g. National Day Surgery Delivery Pack), may induce different organisational responses across ownership types. Throughout the analysis, we account for both observed and unobserved patient characteristics that may vary by ownership. Publicly funded patients can be treated by either public or private providers. The latter providers include private not-for-profit and private for-profit. However, we restrict our attention to public and private because in the English NHS most private providers are for-profit (Crothers et al., 2022).

To investigate the differences in LOS between public and private providers, we implement a two-part model (2PM) that separates same-day discharge from intensity of utilisation among patients who stay overnight. Specifically, the first part comprises a probit model that captures the probability of an overnight stay, and the second part uses a negative binomial model to test for differences in inpatient LOS.

There is evidence indicating that patients treated by private providers differ substantially from those treated in public settings, and the differences in health outcomes and efficiency between ownership types could therefore be mediated by differences in their patient casemix. For example, several studies suggest that public providers treat more complex patients than private providers (Browne et al., 2008; Chard et al., 2011; Cooper et al., 2018; Kelly & Stoye, 2020; Street et al., 2010). To account for unobserved differences in casemix, we adopt an instrumental variable approach that allows us to estimate the causal effect of hospital ownership on LOS. This consists of a two-stage residual inclusion (2SRI) approach, which accommodates the non-linear structure of provider choice, probability of an overnight stay, and inpatient LOS. We exploit the differential distance between the nearest public and private providers as an instrument for hospital ownership.

The key findings are as follows. The results from the 2PM-2SRI approach indicate that inpatient LOS in private providers is 0.58 days shorter relative to public providers. Without correcting for unobserved differences in casemix, the effect is overestimated by roughly 33% (relative to the non-instrumented estimates). Instead, we find no statistically significant differences between public and private providers in the probability of an overnight stay. Heterogeneity analysis shows that LOS in private providers is 6% shorter relative to non-teaching public providers, and 71% shorter relative to teaching public providers. This suggests that pooling teaching and non-teaching public providers masks important heterogeneity when comparing public and private providers. One possible reason for the shorter inpatient LOS in private providers is that they provide lower quality of care. However, we find that emergency readmissions are lower in private hospitals once we control for observed and unobserved casemix, by 0.37 and 0.53 percentage points, respectively. More broadly, the findings show how ownership affects treatment intensity through selective responses across margins of utilisation.

Our study makes four contributions to the literature on provider behaviour and the public-private mix of healthcare provision in publicly funded health systems. First, we model LOS as a two-part process that distinguishes between the probability of staying overnight and inpatient LOS conditional on overnight admission. This distinction matters in settings where day cases are highly prevalent and where same-day discharge involves different organisational decisions and incentives from overnight admission. In doing so, we depart from most of the literature, which treats LOS as a single process, typically using log transformations to address skewness (Farrar et al., 2009; Meng et al., 2021; Shmueli & Savage, 2014; Siciliani et al., 2013; Yau et al., 2003), or excludes day cases altogether (Herr, 2008; Kulinskaya et al., 2005). Our approach aligns with the NHS payment structure, which actively incentivises the management of patients on a day-case basis through instruments such as *Best Practice Tariffs* (Allen et al., 2016; Gaughan et al., 2019; Kreutzberg et al., 2024; NHS England, 2025b).

Second, we account for unobserved patient heterogeneity across types of providers, in line with Anderson et al. (2024) and Moscelli et al. (2018) in the English context. Unlike these studies, we implement a 2SRI approach, which allows us to address endogeneity in a non-linear framework where LOS is a count outcome and the choice of a private provider is a binary endogenous variable. To our

knowledge, this is the first study to jointly model both margins of LOS within a causal inference framework.

Third, the scope of the analysis goes beyond hip and knee replacements, which have been the focus of some previous studies in England (Anderson et al., 2024; Beckert & Kelly, 2021; Chard et al., 2011; Cooper et al., 2018; Fletcher et al., 2024; Gutacker et al., 2016; Kelly & Stoye, 2020; Kirkwood et al., 2024; Siciliani et al., 2013, 2025). We use a set of 70 planned surgical procedures across three high-volume clinical specialties. This wider clinical coverage enhances the generalisability of our findings across the elective care spectrum.

Fourth, we investigate the extent to which public and private providers differ not only in LOS but also in quality of care. Reductions in LOS may reflect efficiency gains, where patients are safely discharged sooner because of better organisation and more effective clinical processes. Conversely, shorter stays may come at the expense of post-discharge outcomes if patients are discharged before the benefit of treatment is realised, potentially reflecting skimping on quality. Quality-efficiency trade-offs have been documented in the literature on hospital performance (Brekke et al., 2021; Bueno et al., 2010; Carey & Lin, 2014; Duggan, 2000; Heggestad, 2002; Martin et al., 2016; Westert et al., 2002). We empirically address this trade-off by employing an instrumental variable strategy for both emergency readmissions (in line with Moscelli et al., 2018) and LOS. Thus, we test whether ownership-related differences in resource use are achieved without compromising quality.

1.1. Related literature

A few studies have investigated the effects of hospital ownership on LOS. The evidence is mostly from Europe and the US, with mixed findings. In England, Siciliani et al. (2013) and Crothers et al. (2022) found that private hospitals have shorter LOS than public hospitals. They used linear, quantile regressions, propensity score matching, and Cox proportional hazards models, controlling for observable patient heterogeneity. The first study analysed elective hip replacement, and the second one covered 18 common surgical procedures, including hip and knee replacements. Using a difference-in-difference approach, Cooper et al. (2018) found that the entry of for-profit surgical centres in England was accompanied by reductions in the pre-surgery LOS for knee and hip replacement surgery at nearby public hospitals. Their analysis of post-surgery LOS concluded that this component was not affected by the entry of surgical centres.

Several studies comparing public and private hospitals on quality and resource utilisation have emphasised that unobserved patient heterogeneity can lead to omitted variable bias (Grabowski et al., 2013; Lien et al., 2008; Moscelli et al., 2018; Moscone et al., 2020). To address this, Anderson et al. (2024) used an instrumental-variable approach to compare pre-operative and post-operative LOS for hip and knee replacement in private and NHS hospitals. The instrument was the differential distance between the nearest NHS and private hospital. They found that patients provided with private elective care were associated with increased post-operative LOS. In contrast, they found no significant differences in pre-operative LOS.

In the US, Bowblis et al. (2016) used a 2SRI approach with differential distance to the provider as the instrument, to examine the causal effect of the profit status of skilled nursing facilities on LOS. They found that profit status does not affect LOS. The range of procedures analysed was general post-acute care, stroke and hip replacement. In contrast, Akintoye et al. (2017) suggested that for-profit hospitals in the US have shorter LOS. They did not control for unobserved patient heterogeneity.

Using state-level data from the US, Villa & Kane (2013) analysed the implications of converting public hospitals to private ownership on hospital performance. Following privatisation, they found significant reductions in the average LOS, indicating that privatised hospitals may operate more efficiently; these findings are similar to that found by Kannan et al. (2023), who investigated the changes in patient outcomes associated with private equity acquisition. In their case, they implemented a difference-in-difference approach using 100% Medicare Part A fee-for-service claims from 2009 to 2019.

In Australia, Meng et al. (2021) examined variation in LOS for hip replacement between public and private hospitals via a Bayesian hierarchical random coefficients model with a trend. They suggested that public patients stay in the hospital for shorter periods than private patients. They argued that this shorter LOS is associated with lower quality, where patients treated by public hospitals are discharged earlier but likely without receiving care proportional to their needs, which is known in the literature as 'quicker but sicker' (see Kosecoff et al., 1990; Martin et al., 2016). In Japan, Kato et al. (2014) analysed the relationship between hospital ownership and LOS. They found that public hospitals achieved lower LOS than private and national government providers, attributing this to their stronger alignment with cost-containment policies.

2. Institutional setting

Hospital treatment provided by the English NHS is tax-funded and free at the point of use. The NHS is managed by the Department of Health & Social Care and locally administered by 36 Integrated Care Systems (Department of Health, 2024; NHS England, 2026). The health system operates on a two-tier model comprising the NHS and a private sector. Most private providers treating NHS patients are owned by for-profit organisations, but there are also a few that operate on a not-for-profit basis (e.g., Nuffield Health, BUPA). Public hospitals are run by organisational units called NHS Trusts or NHS Foundation Trusts, which have greater financial flexibility and the possibility to teach and do research, under teaching status, or specialise in more specific treatments, under specialist status (Bosque-Mercader & Siciliani, 2023).

Since the mid-2000s, the English NHS has experienced a series of market-based healthcare reforms. Predominantly, these have consisted of outsourcing health-care services to the private sector, the adoption of a prospective payment system, and interventions enhancing greater patient choice. For instance, in April 2002, the Labour Government announced a plan to support the establishment of several privately operated surgical centres, known as Independent Sector Treatment Centres (ISTCs). These aimed at increasing capacity for elective care delivery (Cooper et al., 2018). The premise was that if new providers specialised in elective procedures with high demand and low complexity, then greater efficiency in the delivery of healthcare could be achieved (Appleby et al., 2003). The first ISTCs were placed according to local waiting times and the identification of capacity gaps across the country (Anderson, 2006; Aragón et al., 2022; Naylor & Gregory, 2009). In June 2023, NHS England published the Elective Recovery Taskforce Implementation Plan, which aims to boost the private hospital sector's capacity to tackle NHS waiting lists (Department of Health, 2023).

The activity-based payment system for hospitals was introduced in 2003. Under a national rate tariff scheme, the prices for the services provided by both NHS and private hospitals are fixed based on the Healthcare Resource Group (HRG) for the episode of hospitalisation. In terms of LOS, for example, these prospective payments create incentives to reduce LOS to cut costs, as providers can retain any surplus made between actual expenditure and the HRG payment (Propper et al., 2006). Precisely,

earlier causal evidence showed that the adoption of this HRG system led to reductions in LOS (Farrar et al., 2009).

Since January 2006, NHS patients have been offered a choice of hospital at the point of referral for almost all elective treatments, allowing them to access either publicly or privately delivered care (The Kings' Fund, 2010). Explicitly, in 2009, the NHS Constitution for England established that patients "have the right to make choices about the services commissioned by NHS bodies and to information to support these choices". Nevertheless, the demand for elective care is regulated through primary care gatekeeping. Patients first register with a GP of their choice and can only receive elective care if they are referred by their GP.

Public hospitals provide most of the secondary care in England. However, the aforementioned pro-competition reforms have intensified the participation of the private sector in the delivery of NHS-funded elective care in recent years in England. While in 2017/2018 private providers accounted for around £8.7bn of the overall NHS expenditure, in 2023/2024 it was around £12.4bn (Department of Health, 2024). For every ten elective procedures funded by the NHS in 2023, one was conducted by private hospitals (Anderson et al., 2024). In some common elective procedures, the proportion of publicly funded care provided by the private sector is substantially larger. For instance, in 2021/2022, private providers conducted around half of the total cataract repairs, hip and knee replacements (The Nuffield Trust, 2023).

NHS System Scheme (formerly National Tariff) sets out how healthcare providers are paid for NHS-funded care. In our year of analysis (2023/2024), national tariff prices were based on 2018/19 cost and activity data and calculated as the weighted average of the day case and inpatient prices. Public providers were paid under a blended payment, consisting of block-based agreements and activity-based payments at the national HRG tariff. Private providers were paid under an activity-based payment, at the same HRG tariff. Contract values between commissioners and providers are agreed at the start of a contracting period. For those under the activity-based payment scheme, the payment is adjusted one month after the clinical coding information is completed. In addition to the national tariff, a best practice tariff is applicable if the provider meets the relevant eligibility criteria (HFMA, 2024; NHS England, 2023).

3. Data

3.1. Sample and data source

We use data from the NHS England Hospital Episode Statistics (HES). This includes inpatient data of publicly funded care provided by the NHS and private providers. We focus on elective procedures carried out in England between 1 April 2023 and 31 March 2024. This analysis is conducted at the level of admissions[1] and HRG4 (fourth-character HRG).

We focus on three clinical specialties: trauma and orthopaedics, general surgery, and gynaecology. These specialties exhibit both longer LOS and high volumes of surgical procedures delivered by private providers. We restrict our analysis to planned treatments (HRG4) that, in 2023/24, recorded at least 30 observations for each provider type and had an overall day case rate below 95%. Table A1 lists

[1] We analyse the continuous stay of a patient within a particular hospital site, which ends when they are discharged from the facilities of that provider. Therefore, it does not include transfers to other providers.

every HRG that meets these criteria, together with total volume, the private sector share, and the proportion of day cases.

Other specialties also feature substantial private-sector activity—ophthalmology and community dental services, for example—but their day-case rates are virtually 100%, leaving no variation in LOS. By contrast, specialties such as cardiology and neurology exhibit day-case heterogeneity, but private provision accounts for less than 3% of admissions. Therefore, they are not suitable for this analysis and were omitted from the study.

3.2 Hospital length of stay

LOS—our outcome variable—is measured as the difference between the dates of a patient's hospital admission and discharge. It reflects the number of days a patient stays in a single hospital for a continuous sequence of care. We remove outliers from the sample by excluding patients whose LOS is above the 99th percentile of LOS. As a result, admissions with LOS above 29 days are removed from the analysis.

