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JEL Classification: N/A

Keywords: Innovation, medical practice, networks, peer-effects

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1. Introduction

Networks drive innovation take-up in many areas of the economy (Hall 2006; Jackson et al. 2017). The healthcare context is one in which innovation is high (e.g. Newhouse, 1992; US CBO, 2008; Smith et al. 2009) and physician networks are likely to be important because of the length of on-the-job training and the extensive use of team working. Yet there is little robust evidence on the role of physician networks on the diffusion of innovation (Agha and Molitor, 2018). One reason for the paucity of research stems from the lack of detailed longitudinal data tracking physicians' innovation take-up and contact with one another from the introduction of the innovation to its maturity.

This paper addresses the issue by exploiting novel matched patient-physician-hospital data to construct a network based on common workplaces of physicians for over 20 years (1992 to 2014), which is used to examine network features and their impact on innovation diffusion among physicians. Physicians share a link in the network (i.e. are peers) if they have worked in the same hospital at the same time. The network captures physicians' contact with one another and evolves as they move posts between hospitals. We study how innovation take-up depends on the network through the number of peers and proximity to early adopters ('pioneers'), in addition to the effect of peer take-up. We build on existing work by allowing for both contemporaneous and cumulative effects of peer take-up, and for heterogeneous peer-effects through which particular physicians ('key players') disproportionately drive others' take-up. We are agnostic as to the identities of these key players, which we estimate jointly with their effects on others. Identification is based around exogenous evolution of the network over time, which allows us to separate peer and network effects from unobserved physician and hospital heterogeneity.[1]

Our "test bed" is the diffusion of an innovation in cancer treatment in the English National Health Service (NHS). This setting has several advantages. First, the NHS is almost the only provider of such treatment in England so we observe close to the universe of treatment, physicians and hospitals. We can therefore match all NHS physicians to almost all of their patients for 15 years and physicians to all NHS hospitals for over 20, allowing us to construct a dynamic network and examine the behaviour of individuals in that network. Second, we observe take-up of the innovation from the date when it was first introduced to 15 years later. Third, the surgical innovation we study is almost exclusively undertaken by senior physicians who also perform the alternative older surgical technique. Fourth, the allocation of cancer patients to physicians is close to random. Finally, healthcare in the NHS is free at point of use and tax funded, physicians are salaried employees whose compensation does not depend on the treatment provided, and all hospitals operate within the same centrally governed system with the same financial incentives. This allows us to isolate the role of the physician and their network, abstracting from the variation due to different payment regimes, insurance based patient selection, defensive medicine and hospital organisation.

The innovation we consider is minimally invasive (keyhole) surgery for patients with colorectal cancer. Colorectal cancer is the third most common cancer worldwide (Arnold et al. 2017), accounts for a large number of deaths annually and is costly to treat. In

[1] Full details are in Section 4 below.

2017, there were 1.8 million cases, 896,000 deaths and 19 million lost disability adjusted life years worldwide (Safiri et al. 2017). Keyhole surgery for colorectal cancer is an important innovation. Relative to the alternative older procedure of open surgery, it is associated with improved patient survival, better short-term outcomes and lower costs (Lacy et al. 2002, Nelson et al. 2004, Laudicella et al. 2016). Yet its take-up has been relatively slow in England (Green et al., 2009; Taylor et al., 2013) and the US (Kemp et al., 2008; Fox et al., 2012; Robinson et al., 2011), among other countries (Mooloo et al., 2009, Saia et al, 2017, Thompson et al., 2011).

We begin by showing the network is composed of several communities which map closely to geographic areas, reflecting the fact that physician mobility in England tends to be within region (Goldacre et al., 2013). There are persistent differences in community take-up, with communities located in southern England ahead of those located in more northern areas. The observed differences in take-up could be due to peer-effects, which, if positive, increase the variance of take-up between different communities (Graham 2008, Rose 2017) or due to heterogeneous information transmission through different parts of the network. However, differences could also arise from community composition, through observable and unobservable physician, patient, hospital or community level heterogeneity.

Given this, we then exploit the dynamic nature of the network to estimate the causal effects of contemporaneous and cumulative peer take-up, the number of peers, the effect of being a peer of a pioneer and the impact of key players. We find evidence that all of these channels affect the use of the innovation. In terms of magnitude, a standard deviation increase in contemporaneous peer take-up and number of peers respectively lead to 0.12 and 0.15 standard deviation increases in own take-up. Being a peer of a pioneer increases take-up by 0.12 standard deviations. We also find evidence that contemporaneous peer take-up has a larger effect on inexperienced physicians, with effect sizes ranging from 0.17 (no experience) to 0.04 (most experienced). These effect sizes are larger than that of patient suitability for keyhole surgery (0.06) and comparable to the physician's experience in keyhole surgery (0.14). Our results are robust to different specifications of the patient characteristics on which we condition, to different specifications of take-up dynamics, and to non-linear peer-effects. We estimate the identities of 44 key players, whose peer and proximity effects on others are also positive. Key players are comparatively young and have early and rapid take-up. [2]

Finally, we use our estimates to study two counterfactuals, one of which identifies a single physician to be targeted to increase their take-up and another in which links are added between low and high take-up physicians. We estimate that implementing these policies in 2001 would have increased average take-up in 2014 by 8 and 11 percentage points respectively from a base of just under 50%. The most effective interventions target young, well connected physicians with high early take-up.

[2]Though our data do not permit us to be certain of the underlying mechanisms, we conjecture that the number of peers and pioneer proximity capture mobility based information transmission, and the peer-effects are commensurate with peer learning and/or imitation dominating congestion effects arising through shared hospital resources.

1.1. Related Literature

Our work contributes to the literature on innovation in health care. There are large differences in healthcare spending and utilisation across and within regions in the US, the UK, and elsewhere (Finkelstein et al. 2016; Skinner 2012; IOM 2013), with medical outcomes largely unassociated with utilisation (IOM 2013; Fisher et al. 2003). These differences cannot be fully explained by random fluctuations, regional price differences, income, health status (Finkelstein et al. 2016) and patients' preferences and needs (Barnato et al. 2007). Studies have instead suggested that the differences are related to persistent productivity differentials across care providers within regions (Skinner and Staiger, 2015). One driver of this is physician behaviour (e.g. Epstein and Nicholson 2009; Currie et al. 2016; Currie and Macleod 2018; Cutler et al. 2019). A number of studies have focused on peer and work environment effects, showing that peers can determine behaviour with respect to well established medical procedures (Burke et al. 2003; Pollack et al. 2012; Chan 2016, forthcoming; Silver 2016; Molitor 2018; Reagans et al. 2005; Staats et al. 2018; Arrow et al. 2017, Lamiraud and Lhuillery 2016). These studies have not examined the role of peers on innovation diffusion, nor directly considered the effect of peer take-up, focusing instead on the effect of the number of peers or peer experience.

