Received: 29 March 2023 | Revised: 10 March 2024 | Accepted: 8 April 2024

DOI: 10.1002/hec.4838

RESEARCH ARTICLE

Health Economics WILEY

Efficiency and productivity gains of robotic surgery: The case of the English National Health Service

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Funding information
Health Foundation, Grant/Award Number: 7432; Spanish Ministry of Science, Innovation and Universities, Grant/Award Numbers: PID2022-138866OB-I00, CNS2023-144351

Abstract

This paper examines the effect of new medical technology (robotic surgery) on efficiency gains and productivity changes for surgical treatment in patients with prostate cancer from the perspective of a public health sector organization. In particular, we consider three interrelated surgical technologies within the English National Health System: robotic, laparoscopic and open radical prostatectomy. Robotic and laparoscopic techniques are minimally invasive procedures with similar clinical benefits. While the clinical benefits in adopting robotic surgery over laparoscopic intervention are unproven, it requires a high initial investment cost and carries high on-going maintenance costs. Using data from Hospital Episode Statistics for the period 2000–2018, we observe growing volumes of prostatectomies over time, mostly driven by an increase in robotic-assisted surgeries, and further analyze whether hospital providers that adopted a robot see improved measures of throughput. We then quantify changes in total factor and labor productivity arising from the use of this technology. We examine the impact of robotic adoption on efficiency gains employing a staggered difference-in-difference estimator and find evidence of a 50% reduction in length of stay (LoS), 49% decrease in post-LoS and 44% and 46% decrease in postoperative visits after 1 year and 2 years, respectively. Productivity analysis shows the growth in radical prostatectomy volume is sustained with a relatively stable number of urology surgeons. The robotic technique increases total production at the hospital level between 21% and 26%, coupled with a 29% improvement in labor productivity. These benefits lend some, but not overwhelming support for the large-scale hospital investments in such costly technology.

KEYWORDS
efficiency gains, labor productivity, robotic surgery, staggered difference-in-differences, total factor productivity

JEL CLASSIFICATION
O33, I12, C41, C33, J2

1 | INTRODUCTION

While there has been growing interest in the wider economy on the impact of robots on productivity, employment, employees' skill-mix and wages (Acemoglu & Restrepo, 2020; Dauth et al., 2021; Graetz & Michaels, 2018; Koch et al., 2021) there has been little consideration of this topic from the perspective of health care organizations. Economic studies conclude that the introduction of robots reduce employment and wages, changing the composition of labor with a lower share of low-skilled employees and favoring employment of highly skilled workers, and as a result is potentially accompanied by an increase in productivity (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018). Recent analysis at the firm level suggests that robotic use in the manufacturing sector is adopted by more productive firms, and while there are employment losses suffered by low skill workers there are in fact net employment gains as productivity increases (Adachi et al., 2020; Aghion et al., 2020; Hirvonen et al., 2022; Koch et al., 2021).

Within the health care sector technology has been identified as a major driver of expenditure growth (Newhouse, 1992; Lamiraud & Lhuillery, 2016; Smith et al., 2009). Assessing the specific impact of new health care technology on output and productivity is, however, fraught with difficulty and consequently, there has been little analysis undertaken at the producer level. This difficulty reflects, partly, a general complication in defining a meaningful production function for producers within the health care sector, general empirical specification issues arising from measurement and endogeneity problems, and difficulties in attributing the heterogeneous impact of technology on different providers and patient groups (Chandra & Skinner, 2012). It has also been noted that in centralized health care systems health care organizations tend to adopt and diffuse new technologies less rapidly than systems which are more fragmented and have a significant level of private insurance (Chandra & Skinner, 2012; TECH, 2001). In this context it is of interest to consider the impact of robotic surgery both across and within organizations in a major, public health care sector: the English National Health Service (NHS).

The uptake of robotic surgery within the NHS is of special appeal for several reasons. First, robotic surgery within the English NHS, initially introduced for prostatectomy at a London teaching hospital (St Mary's NHS Hospital) in 2000 saw very low adoption rates, but subsequently spread rapidly throughout NHS England.[1] There are three, competing surgical techniques used for radical prostatectomy: open, laparoscopic and, robot-assisted (laparoscopic) surgery. Laparoscopic surgery requires less invasive incisions than open surgery and is often referred to as key-hole or minimally invasive surgery. Robotic surgery, properly termed robotic-assisted laparoscopic surgery, does not replace the surgeon, but is operated by the surgeon through use of a console and is also minimally invasive. The robot provides three dimensional views of the operative field, allows more dexterity in the use of the surgical instruments, more precision and smaller incisions; throughout we refer to this type of surgery as robotic surgery. Not only has robotic surgery replaced the traditional open surgery for the treatment of prostate cancer, but has rapidly begun to replace the newer, less invasive laparoscopic procedure which was only introduced in the early 2000s (Hughes et al., 2016; Marcus et al., 2017; Maynou et al., 2021, 2022). Robotic surgery for radical prostatectomy increased from 5% in 2006 to 88% of all prostatectomies performed within the English NHS by 2018, while open and laparoscopic procedures decreased over that period, from 83% to 6% and 12%–6%, respectively. Similar rapid rates of adoption have been noted elsewhere, including within the US where by 2017, 78% of commercially insured patients and 62% of Medicare Advantage plans had a robotic procedure for prostate surgery (Maynou et al., 2021). Recently, robot use has spread to other treatment areas (Hughes et al., 2016; Marcus et al., 2017; Maynou et al., 2022).

Second, the clinical evidence on the relative patient benefits arising from the new robotic technology, at least when compared directly to the general laparoscopic techniques, suggests that these are at best unproven. Several studies comparing the older open prostatectomy with laparoscopic or robotic techniques do report improved clinical outcomes in some dimensions associated with the use of these newer technologies, including a lower risk of incontinence or sexual dysfunction, reduced blood loss and transfusions and reduced length of stay (LoS) (Moran et al., 2013; NHS, 2015; Robertson et al., 2013; Tewari et al., 2012). However, several medical studies have shown that there is little clinical advantage when comparing the use of robotic over laparoscopic procedures not only for prostatectomy but also within other surgical areas (Hohwu et al., 2009; Lotan et al., 2004; Melamed et al., 2018; Nossiter et al., 2018; Olavarria et al., 2020). A recent paper provides evidence across outcomes between these newer procedures, documenting that while there was no statistically significant difference across a range of measured outcomes, a small clinically significant, but not statistically significant difference, was found only in subjectively measured sexual function (Nossiter et al., 2018).

Third, while currently the minimally invasive techniques of laparoscopic and robotic prostatectomy appear to provide similar patient outcomes (Moran et al., 2013; Nossiter et al., 2018), their costs differ substantially. English NHS hospitals' have considerable discretion over the procurement of this new and costly robotic technology.[2] Despite the lack of a unified procurement framework for the purchase of robots within the NHS, there is centralized guidance over new treatments and procedures. This guidance is produced by the National Institute for Health and Care Excellence (NICE), an agency that provides supportive evidence for the adoption of new technologies into the NHS and publishes clinical guidelines. NICE guidance, which is a non-binding recommendation, suggested robotic surgery should only be based in high volume centers undertaking at least 150 robot-assisted prostatectomies per year (NICE, 2014, 2019). There was, however, a significant lag between the first introduction of a robot in 2000 and the publication of guidance in 2014 and NHS organizations were not required to meet these thresholds when adopting the technology.

Despite recent rapid uptake and diffusion of robotic surgery (Horn et al., 2022; Maynou et al., 2022), there remain wider questions over efficiency and productivity gains in the surgical setting. Studies considering robotic technology generally, highlight the importance of using micro-level data and this is the approach we follow by focusing on individual hospital providers. In their study of the manufacturing sector, Koch et al. (2021), as with most research in manufacturing, presume that robots are substitutes for (low skill) labor. In the context of robotic surgery, robots generally complement highly skilled labor (surgeons) rather than replacing low-skilled workers and we present below some stylized facts that indicate that the adoption and diffusion of robots had little impact on overall skill-mix, indicating one of the differences this technology has on health sector providers.

The determinants of robotic surgery diffusion within the English NHS have been documented with factors such as the size of the relevant medical workforce (urologists), location of a hospital within wealthier catchment areas, as well as procedure substitution identified as the main drivers of robotic adoption (Maynou et al., 2022).[3] However, little is known about the impact robotic adoption has on efficiency and productivity. We address these issues here.

To pursue our analysis, we use distinct identification strategies to consider efficiency and productivity. For the efficiency analysis, we adopt a difference-in-difference approach. We introduce this through a standard two-way fixed effects model but, recognizing that this basic model can introduce bias when dealing with multiple groups affected by differential adoption timings, we move to a preferred staggered adoption specification as introduced by Callaway and Sant'Anna (2021). This estimator allows for heterogenous treatment effects both across time periods and across appropriate control group comparisons. It does so through computing a group-time average treatment effect (ATT) using a doubly-robust estimator, based on pre-treatment propensity score matching to balance appropriate treatment and control groups and an aggregation of within time-group treatment outcomes to provide aggregate treatment estimates. That is, ATTs are computed for each group first treated at a given date and then an overall weighted ATT is estimated. The counterfactual control groups can be based solely on never-treated groups or based on never and not-yet-treated groups, which helps to identify early and late adopters. We detail our application of this estimator below.

For the second question addressing productivity improvements tied to robotic surgery we adopt a structural, semi-parametric production function specification, based on Ackerberg et al. (ACF; 2015), which uses differential input demand timings to overcome issues of endogeneity. The endogeneity is caused through unobservable productivity factors. The ACF, and other semi-parametric specifications, solves this through assuming that differential timing in the adoption of inputs can aid identification of productivity shocks and that any revealed productivity differences are the only unobservable heterogeneity differences across producers. We extend this analysis to take account of potential patient competition bias. For both efficiency and productivity, a range of estimators are presented to verify our identification strategies in calculating the impact of robotic surgery adoption on both aspects.

Our paper is related to the analysis by Horn et al. (2022) examining the impact of adoption of robotic surgery for prostate cancer on patient volume in the USA. They find a significant increase in admissions after robot adoption, partly explained by an expansion in robotic cases that attracted patients that were younger and healthier, as well as through a degree of procedure substitution (Horn et al., 2022). Our paper differs from Horn et al. (2022) in the following aspects: (1) in addition to analyzing changes in volumes in a different setting, we provide evidence on the effect on hospital throughput efficiency analyzing LoS, readmissions and outpatient visits post-surgery. This is to identify whether in the absence of proven clinical superiority of the robotic technique, there may exist incremental benefits attained through increased throughput that justify its widespread use; (2) like them we first use patient volumes to examine overall productivity, but we extend the analysis to quantify specific changes in labor productivity.

Our analysis indicates that for those hospitals acquiring a robot for prostatectomy surgery, the overall patient LoS and post-operative LoS is reduced by 1.7 and 1.5 days (equivalent to a 50% and 49% reduction) respectively, and an average reduction of 1.7 urology outpatient visits within a year and 2.5 outpatient visits within the first 2 years after surgery (which amount to a 44% and 46% decrease, respectively). Total production, measured as the number of urological interventions performed, increases with the adoption of a robot by between 21% and 26%. We also find a 29%

increase in labor productivity in hospital trusts adopting a robot for prostatectomy. Overall, gains in efficiency and productivity arising from the use of robotic surgery therefore appear to be of a substantial magnitude compared to hospital providers that do not adopt the robotic technology. These gains, however, when translated into monetary benefits, do not outweigh the overall current costs of investment in robots.

To validate these findings, we begin by outlining our data set and provide initial descriptive evidence on the use of robotic surgery at the hospital level documenting associated efficiency gains. This is followed by detail on the strategy used to subsequently investigate efficiency gains, total factor productivity (TFP) and labor productivity through the use of empirical analysis aimed at establishing causal impact. We then present the results of our various investigations before concluding with some final remarks.

2 | DATA AND DESCRIPTIVE STATISTICS

We primarily use a rich administrative dataset, the English Hospital Episode Statistics (HES), containing all treatment episodes for patients admitted into hospitals in England. We use all patient records from the financial year 2000/2001 to 2018/2019[4] for all patients admitted for open, laparoscopic or robotic radical prostatectomy based on the OPCS-4 procedure codes for the main operation.[5] Our sample includes a total of 88,335 patients admitted as elective cases.[6] However, due to missing values in outcomes and other variables, the analytical sample at the patient level is of 85,845 male patients. Each patient record contains information on admission date, main operation, date of operation, anonymized code of the consultant in charge of the procedure, discharge date, any other operations the patient might have had, main diagnosis, patient-mix characteristics, surgeon in charge of the operation[7] and detailed information on organizational and geographical characteristics of the hospital.