Figure 1 and Figure 2 illustrate the distribution of hospital LOS in public and private elective providers, respectively. LOS is skewed to the right, with a small proportion of patients having a long LOS. We also observe a higher proportion of day-case patients in the public sector (49% vs 44%).

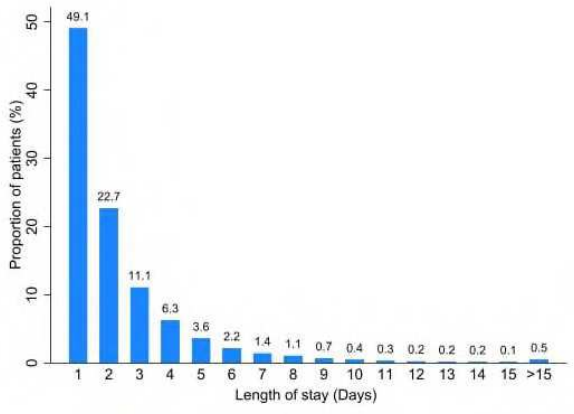


Figure 1. Distribution of length of stay in elective care delivered by public providers.

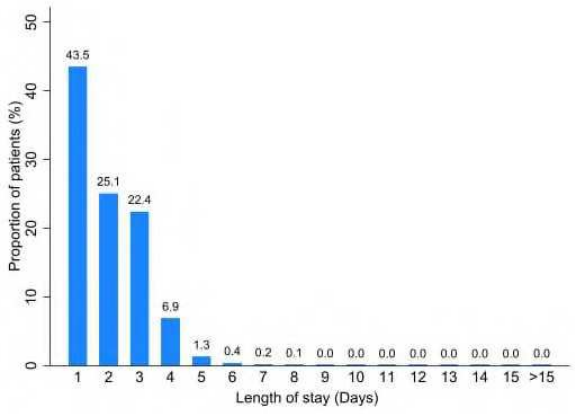


Figure 2. Distribution of length of stay in elective care delivered by private providers.

3.3 Covariates

Hospital ownership is the key explanatory variable, which is a dummy variable equal to one if the hospital is private (known as the Independent Sector) and equal to zero if public (NHS Trust). In this analysis, providers are hospital sites. Hospital ownership is assigned using the HES *Protype* variable, which classifies the type of healthcare provider. We code as public providers all sites identified in HES as part of an NHS trust or NHS foundation trust. We code as private providers all sites classified as part of the independent sector or as a treatment centre at an independent sector provider site. We cross-checked this classification against the two Excel lists of NHS Trusts and independent sector sites published by NHS England Digital.

To control for observed differences in casemix, we include a rich set of control variables. These range from sociodemographic to clinical characteristics, such as age, sex, ethnicity, level of income deprivation, rurality, comorbidity burden, and the number of any publicly funded emergency

admissions in the 365 days preceding the elective procedure. To account for non-linear effects in age, we categorise it into ten groups: 0-17, 18-49, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, 85+ years. Ethnicity is classified into five categories: White, Asian, Black, Mixed, and Other/Unknown.

We use the Index of Multiple Deprivation (IMD) version 2019 as a proxy of socioeconomic status at the Lower Super Output Area (LSOA)[2] level. It measures the relative levels of deprivation across seven domains: income, employment, education, health and disability, crime, barriers to housing and services, and living environment (Ministry of Housing, 2019). This is grouped into quintiles, where the first quintile represents the most deprived areas and the fifth quintile the least deprived areas. The rurality indicator was constructed based on the 2011 rural-urban classification (RUC2011) produced by the Office for National Statistics (ONS), considering each patient's LSOA of residence[3]. To control for comorbidity burden, we use the individual Elixhauser comorbid conditions, represented in 30 dichotomous variables.

3.4 Distance to providers

Two distance variables are the main inputs we use to construct the instrument, addressing the endogeneity associated with the selection of one type of provider: 1) the distance from the patient's residence to the closest public provider; and 2) the distance from the patient's residence to the closest private provider. We use the straight-line distance between the weighted centroid of the patient's LSOA of residence and the nearest public and private sites (in kilometres). The coordinates linked to each site are obtained using the postcodes of NHS organisations and non-NHS organisations published in the ODS portal and merged with the ONS postcode data. Here, we ensure that the choice of provider is a function of the distance within the same surgical procedure (distance is anchored to each HRG).

We then compute our instrumental variable as the difference in distances from the patient's residence to the nearest public and private healthcare providers. We remove the most extreme 1% of the differential distance observations[4], as outliers in this variable can diminish the relevance of the instrument in the prediction of the choice of provider.

The estimation sample includes 596,852 hospital admissions across 70 planned HRGs in trauma and orthopaedics, general surgery, and gynaecology. Data processing, statistical analyses, and estimations are all performed using the software R, V.4.4.1, and Stata V.18 within the University of York's Data Safe Haven—an ISO 27001-certified environment for working with sensitive data.

[2] As of December 2011, patient's LSOA11 is assigned based on their postcode of residence at diagnosis.

[3] https://www.ons.gov.uk/methodology/geography/geographicalproducts/ruralurbanclassifications/2011ruralurbanclassification

[4] The most extreme values occur when the nearest public provider is substantially closer to the patient's residence than the nearest private provider (left tail Figure A1).

4. Methods

4.1. Empirical model: two-part model

The distribution of LOS suggests that a high proportion of patients are treated as a day case in both public and private providers. While private providers have lower LOS, on average, public providers have a higher proportion of day cases (see Figure 1 and Figure 2). This motivates the use of a 2PM which allows to investigate variability in the LOS along two margins by ownership type (Cragg, 1971; Duan et al., 1983; Mullahy, 1986, 1998; Mullahy & Norton, 2024). The first part captures the probability of an overnight stay, and the second part models the number of days conditional on having at least one overnight stay. The participation decision (whether the patient stays overnight) and the intensity of utilisation (how many days) are allowed to differ (Jones, 2000). The participation decision is represented with a probit model, and the intensity of utilisation with a negative binomial model[5] (NB).

This specification mirrors the differences in payment incentives and care pathways. Day case and inpatient care represent distinct organisational modes of service delivery and are supported by different reimbursement incentives under the NHS Payment Scheme. The scheme differentiates between day case and inpatient stays when setting procedure tariffs, weighting the proportion of activity in each to calculate the tariff; this is a design intended to encourage day case activity. Similarly, clinical guidelines such as the National Day Surgery Delivery Pack promote day surgery as the default pathway (GIRFT, 2024). Differences in how public and private providers deliver care and respond to these incentives are thus captured across both margins of utilisation.

Part 1: Probability of overnight stay

The specification of the probit model considers the following equation:

$$Pr(Overnight_{ij} = 1|HO, X) = \Phi\left(\alpha_j + \lambda\, HO_i + X_i'\gamma\right) \qquad (1)$$

where $\Phi(.)$ is the probit link function, $Overnight_{ij}$ is a binary variable that takes 1 if patient *i* requires an overnight stay for treatment *j* and 0 if discharged on the same day. α_j is a vector of HRG fixed effects to control for systematic differences across procedures. Hospital ownership type (HO_i) is a binary variable equal to 1 if the provider where patient *i* is treated is privately owned, and equal to 0 if public. X_i is a vector of sociodemographic and clinical patient characteristics that control for casemix. These include age (in bands), sex, ethnicity, IMD quintile, indicator of rurality, number of emergency admissions in the year prior to the elective treatment, and Elixhauser comorbidities (as dummies). λ is the coefficient of interest, which reflects the effect of private ownership on the probability of overnight stay.

[5] In this framework, where hospital LOS is modelled using a two-part specification with a negative binomial for the second part, enforcing truncation is not necessary, as what the second part is modelling is the LOS variation conditional on selecting the inpatient pathway. In this context, the lower bound of two days represents the minimum duration associated with inpatient care rather than truncation of otherwise latent outcome distribution. The negative binomial model for inpatient LOS is therefore conditional by construction. In the Supplementary Material we provide further details.

Part 2: Inpatient length of stay

For the second part of the model, we use a NB model[6] given that hospital LOS is a count variable with a right-skewed distribution. Thus, the empirical specification for inpatient LOS (conditional on being admitted overnight) is given by:

$$LOS_{ij} = \alpha_j + \delta\, HO_i + X_i'\,\beta + \mu_{ij} \qquad (2)$$

$$\text{with } \mu_{ij} \sim NB(\exp(X_i'\beta)\,, \theta_{ij} + \psi\theta_{ij}^2)$$

where θ_{ij} is the over–dispersion parameter and LOS_{ij} is the LOS of patient *i* with HRG *j*. α_j are the HRG fixed effects. HO_i is hospital ownership type. X_i represents the same covariates presented in Equation (1). μ_{ij} is the idiosyncratic error term. Standard errors are clustered at the trust and HRG level, allowing for correlation among patients treated in the same trust and within the same clinical group.

4.2 Instrumental variable approach

There are several reasons why hospital ownership might be endogenous to LOS, which may introduce biased estimates. From the provider's perspective, unobserved patient characteristics (e.g. morbidity) could influence decisions to admit patients with severe conditions. If, for example, privately-owned hospitals disproportionately treat healthier patients, they would present shorter stays. They may deliberately select patients that they expected to be low-cost compared to the fixed HRG tariff they received. In addition, private providers do not have emergency departments, which can prevent them from taking high-risk patients with an anticipated need for critical care after the elective procedures.

Patient beliefs about hospital performance (unobserved patient selection) might also lead to heterogeneity in casemix across types of providers. For instance, patients with perceived severe conditions may try to choose providers with better indicators of performance. If predominantly the sites with the shortest LOS pertain to one type of provider, this type may attract more complex patients who, consequently, will increase the average LOS.

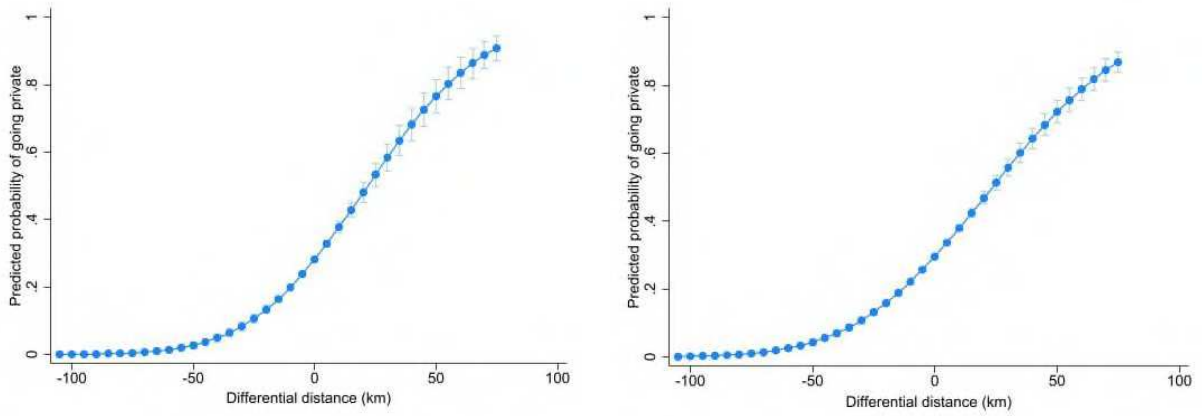
To correct for the endogeneity in ownership, we adopt an instrumental variable approach. Considering the binary choice of type of provider and the skewness in the distribution of hospital LOS, we implement the 2SRI method. This produces consistent estimators in non-linear outcome models (Terza, 2018; Terza et al., 2008; Wooldridge, 2014). In general, the IV-based approach requires finding an instrument for hospital ownership that has the following properties: 1) it is strongly correlated with the endogenous variable (relevance); 2) it is not correlated with the error term in the equation that explains LOS (exclusion restriction); and 3) monotonicity. This property implies that patients tend to choose sites that are closer to their residences.

We employ differential distance as the instrument, defined as the straight-line distance from the patient's residence to the nearest public provider minus the distance to the nearest private provider. This aligns with a large body of evidence showing that distance is a strong predictor of hospital selection (e.g. Bowblis & McHone, 2013; Brekke et al., 2014; Brooks et al., 2006; Grabowski et al., 2013; Gutacker et al., 2016; Hirth et al., 2003; McClellan, 1994).

[6] Using a Poisson regression yields similar results, suggesting our findings are robust to this specific model choice (see Table A2).

4.2.1 Instrument validity

Regarding relevance and monotonicity, Figure 3 provides suggestive evidence. Panel A plots the adjusted predicted probability of going private against differential distance for the full sample, while Panel B plots the corresponding relationship for the inpatient sample. Specifically, they are margins plots derived from the probit model outlined in Equation (3). First, the figures indicate a strong and positive relationship between the probability of choosing a private provider and differential distance. Second, they show a curvilinear relationship, which supports the use of a flexible first-stage specification. We therefore adopt the quadratic specification as our main first-stage specification, since it provides a parsimonious way to capture the observed curvature. Finally, both panels display a pattern consistent with monotonicity: the probability of choosing a private provider increases as the private provider becomes relatively closer. Monotonicity is also supported when we use a categorical specification of the instrument (see Robustness checks).