There are three exceptions. Burke et al. (2007) show that physicians' adoption of bare-metal stents is positively associated with the number of star physicians' working contemporaneously at the same hospital.[3] Burke et al. (2009) show that the effect is driven by the number of stars who have themselves adopted the innovation. Neither paper directly estimates the effect of peer adoption nor accounts for its endogeneity. Agha and Molitor (2018) study innovation take-up in the context of cancer drugs. They examine the role of local opinion leaders in easing information frictions associated with technology adoption, analysing the influence of physician investigators who lead clinical trials for new cancer drugs. By comparing diffusion patterns across 21 new drugs, they separate correlated regional demand for new technology from information spillovers. They find that patients in the lead investigator's region are initially 36% more likely to receive the new drug, but utilisation converges within four years. They also find that superstar physician authors, measured by trial role or citation history, have broader influence than less prominent authors. However, they do not directly examine the effect of peers on physicians' behaviour. Our data allow us to address this directly because we observe take-up at the physician level and match physicians to hospitals over time. We also address uncertainty regarding an appropriate definition of influential physicians (Burke et al. 2009; Huesch 2009) by estimating, rather than imposing, their identities, and allow for these physicians' to have direct effects on others.

Studies have also examined the impact of worker mobility on innovation in settings other than healthcare. Kaiser et al. (2015) show that an increase in the share of workers recently joining from other firms increases firm patenting. Braunerhjelm et al. (2020) show that the effect is largest for workers which previously worked in a patenting firm in the same region. These papers focus on firm-level innovation, whereas our matched firm-worker-task panel allows us to study take-up at the worker level in a setting in which workers are relatively

[3] A star is defined as having completed residency training since 1975 in a hospital ranked in the top 10 nationally for heart surgery.

autonomous, and to control for workers' individual heterogeneity. Our setting is also one in which endogenous worker mobility is less of a concern.

We advance the peer-effects literature by proposing a new identification strategy designed to avoid weak identification when interactions take place in groups (Lee, 2007). Our approach exploits the existence of two types of peer, only one of which exerts the contextual effects that arise when behaviour is determined by peer characteristics. We argue that contextual effects are exerted by 'intra-hospital' peers located in the same hospital but not by 'inter-hospital' peers who no longer work in the same hospital. We consider inter-hospital peers to be peers because England is a small geographical area in which almost all hospital physicians work for a single organisation (the NHS) that is characterised by a high level of central directives, centrally organised training arrangements and common procedures across all its hospitals and staff. In addition, we show that mobility between hospitals is largely confined to the local region. It is therefore expected that some contact will be maintained after a physician moves hospital.[4] This allows us to use peers' exogenous characteristics (age, experience and patient characteristics) as instruments for peer take-up, whilst also conditioning on the characteristics of the physician and their intra-hospital peers. Importantly, it avoids the need to use the characteristics of peers-of-peers as instruments, which can lead to weak identification (Lee, 2007).

We build on panel data models of social interactions (e.g. Lee and Yu, 2010, 2012), through adding an additional cumulative peer-effect on top of the contemporaneous peer-effect. This allows behaviour to depend both on contemporaneous and cumulative peer behaviour, offering dynamic peer-effects with a straightforward interpretation. Regarding particularly influential key players, our work is related to that of Peng (2019), but with crucial differences. We permit key players to have proximity as well as peer-effects, and panel data allow us to separate these from unobserved physician and hospital heterogeneity. We estimate key player identities using the Self Tuned Instrumental Variables (STIV) estimator (Gautier and Rose, 2019) instead of a two-stage Least Absolute Shrinkage and Selection Operator (LASSO) procedure. The advantage of STIV is that the first-stage need not be sparse or even approximately sparse, whereas LASSO can perform poorly without sparsity.[5] The first-stage captures both direct and indirect effects operating through the network, and is not sparse in general, even if the structural equation is.[6]

The paper proceeds as follows. Section 2 describes the setting and our sources of raw data. Section 3 describes the construction of our measures of take-up and the network, documents physicians' mobility patterns and shows that take-up is not uniform over different 'parts' of the network. Section 4 presents our empirical model and identification strategy, provides baseline findings and shows that these are not sensitive to variations in model specification. Section 5 studies key players and the corresponding high-dimensional instrumental variables model. Section 6 considers policy implications and concludes.

[4]Our results are robust to differential weighting of intra- and inter-hospital peers.

[5]Sparsity means that the parameter vector has many entries exactly equal to zero.

[6]First stage sparsity corresponds either to restrictions on the peer-effects (e.g. endogenous peer-effects equal to zero), or to restrictions on the connectedness of the network. See Rose (2018) for further discussion.

2. Institutional Setting and Data

Within the English NHS, all hospital and primary healthcare is free at the point of use and funded by general taxation.[7] Excess demand is rationed by waiting time. Patients needing hospital based care are referred by their primary care physicians to a hospital. In the case of cancer care, a waiting time guarantee mandates that all suspected cases are seen by a specialist in a hospital within two weeks. This means that patients are referred to the nearest hospital with capacity. Once in hospital, patients are allocated to a senior physician (known as a consultant). Allocation to a consultant is on the basis of capacity and, in the case of cancer treatment, the waiting time guarantee means it is essentially random, as patients are allocated to the first consultant with availability. All hospitals operate under the same financial rules set by central government and consultants are salaried employees of one hospital at any point in time.[8]

2.1. Keyhole surgery for colon cancer

The innovation we study is the use of minimally invasive (laparascopic, also known as keyhole) surgery for the treatment of colon cancer. The procedure involves small incisions through which a laparoscope is inserted, which is used to guide resection of the tumour. The alternative open procedure requires a much larger incision. Keyhole surgery for colorectal cancer is important because colon cancer is a leading cause of mortality in the UK, accounts for 10 percent of all cancer deaths annually and has the highest financial burden on NHS among all cancers, costing around $890m per annum (Laudicella et al. 2016). It has improved survival rates, quality of life, recovery time, and shortened length of hospital stay (Lacy et al. 2002; Nelson et al. 2004; Braga et al. 2005; Jayne et al. 2010; Burns et al. 2013) relative to the alternative procedure of open resection. In the UK, it has also been shown to be more cost effective (Laudicella et al. 2016). It was first introduced to the NHS in 2000. However, despite the evidence showing the superiority of keyhole surgery, the take-up of the innovation in England was slow.[9]