Figure 1 shows prostatectomy volumes by surgery type from 2000 to 2018. While open prostatectomy was the leading procedure at the beginning of the period, robotic volumes increased exponentially from 2006.[8] By 2010 robotic interventions overtook the laparoscopic interventions and from 2012 onward robotic surgery overtook open surgery, leaving open and laparoscopic procedures with similar operating volumes as shown in Figure 2, where robotic adopters have higher volumes compared to non-adopters.[9] The volume of prostatectomy undertaken in hospital adopters (those purchasing at least one robot) clearly follows a similar trend in Figure 2, where adopters show higher volume compared to non-adopters.[10]

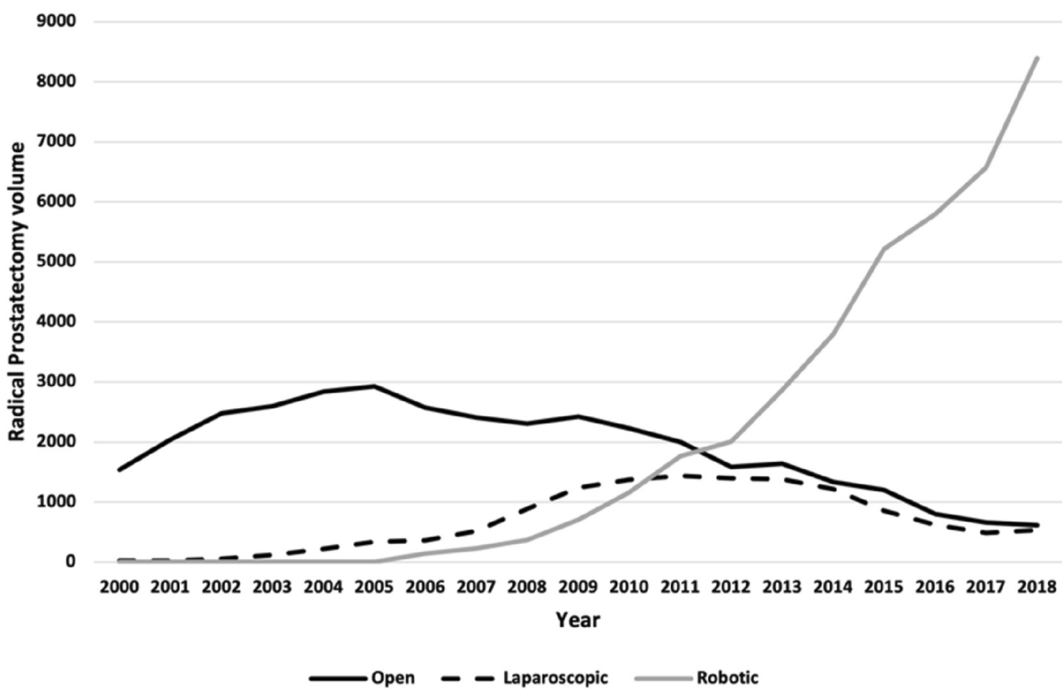

FIGURE 1 Radical prostatectomy volume. *Source*: Hospital Episode Statistics data 2000–2018.

We consider the impact of technology choice on overall LoS and post-operative LoS, emergency readmission within 30 days, number of outpatient visits to the urologist post-surgery within 1 year and 2 years post-discharge and waiting time. All the post-surgical efficiency measures are included on the presumption that post-surgery complications will be lower with the minimally invasive interventions leading to a reduction in resource consumption after prostatectomy. We also include waiting times for the procedure, which we presume will change as a new technology becomes available within a capacity constrained system like the NHS. Outpatient visits are only available from 2006 onward, as prior to this outpatient information was not consistently recorded. Table 1 provides descriptive statistics of these outcomes by intervention type (open, laparoscopic, robotic). While open surgery had a higher LoS and post-operative LoS, laparoscopic surgery had a higher 30-day readmission rate and number of outpatient visits. Both, open and laparoscopic, had

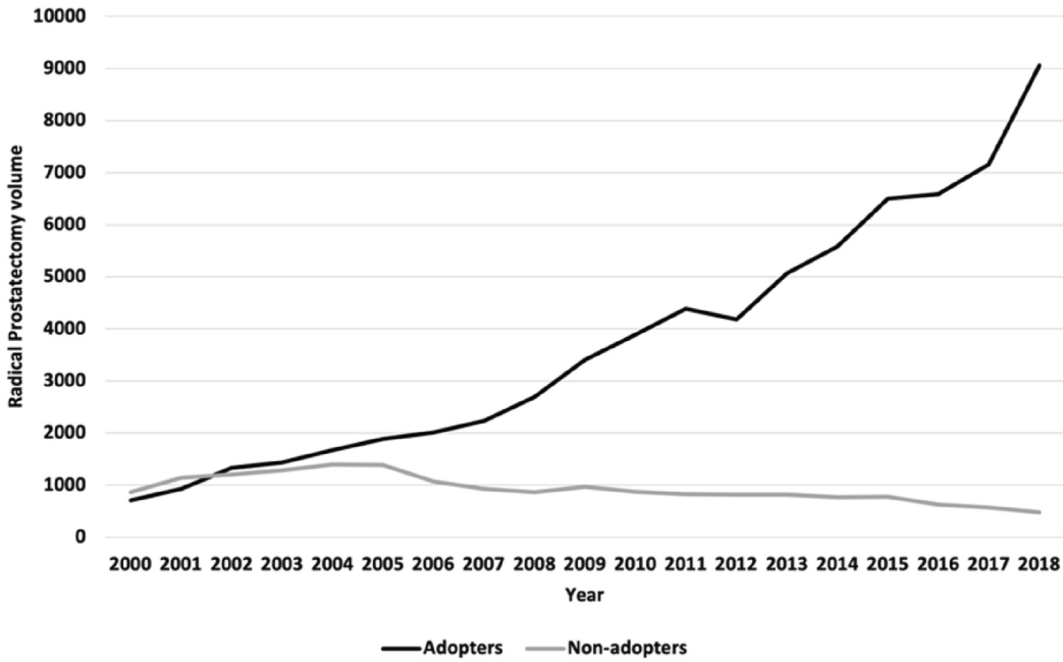

FIGURE 2 Radical prostatectomy volume by adopters and non-adopters. *Source*: Hospital Episode Statistics data 2000–2018.

TABLE 1 Descriptive statistics—efficiency.

	Years	LoS 2000–2018	Post-LoS 2000–2018	30-Day readmission 2000–2018	Outpatient visits (1 year) 2006–2018	Outpatient visits (2 years) 2006–2018	Waiting time 2000–2018
Open	*N*	34,661	34,661	34,661	20,921	20,921	34,661
	Mean	5.475	4.854	0.096	3.383	5.182	40.897
	SD	3.627	3.401	0.294	2.819	4.305	34.282
	Min-Max	0.5–106	0.5–105	0–1	1–32	1–44	0–1123
Lap	*N*	12,813	12,813	12,813	12,038	12,038	12,813
	Mean	2.815	2.542	0.108	4.361	6.580	41.035
	SD	2.516	2.400	0.311	3.023	4.479	31.184
	Min-Max	0.5–124	0.5–123	0–1	1–32	1–54	0–744
Robotic	*N*	38,371	38,371	38,371	38,371	38,371	38,371
	Mean	1.845	1.738	0.099	3.806	5.256	35.991
	SD	1.666	1.606	0.299	2.617	3.865	31.004
	Min-Max	0.5–60	0.5–60	0–1	1–25	1–40	0–1287

Abbreviation: LoS, length of stay.

higher waiting times compared to robotic surgery. In line with Table 1, Table A2 in Appendix A presents the descriptive statistics only for adopter hospitals pre and post adoption where it can be observed that for open and laparoscopic surgeries, LoS, post-LoS and waiting times are lower after the adoption of the robot in the hospital. For post-operative visits, we observe a decrease post-adoption only for laparoscopic procedures. Robotic adoption appears to have an effect on open and laparoscopic procedures for most outcomes.

The efficiency analysis is undertaken using patient-level data and includes (matching) controls for patient-mix and hospital characteristics such as the Charlson Comorbidity Index, Index of Multiple Deprivation (income domain) of the area where the patient resides, age, whether the hospital has foundation trust status, whether a teaching hospital, bed occupancy rate, number of urologists per hospital and an indicator variable reflecting whether the hospital has a tendency toward "high tech" interventions. We define this last variable for each surgeon identified in our sample who we classify as a technology adopter if they do more minimally invasive than open surgeries in a given year. As we are interested in hospital preference for technology, we then create a dummy equal to 1 if in a given hospital the proportion of urologists performing minimally invasive surgeries over the total number of urologists is >50%. This variable encompasses the preferences of surgeons toward minimally invasive over open surgery.[11] Table A3 in Appendix A provides an overview of all these variables, including the outcome variables of interest.

Table 2 provides descriptive statistics of the patient characteristics for four representative years of our study period for the three procedures (Table A4 in Appendix A provides data for all years). We observe a common trend over time for the three technologies as they treat older, sicker and increasingly patients from more income deprived areas. There are little differences in patient characteristics across the three technologies. Any such remaining difference will be controlled for in estimation through propensity score matching across treatment and control groups in our preferred (CS) specification.

In our second analysis examining productivity changes following the adoption of robotic surgery, we use hospital data analyzed at specialty level. From HES data we construct a longitudinal dataset that includes total volumes for each of the three procedures by hospital and year, resulting in an unbalanced panel of 173 hospitals. From these hospitals, 89 perform open prostatectomy only, while 30 perform both, open and laparoscopic, and a further 54 perform all three interventions. Estimation of potential productivity gains from the use of robotic surgery draws on the literature on production functions and requires the inclusion of measures of capital, labor, hospital investment and intermediate inputs. As a measure of capital, we include the bed occupancy rate in urology defined as the ratio of occupied beds divided by available beds per hospital and year. It is common to consider beds as a measure of capital stock (Gaynor & Anderson, 1995), reflecting our interest in specific capital flows and is also a measure available specifically to our clinical specialty of interest, urology.[12]

To construct our labor productivity measure, we use the anonymous identifier for the consultant in charge of the intervention and compute the count of consultant urologists per hospital and year. Figure 3a shows the evolution of all

TABLE 2 Descriptive statistics—patient characteristics.

Year		Open			Laparoscopic			Robotic		
		Age	CCI	IMDI	Age	CCI	IMDI	Age	CCI	IMDI
2006	N	2458	2458	2427	355	355	350	144	144	143
	Mean	62.355	2.136	0.111	61.972	2.158	0.110	60.701	2.167	0.083
	(SD)	(5.963)	(0.461)	(0.100)	(6.240)	(0.473)	(0.102)	(5.993)	(0.392)	(0.074)
2010	N	2136	2137	2120	1328	1329	1314	1145	1146	1122
	Mean	62.979	2.202	0.121	62.614	2.194	0.116	61.756	2.161	0.110
	(SD)	(6.562)	(0.579)	(0.097)	(6.008)	(0.515)	(0.091)	(6.561)	(0.479)	(0.088)
2014	N	1280	1280	1268	1192	1194	1183	3736	3741	3601
	Mean	64.202	2.341	0.117	63.597	2.306	0.114	62.789	2.316	0.119
	(SD)	(6.381)	(0.8119	(0.091)	(6.446)	(0.659)	(0.089)	(6.539)	(0.817)	(0.095)
2018	N	583	584	578	525	526	506	8225	8249	7946
	Mean	64.904	2.510	0.116	63.438	2.338	0.125	63.556	2.377	0.114
	(SD)	(7.263)	(0.984)	(0.102)	(6.527)	(0.771)	(0.093)	(6.645)	(0.847)	(0.090)

Abbreviations: CCI, Charlson Comorbidity Index; IMDI, Index of Multiple Deprivation (income domain).