(A) Full sample (B) Inpatient sample

Figure 3. Relationship between the probability of going private and differential distance. Panel A shows the full sample and Panel B the inpatient sample. Adjusted predictions are shown with 95% confidence intervals.

Regarding the exclusion restriction, the identification strategy relies on the assumption that, conditional on observed covariates, differential distance influences the choice of provider but is exogenous to both LOS and any unobserved factors affecting LOS (e.g. severity at admission). This assumption could be violated if patients choose to live closer to hospitals due to a higher risk of needing health services, also known as spatial sorting (Moscone et al., 2020). However, in the context of elective surgery, this scenario is unlikely for several reasons.

First, the procedure would need to be scheduled at regular intervals to incentivise the patient to live near a specific provider. Second, the patient would have to anticipate their LOS at each provider within their choice set. However, LOS varies over time, and most of the elective procedures considered in our analysis are performed only once in a lifetime. Therefore, it is unlikely that patients choose their residence based on expected LOS at nearby hospitals. Third, even if a patient requires multiple elective treatments within a year and is willing to relocate closer to a hospital, doing so would demand both financial and labour flexibility. We therefore argue that it is plausible to assume the absence of spatial sorting in this context.

If valid, differential distance induces quasi-random variation in provider choice. Although we cannot test this directly, we can check balance by regressing differential distance on observed covariates. The

results indicate that patients living relatively closer to private hospitals do not differ in terms of comorbidities and prior emergency admissions from those living relatively closer to public hospitals (Table 1). This indicates that our instrument is exogenous to observed proxies of patient severity, reducing the likelihood that differential distance is correlated with unobserved patient severity, which is the main concern for unobserved patient selection.

Table 1. Results from the linear regression of differential distance on severity covariates.

VARIABLE	**Estimate**
Any emergency admission in the past 365 days (Ref=Yes)	-0.2448
	(0.2486)
Number of Elixhauser comorbidities	-0.0550
	(0.0791)
R-squared	0.1771
Observations	596,852

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. This regression also adjusts for HRG fixed effects and sociodemographic characteristics of the patient, including age in band groups, sex, ethnicity, IMD quintile, and indicator of rurality.

*** p<0.01, ** p<0.05, * p<0.1

Another potential threat to instrument validity is that private providers may systematically differ in the location choices compared to public providers. Figure 4 maps the distribution of public and private providers across England. It shows that both types of providers appear to be located in broadly similar areas, with a substantial geographic overlap. Both public and private providers are represented in each of the 36 Integrated Care Board (ICB) areas, which are the administratively relevant units for planning and managing NHS-funded services. This geographic overlap provides supportive evidence against the concern that the instrument is driven by comparisons between hospitals located in different areas.

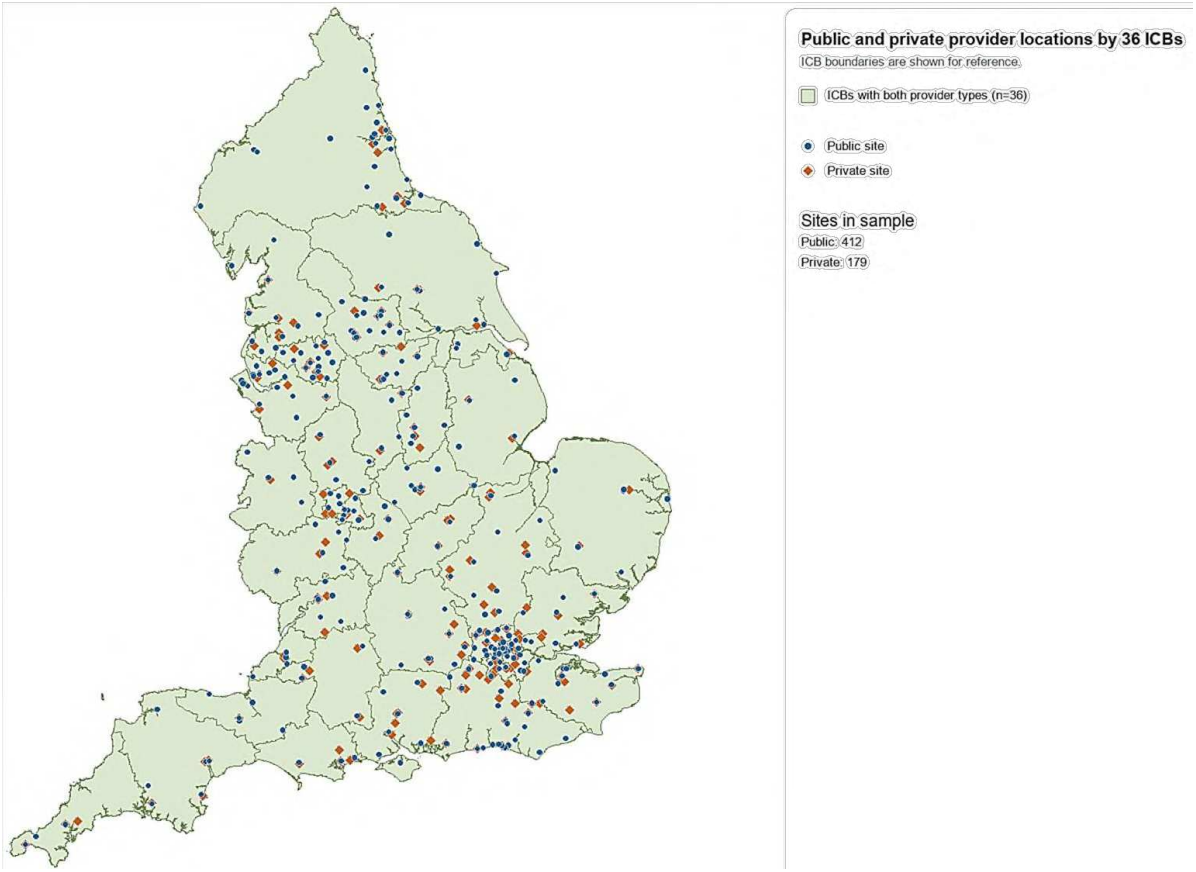


Figure 4. Geographic distribution of public and private hospitals across Integrated Care Boards in England.

4.3 Two-stage residual inclusion

To estimate the causal effect of private ownership on LOS, we use a 2SRI approach, which requires three steps. First, we estimate the first-stage regression of the probability of choosing a private provider as a function of the individual differential distance and other relevant confounders. Second, we compute the generalised residual from this first-stage model, which forms the control function capturing unobserved selection factors. Third, we enter this control function into the second-stage model as an additional regressor.

The first-stage regression is a probit[7] that models a patient's choice between public and private providers as a reduced-form equation, where differential distance is the primary determinant. The specification of the probit model for hospital ownership type is given by:

$$Pr(HO_i = 1|DD, X) = \Phi(\alpha_j + \varphi\, DD_{ij} + X_i'\beta) \quad (3)$$

where $\Phi(.)$ is the probit link function, HO_i is the dependent variable, equal to 1 if patient *i* is treated in a private provider and 0 if public. α_j are the HRG fixed effects, and X_i controls for patient casemix. DD_{ij} is the instrument, which measures the differential distance between the centroid of each patient's LSOA of residence and the nearest public site of treatment *j* and the distance to the nearest private site of treatment *j*. We use generalised residuals for the control function following (Basu et al., 2018; Coe et al., 2025; Lee & Basu, 2025; Wooldridge, 2015). The control function used in our analysis is the linear generalised residuals; this functional form was compared against specifications containing polynomial terms up to the third order. However, these alternative specifications yield similar results (See Table A3).

In the 2PM framework, we address the endogeneity of hospital ownership HO_i on both margins using the same first-stage model outlined in Equation (3). For the second-stage specification of the first part of the 2PM (any overnight stay), we estimate a probit model as presented in Equation (1). The only variant is that we augment the model with the first-stage generalised residual as a control function for endogeneity, thus:

$$Pr(Overnight_{ij} = 1|HO, X) = \Phi\left(\alpha_j + \lambda HO_i + X_i'\gamma + \rho\hat{v}_i\right) \quad (4)$$

where $\hat{v}_i$ is the control function term. Because $\hat{v}_i$ is an estimated regressor, the two-stage standard errors are corrected via bootstrapping with 1,000 replications.

The second-stage specification of inpatient LOS follows Equation (2). The negative binomial model, augmented with the control-function term, is given by:

$$LOS_{ij} = \alpha_j + \delta HO_i + X_i'\,\beta + \eta\hat{v}_i + \mu_{ij} \quad (5)$$

Under the 2SRI approach, the presence of endogeneity is investigated with a Wald test for the significance of the coefficient of the control function term. The null hypothesis is exogeneity ($\rho = 0$ in the first part; $\eta = 0$ in the second part).

The 2SRI estimator is interpreted as the average effect of private ownership on LOS for the study population (ATE), in contrast to two-stage least squares (2SLS), which identifies the local average treatment effect (LATE) for compliers moved by the instrument (Imbens & Angrist, 1994; Lee & Basu, 2025; Terza et al., 2008; Wooldridge, 2015).

In addition to the LOS model, we estimate a model using quality as the outcome variable to assess the extent to which public and private providers differ not only in LOS but also in quality. One mechanism underpinning the relationship between LOS and private ownership is that quality differs across

[7] When we use a LPM to fit the probability of going private, approximately 10% of the fitted values lie outside the range [0,1]. This indicates misspecification and poor predictive calibration. We therefore use a probit specification for the first-stage regression of the 2SRI method, which respects the binary nature of provider choice and constrains predicted probabilities to be weakly above 0 and below 1.

provider types. On one hand, better facilities and practices could lead to faster patient recovery and early patient discharge. On the other hand, a shorter LOS could imply less care provided to patients and, consequently, lower quality. We therefore test for differences in quality.

In line with the main analysis, we estimate a probit model within a 2SRI framework to account for endogeneity. We use 30-day emergency readmissions as a proxy for quality. In the probit model, this enters as a binary variable equal to 1 if the patient has an emergency admission within 30 days of discharge from the elective admission, and 0 otherwise. We control for the same set of covariates as in previous specifications.

5. Results

5.1. Descriptive statistics

Table 2 provides the descriptive statistics. In 2023/24, planned hospital care was delivered by 412 NHS sites and 179 private sites. The private sector accounted for 25% of the total admission volume. Across all providers, 55% of admissions were in orthopaedics, 34% in general surgery, and 11% in gynaecology. Patients treated by private providers more frequently remain overnight (56% vs 51%) and stay 0.3 fewer days in hospital (2.01 vs 2.35 days) than those treated by public providers. The 30-day emergency readmissions rate is about 1.3% for public providers and 0.6% for private providers.

On average, the private sector treated older patients (60 vs 55 years) but with fewer comorbidities (1.24 vs 1.35). Relative to public providers, private providers treated a lower share of female patients (51% vs 57%), a lower share of white patients (52% vs 77%), and a higher share of rural patients (23% vs 21%). Their patients also come from areas with lower deprivation (mean IMD 18.99 vs 21.47). Likewise, patients treated by private providers have lower emergency attendances in the year prior to treatment.

The average patient in our sample has a nearest public provider that is 7.3 km closer than their nearest private provider. This implies that public providers are placed in closer proximity to the patient and also reflects the higher number of public providers in our sample.

Similar descriptive patterns are observed among inpatient admissions (see Table A4).

Table 2. Descriptive statistics by hospital ownership.

	Public providers					Private providers				
	Admissions	*Mean*	*SD*	*Min*	*Max*	*Admissions*	*Mean*	*SD*	*Min*	*Max*
Sample size	450,043 (75%)					146,809 (25%)				
LOS, days		2.35	2.34	1.00	29.00		2.01	1.19	1.00	29.00
Day-case patient		0.49	0.50	0.00	1.00		0.44	0.50	0.00	1.00
30-day emergency readmissions		0.013	0.11	0.00	1.00		0.006	0.07	0.00	1.00
Age, years		55.19	18.80	0.00	103.00		60.11	15.25	7.00	97.00
Female patient		0.57	0.50	0.00	1.00		0.51	0.50	0.00	1.00
White patient		0.77	0.42	0.00	1.00		0.52	0.50	0.00	1.00
Index Multiple Deprivation		21.47	15.01	0.54	92.74		18.99	14.14	0.54	88.77
Differential distance (Dpub-Dpriv, 1st stage)		0.20	0.40	0.00	1.00		0.23	0.42	0.00	1.00
Number of Elixhauser comorbidities		1.35	1.38	0.00	11.00		1.24	1.21	0.00	8.00
N.of past year's emergency hospitalisations	34,596	0.37	0.79	0.00	42.00	10,257	0.05	0.27	0.00	5.00
Instrumental variable										
Distance to nearest public provider (km)		7.44	7.11	0.04	171.91		8.06	7.37	0.06	156.12
Distance to nearest private provider (km)		16.60	17.54	0.05	210.80		9.79	8.66	0.05	136.78
Differential distance (Nearest public-Nearest private)		-9.17	15.76	-103.87	54.23		-1.73	6.89	-87.78	67.96
Number of patients	433,814					141,135				
Number of HRGs	70					70				
Number of sites	412					179				

5.2 Two-part–2SRI estimates

Table 3 presents the results of the 2PM specifications. We first discuss the results for inpatient LOS (second part), and then for the probability of an overnight stay (first part). After controlling for casemix and HRG fixed effects, the non-instrumented MLE estimates (presented as the average marginal effects) suggest that being treated by a private provider is associated with a reduction in inpatient LOS by 0.87 days, compared to a public provider, at a 1% significance level. The difference is larger and equal to 1.08 days when controlling for HRG only with no additional casemix controls, suggesting that private providers treat less complex patients.