2.2. Data

Data were linked from three main sources. The first is the patient level hospital discharge dataset for financial years 2000-2014 (Hospital Episodes Statistics 2014), which covers all patients treated in the NHS in England. The second is consultant level demographic and employment data from NHS Workforce Statistics for 1992-2014 (NHS Workforce Statistics 2014). The third is consultant level demographic and medical education data from the

[7]There is a small private sector in England that mainly provides care for planned procedures for which there are long waiting lists. Private sector provision for (any) cancers during the period we examine was very limited and primarily focused on treatment of overseas patients.

[8]NHS hospitals are known as NHS Trusts and operate in one small geographic area, though this can be from a number of sites. There are no hospital chains in the NHS. We refer here to NHS Trusts as NHS hospitals.

[9]As a response, the National Institute of Health and Care Excellence (NICE) issued national guidelines in 2006 to promote its use, which were followed in 2009 by a national training program for laparoscopy (LAPCO) to train consultants.The guidelines highlighted the cost-effectiveness of laparoscopy (NICE, 2006). A similar training programme to LAPCO was established in the US.

General Medical Council (GMC) register, the national body that determines physicians' qualification to practice in England (General Medical Council Register 2014). All physicians registered to practice in England have a unique GMC code, which is recorded in each dataset, allowing the three data sources to be linked.

Hospital Episodes Statistics (HES) information includes date, hospital and method of admission and discharge, patient characteristics, clinical information on diagnoses, care provided and the GMC code of the consultant who led the surgical team that undertook the procedure. The GMC data provides information on all consultants registered to practice including five-year age bands, gender, education degree, main and sub-specialties, university of qualification, country of qualification if outside the UK, and year of qualification.[10] NHS Workforce Statistics provide information on the consultant's career path between 1992 and 2014, both pre- and post-becoming a consultant, including hospital of practice, job title (career position), and grade.

Using HES data, those colorectal cancer patients for which there was a choice between open and keyhole surgery were identified using the Office of Population Censuses and Surveys Classification of Surgical Operations and Procedures (OPCS) (NHS Digital, 2018).[11] This produced a dataset of 276,073 patients uniquely linked to a consultant (anonymised) code. These data were then collapsed to create a single observation at consultant-hospital-year level.[12]

This resulted in a dataset of 3,522 consultants and 19,834 consultant-hospital-year observations for which we have data on surgical activity for each consultant covering the period 2000-2014. To locate consultants prior to 2000 (the year when keyhole surgery for colon cancer was first used in the NHS and our HES data starts), and to fill in gaps in hospital locations for consultants not recorded as undertaken any hospital care in a particular year, we use the NHS Workforce Statistics 1992-2014.[13] Thus our panel of 3,522 consultants runs from 1992-2014, though the estimation sample is for 2000-2014 as keyhole surgery for colon cancer was not introduced until 2000.

There are a total of 3,522 consultants in this (unbalanced) panel. However, the majority perform very few colorectal cancer surgeries. Between 2000 and 2014 the median consultant

[10] Medical registration dates are also available post-1998.

[11] Colorectal open resections were identified according to the type of resection performed using the following OPCS codes: H05/H29 (subtotal/total colectomy); H06 (extended right hemicolectomy); H07 (right hemicolectomy); H08 (transverse colectomy); H09 (left hemicolectomy); H10 (sigmoid colectomy) and H11 (other colectomy); H04.1/H04.3/H04.8-9 (panproctocolectomy); H33.2-4/H33.6-9 (anterior rectal resection); and H33.5 (rectal resection, Hartmann's procedure). Keyhole surgeries were identified with the additional secondary OPCS codes Y75, Y50.8 or Y71.4. Only the patients' first colorectal surgery was included, as subsequent surgeries are less likely to offer a clinical choice of resection (Burns et al. 2013). We code any keyhole surgery converted into open resection (OPCS: Y71.4) as keyhole surgery to capture intention-to-treat with keyhole surgery.

[12] Only consultants with clinical expertise in performing colorectal cancer surgery and classified as in one of the following three primary specialties: general surgery, gastroenterology, and urology were included to ensure we focused on individuals for whom this kind of surgery was a normal part of their work. In the relatively few cases in which the consultant practised in more than one hospital or moved hospitals in a given year, we assigned the consultant to the hospital in which the consultant has worked the largest number of days during the year (using the HES dataset).

[13] This results in a dataset of 65,366 consultant-hospital-year observations covering 1992-2014 and contains data on consultants prior to their appointment as consultants. We use data from 1992-2014 to construct the network and data from 2000-2014 to study take-up of keyhole surgery for colorectal cancer.

performed just 4.5 per year on average. The 0.1 quantile was 1.75. For this reason, we restrict our estimation sample to those consultants at or above the 0.6 quantile of cancer surgeries per year. This gives a sample of $N = 1,466$ consultants performing 6 or more colorectal cancer surgeries annually. There are no clear differences between the two samples in terms of age composition, patient suitability scores nor number of keyhole surgeries for conditions other than colorectal cancer. By construction, the estimation sample comprises more experienced consultants, who perform more colorectal cancer surgeries. Consultants in the estimation sample also perform a higher proportion of keyhole colorectal cancer surgeries in 2014 (mean of 0.486) compared with all consultants (mean of 0.416), though there is no difference in 2000.

In sum, our estimation sample comprises $N = 1,466$ consultants whose colorectal cancer surgeries we observe for $T = 15$ years between 2000 and 2014. These surgeries take place across $H = 198$ hospitals. We also observe consultants' hospitals from 1992 to 2014, which we use to construct the network for these years.

3. Innovation Take-up and the Network

The dependent variable measures take-up by the proportion of colorectal cancer patients treated by keyhole surgery,

$$y_{it} = \frac{colokey_{it}}{colosur_{it}}, \tag{3.1}$$

where $colokey_{it}$ is the number of keyhole colorectal cancer surgeries and $colosur_{it}$ is the total number of colorectal cancer surgeries. We compute this for years $t = 00, 01, ..., 14$ and consultants $i = 1, ..., N$ using HES data.