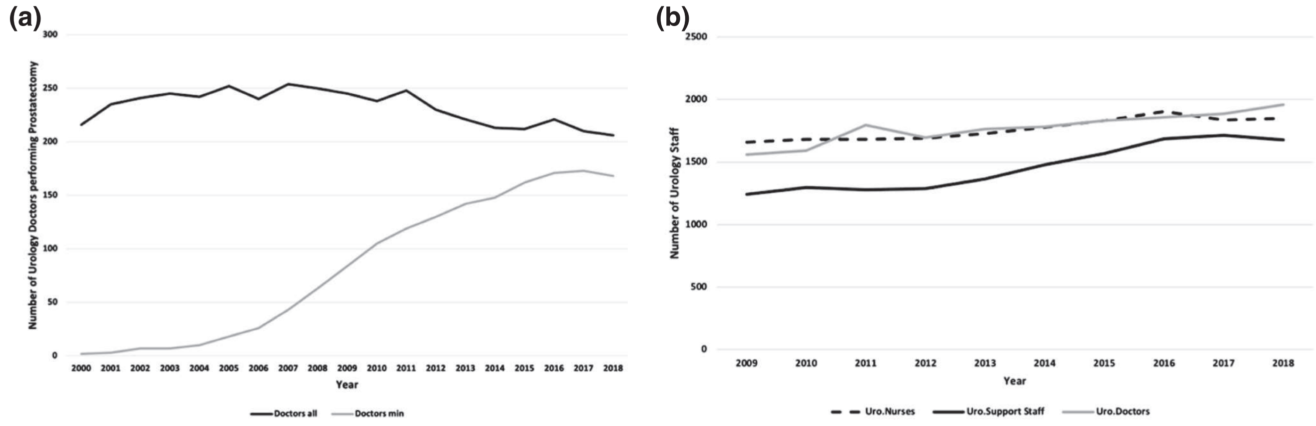

FIGURE 3 Workforce in urology. (a) Doctors performing prostatectomy. Hospital Episode Statistics data. (b) All urology workforce. Electronic Staff Records data.

urologists and urologists doing minimally invasive prostatectomies (laparoscopic and robotic surgeries). We see a gradual decrease in all urologists from 2006, although an increase in urologists who do minimally invasive surgery.[13] HES data only provide information on the consultant in charge of the surgical team but no other information on additional labor inputs is provided. Information on nurses and support staff are obtained from a further data set, the NHS Electronic Staff Records (ESR), which provides information on full-time equivalent count of doctors, nurses and support staff attributed to the specialty of urology. Staff numbers from ESR will be larger than counts retrieved from HES data given that not all urologists perform prostatectomy. Electronic Staff Records data at the specialty level is only available from 2009 onwards but can be disaggregated by staff groups. In Figure 3b we plot workforce count by staff group. While we observe little change for nurses, we do observe a slight increase in urology clinicians and a much larger increase in support staff over time. Table A5 in Appendix A lists all the variables used in the productivity analysis and provides further descriptive statistics at the hospital level. Table A6 in Appendix A shows patient and hospital level characteristics by adopters and non-adopters hospitals.[14]

3 | EMPIRICAL STRATEGY

3.1 | Efficiency gains of minimally invasive and robotic surgery

Our first step is to quantify the effects of the new robotic technology on several throughput measures linked to producer efficiency. We first, simply specify a Two Way Fixed-Effect DiD estimator (TWFE) where our treated units are hospitals that adopted a robot and controls are those hospitals not adopting a robot. We define efficiency through measures of hospital throughput at the patient level with the treatment variable, use of robotic surgery or otherwise, determined at the hospital level and the actual specification is given as:

$$\text{Healthout}_{ijt} = \alpha + \beta \text{adoption}_{jt} + \gamma' X_{ijt} + T_t + \mu_j + e_{ijt} \tag{1}$$

where Healthout_{ijt} refers to one of the efficiency outcomes of interest (LoS, post-surgery LoS, 30-day readmission, outpatient visits (at 1 and 2 years), and surgery waiting time) for patient i treated in hospital j at time t, adoption_{jt} is our treatment variable indicating adoption by hospital j at time t,[15] X_{ijt} is a vector of patient and hospital control variables, T_t are year fixed-effects to control for common unobserved within year effects capturing common unobserved technology, process or organizational changes and μ_j are hospital fixed-effects.

Responding to recent criticism of the potential validity and robustness of the TWFE DiD estimator when there is variation in treatment timing and there are heterogenous treatment effects, we then implement an alternative, preferred staggered estimation procedure (Goodman-Bacon, 2021; Baker et al., 2022). We specifically implement the DiD estimator proposed by Callaway and Sant'Anna (2021) (CS hereafter), that accounts for variation in treatment timing, where the parallel trends assumption holds after conditioning on observables. The ATT at time t for cohorts first treated at time g is:

$$\mathrm{ATT}(g,t) = E\left[Y_t - Y_{g-1} \middle| G_g = 1\right] - E\left[Y_t - Y_{g-1} \middle| C = 1\right] \tag{2}$$

where G_g equals 1 if unit j is first treated at time g, and zero otherwise and C equals to 1 for never-treated units. Y is one of the efficiency outcome measures we consider. Note the pre-treatment period for comparison of outcomes is g−1. CS provide "group-time ATTs" ATT(g,t) which is the ATT in period t for hospitals first adopting robotic surgery in period g and propose a two-step estimation strategy with a bootstrap procedure to provide asymptotically valid inference that adjusts for autocorrelation and clustering (Baker et al., 2022). CS derive estimators based on whether the control group is defined through a never treated control, a unit that never receives treatment, or a control group that includes the never and the not yet treated control, a unit that has not yet received treatment by period t. The ATT(g,t) may be generally specified as:

$$\mathrm{ATT}_{g,t} = E\left[\left(\frac{G_g}{E(G_g)} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{E\left[\frac{p_g(X)C}{1-p_g(X)}\right]}\right)(Y_t - Y_{g-1})\right] \tag{3}$$

Note the estimation still utilizes a difference-in difference Ordinary Least Square (OLS) to recover a long-difference in the outcomes (Y_t − Y_{g-1}), weighted through propensity scores (the $p_g(X)$ defined below) but without regard to fixed effects as the ATT is aggregated across individual time periods.

The estimator allows for the possibility that patients subject to the robotic intervention might differ from those who do not. To ensure that characteristics are balanced between patients and providers in the cohort and control groups, propensity score weighting is used when calculating the $\mathrm{ATT}_{g,t}$. The generalized propensity score is defined as:

$$p_g(X) = P\left(G_g = 1 | X, G_g + C = 1\right) \tag{4}$$

which is the probability that an individual is treated in an adopter hospital, conditional on having characteristics X (these include all the patient and hospital characteristics outlined above) and being a member of treatment group g or the control group, C. This $\mathrm{ATT}_{g,t}$ correction works by up-weighting patients from the control group that have characteristics similar to those frequently found in group g and down-weighting patients from the control group that have characteristics rarely seen in group g (Baker et al., 2022; Callaway & Sant'Anna, 2021). The weighting is designed to establish parallel trends in outcomes prior to the robot adoption for the control and cohort groups. This allows control for potential patient selection into the three types of surgeries.[16] The first term on the right-hand side of Equation (3) is then, a weight which specifies the conditional probability (conditioned on observables) that an individual belongs to the treated group at time t.[17]

Identification of the ATTs relies in one of the following: through using an outcome regression (OR) approach, inverse probability weighting (IPW) or a doubly robust estimator (which combines the OR and IPW approaches) all of which forego the need to incorporate fixed effects (Baker et al., 2022; Callaway & Sant'Anna, 2021). We implement the doubly-robust estimator, with wild bootstrap and clustering of the standard errors at the hospital level. This combines the advantages of using the difference-in-difference identification assumptions of parallel trends and no anticipation in a staggered uptake with heterogenous effects using propensity scores to choose appropriate control groups (either based on never treated or never treated plus not-yet-treated controls). The CS estimator also allows to derive an aggregate ATT based on a weighted average of all estimated ATT(g,t)s defined as:

$$\theta = \sum_G \sum_t \omega(g,t) \cdot \mathrm{ATT}(g,t) \tag{5}$$

The choice for w(g,t) is based on aggregating different definitions of treatment exposure; either a simple weighted average of the cohorts over time or the length of time of exposure for each of the treated units. Our preferred estimator is the doubly-robust CS estimator weighted by length of time of exposure to treatment, that is, the weight is defined using the length of time from the hospital purchasing a robot, so the control group is defined as the "never plus not-yet-treated" which returns true staggered treatment effects. We nonetheless report the simple weighted CS estimator and the TWFE for comparison.

3.2 | Hospital productivity

3.2.1 | Total factor productivity

To quantify the specific impact that adopting robotic surgery has on hospital productivity, we begin by specifying a general Cobb-Douglas production function for hospitals that relates output to inputs, noting that individual provider productivity is generally unobserved, and therefore omitted in a naive estimation:

$$y_{jt} = \beta_0 + \sum_n \beta_n x_{jt}^n + \omega_{jt} + \eta_{jt} \tag{6}$$

where y_{it} is the output measured as volume of prostatectomies, x_{it}^n denotes input n used by hospital j in year t and include a dummy variable for provision of robotic surgery, ω_{jt} is the hospital productivity only known and observed by the hospital and η_{jt} is the unobserved error term. We observe the output and input choices of hospitals, but both productivity and the error term remain unobserved factors. If hospital specific productivity in urological services is correlated with the capital choices (e.g., having a robot) and labor (e.g., number of urologists), estimation of Equation (6) will render biased estimates due to this endogeneity (Lee et al., 2013). To overcome this well-established problem in identifying production functions, we use several structural approaches which correct for the endogeneity in the input choice, such as Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015) (referred as OP, LP, and ACF approach, hereafter). These three approaches employ two-step estimators, using differential timing in the employment of the fixed and variable factors in the production function to identify the unobserved productivity. The methods differ in their assumptions on the evolution of multifactor productivity and in the timing of input choices to identify the production process (Lee et al., 2013). OP uses investment as a proxy variable to identify the production function, on the assumption that varying investment levels across time periods will be correlated with the unobserved productivity. LP assume contemporaneous demand for material inputs, which are assumed to be truly variable factors in the production function, and therefore to be correlated with unobserved productivity, to overcome the endogeneity problem.

Our preferred approach is the ACF estimator, which builds on the work proposed by OP and LP and uses variable inputs to identify productivity levels. To aid outline the ACF method we continue by assuming, only at this point to aid exposition, that all labor is a fixed, state variable.[18] The intermediate variable input demand function $f(k_{jt}, l_{jt}, \omega_{jt})$ is monotonic, increasing in ω_{jt} and can be inverted to express the unobserved hospital productivity as $\omega_{jt} = f^{-1}(k_{jt}, l_{jt}, m_{jt})$. ACF follow a semi-parametric identification of the following production function:

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \omega_{jt} + \eta_{jt} \tag{7}$$

where the variables are defined as in Equation (6) above, but with k_{jt} and l_{jt} defining fixed capital and labor inputs.

The estimation of the ACF procedure mainly relies upon the following three identifying assumptions, which we apply to our hospital production setting. First, the notion that the supply of output in a given period depends, at least partially, on input decisions made in previous periods (e.g., capital and labor decisions). Second, that the hospital's demand function for variable intermediate inputs is given as $m_{jt} = f(k_{jt}, l_{jt}, \omega_{jt})$ and determined contemporaneously with output decisions. Third, the unobserved productivity measure, ω_{jt}, is estimated in a first stage through using an input demand function specified by the contemporaneous variable inputs conditioned on state variables which are monotonically related to the unobserved productivity. Predictions from this first stage are then utilized in a second stage to eliminate the endogeneity problem.

In the first stage of the ACF estimation process, plugging the inverted function as an estimate of unobserved productivity into Equation (7) we obtain:

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + f^{-1}(k_{jt}, l_{jt}, m_{jt}) + \eta_{jt} = \Phi_t(k_{jt}, l_{jt}, m_{jt}) + \eta_{jt} \tag{8}$$

Given that f^{-1} is defined non-parametrically in the ACF approach, none of the coefficients are identified in the first stage. However, the prediction estimates obtained as $\hat{\Phi}_t$ in the first stage can be used in the second stage:

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + g\left(\hat{\Phi}_{t-1} - \beta_0 + \beta_k k_{jt-1} + \beta_l l_{jt-1}\right) + \xi_{jt} + \eta_{jt} \tag{9}$$

Assuming for the moment all labor is fixed, the second stage implies estimating not only β_k but also β_l, as opposed to β_l being estimated in the first stage as in the LP approach. Labor and ξ_{jt} are now correlated and additional moment conditions are needed. The ACF approach exploits the lag of variable inputs, namely the intermediate inputs, in a generalized method of moments estimator to overcome this correlation.