For the 2SRI estimation, our preferred first-stage specification comprises the differential distance that includes its quadratic term. The first-stage results show that differential distance (nearest public vs. nearest private) is a strong predictor of provider choice. The probability of choosing a private provider

increases by 0.79 percentage points[8] (p.p.) as the private option becomes 1 km closer relative to the public one. The Chi-square statistic from the Wald test is high and equal to 100.66, which suggests that the instrument meets the relevance condition.

The coefficient of the control function term is statistically significant in the outcome equation, which confirms that hospital ownership is endogenous to inpatient LOS. The 2SRI-NB estimates indicate that private providers are associated with shorter inpatient LOS by about 0.58 days (≈14 hours) relative to public providers.

The direction of the effects attached to the covariates is as expected in both the first- and second-stage regressions. Inpatient LOS is longer for patients who are older (aged 65 or above), female, non-white, more deprived, have more prior emergency admissions, or live in urban areas; patients with comorbidities also tend to experience longer stays. Generally, these groups are less likely to receive care from private providers, except for older patients (Table A5).

For the first part of the 2PM, after controlling for casemix and HRG fixed effects, the results suggest that private patients are associated with a lower probability of being admitted with an overnight stay by 4.6 p.p. relative to public providers. The Wald test for the significance of the coefficient of the control function term fails to reject the null hypothesis that hospital ownership is exogenous. The results from the 2SRI approach suggest instead that there are no differences in the probability of staying overnight between public and private providers in England. The probability of staying overnight is smaller for private providers and equal to 2.2 p.p., but it is not statistically significant.

[8] This coefficient is the average marginal effect of differential distance, which is derived from the quadratic function of differential distance and given by $\varphi_1^{DD} + 2\varphi_2^{DD}(D_i)$, where $\varphi_1^{DD} = 0.0081$, and φ_2^{DD}=0.00003. For reference, the mean differential distance in the inpatient sample is -7.0 km.

Table 3. Average marginal effects from the two-part-2SRI regressions for the effect of private ownership on hospital length of stay.

	Overnight equation			**Inpatient LOS equation**		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLE	**HRG FE only**	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE only**	**HRG FE + casemix adjusters**	**2SRI**
Private ownership	**-0.0606****	**-0.0458*****	**-0.0215**	**-1.0791*****	**-0.8657*****	**-0.5824*****
	(0.0105)	(0.0108)	(0.0301)	(0.0733)	(0.0750)	(0.1520)
Control function term			-0.0150			-0.1771**
			(0.0136)			(0.0814)
Differential distance ($Dist_{Pub}$-$Dist_{Priv}$, 1st stage)			0.0088***			0.0079***
			(0.0007)			(0.0008)
COVARIATES						
Age group, years [Ref=18-49]						
0-17		0.0407***	0.0465***		-0.0849	-0.0362
		(0.0112)	(0.0131)		(0.0816)	(0.0615)
50-54		0.0230***	0.0223***		0.0069	0.0002
		(0.0029)	(0.0028)		(0.0191)	(0.0191)
55-59		0.0379***	0.0371***		0.0231	0.0142
		(0.0037)	(0.0035)		(0.0206)	(0.0211)
60-64		0.0626***	0.0618***		0.0361*	0.0255
		(0.0045)	(0.0042)		(0.0219)	(0.0224)
65-69		0.0871***	0.0862***		0.0777***	0.0658***
		(0.0055)	(0.0053)		(0.0229)	(0.0234)
70-74		0.1121***	0.1114***		0.1917***	0.1815***
		(0.0057)	(0.0055)		(0.0228)	(0.0240)
75-79		0.1421***	0.1417***		0.3860***	0.3793***
		(0.0055)	(0.0054)		(0.0244)	(0.0246)
80-84		0.1779***	0.1782***		0.7264***	0.7306***
		(0.0060)	(0.0061)		(0.0336)	(0.0343)
85+		0.1943***	0.1954***		1.2178***	1.2391***
		(0.0077)	(0.0078)		(0.0526)	(0.0538)
Female patient		0.0189***	0.0189***		0.1936***	0.1941***
		(0.0018)	(0.0018)		(0.0121)	(0.0120)
Ethnic group [Ref=White]						
Asian		0.0428***	0.0435***		0.3551***	0.3671***
		(0.0034)	(0.0035)		(0.0366)	(0.0381)
Black		0.0407***	0.0420***		0.6061***	0.6248***
		(0.0045)	(0.0047)		(0.0439)	(0.0468)
Mixed		0.0222***	0.0222***		0.1884***	0.1906***
		(0.0051)	(0.0051)		(0.0487)	(0.0491)
Other/Unknown		0.0014	-0.0052		-0.0070	-0.0835**
		(0.0026)	(0.0065)		(0.0236)	(0.0391)
IMD [Ref=Least deprived]						
Second least deprived		0.0040**	0.0043**		0.0387**	0.0436***
		(0.0017)	(0.0017)		(0.0151)	(0.0149)
Third most deprived		0.0048**	0.0056***		0.0374**	0.0493***
		(0.0020)	(0.0020)		(0.0161)	(0.0156)
Second most deprived		0.0089***	0.0099***		0.1023***	0.1176***
		(0.0024)	(0.0024)		(0.0194)	(0.0190)

	Overnight equation			Inpatient LOS equation		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLE	**HRG FE only**	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE only**	**HRG FE + casemix adjusters**	**2SRI**
Most deprived		0.0190***	0.0201***		0.1679***	0.1843***
		(0.0029)	(0.0029)		(0.0251)	(0.0256)
Patient living in rural area (LSOA11)		-0.0064**	-0.0063**		-0.1476***	-0.1469***
		(0.0029)	(0.0028)		(0.0193)	(0.0191)
Number of past year emergency admissions [Ref=None]						
1		0.0561***	0.0580***		0.7041***	0.7243***
		(0.0043)	(0.0046)		(0.0600)	(0.0624)
2		0.0621***	0.0638***		0.6776***	0.6963***
		(0.0089)	(0.0089)		(0.1238)	(0.1275)
3		0.0651***	0.0667***		0.5154**	0.5246**
		(0.0172)	(0.0172)		(0.2134)	(0.2173)
4+		0.1206***	0.1220***		1.9259***	1.9377***
		(0.0234)	(0.0234)		(0.3841)	(0.3928)
Wald test for instrument strength (χ^2)			173.03			100.66
P-value instrument (1st stage)			0.0000			0.0000
P-value control-function term (2nd stage)			0.2730			0.0351
Pseudo R-squared	0.3924	0.4193	0.4193	0.0594	0.0594	0.0594
Observations	596,852	596,852	596,852	312,128	312,128	312,128

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Elixhauser comorbidities and HRG fixed effects are also included in the models but not presented.

*** p<0.01, ** p<0.05, * p<0.1

5.3 Quality of care

Table 4 presents the results of the probit model within the 2SRI framework, which tests for differences in quality between public and private providers. The coefficient on the control-function term is statistically insignificant in the quality equation. Accordingly, we cannot conclude that hospital ownership is endogenous to our measure of quality.

When controlling for HRG fixed effects only, the results suggest that private hospitals have a lower readmission rate by 0.72 p.p and the effect is statistically significant at 1% level. This difference reduces to 0.53 p.p. once further controlling for patient casemix (and still significant). It further reduces to 0.37 p.p. with the 2SRI approach (but only at 10% significance level). The results are robust to restricting the analysis to the inpatient sample (Table A6). This suggests that the shorter LOS by private providers is not due to lower quality, as proxied by emergency readmission rates.

Additionally, we re-estimated the LOS 2PM model using a sample that excludes readmitted patients, in order to isolate the quality effect. The results remain highly stable, providing reassurance that they are not driven by readmissions (see Table A7).

Table 4. Average marginal effects from the 2SRI regressions for the effect of private ownership on 30-day emergency readmissions.

VARIABLE	(1) MLE with HRG FE only	(2) MLE with HRG and casemix	(3) 2SRI
Private ownership	-0.0072***	-0.0053***	-0.0037*
	(0.0010)	(0.0011)	(0.0020)
Control function term			-0.0010
			(0.0010)
Differential distance ($Dist_{Pub}$-D_{Priv}, 1st stage)			0.0088***
			(0.0010)
Wald test for instrument strength (χ^2)			173.03
P-value instrument (1st stage)			0.0000
P-value control-function term (2nd stage)			0.3715
Pseudo R-squared	0.0328	0.0470	0.0470
Observations	596,852	596,852	596,852

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects. In the 2SRI model, the quadratic term of the IV is also part of the model, as in previous specifications.

*** p<0.01, ** p<0.05, * p<0.1

5.4 Robustness checks, heterogeneity and possible mechanisms

We conducted several robustness checks to check the sensitivity of our results to subpopulations and specifications.

5.4.1 Differential distance specifications

We investigate alternative specifications of the first stage. We split the differential distance into quintiles to allow for non-linear effects, as the probability of choosing a private provider can shift markedly from one group to the next. We also used linear and cubic terms of differential distance. Table A8 presents the results from the 2PM-2SRI and suggests that the main findings are robust.

5.4.2 Regional effects and geographic heterogeneity

First, we augment Equations (4) and (5) with region fixed effects to account for any systematic variations in LOS that may exist across regions (as illustrated in Figure A2). These correspond to the seven NHS England regions: East of England, London, Midlands, North East and Yorkshire, North West, South East, and South West. Relative to London, all other regions show both a lower probability of overnight admission and a shorter inpatient LOS (see Table A9). The estimated effect of private ownership remains robust to the inclusion of region fixed effects.

A further concern is that private providers may locate systematically in different areas than public providers. To address this, we restrict the sample to patients for whom both public and private providers are available within a 30 km radius of their residence. This reduces the estimation sample by about 12%. The results in Table A10 are similar to those from the main specification: we find no statistically significant difference at the extensive margin, while private providers have shorter inpatient LOS, by approximately 0.5 days.

We also restrict the analysis to urban areas and find similar results (Table A11). Additionally, private providers, given their profit-maximising objective, may be more likely to locate in more affluent areas and attract less deprived patients. We therefore investigate whether differences in deprivation composition drive the results by estimating the effect of private ownership separately for patients in the least-deprived and most-deprived quintiles. The results indicate that private providers remain associated with shorter LOS in both subsamples. Among the most deprived patients, private providers are also associated with an 8.2 p.p. lower probability of overnight admission. The estimated difference in inpatient LOS is larger among the most deprived patients than among the least deprived patients —1.03 days compared with 0.48 days, respectively (Table A12). Taken together, this set of robustness checks suggests that geographic sorting between ownership types is unlikely to explain the main findings of this study.

5.4.3 Propensity score matching and a single-equation model

We use propensity score matching to ascertain if the results change after balancing observed covariates between private and public patients. We estimate the propensity score using a probit regression with the same covariates as in Equations (1) and (2). Each private patient is matched one-to-one to the nearest NHS patient within a calliper (maximum distance) of 0.01 on the propensity score, with replacement, and imposing common support. The standard errors were bootstrapped with 1,000 iterations[9]. This approach shows wider differences in LOS between public and private providers (both in the overnight and inpatient equations) than the 2SRI approach, but the main conclusions hold (Table A13).

Similarly, we compare our findings to a specification that uses the negative binomial model with 2SRI for the whole sample without distinguishing between day cases and overnight stays (as we do in the 2PM). Table A14 shows that LOS is lower in private providers by 0.31 days.

5.4.4 Procedure heterogeneity

We re-estimate the main specifications using only hip and knee procedures, which are the most common procedures in our sample and the focus of some previous studies. This analysis yields similar findings regarding the probability of an overnight stay (no differences between ownership types) and further indicates that public and private providers do not differ in terms of inpatient LOS (see Table A15). This suggests that the reductions in LOS for private providers arise mainly from the other analysed procedures.

When we extend this analysis to other procedures with substantial private participation, defined as at least 30% of activity, we obtain similar results across 11 procedures in total, as shown in Table A16.

5.4.5 Teaching and non-teaching providers

Some public providers can be teaching hospitals. Given that private providers do not have teaching activities, private providers may be more comparable to non-teaching public providers. Patients treated by teaching hospitals might experience longer LOS since they have a dual role of healthcare provision and medical education, typically treat more severe patients, and conduct research, which potentially demands a longer stay. Thus, we re-estimate Equation (5) on two subsamples, one where

[9] The STATA command is psmatch2.

we compare private providers with non-teaching public hospitals, and one with teaching public hospitals. Non-teaching providers treat approximately 63% of all public-sector patients in our sample. As expected, the effect of private ownership is less pronounced when comparing private providers with non-teaching public providers. The 2SRI results suggest that the effect of being treated as an inpatient by a private provider reduces from -0.58 to -0.54 days.