We define the network for the years 1992-2014. It is characterised by the dynamic, symmetric $N \times N$ adjacency matrix $\overline{\mathbf{A}}_t$ for $t = 92, 93, ..., 14$, with entries

$$\overline{\mathbf{A}}_{ijt} = \begin{cases} 1 & \text{i and j have worked concurrently in the same hospital} \\ & \text{between 92 and t, and } j \neq i \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

We consider peers to be all those who have previously worked simultaneously in the same hospital because we do not expect contact to be severed once a consultant moves hospital. This is because mobility is largely confined to the local region, which we show below. We also construct a $H \times H$ hospital level network, defined by the symmetric $H \times H$ adjacency matrix $\overline{\mathbf{B}}_t$, with entries

$$\overline{\mathbf{B}}_{klt} = \begin{cases} \frac{\sum_{i:h(i,t)=k} \sum_{j:h(j,t)=l} \overline{\mathbf{A}}_{ijt}}{\sum_{i:h(i,t)=k} \sum_{j:h(j,t)=l} 1} & k \neq l \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

where $h(i, t)$ is the hospital in which consultant i practices in year t. This means that the magnitude of a link is equal to the proportion of consultant level links.

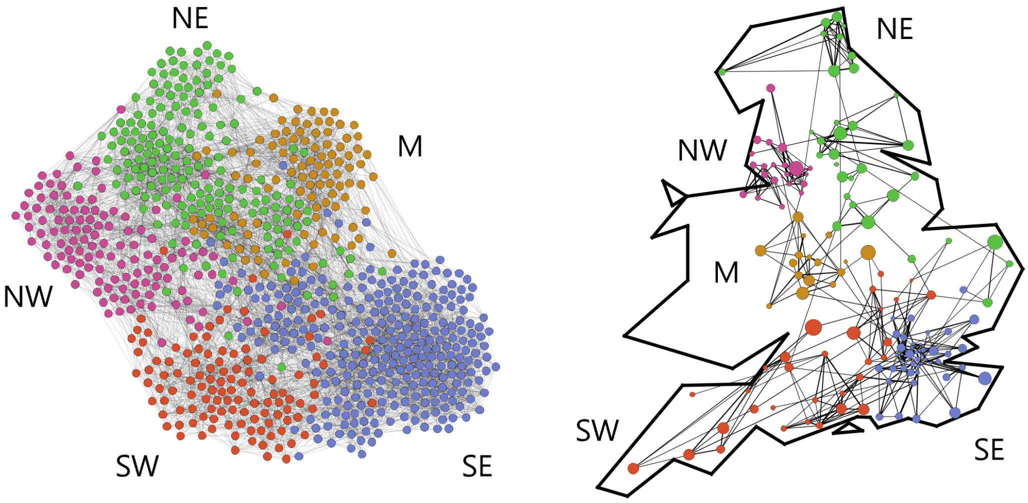


Figure 1: *Networks and communities in 2007*
Notes: The consultant (hospital) network is on the left (right). Consultants are located using a spring algorithm, which places linked consultants near to one another. Hospitals are located geographically. Larger hospitals imply higher annualised total volume of colorectal cancer surgeries performed between 2000 and 2014. Links between hospitals are drawn only if they have magnitude greater than or equal to 0.15, meaning that at least 15% of consultants are peers. Consultants and hospitals are shaded by community membership.

We summarise the network and document the take-up of keyhole surgery for colorectal cancer between 2000 and 2014. Figure 1 depicts a snapshot of the consultant (left) and hospital (right) networks in 2007. A natural starting point is to establish the extent to which take-up is heterogeneous over different parts of these networks. We divide consultants into different 'communities', such that links are denser within communities than between communities. For simplicity, we treat community membership as static,[14] and apply the community detection algorithm of Blondel et al. (2008) to the aggregated adjacency matrix $\sum_{t=00}^{14} \overline{\mathbf{A}}_t$. This yields the five communities shaded on the left of Figure 1, which we label by regions of England (North-East, South-East, South-West, Midlands, North-West). We apply the same community detection algorithm at the hospital level, yielding the five communities in the right hand panel of Figure 1, which we give the same labels and colours as for the consultant communities. This is because there is a strong correspondence between the consultant and hospital communities, as shown in Table 1. Together, Figure 1 and Table 1 show that mobility is largely intra-region. Though there is inter-region mobility, consultant communities correspond broadly to regions of England. These patterns are also documented by Goldacre et al. (2013) using survey data.

Figure 2 depicts take-up of keyhole surgery over time. There are persistent differences in community take-up, with 'southern' communities ahead of 'northern' communities. The observed differences in take-up could be due to peer-effects, which, if positive, increase the variance of take-up between different communities (Graham 2008, Rose 2017) or due

[14]Otherwise it would be impossible to separate community composition from community take-up.

to heterogeneous information transmission through different parts of the network. The differences could also be attributed to community composition, through observable and unobservable consultant heterogeneity (e.g. age, experience and ability), patient heterogeneity (e.g. age, underlying health conditions), hospital heterogeneity (e.g. facilities) or other sources of community level heterogeneity (e.g. regional health policy).

Table 1: *Frequency of consultant-year observations by community membership, 2000-2014*

	Hospital community ($\overline{\mathbf{B}}$)					
Consultant community ($\overline{\mathbf{A}}$)	SE	NW	NE	SW	M	Total
SE	3158	42	506	746	275	4727
NW	29	1541	43	54	31	1698
NE	27	64	2441	70	89	2691
SW	68	31	40	1565	24	1728
M	39	33	42	21	1087	1222
Total	3321	1711	3072	2456	1506	12066

3.1. Consultant and Patient Characteristics

We use the GMC register and HES data to construct consultant age in bands ($< 40, 40 - 44, 45 - 59, 50 - 54, > 55$), experience in keyhole surgery ($expkey_{it}$), measured by hundreds of keyhole surgeries performed for conditions other than colorectal cancer from 2000 up to and including year $t - 1$, and consultant experience in colorectal cancer surgery ($expcolosur_{it}$), measured by hundreds of colorectal cancer surgeries performed from 2000 up to and including year $t - 1$. The experience variables are constructed using data from $t = 00, 01, ..., 14$. They are equal to zero for every consultant in 2000. Pre-2000 experience (and all other time-invariant consultant heterogeneity) is captured by consultant fixed effects.