One of the main differences of the ACF model with respect to OP and LP is that they propose some labor input may be defined as a fixed or semi-fixed input due to hiring/firing costs and general adjustment costs. Some labor input can be considered a fully variable input and the fixed or semi-fixed component of labor becomes an argument to identify the demand function of the intermediate input. This is useful for hospital production functions, as Gaynor and Anderson (1995) argue clinicians are fixed or semi-fixed inputs, while other staff categories are variable inputs. They adopt a similar approach to the flexible timing of input demand for these intermediate inputs to identify a reduced form production function, arguing that intermediate variable input demand will vary in response to unobserved aspects, such as productivity shocks associated with emergency case arrivals in their case, while conditioned on the level of the state variables. We exploit this difference in the type of hospital labor input when applying the ACF model to our hospital setting. We subsequently assume that clinical labor is a fixed, state variable and that urology support staff define our intermediate variable.[19] We provide results for the three methods (OP, LP, ACF) for comparison.

Our identification strategy rests on the notion, adopted by all the semi-parametric approaches, that the only unobserved heterogeneity at the producer level is productivity and this can be revealed through differential input demand timings, as defined through variable and fixed inputs.[20] Different assumptions concerning the timing and role of input adoption are reflected in the different OP/LP/ACF specifications. A potential threat to this identification strategy is that the output of hospitals may depend on the treatment assignment by other hospitals (i.e., adopters may "steal" patients from non-adopters), which would violate the Stable Unit Treatment Values Assumption, reflecting that potential outcomes are dependent on the treatment assignments of patients to other hospitals (Horn et al., 2022). To address this issue, we employ an approach similar to Horn et al. (2022), including a variable that controls for the number of hospital adopters in the market for each non-adopter to reflect the strength of this treatment adoption effect. The variable is defined as an indicator of non-adopter hospitals in markets (over a radius of 30 miles) where at least two or more other hospitals have adopted.[21]

3.2.2 | Labor productivity

We next examine how the use of robotic surgery changes labor productivity through utilizing our hospital-level structural productivity results. Our main variable of interest here is the total volume of surgery divided by the count of urology consultants performing prostatectomies in hospital j at time t. We relate this measure of labor productivity to the use of robotic surgery in the following specification:

$$\frac{\text{Volume}}{\text{Urologists}_{jt}} = \alpha + \beta_1 \text{adoption}_{jt} + \beta_2 \text{market}_{jt} + \gamma' X_{jt} + c_j + T_t + \hat{\omega}_{jt} + u_{jt} \tag{10}$$

where adoption$_{jt}$ is a dummy equal 1 for the year when hospital j first adopted the robot and for all subsequent years, market is an indicator for non-adopters determining if there are adopter hospitals in the market (within a 30-mile radius), c_j is the unobserved hospital FE, T_t are time fixed effects and u_{jt} is the unobserved error term. X_{jt} is a set of covariates including patient case-mix and hospital characteristics. We use $\hat{\omega}_{jt}$ from the TFP specification above to address the traditional source of production specification endogeneity.[22] However, even after controlling for unobserved productivity through $\hat{\omega}_{jt}$, our estimates will only show associations between the labor productivity and the robot adoption as residual unobservables might still bias the estimates. To assess the direction and magnitude of any such bias, we follow Oster (2019) and test for the stability of coefficients. Oster's approach assesses potential bias through providing a bounding set $[\tilde{\beta}_1, \beta_1^*]$ within which the true value of the adoption coefficient lies, where $\tilde{\beta}_1$ is the coefficient of interest in the regression that controls for all observables (including $\hat{\omega}_{jt}$) and β_1^* is the bias-adjusted coefficient for the robot dummy.[23] We present three specifications of labor productivity, using the OP, LP, and ACF estimates of overall productivity, $\hat{\omega}_{it}$, as obtained from these TFP specifications.

4 | RESULTS

4.1 | Does robotic adoption bring efficiency gains?

As the clinical literature shows no proven clinical gain of robotic over laparoscopic surgery, we focus on intermediate throughput measures for efficiency. We first present, in Table 3, the simple TWFE DiD model estimates of the effect of adopting robotic surgery at the hospital level. Panel (A) shows the estimates for all types of prostatectomies, including the robotic technique. The robotic adoption effect is only significant for LoS and post-operative LoS, where adoption reduces stay by 0.3 days on average. In panel (B) we assess the stability of the results by restricting the sample to only open and robotic interventions. Panel (C) restricts the sample to only laparoscopic and robotic interventions. In both panels (B and C) the adoption of robots remains significant for LoS and post-operative LoS. The reduction is higher in

TABLE 3 Two Way Fixed-Effect DiD estimator—Robotic surgery adoption at hospital-level.

Dep. var	LoS	Post-operative LoS	30-Day readmission	Outpatient visits (1 year)	Outpatient visits (2 years)	Waiting time
Panel A: Open + Lap + Rob						
Robot adoption (hospital)	−0.324*	−0.349**	−0.010	−0.162	−0.321	−0.452
	(0.172)	(0.166)	(0.008)	(0.248)	(0.340)	(1.770)
N	83,783	83,783	83,783	69,414	69,414	83,783
No. hospitals	173	173	173	133	133	173
Panel B: Open + Rob						
Robot adoption (hospital)	−0.706***	−0.756***	−0.009	0.061	0.005	0.055
	(0.195)	(0.198)	(0.008)	(0.283)	(0.376)	(2.125)
N	71,162	71,162	71,162	57,558	57,558	71,162
No. hospitals	173	173	173	132	132	173
Panel C: Lap + Rob						
Robot adoption (hospital)	−0.412**	−0.381**	−0.008	−0.211	−0.458	0.189
	(0.169)	(0.155)	(0.011)	(0.311)	(0.442)	(2.402)
N	49,536	49,536	49,536	48,771	48,771	49,536
No. hospitals	84	84	84	82	82	84
Patient controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes
Years	2000–2018	2000–2018	2000–2018	2006–2018	2006–2018	2000–2018

Note: Control variables: Charlson Comorbidity Index, Index of Multiple Deprivation of the area where the patient resides, age, foundation trust, teaching trust, bed occupancy rate per hospital, number of urologists and high tech hospitals (=1 if proportion of minimally invasive urologist over total number of urologists >50%, except for models in panel C). Outpatient visits were only recorded from 2006 onwards, explaining the difference in sample size compared to other efficiency measures. Average Marginal Effects reported. Standard errors in parentheses and clustered at hospital-level.

Abbreviation: LoS, length of stay.

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

panel (B) where stay is reduced between 0.7 and 0.8 days, as expected, given robotic surgery is superior to the open procedure, compared to panel (C) where robotic adoption reduced stay by 0.4 days on average, but where both technologies are deemed minimally invasive.

We presume the TWFE DiD is biased as there is variation in the timing of treatment adoption, and now report our preferred DiD estimates as proposed by CS, which incorporate weightings to estimate the staggered, differential treatment timings and accommodate heterogeneous treatment effects. We present the CS estimator, including variables for the propensity score matching to fulfill the conditional parallel trend assumption using the doubly robust method.[24] The treated group are hospitals adopting the robot in year *t*. Two control counterfactuals are considered: (1) a pure control of never adopters; (2) a control group including never adopters plus the not-yet-treated in any given year.

Table 4 reports the results of the CS estimator when using the counterfactual of never adopting hospitals and including matching covariates, with standard errors clustered at the hospital level. Panel (A) shows the results when we use the sample of robot adopting hospitals who performed any of three surgical interventions over the study period. The coefficients for LoS and post-LoS are significant, showing between a 1.4 and 1.2 days reduction once adopting robotic surgery. Outpatient visits (1 year and 2 years) are also statistically significant, indicating that having a robot leads to a reduction in prostatectomy outpatient visits of 3–4 visits. In panel (B), we restrict the sample using only the open and robotic procedures alone to disentangle potential differences between the open versus the minimally invasive robotic procedure. The adoption of a robot leads to a reduction in LoS and post-operative LoS of 2 days on average and 3–5 outpatient visits (1 year and 2 years). In panel (C) we further restrict the sample to patients receiving any of the two

TABLE 4 Robotic surgery adoption at hospital level—CS estimates with never treated control units.

Dep. var	LoS	Post-operative LoS	30-day readmission	Outpatient visits (1 year)	Outpatient visits (2 years)	Waiting time
Panel A: Open + Lap + Rob						
ATT	−1.369**	−1.156**	−0.007	−2.635***	−4.080***	5.354
	(0.606)	(0.588)	(0.040)	(0.765)	(1.169)	(6.176)
N	78,415	78,415	78,415	56,465	56,465	78,415
No. hospitals	173	173	173	127	127	173
Panel B: Open + Rob						
ATT	−2.147***	−1.761***	−0.018	−2.636***	−4.718***	−9.557
	(0.624)	(0.570)	(0.063)	(0.936)	(1.299)	(8.755)
N	66,938	66,938	66,938	46,313	46,313	66,938
No. hospitals	173	173	173	126	126	173
Panel C: Lap + Rob						
ATT	−3.292	−3.166	−0.042	−3.162***	−4.367***	21.640*
	(2.670)	(2.709)	(0.069)	(0.809)	(1.298)	(12.300)
N	41,146	41,146	41,146	33,683	33,683	41,146
No. hospitals	84	84	84	76	76	84
Patient controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster: hospital	Yes	Yes	Yes	Yes	Yes	Yes
Years	2000–2018	2000–2018	2000–2018	2006–2018	2006–2018	2000–2018

Note: Control variables: Charlson Comorbidity Index, Index of Multiple Deprivation of the area where the patient resides, age, foundation trust, teaching trust, bed occupancy rate per hospital, number of urologists and high tech hospitals (=1 if proportion of minimally invasive urologist over total number of urologists >50%, except for models in panel C). Outpatient visits were only recorded from 2006 onwards, explaining the difference in sample size compared to other efficiency measures. Average Marginal Effects reported. Standard errors in parentheses and clustered at hospital-level.

Abbreviations: ATT, average treatment effect; LoS, length of stay.

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

minimally invasive procedures, laparoscopic or robotic. For patients receiving either of these two surgeries in a hospital that adopts a robot, efficiency gains arise in the form of a reduction in outpatient visits by 3 to units. In panel (C), the effect on LoS is not significant as robotic surgery does not seem to be different in LoS to laparoscopic, while it is to the open procedures.

While Table 4 reports the aggregate results for the ATT as associated with Equation (5) and with the control group defined as never adopters, we also plot the evolution of adoption over time. This is done in Figure 4 where we show the pre- and post-treatment effect at each point in time. The pre-treatment period indicates the conditional parallel trend assumption is met. In the post-treatment, we observe the effects are modest in the years immediately after adopting the robot, but they become increasingly larger in the long-term. Figure 4 shows that there is a small effect on the reduction of LoS, post-LoS and outpatient visits, with an estimated effect that dips around 6 and 10 years after treatment, bouncing back afterwards. The effects are not immediate, it takes at least 6 years to have substantially important effects. These effects could be potentially driven by a learning curve related to physician's skills in the use of a robot. This would be in line with some evidence that the use of robots may exhibit a learning curve with improved surgical outcomes a few years on from the baseline (Bock et al., 2022; Hughes et al., 2023). As robotic surgery becomes more prevalent across different specialties this surgeon learning effect would be an interesting aspect to investigate further in its own right. This can also be linked to the differences in technology uptake across England and other countries, such as, the USA (Maynou et al., 2021). The TECH investigators noted some time ago (TECH, 2001) that the UK is a centralized, lower funded system which has slower uptake and diffusion for new surgical procedures than the USA and we believe this can explain some of the differences in the findings. In Figure 4, we observe a larger confidence interval 10 years after adoption (although the trend remains). This is due to a very low number of hospitals adopting in that particular year (reducing the number of observations), that is, both, in 2007 and 2011, only 2 hospitals adopted a robot.