The results of the comparison of private versus teaching providers in Table 5 suggest that the effect of being treated as an inpatient by a private provider increases from -0.58 to -0.99 days (71% increase), which confirms that the teaching responsibilities contribute to LOS.

Table 5. Average marginal effects for the effect of private ownership on inpatient length of stay compared with teaching status.

VARIABLE	Private vs non-teaching public providers 2SRI	Private vs teaching public providers 2SRI
Private ownership	-0.5479***	-0.9944***
	(0.0750)	(0.0834)
Control function term	-0.0979**	-0.1297***
	(0.0445)	(0.0456)
Differential distance (1st stage)	0.0112***	0.0116***
	(0.0004)	(0.0004)
Wald test for instrument strength (χ^2)	600.53	686.40
P-value instrument (1st stage)	0.0000	0.0000
P-value control function term (2nd stage)	0.0280	0.0044
Pseudo R-squared	0.0543	0.0693
Observations	224,214	165,860

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

6. Discussion

In this study, we have tested a key prediction of economic theory, which is that private providers are more efficient. Using data from the English NHS, we show that public and private providers differ in inpatient LOS but not in their day-case activity. An elective patient treated by a private provider is expected to spend, on average, 14 hours less in the hospital than a comparable patient treated by a public provider. These results account for unobserved differences in patient casemix.

When controlling only for observed casemix adjusters, private treatment appears to have a 33% larger effect on reducing LOS and is associated with a higher probability of day-case treatment. This suggests that unobserved differences in patient severity benefit private providers, either because of cream-skimming or because healthier patients self-select into private providers. The estimated effect of private ownership falls by around 20% once casemix is controlled for, relative to the unadjusted model. This upward bias likely reflects that privately treated patients have fewer comorbidities and fewer past emergency admissions, indicating a less complex casemix. Overall, this study shows that it

is important to control for unobserved dimensions of patient casemix when comparing public and private providers.

These findings are consistent with previous associational evidence from England indicating that treatment in private providers is associated with shorter LOS (Siciliani et al., 2013; Crothers et al., 2022). Similarly, a study investigating the effect of the entry of private surgical centres in England on the efficiency of incumbent public hospitals found that private entrants led to reductions in pre-surgery LOS at nearby NHS hospitals (Cooper et al., 2018). A study from Norway also suggested that private hospitals have shorter LOS than public hospitals (Bjorvatn, 2018). In contrast, Anderson et al. (2024) concluded that private hospitals are more likely to have longer post-operative LOS than NHS hospitals. Their study employed a semi-linear instrumental variable approach (IV probit) and focused on a narrower set of procedures (hip and knee replacements). Evidence from Japan and Australia also contrasts with our findings (Kato et al., 2014; Meng et al., 2021). On the other hand, a 2SRI analysis from the US that compared for-profit and not-for-profit skilled nursing facilities found no effect of profit status on LOS (Bowblis et al., 2016).

We also show that the teaching status of public hospitals matters when comparing public and private providers. Teaching responsibilities substantially widen the LOS gap between teaching and private providers.

Our results on LOS may effectively imply better organisation and efficiency, but for this to hold, patients treated by private providers should not experience poorer quality. If patients are discharged "quicker but sicker", this may reflect a quality-efficiency trade-off, whereby efforts to reduce LOS result in adverse patient outcomes. In those cases, early discharge could increase the risk of emergency readmissions (Brekke et al., 2021; Kosecoff et al., 1990; Martin et al., 2016).

We therefore investigated differences in quality between ownership types and found a modest effect of private ownership in reducing 30-day emergency readmissions. Thus, earlier discharge in private providers does not appear to compromise quality, supporting the interpretation of shorter LOS as reflecting greater efficiency. Recent studies from England comparing emergency readmission risk between public and private providers also suggest no differences in quality after accounting for unobserved patient heterogeneity (Anderson et al., 2024; Moscelli et al., 2018). Evidence from other tax-funded health care systems, such as Italy and Norway, similarly finds no significant quality differences between public and private hospitals when instrumenting hospital ownership (Holom & Hagen, 2017; Moscone et al., 2020). In other settings, such as the US, the evidence is less conclusive (Anderson et al., 2025; Eggleston et al., 2008).

This study is among the few to compare management of hospital LOS between public and private providers in England using a causal framework, and the first to do so with a 2PM that separates same-day discharge from overnight admission. This distinction is important because this study has shown that provider behaviour differs between day-case and inpatient care. Organisationally, the NHS has long promoted day-case surgery for planned care when clinically appropriate and has financially incentivised same-day discharge (Gaughan et al., 2019; Kreutzberg et al., 2024). Most elective procedure tariffs are set as a single rate averaged across day -case and inpatient costs (NHS England, 2025a). Our finding of no effect of hospital ownership on overnight admission may therefore not align with the hypothesis that private providers' stronger cost-containment incentives should lead to fewer overnight stays. We find no evidence suggesting that these incentives operate at this margin.

One potential explanation is that both types of hospitals may be equally conservative about discharging patients on the same day unless they are medically fit. In this regard, adherence to best practice likely guides day-case decisions in both settings. National initiatives such as Getting It Right First Time (GIRFT) and advocacy from professional bodies like the British Association of Day Surgery (BADS) may also have contributed to narrowing any performance gap in day-case management. By contrast, variation in inpatient LOS can be shaped not only by clinical considerations but also by non-medical factors and managerial practices. For example, Siciliani et al. (2025) show that elective patients living alone are discharged later in England, with a smaller effect observed in private hospitals, suggesting that discharge decisions in private providers are less influenced by non-medical factors.

Private hospitals in our sample treated 141,135 patients, though only 56% involved an overnight stay (79,036 patients). We find that for patients requiring an overnight stay, private hospitals have a shorter LOS of 0.58 days. This is therefore equivalent to a reduction of 46,030 bed days (0.58x79,036), or about 126 beds (46,030/365). Reductions in LOS, however, will not translate into savings to the funder (at least in the short run) because the NHS reimburses the same tariff to both public and private providers.

Overall, our analysis suggests that there is scope for expanding privately-provided care to publicly funded patients. Contracting with the private sector may, however, have some disadvantages. As mentioned above, the private sector may have incentives to cream skim and only select less severe patients. Moreover, it can increase inequalities in access to care, mainly through waiting times (Kirkwood et al., 2024; Kirkwood & Pollock, 2025; Sutaria et al., 2019).

Conclusion

Our study has investigated whether the behaviour of private providers differs from that of public providers in the efficiency of hospital stays. We find that private providers have shorter inpatient length of stay at no expense of lower quality. Any apparent differences in day-case management disappear once unobserved differences in patient characteristics are accounted for. Taken together, these findings suggest that stronger efficiency incentives among private providers operate primarily through the management of inpatient stays rather than through same-day discharge decisions. The study can inform policy discussions on the scope for expanding the role of the private sector in the provision of publicly funded care.

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Supplementary Material

Table A1. Volume, share, length of stay, and day-case rate in public and private providers, by HRG4.

HRG4	Description HRG4	Specialty	Public	Private		All		Public	Private	All	Public	Private	All
			Volume	Volume	%	Volume	%	Mean length of stay			Day case (%)		
Total			**450,043**	**146,809**	**24.6%**	**596,852**	**100%**	**2.35**	**2.01**	**2.27**	**49.%**	**43.5%**	**48%**
HN22	Very Major Knee Procedures for Non-Trauma	Trauma & Orthopaedics	55,716	39,353	41.4%	95,069	15.9%	3.74	2.82	3.36	9.0%	7.0%	8.2%
HN12	Very Major Hip Procedures for Non-Trauma	Trauma & Orthopaedics	44,696	28,207	38.7%	72,903	12.2%	3.90	2.88	3.50	4.2%	1.9%	3.3%
FF62	Inguinal, Umbilical or Femoral Hernia Procedures	General Surgery	47,447	19,172	28.8%	66,619	11.2%	1.29	1.12	1.24	79.8%	89.1%	82.5%
HN23	Major Knee Procedures for Non-Trauma	Trauma & Orthopaedics	13,622	6,933	33.7%	20,555	3.4%	1.77	1.17	1.57	65.4%	85.4%	72.2%
GA10	Cholecystectomy	General Surgery	43,935	5,742	11.6%	49,677	8.3%	1.56	1.24	1.53	67.9%	78.6%	69.2%
HN32	Very Major Foot Procedures for Non-Trauma	Trauma & Orthopaedics	7,993	4,672	36.9%	12,665	2.1%	1.98	1.15	1.68	55.4%	86.6%	66.9%
HN53	Major Shoulder Procedures for Non-Trauma	Trauma & Orthopaedics	9,563	4,385	31.4%	13,948	2.3%	1.38	1.14	1.31	78.9%	86.9%	81.4%
HN33	Major Foot Procedures for Non-Trauma	Trauma & Orthopaedics	10,035	3,760	27.3%	13,795	2.3%	1.90	1.20	1.71	60.6%	81.4%	66.3%
HN52	Very Major Shoulder Procedures for Non-Trauma	Trauma & Orthopaedics	8,109	3,574	30.6%	11,683	2.0%	2.29	1.60	2.08	36.2%	52.2%	41.1%
HN34	Intermediate Foot Procedures for Non-Trauma	Trauma & Orthopaedics	12,516	3,110	19.9%	15,626	2.6%	1.36	1.08	1.30	83.4%	92.7%	85.2%
FF41	Intermediate Anal Procedures	General Surgery	23,203	3,096	11.8%	26,299	4.4%	1.15	1.09	1.14	89.8%	91.6%	90.0%
FF61	Abdominal Hernia Procedures	General Surgery	6,817	2,035	23.0%	8,852	1.5%	2.23	1.16	1.98	55.7%	85.9%	62.7%
FF60	Complex Hernia Procedures	General Surgery	6,150	1,990	24.4%	8,140	1.4%	2.97	1.23	2.55	47.9%	79.7%	55.7%
HN42	Very Major Hand Procedures for Non-Trauma	Trauma & Orthopaedics	3,563	1,670	31.9%	5,233	0.9%	1.20	1.08	1.16	87.8%	93.7%	89.7%

HRG4	Description HRG4	Specialty	Public	Private		All		Public	Private	All	Public	Private	All
			Volume	Volume	%	Volume	%	Mean length of stay			Day case (%)		
HC64	Intermediate Extradural Spinal Procedures	Trauma & Orthopaedics	3,646	1,622	30.8%	5,268	0.9%	2.58	1.99	2.40	15.9%	16.2%	16.0%
HN54	Intermediate Shoulder Procedures for Non-Trauma	Trauma & Orthopaedics	4,515	1,575	25.9%	6,090	1.0%	1.34	1.09	1.27	82.7%	91.3%	84.9%
HC63	Major Extradural Spinal Procedures	Trauma & Orthopaedics	3,271	1,404	30.0%	4,675	0.8%	3.05	2.18	2.79	5.8%	6.6%	6.1%
HN25	Minor Knee Procedures for Non-Trauma	Trauma & Orthopaedics	3,749	1,345	26.4%	5,094	0.9%	1.21	1.30	1.24	78.5%	69.7%	76.2%
MA10	Minor, Laparoscopic or Endoscopic, Upper Genital Tract Procedures	Gynaecology	9,432	1,229	11.5%	10,661	1.8%	1.12	1.09	1.12	88.1%	90.6%	88.4%
MA07	Major Open Upper Genital Tract Procedures	Gynaecology	9,861	977	9.0%	10,838	1.8%	3.08	2.60	3.04	5.3%	4.0%	5.2%
MA08	Major, Laparoscopic or Endoscopic, Upper Genital Tract Procedures	Gynaecology	11,971	919	7.1%	12,890	2.2%	1.96	1.96	1.96	35.1%	23.9%	34.3%
MA30	Intermediate Female Pelvic Peritoneum Adhesion Procedures	Gynaecology	3,460	707	17.0%	4,167	0.7%	1.27	1.16	1.25	80.6%	88.1%	81.9%
MA04	Intermediate Open Lower Genital Tract Procedures	Gynaecology	4,995	639	11.3%	5,634	0.9%	1.70	1.65	1.69	45.9%	43.8%	45.7%
HC62	Very Major Extradural Spinal Procedures	Trauma & Orthopaedics	1,419	586	29.2%	2,005	0.3%	3.47	2.30	3.13	3.5%	3.6%	3.5%
HN81	Complex, Hip or Knee Procedures for Non-Trauma	Trauma & Orthopaedics	7,590	562	6.9%	8,152	1.4%	5.73	3.41	5.57	1.5%	2.3%	1.6%
MA29	Major Female Pelvic Peritoneum Adhesion Procedures	Gynaecology	2,865	556	16.3%	3,421	0.6%	1.51	1.17	1.46	67.3%	83.5%	70.0%
HN86	Complex, Foot, Hand, Shoulder or Elbow Procedures for Non-Trauma	Trauma & Orthopaedics	1,983	519	20.7%	2,502	0.4%	2.89	1.41	2.59	35.4%	73.4%	43.2%
MA03	Major Open Lower Genital Tract Procedures	Gynaecology	2,910	447	13.3%	3,357	0.6%	2.29	2.16	2.27	14.9%	13.0%	14.6%