HES contains a large set of patient characteristics. We construct a single index of patient suitability for keyhole surgery ($patientscore_{it}$) using the matched patient-consultant HES data described in Section 2.2.[15] Full details of its construction are in the appendix. The basic idea is to construct an index by using a Logit model to predict patient suitability for keyhole surgery on the basis of a wide number of observed patient characteristics (i.e. the probability of keyhole surgery conditional on patient characteristics). We use only the years at the end of the period we observe in HES (2012-14) to estimate this. This is after the initial diffusion phase, the issuance of national guidance in 2006 on use of keyhole surgery for colorectomy, and a training programme for colorectal consultants in keyhole surgery in 2009. Thus which patients are selected for laparoscopy should reflect good practice rather than consultant taste. The index of patient suitability is the mean of the suitability scores over all patients of consultant i in year t. We defer to Section 4.3 the discussion of the limitations of constructing patient suitability in this way, as well as the sensitivity of our findings to its specification.

[15] We use the subset of patients eligible for the procedure based on OPCS codes in footnote 10.

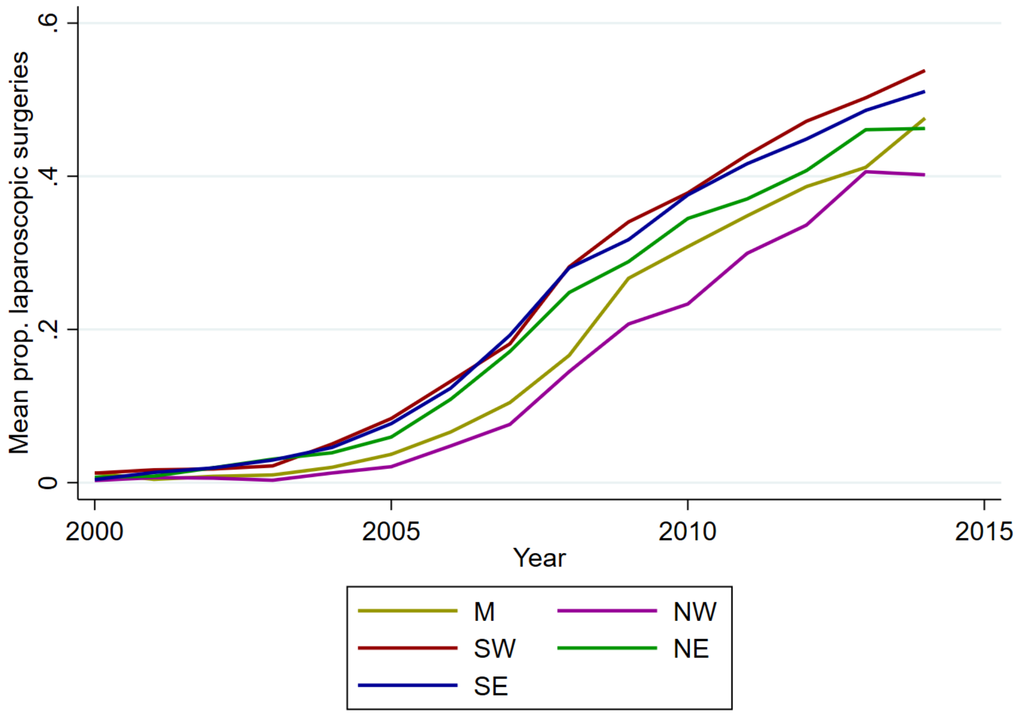


Figure 2: *Take-up of keyhole colorectal cancer surgery by consultant community.*

3.2. Peer-effects

Since diffusion of innovation is inherently a dynamic process, we aim to quantify dynamic peer-effects. We postulate that consultants build up a stock of exposure to peer innovation over time, hence, in addition to the contemporaneous 'flow' peer-effect, we consider a 'stock' peer-effect measuring cumulative exposure to peer take-up. To construct contemporaneous peer take-up, we define

$$\bar{y}_{it} = \sum_{j=1}^{N} \mathbf{W}_{ijt} \overline{\mathbf{A}}_{ijt} y_{jt} \tag{3.4}$$

$$= \frac{\sum_{j=1}^{N} \overline{\mathbf{A}}_{ijt} colokey_{jt}}{\sum_{j=1}^{N} \overline{\mathbf{A}}_{ijt} colosur_{jt}} \tag{3.5}$$

$$\mathbf{W}_{ijt} = \frac{colosur_{jt}}{\sum_{k=1}^{N} \overline{\mathbf{A}}_{ikt} colosur_{kt}} \tag{3.6}$$

where $\mathbf{W}_{ijt}$ weighs each peer by the number of colorectal cancer surgeries performed and the weights are normalised to sum to one. Weighting in this way implies that take-up is equally influenced by each surgery performed by a peer, implying the equivalent definition in (3.5), which is the proportion of keyhole surgeries among all surgeries conducted by peers. For consultants with no peers we use the convention $\bar{y}_{it} = 0$. For cumulative peer take-up, we define

$$\overline{y}_{i,00\to t-1} = \sum_{s=00}^{t-1}\sum_{j=1}^{N}\mathbf{V}_{ijs}\overline{\mathbf{A}}_{ijs}y_{js} \tag{3.7}$$

$$= \frac{\sum_{s=00}^{t-1}\sum_{j=1}^{N}\overline{\mathbf{A}}_{ijs}colokey_{js}}{\sum_{s=00}^{t-1}\sum_{j=1}^{N}\overline{\mathbf{A}}_{ijs}colosur_{js}} \tag{3.8}$$

$$\mathbf{V}_{ijs} = \frac{colosur_{js}}{\sum_{r=00}^{t-1}\sum_{k=1}^{N}\overline{\mathbf{A}}_{ikr}colosur_{kr}} \tag{3.9}$$

for $t = 01, ..., 14$. Since keyhole colorectal cancer surgery did not take place prior to 2000, we set $\overline{y}_{i,00\to t-1} = 0$ for all consultants in 2000. The weights $\mathbf{W}$ and $\mathbf{V}$ give equal weight to intra and inter hospital peers. It could be argued that one would expect stronger effects from intra-hospital peers, whose take-up is likely more salient. Section 10 shows that our findings are robust to weights which depreciate geometrically in the number of years since inter-hospital peers ceased to be a intra-hospital peers.