We then estimate the CS model including those units never treated as well as not yet treated in the control group as a counterfactual which is our preferred CS specification throughout as it exploits the contribution and timing of both control groups. We replicate the sub-sample analysis followed in Table 4 and present the results in Table 5. The sign of the estimates is very similar but the magnitude of the coefficient is slightly higher. As such, the results suggest that LoS and post-operative LoS are reduced by 1.7 and 1.5 days, respectively. This corresponds to a 50% and 49% reduction of prostatectomy in-hospital stays. Similarly, there is a reduction in outpatient visits within 1 year of 1.7 and 2.5 within 2 years corresponding to a reduction of 44% and 46% visits, respectively. Panel (B) shows the results for the sub-sample that includes only open and robotic procedures. Efficiency gains in this case arise from lower LoS and post-operative LoS of 2.5 and 2 days and equivalent to a reduction of about two thirds in prostatectomy hospital stays. In line with the results in Panel (A, there is a reduction of 1.8 and 3 outpatient visits. Panel (C) includes the results of using the sample of laparoscopic and robotic procedures, where the only effects found are for outpatient visits, indicating a reduction by 3–4 visits (equivalent to a reduction by 77% and 73) within one or 2 years, respectively. As shown in Table 4, LoS is not significant again in panel (C), when the sample is restricted to laparoscopic and robotic interventions.

Figure 5 shows the pre- and post-treatment trends for our preferred specification which allows us to pick up the staggered adoption as controls are also based on the not yet treated units. The same patterns as in Figure 4 are observed. Tables A8–A10 in Appendix A present the estimated coefficients for the post-treatment ATTs corresponding to Figure 5.

The pattern of results in both Tables 4 and 5 are right signed and do not differ much from the potentially biased TWFE DiD models for LoS and post-LoS. These also follow the same pattern but with increased significance shown in those reported in Table 3. However, Tables 4 and 5 show a significant reduction of outpatient visits (1 and 2 years) that is not shown in the TWFE DiD. Overall, robotic adoption appears to increase hospital efficiency, as attributable to reductions in LoS and outpatient visits.

Although the main interest of the efficiency analysis is the overall effect at the hospital level, as a robustness check, we quantify the effect of robotic adoption at the patient level, where the treatment effect is defined as a pure robotic intervention following adoption of a robot by a hospital. Results, reported in Table A11 in Appendix A, follow the same pattern as in Tables 4 and 5.

We have included across all specifications an indicator variable to proxy "high tech" hospitals. Our indicator was based on the number of urologists defined as minimally invasive over the total urologists count being higher than 50%. As a further robustness check, we run the same specification as in Table 5, but with the variable "high tech" hospital defined differently for panels (A and B), using as thresholds 60% and 70%. Results are reported in Table A12 in Appendix A and are in line with those in Table 5.

We then run a placebo test to rule out that these changes in efficiency are driven by changes that affect hospitals in their overall performance. To set up the placebo test we examine whether the effect of robotic adoption on LoS and post-

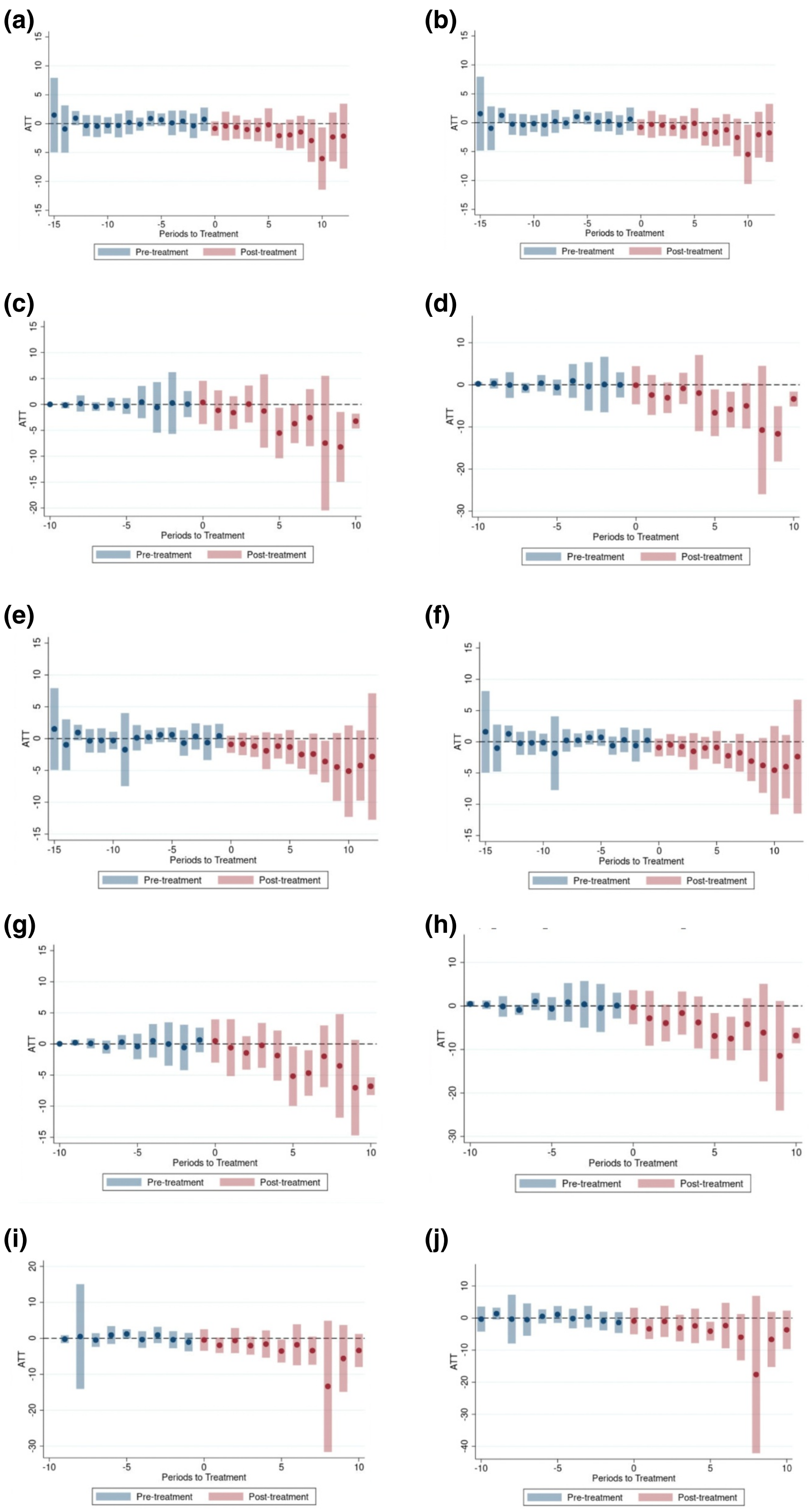

FIGURE 4 CS—event study estimates—significant effects at 1% and 5% (never treated control units). (a) LoS—Open + Lap + Rob. (b) Post-operative LoS—Open + Lap + Rob. (c) Outpatient visits (1 year)—Open + Lap + Rob. (d) Outpatient visits (2 years)—Open + Lap + Rob. (e) LoS—Open + Rob. (f) Post-operative LoS—Open + Rob. (g) Outpatient visits (1 year)—Open + Rob. (h) Outpatient visits (2 years)—Open + Rob. (i) Outpatient visits (1 year)—Lap + Rob. (j) Outpatient visits (2 years)—Lap + Rob. LoS, length of stay.

operative LoS has an impact on a different patient cohort; namely those coronary disease patients receiving a Percutaneous Coronary Intervention (PCI) from 2000 to 2018. Here we test whether the treatment, namely the adoption of a robot in the hospitals where PCI was performed, improved efficiency. As reported in Table A13 and Figure A2 in Appendix A, the effect of robotic adoption is not significant for LoS or post-operative LoS for PCI.

TABLE 5 Robotic surgery adoption at hospital level—CS estimates with never treated and not-yet-treated control units.

Dep. var	LoS	Post-operative LoS	30-Day readmission	Outpatient visits (1 year)	Outpatient visits (2 years)	Waiting time
Panel A: Open + Lap + Rob						
ATT	−1.739***	−1.541***	−0.016	−1.675**	−2.486**	6.541
	(0.595)	(0.597)	(0.033)	(0.747)	(1.146)	(5.039)
N	81,177	81,177	81,177	59,168	59,168	81,177
No. hospitals	173	173	173	127	127	173
Mean outcome	3.456	3.116	0.099	3.776	5.458	38.725
Panel B: Open + Rob						
ATT	−2.460***	−2.164***	−0.013	−1.881**	−3.092***	−5.341
	(0.574)	(0.526)	(0.055)	(0.821)	(1.176)	(7.702)
N	68,856	68,856	68,856	48,172	48,172	68,856
No. hospitals	173	173	173	126	126	173
Mean outcome	3.568	3.217	0.097	3.657	5.230	38.320
Panel C: Lap + Rob						
ATT	−3.358	−3.262	−0.007	−3.048***	−4.074***	14.020
	(2.661)	(2.668)	(0.058)	(0.804)	(1.299)	(11.900)
N	42,424	42,424	42,424	34,713	34,713	42,424
No. hospitals	84	84	84	76	76	84
Mean outcome	2.088	1.939	0.101	3.939	5.572	37.254
Patient controls	Yes	Yes	Yes	Yes	Yes	Yes
Hospital controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster: hospital	Yes	Yes	Yes	Yes	Yes	Yes
Not-yet-treated	Yes	Yes	Yes	Yes	Yes	Yes
Years	2000–2018	2000–2018	2000–2018	2006–2018	2006–2018	2000–2018

Note: Control variables: Charlson Comorbidity Index, Index of Multiple Deprivation of the area where the patient resides, age, foundation trust, teaching trust, bed occupancy rate per hospital, number of urologists and high tech hospitals (=1 if proportion of minimally invasive urologist over total number of urologists >50%, except for models in panel C). Outpatient visits were only recorded from 2006 onwards, explaining the difference in sample size compared to other efficiency measures. Average Marginal Effects reported. Standard errors in parentheses and clustered at hospital-level.

Abbreviations: ATT, average treatment effect; LoS, length of stay.

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

4.2 | Surgical productivity

4.2.1 | Changes in TFP

The CS estimator has shown that overall, robotic adoption appears to increase hospital efficiency, as attributable to reductions in LoS and outpatient visits. The related additional question as to whether adoption of robotic surgery improves productivity remains. Our productivity analysis is motivated by the stylized fact observed from the crude data that large volumes over time have been sustained by a relatively stable workforce. In this section, we assess the effect of robotic adoption on TFP using production functions as specified by the OP, LP, and ACF methods.

The identification strategy relies on all the unobservable heterogeneity being associated only with the internal, unobservable productivity shocks at the hospital level identified through the differential input demand timings of the following parameters: capital, labor and intermediate inputs. We use urology specialty bed occupancy rate in the hospital (as a measure of capacity) and a dummy on whether the hospital has a robot as proxies for capital. Our measure