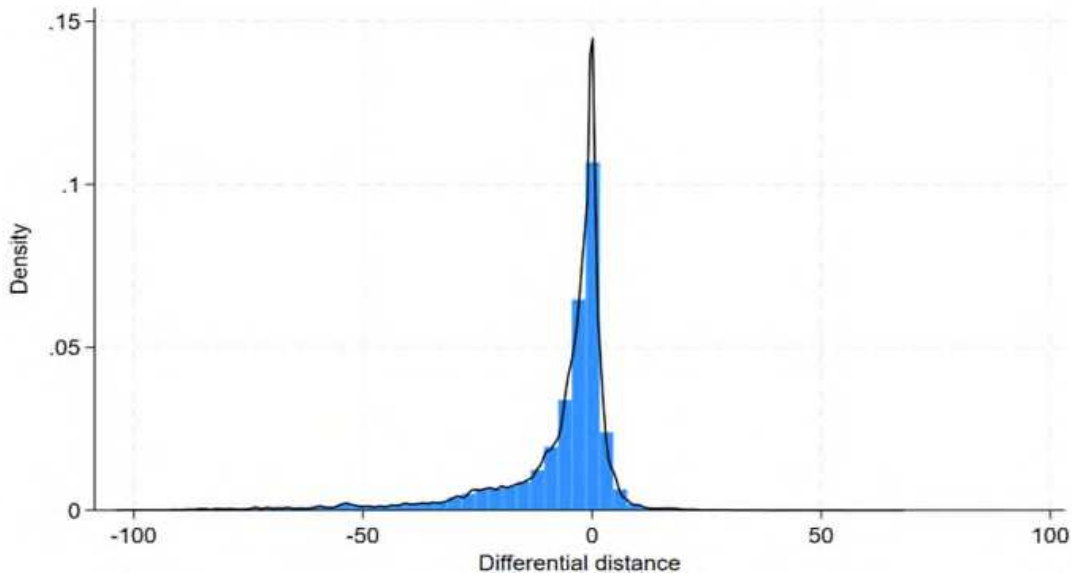
HRG4	Description HRG4	Specialty	Public	Private		All		Public	Private	All	Public	Private	All
			Volume	Volume	%	Volume	%	Mean length of stay			Day case (%)		
FF33	Distal Colon Procedures, 19 years and over	General Surgery	2,858	442	13.4%	3,300	0.6%	4.87	1.14	4.37	13.6%	86.9%	23.4%
MA09	Intermediate, Laparoscopic or Endoscopic, Upper Genital Tract Procedures	Gynaecology	3,914	413	9.5%	4,327	0.7%	1.23	1.11	1.22	81.8%	89.6%	82.6%
HT23	Major Knee Procedures for Trauma	Trauma & Orthopaedics	3,212	381	10.6%	3,593	0.6%	1.84	1.23	1.78	56.9%	78.7%	59.2%
FF40	Major Anal Procedures	General Surgery	5,458	366	6.3%	5,824	1.0%	1.25	1.10	1.24	87.7%	91.0%	87.9%
HC61	Complex Extradural Spinal Procedures	Trauma & Orthopaedics	716	281	28.2%	997	0.2%	4.07	2.56	3.64	14.4%	1.4%	10.7%
HD24	Non-Inflammatory, Bone or Joint Disorders	Trauma & Orthopaedics	2,418	261	9.7%	2,679	0.4%	1.89	1.59	1.86	70.5%	64.4%	69.9%
HC60	Very Complex Extradural Spinal Procedures	Trauma & Orthopaedics	909	232	20.3%	1,141	0.2%	4.58	3.11	4.28	6.4%	0.4%	5.2%
HN14	Intermediate Hip Procedures for Non-Trauma	Trauma & Orthopaedics	2,915	222	7.1%	3,137	0.5%	2.21	1.48	2.15	57.2%	58.1%	57.3%
JC42	Intermediate Skin Procedures	Trauma & Orthopaedics	3,024	214	6.6%	3,238	0.5%	1.10	1.13	1.10	91.3%	86.9%	91.0%
FF36	Intermediate Large Intestine Procedures, 19 years and over	General Surgery	5,546	207	3.6%	5,753	1.0%	1.14	1.05	1.14	86.6%	94.7%	86.9%
HN63	Major Elbow Procedures for Non-Trauma	Trauma & Orthopaedics	1,427	200	12.3%	1,627	0.3%	1.61	1.10	1.55	73.6%	91.0%	75.7%
HN13	Major Hip Procedures for Non-Trauma	Trauma & Orthopaedics	1,751	189	9.7%	1,940	0.3%	4.04	1.59	3.80	31.6%	49.7%	33.4%
HD21	Soft Tissue Disorders	Trauma & Orthopaedics	932	184	16.5%	1,116	0.2%	1.82	1.28	1.73	72.6%	88.0%	75.2%
MA02	Very Major Open, Upper or Lower Genital Tract Procedures	Gynaecology	3,626	176	4.6%	3,802	0.6%	4.04	3.06	3.99	2.9%	0.6%	2.8%

HRG4	Description HRG4	Specialty	Public	Private		All		Public	Private	All	Public	Private	All
			Volume	Volume	%	Volume	%	Mean length of stay			Day case (%)		
FF52	Intermediate Therapeutic General Abdominal Procedures	Gynaecology	593	127	17.6%	720	0.1%	1.33	1.09	1.29	78.9%	90.6%	81.0%
HT22	Very Major Knee Procedures for Trauma	Trauma & Orthopaedics	1,039	120	10.4%	1,159	0.2%	1.75	1.37	1.71	58.7%	64.2%	59.3%
FF52	Intermediate Therapeutic General Abdominal Procedures	General Surgery	1,433	115	7.4%	1,548	0.3%	1.94	1.16	1.88	68.8%	89.6%	70.3%
WH07	Infections or Other Complications of Procedures	Trauma & Orthopaedics	424	108	20.3%	532	0.1%	4.75	3.01	4.39	35.8%	24.1%	33.5%
HC70	Complex Intradural Spinal Procedures	Trauma & Orthopaedics	59	102	63.4%	161	0.0%	4.37	2.25	3.02	13.6%	63.7%	45.3%
HC54	Major Spinal Reconstructive Procedures	Trauma & Orthopaedics	458	100	17.9%	558	0.1%	5.52	3.40	5.14	2.4%	1.0%	2.2%
YQ15	Open Treatment of Recurrent Unilateral Varicose Veins	General Surgery	157	99	38.7%	256	0.0%	1.11	1.05	1.09	89.2%	94.9%	91.4%
FD10	Non-Malignant Gastrointestinal Tract Disorders	General Surgery	9,521	94	1.0%	9,615	1.6%	2.29	1.91	2.28	67.7%	56.4%	67.6%
MA28	Complex, Laparoscopic or Endoscopic, Upper Genital Tract Procedures	Gynaecology	3,801	90	2.3%	3,891	0.7%	2.23	2.14	2.23	23.5%	17.8%	23.4%
FF34	Major Large Intestine Procedures, 19 years and over	General Surgery	1,207	88	6.8%	1,295	0.2%	3.67	1.32	3.51	24.9%	76.1%	28.4%
HC27	Degenerative Spinal Conditions	Trauma & Orthopaedics	674	82	10.8%	756	0.1%	1.94	2.17	1.97	54.5%	13.4%	50.0%
FF10	Complex Surgical Procedures for Obesity	General Surgery	666	79	10.6%	745	0.1%	2.93	2.01	2.83	4.2%	0.0%	3.8%
HD26	Musculoskeletal Signs or Symptoms	Trauma & Orthopaedics	382	77	16.8%	459	0.1%	2.38	1.58	2.25	51.3%	61.0%	52.9%
MB09	Non-Malignant Gynaecological Disorders	Gynaecology	2,899	77	2.6%	2,976	0.5%	2.01	2.51	2.02	62.3%	54.5%	62.1%

HRG4	Description HRG4	Specialty	Public	Private		All		Public	Private	All	Public	Private	All
			Volume	Volume	%	Volume	%	Mean length of stay			Day case (%)		
JD07	Skin Disorders	General Surgery	2,281	74	3.1%	2,355	0.4%	1.67	1.54	1.67	73.2%	54.1%	72.6%
FF53	Minor Therapeutic or Diagnostic, General Abdominal Procedures	General Surgery	2,754	69	2.4%	2,823	0.5%	1.18	1.06	1.18	83.7%	94.2%	84.0%
HE81	Infection or Inflammatory Reaction, due to, Internal Orthopaedic Prosthetic Devices, Implants or Grafts	Trauma & Orthopaedics	481	68	12.4%	549	0.1%	2.31	1.38	2.19	81.5%	89.7%	82.5%
HC65	Minor Extradural Spinal Procedures	Trauma & Orthopaedics	337	63	15.8%	400	0.1%	1.14	1.21	1.15	88.4%	79.4%	87.0%
KA09	Thyroid Procedures	General Surgery	2,265	61	2.6%	2,326	0.4%	2.35	2.15	2.35	9.9%	3.3%	9.8%
HN62	Very Major Elbow Procedures for Non-Trauma	Trauma & Orthopaedics	664	58	8.0%	722	0.1%	2.43	1.34	2.34	42.3%	65.5%	44.2%
LB60	Complex, Open or Laparoscopic, Kidney or Ureter Procedures	Gynaecology	350	58	14.2%	408	0.1%	2.94	1.57	2.75	33.4%	56.9%	36.8%
FF02	Complex, Oesophageal, Stomach or Duodenum Procedures, 19 years and over	General Surgery	2,953	56	1.9%	3,009	0.5%	5.03	2.02	4.98	6.8%	14.3%	7.0%
LB62	Major Laparoscopic, Kidney or Ureter Procedures, 19 years and over	Gynaecology	237	55	18.8%	292	0.0%	1.68	1.27	1.60	56.5%	74.5%	59.9%
FF51	Major General Abdominal Procedures	Gynaecology	966	54	5.3%	1,020	0.2%	2.66	1.39	2.60	39.8%	74.1%	41.6%
HE82	Other Complications of, Internal Orthopaedic Prosthetic Devices, Implants or Grafts	Trauma & Orthopaedics	367	53	12.6%	420	0.1%	2.96	2.75	2.93	35.4%	22.6%	33.8%
HT53	Major Shoulder Procedures for Trauma	Trauma & Orthopaedics	3,785	53	1.4%	3,838	0.6%	1.58	1.68	1.58	62.5%	73.6%	62.6%
HC53	Very Major Spinal Reconstructive Procedures	Trauma & Orthopaedics	252	52	17.1%	304	0.1%	6.90	3.67	6.35	0.0%	1.9%	0.3%

HRG4	Description HRG4	Specialty	Public	Private		All		Public	Private	All	Public	Private	All
			Volume	Volume	%	Volume	%	Mean length of stay			Day case (%)		
FF51	Major General Abdominal Procedures	General Surgery	2,053	46	2.2%	2,099	0.4%	4.22	1.61	4.16	36.9%	71.7%	37.6%
GA07	Intermediate, Hepatobiliary or Pancreatic Procedures	General Surgery	2,001	45	2.2%	2,046	0.3%	3.40	1.93	3.36	27.4%	31.1%	27.5%
HT52	Very Major Shoulder Procedures for Trauma	Trauma & Orthopaedics	1,246	32	2.5%	1,278	0.2%	2.36	1.22	2.33	37.0%	78.1%	38.0%

Figure A1. Histogram of differential distance ($Dist_{public}$ - $Dist_{private}$).



Notes: Negative values indicate that the nearest public provider is closer to the patient's place of residence than the nearest private provider, while positive values indicate that the nearest private provider is relatively closer.

[7] Our approach differs from hurdle models of hospital utilisation based on counts such as doctor visits, where individuals with zero use are unobserved in the second part and truncation is required. In our setting, all individuals in the sample receive treatment; even those treated as day cases benefited from hospital resources and are fully observed in the data. The excess mass of day cases is explicitly modelled in the first part of the model. This approach reflects the two pathways faced by patients when admitted for elective surgery, which involve distinct economic and clinical decisions. Public and private providers might respond differently to the incentives for same-day discharge and adopt distinct clinical protocols.

For the control function in the second stage of the 2SRI approach, we compute the generalised residual (Gourieroux et al., 1987) from the first-stage model, which is defined by:

$$\hat{v}_i = \frac{\phi(\hat{w}_i)}{\hat{p}_i(1-\hat{p}_i)}(HO_i - \hat{p}_i),$$

$$\hat{p}_i = \Phi(\hat{w}_i),\ \hat{w}_i = \hat{\varphi} DD_{ij} + X_i'\hat{\beta}$$

where Φ is the cumulative standard normal distribution function and $\hat{p}_i$ is the fitted probability from Equation (3).

Table A2. Average marginal effects from the second part of the two-part model with a Poisson specification.