As is the case in almost all observational studies of peer-effects, our data do not permit us to disentangle the underlying mechanisms. Peer-effects may capture peer learning and/or peer imitation. Due to keyhole surgery's cost-effectiveness and improved patient survival, quality of life and length of hospital stay, we expect peer learning to be positive. The contemporaneous peer-effect may also capture congestion due to shared resources in the hospital, though we do not expect this to be large due to the wide availability of the requisite technology. Our peer-effects measure the net impact of these (and possibly other) channels on take-up.

3.3. Peer Characteristics

Given a vector of consultant and patient characteristics $\mathbf{x}_{it}$ comprising age, experience and patient suitability, to construct peer characteristics, we replace y with $\mathbf{x}$ in (3.4), yielding $\overline{\mathbf{x}}_{it}$. We obtain $\overline{\mathbf{x}}_{i,00\to t-1}$ equivalently using (3.7). We sometimes consider only intra-hospital peers, in which case we replace $\overline{\mathbf{A}}_t$ with the intra-hospital network $\widetilde{\mathbf{A}}_t$,

$$\widetilde{\mathbf{A}}_{ijt} = \begin{cases} 1 & \text{if i and j work in the same hospital in year t and } j \neq i \\ 0 & \text{otherwise} \end{cases} \tag{3.10}$$

which we use to define $\widetilde{\mathbf{x}}_{it}$ and $\widetilde{\mathbf{x}}_{i,00\to t-1}$.

3.4. Network Effects

We construct two network variables which we conjecture serve as proxies for information transmission through the network. The first is

$$degree_{it} = \sum_{j=1}^{N}\overline{\mathbf{A}}_{ijt} \tag{3.11}$$

Table 2: *Descriptive statistics*

	Mean	SD	Min	Max	Mean	SD	Min	Max
Year	**2000** (650 consultants)				**2014** (923 consultants)			
Dependent variable								
$y_{it} = colokey_{it}/colosur_{it}$	0.008	0.03	0	0.256	0.486	0.290	0	1
$colokey_{it}$	0.24	0.897	0	10	12.966	11.079	0	66
$colosur_{it}$	27.409	19.334	1	112	23.629	13.953	1	71
Peer take-up								
$\overline{y}_{it}$	0.009	0.015	0	0.107	0.562	0.068	0.293	0.787
$\overline{y}_{i,00\rightarrow t-1}$	0	0	0	0	0.259	0.111	0	0.784
Network characteristics								
$degree_{it}$	16.763	8.872	1	50	52.863	20.153	6	116
$pioprox1_{it}$	0.52	0.5	0	1	0.764	0.425	0	1
$pioprox2_{it}$	0.385	0.487	0	1	0.172	0.378	0	1
Consultant characteristics								
$age_{it}^{<40}$	0.176	0.381	0	1	0.284	0.451	0	1
age_{it}^{40-44}	0.274	0.446	0	1	0.279	0.449	0	1
age_{it}^{45-49}	0.227	0.419	0	1	0.207	0.405	0	1
age_{it}^{50-54}	0.196	0.398	0	1	0.15	0.357	0	1
$expkey_{it}$	0	0	0	0	5.011	5.282	0	47.56
$expcolosur_{it}$	0	0	0	0	2.331	2.039	0	9.370
$patientscore_{it}$	0.590	0.035	0.399	0.682	0.541	0.046	0.145	0.669
Peer characteristics								
$\overline{age}_{it}^{<40}$	0.262	0.245	0	1	0.368	0.117	0	1
$\overline{age}_{it}^{40-44}$	0.316	0.235	0	1	0.302	0.100	0	1
$\overline{age}_{it}^{45-49}$	0.177	0.197	0	1	0.175	0.083	0	1
$\overline{age}_{it}^{50-54}$	0.148	0.197	0	1	0.112	0.071	0	1
$\overline{expkey}_{it}$	0	0	0	0	4.260	1.017	0.746	8.955
$\overline{expcolosur}_{it}$	0	0	0	0	2.451	1.116	0	8.772
$\overline{patientscore}_{it}$	0.588	0.060	0	0.648	0.550	0.008	0.503	0.580
Intra-hospital peer characteristics								
$\widetilde{age}_{it}^{<40}$	0.168	0.263	0	1	0.301	0.218	0	1
$\widetilde{age}_{it}^{40-44}$	0.289	0.296	0	1	0.294	0.234	0	1
$\widetilde{age}_{it}^{45-49}$	0.218	0.277	0	1	0.201	0.194	0	1
$\widetilde{age}_{it}^{50-54}$	0.189	0.278	0	1	0.141	0.169	0	1
$\widetilde{expkey}_{it}$	0	0	0	0	4.656	2.237	0	15.82
$\widetilde{expcolosur}_{it}$	0	0	0	0	2.673	0.997	0	7.373
$\widetilde{patientscore}_{it}$	0.575	0.103	0	0.648	0.548	0.027	0	0.607
Other								
$move_{it}$	0.110	0.314	0	1	0.062	0.241	0	1

The degree measures the number of links a consultant has in the network. It is a measure of network centrality, and we conjecture that those with higher degree receive information at a faster rate. We do not consider other centrality measures since they are strongly correlated with degree, making it difficult to disentangle their effects. We only measure links made since the beginning of the NHS Workforce Statistics data in 1992. The number of links made prior to 1992 is captured by consultant fixed effects.

To capture the notion that the weight given to information might depend on its source, we also construct the proximity in the network to the nearest pioneer, defined as a consultant who has performed at least 15 keyhole surgeries for colorectal cancer patients eligible for the procedure up to and including 2005.[16] We measure proximity by

$$pioprox_{it} = \text{number of links traversed in the network from } i \text{ to the nearest pioneer performing at least one colorectal cancer surgery in year } t \quad (3.12)$$

That the nearest pioneer must perform at least one surgery is to avoid inactive (e.g. retired) pioneers. Proximity has range $0, 1, 2, ..., \infty$. A value of 0 means that a consultant is a pioneer, 1 means that they have worked in the same hospital as a pioneer up to and including year t (but they are not a pioneer), 2 means that they have worked in the same hospital as a consultant who has worked in the same hospital as a pioneer (but they are not a pioneer and have not worked in the same hospital as a pioneer), and so on. A value of ∞ means that a consultant is not a pioneer and cannot reach a pioneer by traversing links in the network. We construct indicators for proximity equal to 1 and 2 ($pioprox1_{it}, pioprox2_{it}$). Pioneer status (i.e. proximity 0) is not time-varying so is absorbed into the consultant fixed effect.