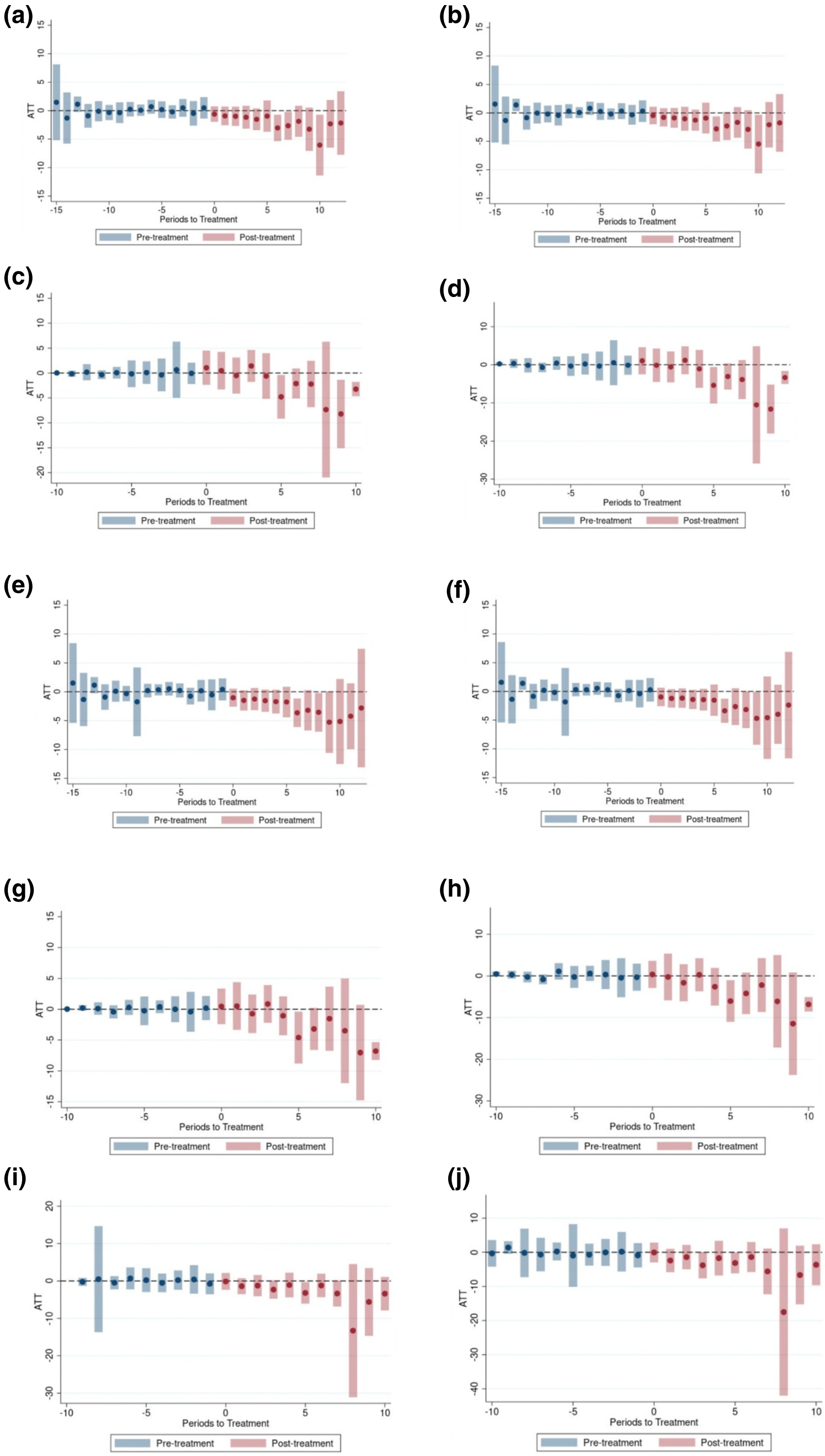

FIGURE 5 CS event study estimates—significant effects significant effects at 1% and 5% (never treated and not-yet-treated control units). (a) LoS—Open + Lap + Rob. (b) Post-operative LoS—Open + Lap + Rob. (c) Outpatient visits (1 year)—Open + Lap + Rob. (d) Outpatient visits (2 years)—Open + Lap + Rob. (e) LoS—Open + Rob. (f) Post-operative LoS—Open + Rob. (g) Outpatient visits (1 year)—Open + Rob. (h) Outpatient visits (2 years)—Open + Rob. (i) Outpatient visits (1 year)—Lap + Rob. (j) Outpatient visits (2 years)—Lap + Rob. LoS, length of stay.

of labor is the count of consultant urologists. The intermediate factor is proxied by the count of support staff in urology.[25] This variable is extracted from the NHS ESR dataset. The ESR count of workforce represents all workforce in Urology, including those not directly related to prostatectomies. Therefore, we adjust the staff figures weighting by the proportion of prostatectomies out of the total urology admissions per hospital and year. To control for potential hospital selection, we also include a dummy variable to indicate whether non-adopters have hospitals within 30-mile radius that have adopted the robot.

Due to data limitations in the ESR data, our period of productivity analysis is restricted to 2010–2018. While our preferred specification relies on the ACF approach, we also include the OP and LP methods as comparators. The OP approach requires the use of capital investment which is only available at the hospital, not specialty level. This variable, extracted from the NHS Estates Return Information Collection dataset, reflects the investment in existing and new building per hospital-year.[26]

Table 6 presents the results. In all models, the outcome variable is the total volume of radical prostatectomy performed (open, laparoscopic, and robotic). All variables are in logarithmic terms, except for the dummy variable indicating robotic surgery and the variable indicating the presence of adopters within a given market, and hence the coefficients generally represent elasticities. In columns (1) and (2) we show the estimates using an OLS and FE model estimators for calibration only, given the assumed endogeneity that renders biased estimates. The labor and capital variables in these specifications are positive, significant and follow the expected direction. Columns (3) to (6) report the results for the semi-parametric methods proposed by OP, LP and ACF. Columns (3) and (4) show the results using the OP approach using two proxy variables, support staff and capital investment, respectively. In all four models, the adoption of a robot increases prostatectomy volumes by 21%–26% (noting that for the model in Columns (4) and (5), adoption of a robot is not significant). Across specifications, the impact of a 1% increase in Urology consultants is consistent with an increase in prostatectomy volumes of between 0.6% and 2%. For our other measure of capital, occupancy rate, a 1% increase in occupancy rate increases prostatectomy volumes between 0.6% and 2%. For the market variable, if there are two or more adopter hospitals for each non-adopter in the market, prostatectomy volumes decrease by 17%–27%.[27]

Although results are generally consistent across the approaches, our preferred model remains the ACF specification as described in the methods section above. This reflects the notion that we consider the ACF specification to be more realistic in the input timing assumptions. In one of the OP specifications (column 4) the lack of significance on the robot adoption variable reflects, we believe, its reliance on a highly aggregated (at the hospital level) capital variable giving a large loss of signal. While the LP specification is also insignificant on the robot adoption variable, as the fixed labor input (surgeons), unlike in the ACF specification, plays no direct role in identifying the unobserved productivity. That said, all coefficients are correctly signed and of the same broad order of magnitude. As a further robustness check, we also estimate the productivity models by including the number of nurses in urology as a state variable (semi-fixed). Results, shown in Table A15 in Appendix A, are similar to those reported above. In summary, our analysis demonstrates a clear, if small, causal impact of robotic surgery on hospital-level productivity.

Figure 6 presents the evolution of the TFP (i.e., the returned $\hat{\omega}_{jt}$) in hospitals that adopt a robot or not using the ACF specification. Panel (a) shows that adopters of robots are more productive than non-adopters from 2015 onwards. When disaggregating the non-adopter hospitals by those hospitals that also perform laparoscopic procedures or those that only perform open surgeries, as reported in panel (b), the difference in TFP comes largely from those hospitals that do not perform any minimally invasive surgery (laparoscopic or robotic) at all. Figure 7 confirms the previous finding showing that, in contrast to non-adopters, robot adopters were able to significantly increase their productivity. Panel (a) presents a before-and-after comparison among robot adopters showing that the TFP distribution when the robot was adopted (defined by "*t*," which represents the year of adoption for each of the adopting hospitals) is clearly dominated by the TFP distribution at the end of the period of analysis (2018). Panel (b) makes a similar comparison for non-adopters (*t* is equal to 2006, when the robot is adopted by the first hospital, to signal a potential change in the production process, although all hospitals in this figure are non-adopters) and reveals no change in the TFP distribution before and after robot adoption within the total sample.[28]

4.2.2 | Labor productivity

Finally, to complete our analysis, we examine the effect of robotic adoption on labor productivity. Our measure of labor productivity is the ratio of total volume of prostatectomies (open, laparoscopic and robotic) divided by the number of urologists. Figure 8a clearly shows that adopters of robots have a higher labor productivity. When disaggregating the non-adopting hospitals by those hospitals that also perform laparoscopic procedures or those that only perform open surgeries, as reported in panel (b), the difference in labor productivity comes largely from those hospitals that do not perform any minimally invasive surgery (laparoscopic or robotic).

TABLE 6 Production function results.

Dep. var Gross output Prostatectomies	(1) OLS	(2) Panel FE	(3) OP	(4) OP	(5) LP	(6) ACF
Adoption (=1 yes)	0.570***	0.302**	0.259*	0.212	0.109	0.208***
	(0.095)	(0.138)	(0.139)	(0.160)	(0.099)	(0.068)
Number of urologists	1.978***	0.766***	0.630***	1.982***	0.630***	0.660***
	(0.092)	(0.150)	(0.116)	(0.152)	(0.118)	(0.041)
Occupancy rate	1.905***	0.478	1.937***	1.963***	0.611***	0.578***
	(0.585)	(0.731)	(0.083)	(0.050)	(0.077)	(0.028)
Non-adopter (market >1 adopters)	−0.428***	−0.036	−0.269**	−0.253***	−0.174**	−0.266***
	(0.127)	(0.172)	(0.114)	(0.096)	(0.073)	(0.070)
N	602	602	552	600	552	552
No. hospitals	110	110	100	110	100	100
Proxy			Support staff	Capital inv.	Support staff	Support staff
Years	2010–2018	2010–2018	2010–2018	2010–2018	2010–2018	2010–2018

Note: Robust standard errors in parentheses. Analysis at hospital level. Gross output, number of consultants and occupancy rate in logarithmic terms.
Abbreviations: FE, Fixed-Effect; OLS, Ordinary Least Square.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

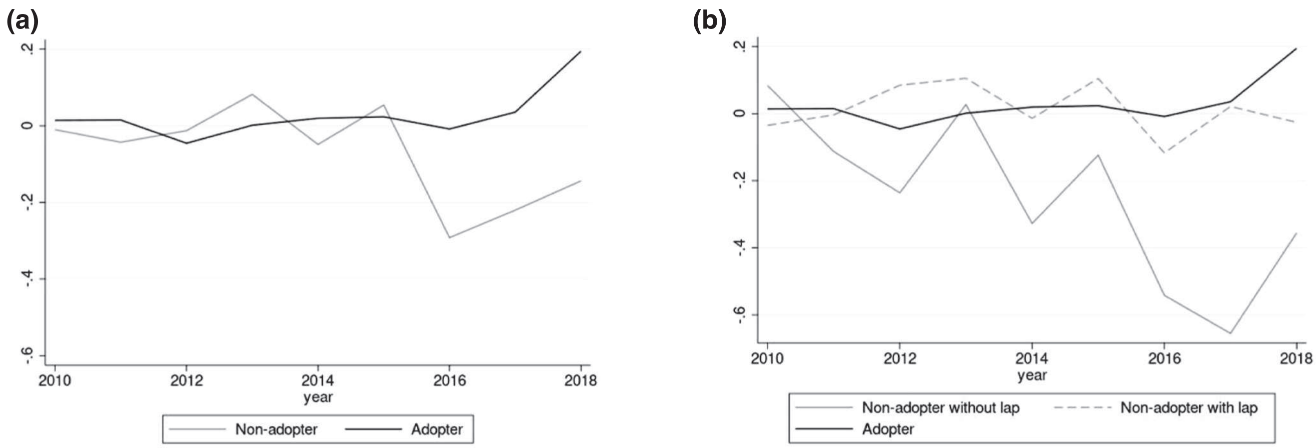

FIGURE 6 TFP evolution for adopters/non-adopters (ACF). (a) Adopter versus non-adopter. (b) Adopter versus non-adopter (with and without lap). TFP, total factor productivity.