VARIABLE	(1) HRG FE only	(2) HRG FE + casemix adjusters	(3) 2SRI
Private ownership	-1.0828***	-0.8734***	-0.5972***
	(0.0534)	(0.0531)	(0.1576)
Control function term			-0.1728**
			(0.0841)
Age group, years [Ref=18-49]			
0-17		-0.0873	-0.0406
		(0.0324)	(0.1506)
50-54		0.0083	0.0017
		(0.0195)	(0.0195)
55-59		0.0245	0.0158
		(0.0210)	(0.0215)
60-64		0.0372*	0.0268
		(0.0222)	(0.0227)
65-69		0.0779***	0.0664***
		(0.0234)	(0.0238)
70-74		0.1934***	0.1834***
		(0.0233)	(0.0244)
75-79		0.3874***	0.3810***
		(0.0249)	(0.0250)
80-84		0.7290***	0.7331***
		(0.0343)	(0.0349)
85+		1.2214***	1.2418***
		(0.0531)	(0.0542)
Female patient		0.1927***	0.1931***
		(0.0123)	(0.0122)
Ethnic group [Ref=White]			
Asian		0.3596	0.3713
		(0.0783)	(0.0879)
Black		0.6091***	0.6270***
		(0.0447)	(0.0475)
Mixed		0.1933***	0.1954***
		(0.0498)	(0.0504)
Other/Unknown		-0.0059	-0.0803**
		(0.0237)	(0.0393)
IMD [Ref=Least deprived]			
Second least deprived		0.0385**	0.0433***
		(0.0152)	(0.0150)
Third most deprived		0.0373**	0.0488***
		(0.0164)	(0.0158)
Second most deprived		0.1037***	0.1184***
		(0.0197)	(0.0192)
Most deprived		0.1705***	0.1863***
		(0.0256)	(0.0261)
Patient living in rural area (LSOA11)		-0.1487***	-0.1480***
		(0.0196)	(0.0193)
Number of past year emergency admissions [Ref=None]			
1		0.7125***	0.7320***

VARIABLE	(1) HRG FE only	(2) HRG FE + casemix adjusters	(3) 2SRI
		(0.0612)	(0.0637)
2		0.6809***	0.6988***
		(0.1259)	(0.1293)
3		0.5231**	0.5310**
		(0.2215)	(0.2253)
4+		2.0058***	2.0175***
		(0.4009)	(0.4096)
P-value control function term (2nd stage)			0.0336
Observations	312,128	312,128	312,128

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Elixhauser comorbidities and HRG fixed effects are also included in the models but not presented.

*** p<0.01, ** p<0.05, * p<0.1

Table A3. Average marginal effects from the two-part-2SRI model with higher order terms of the control function.

VARIABLE	Second-order control function		Third-order control function	
	Overnight equation	Inpatient LOS equation	Overnight equation	Inpatient LOS equation
Private ownership	-0.0246	-0.6321***	-0.0036	-0.5988***
	(0.0435)	(0.1813)	(0.0439)	(0.2062)
Control function term				
Linear	-0.0111	-0.1146	-0.0288**	-0.1440
	(0.0121)	(0.1103)	(0.0135)	(0.1339)
Quadratic	-0.0030	-0.0654***	-0.0107**	-0.0753***
	(0.0054)	(0.0190)	(0.0052)	(0.0154)
Cubic			0.0068***	0.0104
			(0.0017)	(0.0125)
Age group, years [Ref=18-49]				
0-17	0.0444*	-0.0675	0.0482**	-0.0620
	(0.0234)	(0.1453)	(0.0233)	(0.1478)
50-54	0.0224**	0.0009	0.0221**	0.0007
	(0.0100)	(0.0572)	(0.0100)	(0.0573)
55-59	0.0372**	0.0151	0.0370**	0.0149
	(0.0162)	(0.0703)	(0.0162)	(0.0703)
60-64	0.0619***	0.0264	0.0616***	0.0260
	(0.0203)	(0.0777)	(0.0203)	(0.0777)
65-69	0.0863***	0.0677	0.0860***	0.0672
	(0.0246)	(0.0807)	(0.0246)	(0.0806)
70-74	0.1115***	0.1828**	0.1113***	0.1824**
	(0.0267)	(0.0797)	(0.0267)	(0.0796)
75-79	0.1416***	0.3790***	0.1415***	0.3787***
	(0.0276)	(0.0862)	(0.0276)	(0.0861)
80-84	0.1779***	0.7258***	0.1780***	0.7261***
	(0.0283)	(0.1307)	(0.0283)	(0.1310)
85+	0.1950***	1.2279***	0.1955***	1.2292***
	(0.0306)	(0.2159)	(0.0307)	(0.2169)
Female patient	0.0189*	0.1940***	0.0189*	0.1940***
	(0.0101)	(0.0487)	(0.0101)	(0.0487)

VARIABLE	Second-order control function		Third-order control function	
	Overnight equation	Inpatient LOS equation	Overnight equation	Inpatient LOS equation
Ethnic group [Ref=White]				
Asian	0.0432***	0.3605***	0.0434***	0.3612***
	(0.0061)	(0.0888)	(0.0061)	(0.0895)
Black	0.0416***	0.6127***	0.0421***	0.6142***
	(0.0071)	(0.0910)	(0.0071)	(0.0919)
Mixed	0.0221***	0.1888***	0.0221***	0.1889***
	(0.0059)	(0.0597)	(0.0059)	(0.0598)
Other/Unknown	-0.0039	-0.0611	-0.0061	-0.0648
	(0.0064)	(0.0631)	(0.0066)	(0.0658)
IMD [Ref=Least deprived]				
Second least deprived	0.0042**	0.0422***	0.0043**	0.0424***
	(0.0019)	(0.0099)	(0.0019)	(0.0100)
Third most deprived	0.0054*	0.0456***	0.0057*	0.0462***
	(0.0030)	(0.0170)	(0.0030)	(0.0175)
Second most deprived	0.0097***	0.1120***	0.0100***	0.1128***
	(0.0030)	(0.0140)	(0.0030)	(0.0146)
Most deprived	0.0198***	0.1779***	0.0201***	0.1786***
	(0.0037)	(0.0273)	(0.0037)	(0.0278)
Patient living in rural area (LSOA11)	-0.0064*	-0.1485***	-0.0064*	-0.1485***
	(0.0033)	(0.0214)	(0.0033)	(0.0214)
Number of past year emergency admissions [Ref=None]				
1	0.0573***	0.7112***	0.0584***	0.7134***
	(0.0051)	(0.1540)	(0.0051)	(0.1541)
2	0.0631***	0.6814***	0.0643***	0.6843***
	(0.0101)	(0.1918)	(0.0102)	(0.1915)
3	0.0660***	0.5159**	0.0674***	0.5180**
	(0.0173)	(0.2300)	(0.0174)	(0.2302)
4+	0.1213***	1.9213***	0.1226***	1.9249***
	(0.0265)	(0.4858)	(0.0266)	(0.4857)
P-value control function term (2nd stage)	0.6503	0.0018	0.0011	0.0000
Pseudo R-squared	0.4194	0.0595	0.4194	0.0595
Observations	596,852	312,128	596,852	312,128

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Elixhauser comorbidities and HRG fixed effects are also included in the models but not presented.

*** p<0.01, ** p<0.05, * p<0.1

Table A4. Descriptive statistics for the inpatient sample.

	Public providers					Private providers				
	Admissions	*Mean*	*SD*	*Min*	*Max*	*Admissions*	*Mean*	*SD*	*Min*	*Max*
Sample size	229,199					82,929				
LOS, days		3.66	2.69	2.00	29.00		2.80	1.05	2.00	29.00
30-day emergency readmissions		0.02	0.12	0.00	1.00		0.01	0.08	0.00	1.00
Age, years		60.94	17.42	0.00	103.00		65.69	12.34	15.00	97.00
Female patient		0.62	0.49	0.00	1.00		0.57	0.49	0.00	1.00
White patient		0.78	0.41	0.00	1.00		0.55	0.50	0.00	1.00
Index Multiple Deprivation		21.04	14.79	0.54	92.74		18.22	13.66	0.54	88.77
Differential distance (Dpub-Dpriv, 1st stage)		0.21	0.41	0.00	1.00		0.25	0.43	0.00	1.00
Number of Elixhauser comorbidities		1.69	1.47	0.00	11.00		1.46	1.25	0.00	8.00
N.of past year's emergency hospitalisations	16,236	0.34	0.80	0.00	42.00	6,511	0.03	0.20	0.00	4.00
Instrumental variable										
Distance to nearest public provider (km)		7.86	7.62	0.04	171.91		8.66	8.12	0.12	156.12
Distance to nearest private provider (km)		16.83	18.14	0.05	210.80		10.21	9.13	0.05	136.78
Differential distance (Nearest public-Nearest private)		-8.97	16.16	-103.87	54.23		-1.54	7.30	-74.27	54.23
Number of patients	224,617					79,709				
Number of HRGs	70					70				
Number of sites	368					163				

Table A5. First-stage estimates for the main empirical specification (2PM-2SRI presented in Table 3).

VARIABLE	Overnight equation	Inpatient LOS equation
Differential distance (Dpub-Dpriv)	0.0088***	0.0079***
	(0.0007)	(0.0008)
Age group, years [Ref=18-49]		
0-17	-0.2338***	-0.2477***
	(0.0274)	(0.0429)
50-54	0.0261***	0.0223***
	(0.0042)	(0.0070)
55-59	0.0283***	0.0287***
	(0.0046)	(0.0083)
60-64	0.0278***	0.0328***
	(0.0053)	(0.0091)
65-69	0.0287***	0.0369***
	(0.0057)	(0.0094)
70-74	0.0222***	0.0308***
	(0.0060)	(0.0095)
75-79	0.0119*	0.0206**
	(0.0064)	(0.0090)
80-84	-0.0172***	-0.0118
	(0.0063)	(0.0076)
85+	-0.0561***	-0.0540***
	(0.0081)	(0.0079)
Female patient	0.0008	-0.0017
	(0.0022)	(0.0026)
Ethnic group [Ref=White]		
Asian	-0.0491***	-0.0587***
	(0.0096)	(0.0159)
Black	-0.0851***	-0.1013***
	(0.0109)	(0.0182)
Mixed	-0.0136**	-0.0273**
	(0.0066)	(0.0113)
Other/Unknown	0.2577***	0.2495***
	(0.0171)	(0.0232)
IMD [Ref=Least deprived]		
Second least deprived	-0.0062**	-0.0101**
	(0.0031)	(0.0045)
Third most deprived	-0.0229***	-0.0286***
	(0.0046)	(0.0067)
Second most deprived	-0.0323***	-0.0365***
	(0.0056)	(0.0079)
Most deprived	-0.0327***	-0.0410***
	(0.0067)	(0.0100)
Patient living in rural area (LSOA11)	0.0120*	0.0115
	(0.0071)	(0.0099)
Number of past year emergency admissions [Ref=None]		
1	-0.1243***	-0.1242***
	(0.0119)	(0.0164)
2	-0.1384***	-0.1618***

VARIABLE	Overnight equation	Inpatient LOS equation
	(0.0155)	(0.0243)
3	-0.1544***	-0.1382***
	(0.0239)	(0.0392)
4+	-0.1401***	-0.1781***
	(0.0257)	(0.0368)
Pseudo R-squared	0.2349	0.2487
Observations	596,852	312,128

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Elixhauser comorbidities and HRG fixed effects are also included in the models but not presented. In the 2SRI model, the quadratic term of the IV is also part of the model, as in previous specifications.

*** p<0.01, ** p<0.05, * p<0.1

Table A6. Average marginal effects from the 2SRI regressions for the effect of private ownership on 30-day emergency readmissions among inpatient admissions.

	Inpatient sample		
	(1)	(2)	(3)
VARIABLE	HRG FE only	HRG FE + casemix adjusters	2SRI
Private ownership	-0.0072***	-0.0047***	-0.0039
	(0.0011)	(0.0010)	(0.0026)
Control function term			-0.0005
			(0.0014)
Differential distance (1st stage)			0.0079***
			(0.0015)
Wald test for instrument strength (χ^2)			100.66
P-value instrument (1st stage)			0.0000
P-value residual term (2nd stage)			0.761
Pseudo R-squared	0.0299	0.0446	0.0446
Observations	312,128	312,128	312,128

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects, but not presented.

*** p<0.01, ** p<0.05, * p<0.1

Table A7. Average marginal effects from the two-part-2SRI regressions for the effect of private ownership on hospital length of stay, excluding readmitted patients.

	Overnight equation		Inpatient LOS equation	
	(1)	(2)	(1)	(2)
VARIABLE	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**
Private ownership	-0.0452***	-0.0214	-0.8581***	-0.5851***
	(0.0100)	(0.0357)	(0.0519)	(0.1555)
Control function term		-0.0147		-0.1707**
		(0.0170)		(0.0830)
Differential distance (1st stage)		0.0088***		0.0079***
		(0.0007)		(0.0008)
Wald test for instrument strength (χ^2)		182.43		95.78
P-value instrument (1st stage)		0.0000		0.0000
P-value control-function term (2nd stage)		0.271		0.040
Pseudo R-squared	0.402	0.402	0.059	0.059
Observations	590,187	590,187	307,989	307,989

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table A8. Average marginal effects from the two-part-2SRI model with variants of the instrument.