3.5. Descriptive Statistics

Table 2 summarises the consultant-year panel for the years 2000 and 2014. Average take-up increased from 0.008 in 2000 to to 0.486 by 2014. By construction, peer take-up exhibited a similar increase. Increased take-up cannot be accounted for by changes in patient suitability for the procedure, which fell slightly. The average degree increased from 16.763 to 52.863. The increase can be attributed to consultants acquiring more links as they move between hospitals over time, which dominates the opposing effect of retiring consultants leaving the panel. Pioneer proximity fell between 2000 and 2014 due to increased number of links. Consultant age fell over the sample period, whereas experience rose. This is because experience is measured using HES data starting in 2000. The variable $move_{it}$ is an indicator for the consultant being in a different hospital in year t than in year $t-1$. In 2000, 11% of consultants were in a different hospital to 1999. In 2014 there was less mobility, with 6.2% of consultants moving hospital.

4. Empirical Analysis

Our baseline specification for consultant $i = 1, 2, ..., N$ in year $t = 00, 01, ..., 14$ in hospital $h(i, t)$ is,

$$y_{it} = \beta_1 \bar{y}_{it} + \beta_2 \bar{y}_{i,00\to t-1} + \gamma_1 degree_{it} + \gamma_2 pioprox1_{it} + \gamma_3 pioprox2_{it} + \mathbf{x}'_{it}\theta + \widetilde{\mathbf{x}}'_{it}\widetilde{\theta} + u_{it} \quad (4.1)$$

$$u_{it} = \alpha_i + \mu_{h(i,t)} + \zeta_{c(h(i,t))t} + \epsilon_{it} \quad (4.2)$$

$$\mathbb{E}[\epsilon_{it} | \alpha_i, (\mathbf{z}_{is}, \mu_{h(i,s)}, \zeta_{c(h(i,s))s})_{s=00}^{14}] = 0 \quad (4.3)$$

[16] We define pioneer status as a time invariant characteristic. Around 5% of consultants are classified as pioneers (73/1466). The year 2005 is selected as it was prior to the issuance of national guidelines in 2006. The 15-threshold is considered to be the plateau of proficiency in the learning curve of keyhole surgery by a large number of clinical experts, surgeons and educational representatives of surgical training (see Wheelock et al. 2017).

where $\mathbf{x}_{it}$ comprises consultant characteristics and patient suitability, $\widetilde{\mathbf{x}}_{it}$ comprises the characteristics and patient suitability of intra-hospital peers, $c(h(i,t))$ is the community of hospital $h(i,t)$ (right side of Figure 1), α_i, $\mu_{h(i,t)}$, $\zeta_{c(h(i,t))t}$ are respectively consultant, hospital and community-year fixed effects, $\mathbf{z}_{is}$ is a vector of strictly exogenous instruments discussed below, and ϵ_{it} is the disturbance. The consultant fixed-effects control for all time-invariant consultant heterogeneity, including gender, time-invariant preferences, ability, education, pre-2000 training and experience, and the properties of their pre-1992 network.

4.1. Identification

Our identification strategy uses two key arguments. The first is that the network evolves exogenously, which implies that consultant mobility between hospitals over time is not driven by take-up of keyhole surgery. This, along with the network's dynamic nature, identifies the network effects (degree and pioneer proximity). To identify the peer-effects we must also deal with the endogeneity arising from simultaneity of take-up among a consultant and their peers. We follow an instrumental variables approach which exploits variation in the characteristics of inter-hospital peers (i.e. those practicing in *different* hospitals).

We treat consultant and patient characteristics as exogenous. Due to capacity based allocation of patients to consultants and the two week waiting time guarantee, we expect that sorting of more suitable patients to high take-up consultants be limited. Moreover, due to the consultant fixed effect, only sorting based on annual take-up shocks would be problematic, further limiting its potential.

We also treat the network as exogenous. Network exogeneity is a standard assumption in the literature on identification of peer-effects (e.g. Bramoullé et al. 2009). In our context it requires exogenous mobility of consultants between hospitals over time.[17] We do not expect that mobility be driven by take-up conditional on age, experience and patient characteristics, time-invariant consultant and hospital heterogeneity and community-year heterogeneity. All hospitals in our sample have the requisite technology for the procedure, hence there are no incentives to move hospital for technological reasons. The consultants in our sample also perform a range of other procedures, making it is unlikely that take-up of keyhole surgery for colorectal cancer plays a major role in mobility decisions. Goldacre et al. (2013) show that geographical considerations play a crucial role, finding that UK-trained consultants' tend to be located in close proximity to their pre-medical school family home, medical school, place of training and place of first career post. These associations are more pronounced among more recent cohorts. Goldacre et al. (2013) also document limited mobility between regions as shown in Figure 1 and Table 1.

However, to test exogenous mobility, we estimate a linear probability model in which the dependent variable is an indicator for moving hospitals between years t and $t+1$ ($move_{it+1}$).[18] The covariates of interest are take-up in year t (y_{it}) and the proportion of keyhole colorectal cancer surgeries in year t in hospital $h(i,t+1)$ minus the proportion of keyhole colorectal cancer surgeries in year t in hospital $h(i,t)$ (equal to zero if there is no

[17] Our specification with consultant fixed-effects implies that we require exogeneity of the evolution of the network rather than its initial state.

[18] We use a linear probability model due to the large number of fixed effects.