Table 7 reports the results. All specifications include the dummy for robot adoption and the market variable. As in Table 6, we start by specifying a simple OLS model without fixed effects in Column (1), which shows that having a robot in the hospital increases the volume of prostatectomies by 14 cases per urologist. In Column (2) we specify a panel fixed-effects model. As in the main total productivity analysis, if we do not control for unobserved productivity, we introduce traditional production function bias. Therefore, we incorporate the hospital-level productivity estimates $\hat{\omega}_{jt}$ from the main analysis obtained from each model in Columns (3) to (6) in Table 6. This adds the complication, as noted above, that given robot adoption and total productivity correlation, we introduce further bias. We interpret the labor coefficient result therefore as indicating the broad degree of association between labor productivity and robot adoption and do not claim causality for this part of our analysis; although we do assess the degree of bias imparted. In Columns (3) to (6), results show a positive and significant effect for robot adoption, with an estimated 8–9 additional surgeries per urologist, representing a 29% increase. The point estimates for productivity indicate that an additional unit increase in TFP brings between 16 and 22 cases extra per urologist. Results are consistent across these structural approaches.[29]

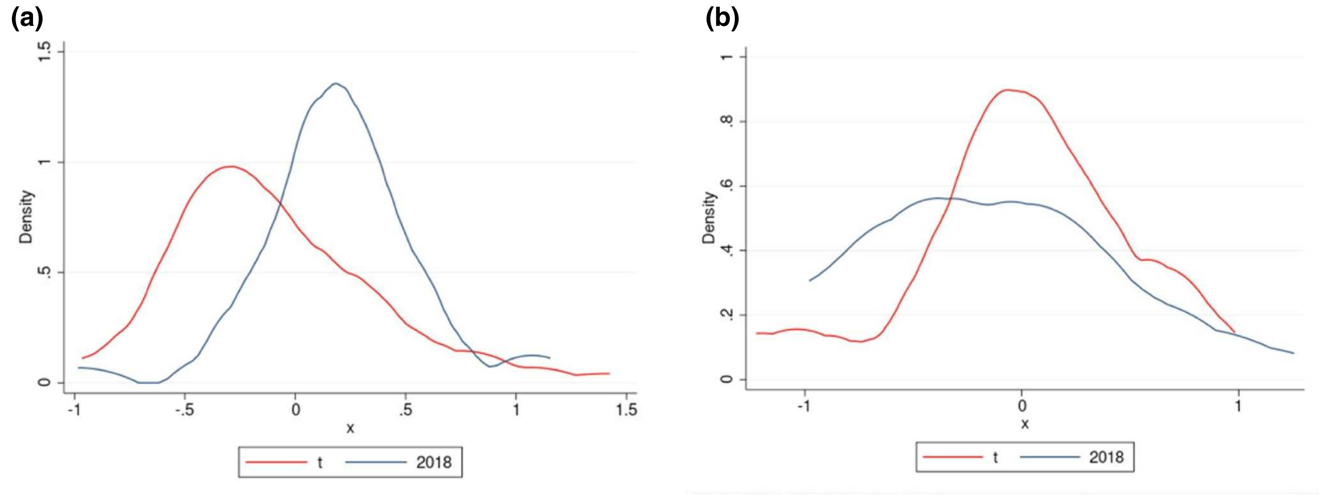

FIGURE 7 Before–after comparison of TFP (ACF) distribution. (a) Adopters. (b) Non-adopters. TFP, total factor productivity.

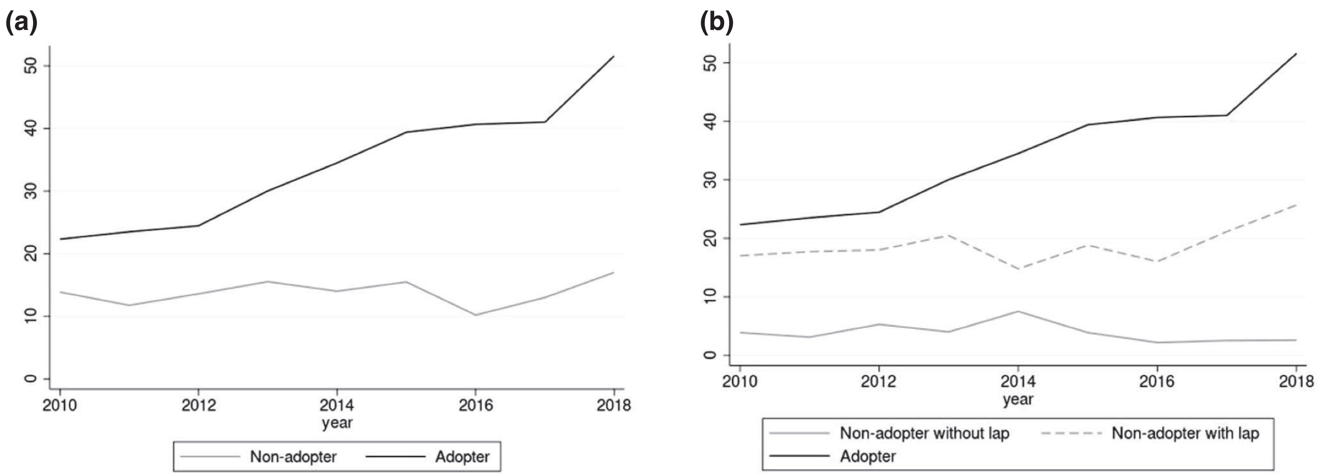

FIGURE 8 Labor productivity for adopters/non-adopters. (a) Adopter versus non-adopter. (b) Adopter versus non-adopter (with and without lap).

After controlling for $\hat{\omega}_{jt}$, if robot adoption and total productivity are correlated the estimates will be biased. To assess the stability of our coefficients to the presence of other unobserved factors, we adopted the approach by Oster (2019) and define a bounding set for the coefficient β_1 assuming $R_{\max} = 1.3\hat{R}$, and several values of δ, set at 1, 0.5, 0.2, and 0.1. Table A17 in Appendix A shows the bounding sets for the different values of δ, the parameter that reflects the contribution of unobservables relative to observables on the coefficient of interest. Oster (2019) suggests the use of 1 as an upper bound for δ. However, given that the specification in Equation (10) includes $\hat{\omega}_{it}$, as a purged estimate of unobservable total productivity, this value is an implausible upper bound. As the proportionality coefficient δ decreases, the lower and upper values of the bounding set are closer in magnitude, suggesting that any further bias introduced by further unobservables has a negligible effect on the estimated coefficient for the robot dummy.

5 | CONCLUSION

The aim of this paper was twofold. First, to analyze the effect of the introduction of laparoscopic and robotic surgeries (both defined to be minimally invasive procedures) on hospital efficiency as measured by estimates of utilization, given findings of no difference in clinical outcomes across these procedures in the medical literature looking at prostatectomy; specifically, LoS, post-operative LoS, read-missions within 30 days of discharge, number of outpatient visits within

TABLE 7 Labor productivity with market.

Dep. var Labor productivity	(1)	(2)	(3)	(4)	(5)	(6)
Adoption (=1 yes)	13.90***	4.060	8.137***	9.164***	8.137***	8.038***
	(3.254)	(3.182)	(2.482)	(1.722)	(2.482)	(2.625)
Non-adopter (market >1 adopter)	−5.243*	−1.881	−5.691*	−6.880***	−5.591*	−4.321*
	(3.103)	(3.198)	(2.899)	(1.775)	(2.899)	(2.501)
Total factor productivity			22.390***	15.790***	22.390***	17.950***
			(3.002)	(1.082)	(3.002)	(3.540)
Mean outcome	27.554	27.554	27.554	27.554	27.554	27.554
N	600	600	551	598	551	551
No. hospitals	110	110	100	110	100	100
R^2	0.305	0.273	0.542	0.735	0.542	0.438
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	No	Yes	Yes	Yes	Yes	Yes
Control patients	Yes	Yes	Yes	Yes	Yes	Yes
Control hospital	Yes	Yes	Yes	Yes	Yes	Yes
Productivity (method)			OP	OP	LP	ACF
Years	2010–2018	2010–2018	2010–2018	2010–2018	2010–2018	2010–2018

Note: Analysis at hospital level. Controls include patient case-mix (Charlson Comorbidity Index, Index of Multiple Deprivation of the area where the patient resides, age) and hospital characteristics (foundation trust, teaching trust, bed occupancy rate per hospital). Robust standard errors in parentheses. Model (3), (5), and (6) proxy variable is support staff and Model (4) is capital investment.

Abbreviation: FE, Fixed-Effect.

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

1 year and 2 years and waiting times. Second, to examine the impact of robotic surgery on provider productivity. Using rich administrative databases, the first objective was pursued through patient- and hospital-level analysis and the second through using structural, semi-parametric approaches to identify hospital production functions.

In summary, our results reveal hospital efficiency gains through robotic surgery adoption in NHS hospitals, associated with significant reductions in the number of postoperative visits to the urologist (of around 46%) and a reduction in LoS and post-operative LOS (equivalent to a reduction of 50%). Total production, measured as the number of surgical interventions, increases with the adoption of a robot (between 21% and 26%), the number of urologists within a hospital and the specialty occupancy rate. We find a 29% increase in labor productivity when robotic surgery is introduced and as well as higher TFP. These findings are robust when controlling for potential endogeneity arising from any unobserved productivity shocks by using a variety of different methods.

To put these gains into context, we can calculate the savings that could arise from the lower outpatient visits and shorter LoS attributable to robotic surgery compared to periods when hospitals had not acquired a robot. Our estimates in Table 5 indicate a reduction in outpatient visits by −1.675. In 2018 alone there were 9536 prostatectomy patients and, at a cost of £105 per follow-up visit, this implies savings of £1,677,144.[30] From the same table, we see there is a reduction in LoS of −1.739 at a cost of £216 for each in-hospital stay,[31] this implies a reduction in cost of £3,581,950.5.[32] Of course, in a capacity constrained system like the English NHS, these savings may not be actually realized, but the resources released could be used in the provision of other health care services. These computations do, however, give an indicative estimate of resultant welfare gains.

That said, while our findings do indicate hospital efficiency and productivity gains, it remains the case that there is scant evidence of improved clinical outcomes attributable to robotic surgery compared to general laparoscopic outcomes. A robotic surgical procedure in 2018 cost £6462 and is more expensive than a general laparoscopic procedure for this condition, which cost £4264. There were 8388 robotic surgeries in 2018 that could therefore have been performed as laparoscopic, given the similar clinical outcomes. If general laparoscopic procedures replaced robotic procedures for prostatectomy, the NHS could save around £18.5 million (£18,436,824 = 8388 × (£6462–£4264)). In contrast the direct estimated benefits of using robotic procedures, as calculated above as approximately £5.3 million (£5,259,094.5 = £1,677,144 + £3,581,950.5) are far lower than the £18.5 million arising from substitution with the earlier, but as effective laparoscopic procedure. Of course, these are only partial effects, as we do not consider the rollout of robotic surgery to other specialties, although here the treated volumes remain small and it is unlikely there are substantive savings generated by these specialties. Nor is it likely that there are hospital wide spillover effects providing savings in other areas, given the results of our placebo test.

To conclude, the introduction of novel robotic surgery does deliver efficiency gains, defined in terms of hospital utilization and throughput, at the patient level compared to laparoscopic surgery. Surgical robotic adoption by a hospital also has a significant impact on total production and in labor productivity. Nonetheless, the significant upfront acquisition cost of purchasing a surgical robot and the lack of clear clinical benefit in its use, would suggest that this technology remains far from cost-effective when compared to general laparoscopic procedures for prostatectomy. As was noted, robotic surgery is now being rolled out further across an increasing number of surgical procedures treating different conditions. We cannot comment on these developments. Nor can we say much about improvements in outcomes that may arise if volume-outcome benefits, reflecting greater use by individual surgeons, are achieved. At present, it is clear that modest hospital efficiency gains and increased productivity is achieved in the one surgical procedure studied. It remains unclear, given the financial and opportunity costs, that these efficiency and productivity gains are supportive of the witnessed rapid adoption.

AUTHOR CONTRIBUTIONS

Laia Maynou: Conceptualization, data curation, methodology, formal analysis, visualization, writing—original draft preparation, reviewing and editing, validation. **Alistair McGuire**: Supervision, conceptualization, methodology, validation, writing—reviewing and editing. **Victoria Serra-Sastre**: Supervision, conceptualization, methodology, validation, writing—reviewing and editing.

ACKNOWLEDGMENTS

This paper was produced using HES provided by NHS Digital under Data Sharing Agreement (DSA) NIC-354497-V2J9P. This paper has been screened to ensure no confidential information is revealed. We thank Georgia Pearson for her work in a preliminary work of this study. We thank participants at Jornadas AES organized by the Asociación Espanola Economía de la Salud where a preliminary version of this paper was awarded with the best paper presented by a young researcher, VIII Taller EvaluAES, Department Health Policy Seminar Series LSE, Departament d'Economia Aplicada, Universitat Autónoma de Barcelona, London Health Economists' Study Group seminar, Departament d'Economia, Universitat Rovira i Virgili, NHS Improvement seminar and comments received by the Advisory Committee of the Efficiency Research Program. We also thank colleagues at the LSE, in particular Guy Michaels and John Van Reenen for their comments. This work was supported by the Efficiency Research Program funded by The Health Foundation, Award Reference Number 7432. Laia Maynou is funded by the Spanish Ministry of Science, Innovation and Universities (PID2022-138866OB-I00 and CNS2023-144351).

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest for any of the authors. All authors freely disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations that could inappropriately influence, or be perceived to influence, their work.

DATA AVAILABILITY STATEMENT

This paper was produced using HES provided by NHS Digital under DSA NIC-354497-V2J9P. This data cannot be submitted to the journal based on the DSA. This paper has been screened to ensure no confidential information is revealed. We have used STATA 17 for the data analysis.