	Overnight equation			Inpatient LOS equation		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLE	**2SRI with linear IV**	**2SRI with cubic IV**	**2SRI with quintile IV**	**2SRI with linear IV**	**2SRI with cubic IV**	**2SRI with quintile IV**
Private ownership	-0.0204	-0.0216	-0.0340	-0.5707***	-0.5817***	-0.6967***
	(0.0308)	(0.0302)	(0.0294)	(0.1539)	(0.1522)	(0.1483)
Control function term	-0.0156	-0.0149	-0.0072	-0.1843**	-0.1775**	-0.1053
	(0.0140)	(0.0137)	(0.0132)	(0.0825)	(0.0816)	(0.0797)
Differential distance (1st stage)	0.0079***	0.0087***		0.0072***	0.0079***	
	(0.0005)	(0.0005)		(0.0003)	(0.0004)	
Differential distance category [Ref=Public much closer, 12-104 km]						
Public closer (4-12 km)			0.0949***			0.0947***
			(0.0039)			(0.0049)
Public slightly closer (1-4 km)			0.1518***			0.1436***
			(0.0067)			(0.0069)
≈ equal distance			0.1821***			0.1710***
			(0.0083)			(0.0075)
Private closer (up to 68 km)			0.2158***			0.2079***
			(0.0072)			(0.0076)
Wald test for instrument strength (χ^2)	229.35	179.93	227.93	124.34	96.40	123.88
P-value instrument (1st stage)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P-value control-function term (2nd stage)	0.2658	0.3837	0.5231	0.0255	0.0296	0.1865
Pseudo R-squared	0.4193	0.4193	0.4193	0.0594	0.0594	0.0594
Observations	596,852	596,852	596,852	312,128	312,128	312,128

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects.
*** p<0.01, ** p<0.05, * p<0.1

Figure A2. Average length of stay by sub-integrated care boards.

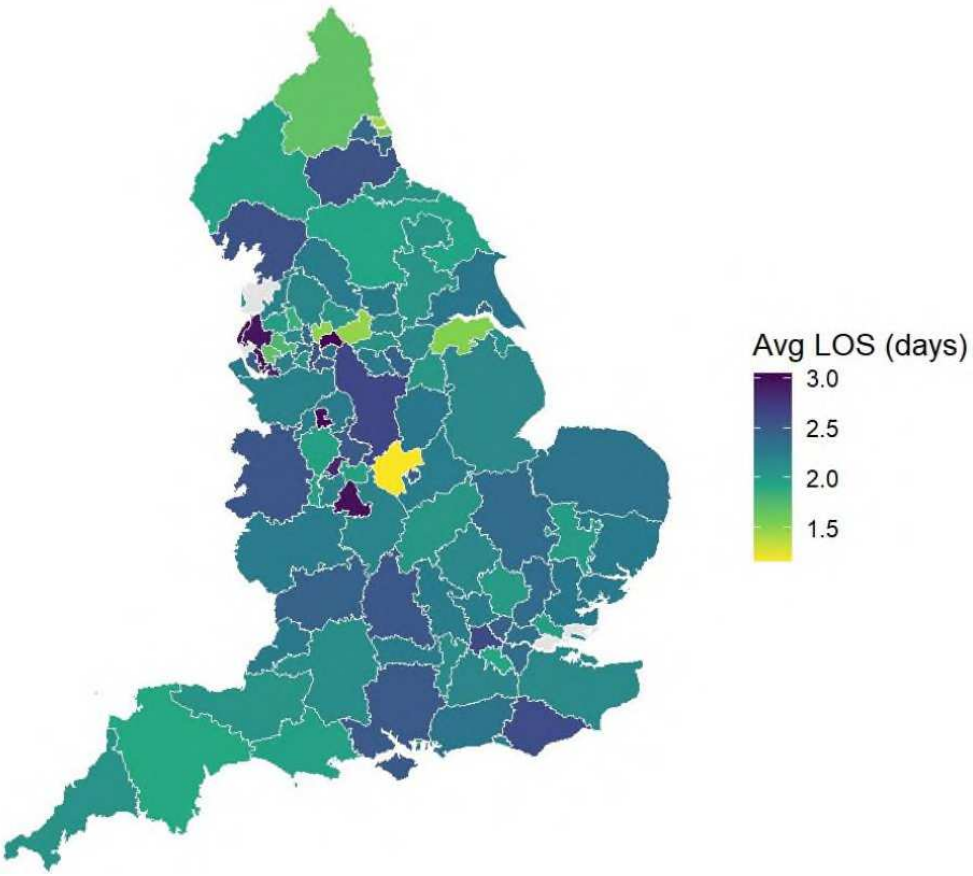


Table A9. Two-part-2SRI estimates with region fixed effects.

	Overnight equation		Inpatient LOS equation	
	(1)	(2)	(1)	(2)
VARIABLE	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**
Private ownership	-0.0441***	-0.0228	-0.8310***	-0.6290***
	(0.0104)	(0.0264)	(0.0744)	(0.1318)
NHS England region (Ref=London)				
South West	-0.0646***	-0.0670***	-0.5472***	-0.5764***
	(0.0175)	(0.0099)	(0.1239)	(0.0738)
South East	-0.0257**	-0.0276***	-0.3335***	-0.3592***
	(0.0130)	(0.0082)	(0.1258)	(0.0657)
Midlands	0.0003	-0.0014	-0.3209***	-0.3379***
	(0.0120)	(0.0063)	(0.1137)	(0.0608)
East of England	-0.0191*	-0.0218***	-0.3190***	-0.3451***
	(0.0116)	(0.0069)	(0.0996)	(0.0530)
North West	-0.0076	-0.0113	-0.2624***	-0.2976***
	(0.0126)	(0.0071)	(0.0945)	(0.0562)
North East and Yorkshire	-0.0284	-0.0314***	-0.5510***	-0.5837***
	(0.0174)	(0.0082)	(0.1181)	(0.0654)
Control function term		-0.0133		-0.1275*
		(0.0114)		(0.0678)
Differential distance (1st stage)		0.0091***		0.0079***
		(0.0017)		(0.0015)
Wald test for instrument strength (χ^2)		174.45		89.98
P-value instrument (1st stage)		0.0000		0.0000
P-value control-function term (2nd stage)		0.2465		0.0601
Pseudo R-squared	0.4213	0.4214	0.0608	0.0608
Observations	596,852	596,852	312,128	312,128

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table A10. Average marginal effects from the two-part-2SRI regressions using patients with both public and private providers within 30 km.

	Overnight equation		Inpatient LOS equation	
	(1)	(2)	(1)	(2)
VARIABLE	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**
Private ownership	-0.0492***	-0.0490	-0.8933***	-0.5036***
	(0.0095)	(0.0315)	(0.0484)	(0.1447)
Control function term		-0.0001		-0.0303
		(0.0150)		(0.0852)
Differential distance (1st stage)		0.0097***		0.0086***
		(0.0008)		(0.0011)
Wald test for instrument strength (χ^2)		146.62		55.91
P-value instrument (1st stage)		0.0000		0.0000
P-value control-function term (2nd stage)		0.995		0.723
Pseudo R-squared	0.4267	0.4267	0.0594	0.0594
Observations	525,353	525,353	274,242	274,242

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects. Note that differential distance enters here as a linear term, given the linear relationship between the instrument and the probability of going private in this estimation sample.

*** p<0.01, ** p<0.05, * p<0.1

Table A11. Average marginal effects from the two-part-2SRI regressions in urban areas.

	Overnight equation		Inpatient LOS equation	
	(1)	(2)	(1)	(2)
VARIABLE	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**
Private ownership	-0.0502***	-0.0433	-0.9210***	-0.7512***
	(0.0097)	(0.0317)	(0.0477)	(0.1396)
Control function term		-0.0042		-0.1054
		(0.0149)		(0.0774)
Differential distance (1st stage)		0.0089***		0.0079***
		(0.0008)		(0.0010)
Wald test for instrument strength (χ^2)		140.33		65.79
P-value instrument (1st stage)		0.0000		0.0000
P-value control-function term (2nd stage)		0.741		0.304
Pseudo R-squared	0.4136	0.4136	0.0604	0.0604
Observations	471,249	471,249	242,813	242,813

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table A12. Average marginal effects from the two-part-2SRI regressions for the bottom and top deprivation quintiles.

	Least deprived quintile				Most deprived quintile			
	Overnight equation		Inpatient LOS equation		Overnight equation		Inpatient LOS equation	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
VARIABLE	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**
Private ownership	-0.0303***	-0.0091	-0.7397***	-0.4799***	-0.0717***	-0.0815**	-1.1263***	-1.0293***
	(0.0116)	(0.0308)	(0.0552)	(0.1667)	(0.0099)	(0.0338)	(0.0567)	(0.1944)
Control function term		-0.0132		-0.1624*		0.0059		-0.0592
		(0.0142)		(0.0917)		(0.0162)		(0.1080)
Differential distance (1st stage)		0.0095***		0.0089***		0.0089***		0.0081***
		(0.0007)		(0.0010)		(0.0009)		(0.0011)
Wald test for instrument strength (χ^2)		175.20		85.21		109.4		57.82
P-value instrument (1st stage)		0.0000		0.0000		0.0000		0.0000
P-value control-function term (2nd stage)		0.3540		0.076		0.7140		0.584
Pseudo R-squared	0.4358	0.4358	0.0618	0.0615	0.3866	0.3866	0.0621	0.0621
Observations	133,975	133,975	72,836	72,836	97,970	97,970	47,772	47,772

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Table A13. Estimates using nearest neighbour propensity score matching as an alternative approach.

VARIABLE	Overnight equation	Inpatient LOS equation
Private ownership	-0.0398***	-0.7635***
	(0.0040)	(0.0241)
Observations	596,852	312,128

Notes: Standard errors in parentheses, bootstrapped with 1,000 replications. The matching variables are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG dummies.

*** p<0.01, ** p<0.05, * p<0.1

Table A14. Average marginal effects from the negative binomial 2SRI model with the full sample.

VARIABLE	HRG FE + casemix adjusters	2SRI
Private ownership	-0.5330***	-0.3137***
	(0.0377)	(0.1116)
Control function term		-0.1371**
		(0.0561)
Wald test for instrument strength (χ^2)		173.03
P-value instrument (1st stage)		0.0000
P-value control-function term (2nd stage)		0.015
Pseudo R-squared	0.1256	0.1256
Observations	596,852	596,852

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects, but not presented.

*** p<0.01, ** p<0.05, * p<0.1

Table A15. Average marginal effects from the two-part-2SRI regressions for the effect of private ownership on hospital length of stay for hip and knee procedures.

	Overnight equation		Inpatient LOS equation	
	(1)	(2)	(1)	(2)
VARIABLE	HRG FE + casemix adjusters	2SRI	HRG FE + casemix adjusters	2SRI
Private ownership	0.0048	0.0489	-0.8972***	0.0378
	(0.0209)	(0.0462)	(0.0243)	(0.2783)
Control function term		-0.0276		-0.5830***
		(0.0238)		(0.1576)
Differential distance (1st stage)		0.0093***		0.0091***
		(0.0003)		(0.0003)
Wald test for instrument strength (χ^2)		635.93		834.96
P-value instrument (1st stage)		0.0000		0.0000
P-value control-function term (2nd stage)		0.2460		0.0000
Pseudo R-squared	0.4135	0.4137	0.0559	0.0563
Observations	211,602	211,602	177,324	177,324

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects. The HRGs corresponding to hip and knee procedures in this sample are: HN12, HN13, HN14, HN22, HN23, HN25, HN81, HT22, and HT23.

*** p<0.01, ** p<0.05, * p<0.1

Table A16. Average marginal effects from the two-part-2SRI regressions for procedures with at least 30% private participation.

	Overnight equation		Inpatient LOS equation	
	(1)	(2)	(1)	(2)
VARIABLE	**HRG FE + casemix adjusters**	**2SRI**	**HRG FE + casemix adjusters**	**2SRI**
Private ownership	-0.0157	0.0443	-0.8403***	0.1295
	(0.0127)	(0.0460)	(0.0613)	(0.2519)
Control function term		-0.0374		-0.6032***
		(0.0245)		(0.1443)
Differential distance (1st stage)		0.0088***		0.0079***
		(0.0007)		(0.0008)
Wald test for instrument strength (χ^2)		182.43		95.78
P-value instrument (1st stage)		0.0000		0.0000
P-value control-function term (2nd stage)		0.1270		0.0000
Pseudo R-squared	0.4525	0.4528	0.0497	0.0498
Observations	242,416	242,416	186,646	186,646

Notes: Standard errors in parentheses, clustered at the trust and HRG level, and bootstrapped with 1,000 replications. Other covariates included in the regression are age in band groups, sex, ethnicity, IMD quintile, indicator of rurality, number of past year emergency admissions, Elixhauser comorbidities, and HRG fixed effects. The 11 HRGs included, where the private have a participation of at least 30% are: HC63, HC64, HC70, HN12, HN22, HN23, HN32, HN42, HN52, HN53, and YQ15.

*** p<0.01, ** p<0.05, * p<0.1



Part of