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ENDNOTES

[1] The uptake and diffusion of robotic surgery in the NHS was initially for a specific surgical procedure; the treatment of prostate cancer through radical prostatectomy. Prostate cancer is the second most common cancer in men worldwide. In the UK around 52,000 people are diagnosed with prostate cancer and 12,000 die from the disease each year (Prostate Cancer Research UK, 2022), although the survival rate is relatively high with a rate at 10 years of 78%. Surgery can be beneficial in these patients and in the UK around 15% of diagnosed patients undergo surgery of some form (Cancer Research, 2021). The specific surgical treatment performed in patients with prostate cancer is radical prostatectomy, defined as the removal of the prostate gland and attached seminal vesicles (NHS, 2015).

[2] Individual NHS hospitals must reach approval of a business-case through the hospital's Board of Directors, which must then agree with the relevant Clinical Commissioning Group (formerly Primary Care Trust) who act as the purchasers of health care on behalf of a geographically determined treatment population (Murphy et al., 2009).

[3] See Table A1 in Appendix A drawn from Maynou et al. (2022). Note also that in the NHS, unlike the USA or other health care systems, physicians' income is unrelated to the surgical technique used and hospitals receive a different tariff for each type of surgical procedure undertaken.

[4] Hereafter, we refer to each financial year by the year in which it starts, for example, 2000 refers to financial year 2000/2001. We end at 2018/19 given the distortion in hospital episodes arising from the COVID-19 pandemic.

[5] The OPCS-4 classification is a coding system for all interventions and surgical procedures, defining resource groups and used for reimbursement and statistical analysis.

[6] Prostatectomy is almost exclusively an elective procedure and we do not include emergency cases, as these represent only 415 cases over the 19 years (0.5% of the total sample). We included emergency cases in the sample as robustness and the results of the econometric analysis are virtually identical to the estimates obtained using elective cases only. Transfers from one hospital to another were considered an elective admission.

[7] Prostatectomy, while the dominant use of robotic surgery, is only performed on males. Moreover, NHS urologists are mostly male, with only 10% of consultant urologists being female in 2019 (Somani et al., 2021). While there is some evidence suggesting that patient concordance reduces mortality rates generally (Greenwood et al., 2018; McDevitt & Roberts, 2014; Zhao et al., 2019), these differences may not be clinically relevant (Wallis et al., 2023). We were not able to address this issue specifically given workforce data anonymity; however, as robotic surgery rolls out to other specialities it is a potential factor that will warrant further investigation.

[8] As pointed out in the introduction the first robot was acquired in the NHS in 2000. However, HES did not start recording robotic prostatectomies until 2006 as the numbers subject to robotic procedure were extremely small and largely "experimental." Figure 1 shows that the volume of cases for robotic was initially very small suggesting that even for early adopters the robot was rarely used. Any use of the robot before 2006 is not officially recorded or shown in the HES dataset. Data from 2006 shows only 6 hospitals have adopted and their volume is minimal as shown in Figure 1. This suggests it is safe to assume including these adopters in the sample does not bias our subsequent estimates.

[9] Hospital adopters are defined as hospitals that purchase a robot at any point during the study period. Non-adopters are hospitals that only perform open or/and laparoscopic surgery and do not purchase a robot during our study period. For the econometric analysis, we use a different definition and the variable "Adoption" equals 1 from the year a hospital adopts and for any subsequent year, and 0 for any year pre-adoption. For non-adopters this variable is always equal to 0.

[10] Figure A1 in Appendix A shows the geographical distribution of hospital trusts performing prostatectomy, differentiating by types of surgery they provide, and indicating the diffusion and increase in hospitals adopting robots.

[11] While reflecting preferences, we recognize that this is only a proxy for individual surgeon preferences, which in a true sense remain unobserved. Including this variable in the propensity score matching for the CS estimator, aggregated at the hospital level, does however allow for some consideration of surgeon preference for laparoscopic or robotic surgery, ameliorating any selection preferences. We cannot further distinguish between laparoscopic and robotic in this variable definition as they form our treatment variable.

[12] Beds are used as a common proxy for capital flows given data constraints on capital measurement (Street & Ward, 2009), as beds heavily correlate with other measures of capital while also allowing estimation of economies of scale (Gaynor & Anderson, 1995). Other data on capital, namely capital investment, while also a proxy in nature, is used in one of our production specifications as an intermediate factor, although this measure cannot be used in our preferred production specification as it is a value added, rather than output, measure of capital. Capital investment is also only available at the aggregate hospital level, rather than at the specialty level which is the analysis level of interest.

[13] We also observe that surgeons tend to specialize in one of the surgical types, that is, open, laparoscopic or robotic. In hospitals where the three interventions are performed, over time, we typically observe one surgeon per intervention type.

[14] Within adopter hospitals, there is a higher proportion of foundation trusts and teaching hospitals. They also treat younger patients, have more urologists, more urology nurses, more urology support staff and higher labor productivity (Table A6 in Appendix A).

[15] From 2006 to 2018, there were 0 to 7 hospitals adopting the robot per year. This justifies the staggered approach adopted.

[16] As a further check for selection, we run the CS analysis in a matched subsample. The results are very similar confirming that the propensity score matching incorporated in the CS model works well.

[17] We also explored the possibility of using the CS estimator at the patient level using as treatment the type of surgery they received. However, it was not possible to define treatment in such manner given that laparoscopic and robotic surgeries were almost simultaneously introduced (based on our Figure 1), and we could not define a pre- and post-treatment period when comparing between minimally invasive techniques. We did examine the impact of choice of technology on efficiency based on patient-level indicators of surgery choice. Overall the analysis indicates that minimally invasive surgery leads to a reduction in LoS, post-operative LoS and readmission. Results hold when comparing between laparoscopic and robotic techniques (both minimally invasive), except that readmission is no longer precisely estimated. These results, although indicative of the direction of the effects, merely reflect associations. Details of the specifications and results can be found in Appendix B.

[18] ACF provides a detailed explanation of the data generating processes underlying each of the OP/LP/ACF approaches. Indeed, they provide detail on the underlying assumptions generally noting, for example, that these approaches are useful where prices are not exogenously determined and cannot therefore provide useful IVs. This is the case in the English NHS where input prices, particularly for labor, are determined centrally through a Remuneration Review panel with small local adjustments. They also note that for gross output production specification, as we have intermediate inputs, should be Leontief in their determination. This again is taken to be the case in the English NHS for our support (and even nursing staff) where historic rules of thumb tend to give rise to fixed coefficient staffing ratios (e.g., beds to nurses and beds to support staff ratios).

[19] We define support staff as the intermediate good based on the assumption that support staff are more variable than other labor inputs in the hospital sector, and as we have no physical measure of hospital materials, such as surgical supplies. As a robustness check, we also use the number of nurses as a state variable as it may be that they are also considered semi-fixed labor. These results are provided in Table A15 in Appendix A.

[20] Note that this unobserved productivity is assumed to capture all other aspects of producers, including for example, any preference for technology. Note also that hospital fixed effects are precluded by this unobserved productivity assumption. However, external factors, such as systematic influences on demand (as represented by the treatment assignment of other hospitals) may have an influence, which is why include a market adoption variable in our preferred specification.

[21] The reference category is the non-adopters in markets with zero or only one adopter. In Horn et al. (2022) specification, the indicator for non-adopter' hospitals in markets (already pre-defined USA markets) is equal to zero (reference category) if there are zero adopters. In our case, we had to change this definition because we only had two hospitals under this definition. As a result, the reference category is equal to zero or one adopter and the indicator is equal to one if there are two or more adopters in 30 miles.

[22] The endogeneity problem threatening the identification strategy of the production function outlined in Equation (7) is addressed in the estimation procedures proposed by OP, LP, and ACF. These approaches allow estimation of the productivity shock $\hat{\omega}_{it}$, which captures the effect on the TFP clean from all other inputs, capital and labor. By including $\hat{\omega}_{it}$ in Equation (10), we rule out any circularity problem arising from our definition of the dependent variable given the productivity shock is independent of labor inputs and by definition it is an unobservable that invariably affects prostatectomy volumes. $\hat{\Phi}_t$ in Equation (9) is the estimated function of productivity from which the productivity estimate, $\hat{\omega}_{it}$ used in Equation (10) is gained.

[23] The bias-adjusted coefficient for the robot dummy is:

$$\beta_1^* \approx \tilde{\beta}_1 - \delta\left[\beta_1^{\circ} - \tilde{\beta}_1\right]\frac{R_{\max} - \tilde{R}}{\tilde{R} - R^{\circ}}$$

where $\tilde{\beta}_1$ is the robot coefficient estimated including all observed variables and $\tilde{R}$ is the corresponding R-squared of this regression; β_1° is the coefficient resulting from regressing the labor productivity only on the robot dummy and R° is the R-squared of this regression. β_1^* depends on δ, the proportionality coefficient reflecting the contribution of the unobservables relative to the observables, and $R_{\max}$, the maximum R^2 that could be achieved when controlling for all observables and unobservables. We follow Oster (2019) and use $R_{\max} = 1.3\tilde{R}$. An upper bound for δ is 1, which implies an equal selection on observables and unobservables. This assumption does not seem plausible as we are already accounting for $\hat{\omega}_{jt}$, the estimated hospital-level time-varying productivity shock. $\hat{\omega}_{jt}$ is likely to capture all, if not a large, share of the unobservable component and therefore the assumption of $\delta = 1$ does not seem to be a relevant upper bound. We will explore changes to the bounding set for different levels of δ.

[24] We first estimate the CS model without covariates (see Table A7 in Appendix A); however, as the parallel trend assumption does not hold across all models, CS recommend the use of covariates to generate propensity scores to fulfill the conditional parallel trend assumption.

[25] As seen in Figure 3, there has been a slight decrease in all urologists performing radical prostatectomy and a slight increase in urologist performing minimally invasive procedures for radical prostatectomy. Even if the surgeon still needs to be in the operation theater during the robotic surgery, other staff categories such as nurses or support staff to doctors and nurses, might adjust to the adoption of the technology accordingly. Figure 3 shows a slight increase in support staff, while nurses have remained relatively stable. Hence, we exploit information on support staff as intermediate input.

[26] Investment at the hospital aggregate level is not a clear measure of capital flow at the urological surgical level, again highlighting the difficulties encountered in finding appropriate proxies for capital.

27 In Table A14 in Appendix A, we include the results when excluding the market variable. Comparing the results in Table 6 and Table A14 in Appendix A, we observe that adjusting for the number of adopters for each non-adopter in the market reduces the effect of the adoption of robot on volume of prostatectomies by 38% (Column (6)). The sign of the market variable and the reduction on the effect of robot adoption goes in the same direction as in Horn et al. (2022).

28 Figure A3 in Appendix A presents the TFP distribution disaggregating the non-adopter hospitals by those hospitals that also perform laparoscopic procedures (I) or those that only perform open surgeries (II). Figure A3(I) in Appendix A is very similar to Figure 7b, the total non-adopters, but Figure A3(II) in Appendix A has few observations for "t" which explains the curve shape.

29 As we have done for the analysis of TFP, we present the same specification without controlling for the market adjustment variable. Results, available in Table A16 in Appendix A, are similar to those in Table 7, but the effect of the adoption of a robot on labor productivity is smaller, by 18. This market effect on robotic productivity is in line with the US results for a different market structure presented by Horn et al. (2022).

30 We use the cost of an outpatient follow-up visit led by a single professional for medical oncology, equal to £105. This would be a lower bound as it assumes the visit is only attended by a single professional but the cost differs if the visit includes a team of clinical professionals (costing £116). The cost of the outpatient visit is extracted from the National Tariff 2017/19 available from https://www.england.nhs.uk/publication/past-national-tariffs-documents-and-policies/.

31 The cost for the computation of the savings in LoS is obtained from the National Tariff 2017/19 available from https://www.england.nhs.uk/publication/past-national-tariffs-documents-and-policies/. We use the daily cost for long stays that exceed a trim point, which is £216 for open, laparoscopic and robotic prostatectomy.

32 Taking the National Tariff we also calculate the cost by dividing the cost of each type of procedure by the average LoS for each surgery to obtain the cost per day and then weighting it by the percentage of each procedure type in 2018/19. The cost saving calculated in this manner sums to £43,222,784. This is likely an overestimation of the savings as the tariff includes to total cost of surgery and hospital stay.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Maynou, L., McGuire, A., & Serra-Sastre, V. (2024). Efficiency and productivity gains of robotic surgery: The case of the English National Health Service. *Health Economics*, 1–26. https://doi.org/10.1002/hec.4838