Table 3: *Mobility*

Dep. var. $move_{it+1}$ (range $\{0,1\}$)			
	LPM	LPM	LPM
	Consultant take-up		
y_{it}	-0.0100		-0.00720
	(0.0103)		(0.00795)
	Hospital take-up		
$hospydiff_{it}$		-0.566	-0.567
		(0.464)	(0.464)
	Consultant characteristics		
$age_{it}^{<40}$	0.0338	0.0286	0.0287
	(0.0225)	(0.0188)	(0.0188)
age_{it}^{40-44}	0.0297*	0.0246*	0.0249*
	(0.0165)	(0.0137)	(0.0137)
age_{it}^{45-49}	0.0138	0.0115	0.0119
	(0.0123)	(0.00976)	(0.00980)
age_{it}^{50-54}	-0.00424	-0.00385	-0.00360
	(0.00796)	(0.00628)	(0.00629)
$expkey_{it}$	0.00119	0.000117	0.000192
	(0.00115)	(0.000753)	(0.000778)
$expcolosur_{it}$	-0.00318*	-0.00201	-0.00162
	(0.00190)	(0.00177)	(0.00182)
$patientscore_{it}$	-0.0182	0.0118	0.0138
	(0.0494)	(0.0416)	(0.0413)
	Intra-hospital peer characteristics		
$\widetilde{age}_{it}^{<40}$	-0.0631***	-0.0313**	-0.0310**
	(0.0206)	(0.0135)	(0.0136)
$\widetilde{age}_{it}^{40-44}$	-0.0289	-0.00755	-0.00741
	(0.0193)	(0.0127)	(0.0127)
$\widetilde{age}_{it}^{45-49}$	-0.0296*	-0.00646	-0.00642
	(0.0173)	(0.0116)	(0.0117)
$\widetilde{age}_{it}^{50-54}$	-0.0266*	-0.01000	-0.0101
	(0.0156)	(0.00880)	(0.00880)
$\widetilde{expkey}_{it}$	0.00135	0.00209	0.00214
	(0.00233)	(0.00170)	(0.00169)
$\widetilde{expcolosur}_{it}$	-0.0199***	-0.0136***	-0.0136***
	(0.00659)	(0.00365)	(0.00365)
$\widetilde{patientscore}_{it}$	-0.0244	-0.0726	-0.0734
	(0.0791)	(0.0581)	(0.0582)
Consultant FE	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
Sample size	10898	10720	10720
H_0: Exogenous mobility	0.33	0.22	0.35

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. 'H_0: Exogenous moving' gives the p-value for the hypothesis test that y_{it} and $hospydiff_{it}$ jointly have coefficients equal to zero. We use a linear probability model (LPM) for all specifications.

move). We also include consultant characteristics, characteristics of intra-hospital peers, and consultant, hospital and community-year fixed effects. This specification allows us to test the null hypothesis that moving is associated with changes to a consultant's own take-up or the difference in take-up between their year $t+1$ and year t hospital. Table 3 presents the results. We find no evidence that mobility is associated with changes in take-up at the consultant nor hospital levels. The last row of Table 3 tests this hypothesis formally. We fail to reject exogenous mobility in all specifications.

Given exogenous mobility, the network's dynamic nature identifies the effects of degree and pioneer proximity on take-up. If the network were static, these variables would be time-invariant, hence indistinguishable from the consultant fixed effect. An exogenous and dynamic network does not suffice to identify the peer-effects. This is because peer take-up is endogenous due to simultaneity of take-up and correlated unobservables (Manski, 1993). For example, intra-hospital peers share the same facilities and management. To allow for contextual effects at the hospital-year level, we control for the characteristics of intra-hospital peers ($\widetilde{\mathbf{x}}_{it}$). In doing so, we allow for some hospitals to have more suitable patients than others (e.g. due to differing local demographics) and for these differences to vary over time. We also control for differing experience and age profiles of consultants between hospitals. We include hospital and community-year fixed effects to account for other sources of heterogeneity common to a consultant and their peers. Due to the regional overlap documented in Figure 1, community-year effects also largely control for unobserved regional heterogeneity. We use the community (see Figure 1) rather than the region since the former is explicitly based on mobility patterns, and hence more relevant to our application.[19]

Despite conditioning on sources of common heterogeneity, simultaneity at the consultant-year level implies that we need at least two strictly exogenous excluded instruments for $\overline{y}_{it}$ and $\overline{y}_{i,00\to t-1}$.[20] Instruments can be constructed using the exogenous characteristics of peers, or even peers-of-peers (Bramoullé et al. 2009). We use peer characteristics ($\overline{\mathbf{x}}_{it}, \overline{\mathbf{x}}_{i,00\to t-1}$). The exclusion restriction is that, conditional on consultant characteristics, the characteristics of intra-hospital peers, and consultant, hospital and community-year fixed effects, peer characteristics do not directly determine take-up. The intuition is that we do not expect contextual effects common to consultants practicing in *different* hospitals. Hence, we can exclude the characteristics of inter-hospital peers. This aspect of our identification strategy also hinges on a dynamic network. In the absence of mobility there are no inter-hospital peers, implying $\overline{\mathbf{x}}_{it} = \widetilde{\mathbf{x}}_{it}$, and hence that the excluded instruments are collinear with the included exogenous covariates.

To present our identification strategy more formally, we can stack (4.1) first by individual and then by year, yielding

$$\mathbf{y} = \beta_1 \overline{\mathbf{G}}_1 \mathbf{y} + \beta_2 \overline{\mathbf{G}}_2 \mathbf{y} + \mathbf{N}\gamma + \mathbf{X}\theta + \widetilde{\mathbf{G}}\mathbf{X}\widetilde{\theta} + \mathbf{u} \tag{4.4}$$

where $T = 15$, $\mathbf{y}$ is $NT \times 1$ vector of take-up, $\mathbf{N}$ is the $NT \times 3$ matrix of network characteristics and $\mathbf{X}$ is the $NT \times 7$ matrix of consultant and patient characteristics. The matrices $\overline{\mathbf{G}}_1, \overline{\mathbf{G}}_2, \widetilde{\mathbf{G}}$ are $NT \times NT$, and can be decomposed as a $T \times T$ block matrices with blocks of size $N \times N$. The matrix $\overline{\mathbf{G}}_1$ is block diagonal. Entry (i, j) of block (t, t) is $\mathbf{W}_{ijt}\overline{\mathbf{A}}_{ijt}$. The matrix $\widetilde{\mathbf{G}}$ is defined identically, replacing $\overline{\mathbf{A}}$ with $\widetilde{\mathbf{A}}$. The matrix $\overline{\mathbf{G}}_2$ is strictly upper-triangular.

[19]We do not use hospital-year fixed effects because there are many hospital-years relative to observations in the estimation sample.

[20]$\overline{y}_{i,00\to t-1}$ is not strictly exogenous.

For block (s,t) and $t > s$, entry (i,j) is $\mathbf{V}_{ijs}\overline{\mathbf{A}}_{ijs}$. Omitting fixed effects and assuming that $(\mathbf{I}_{NT} - \beta_1\overline{\mathbf{G}}_1 - \beta_2\overline{\mathbf{G}}_2)^{-1}$ exists, we have

$$\mathbb{E}[\mathbf{y}|\mathbf{N},\mathbf{X},\overline{\mathbf{G}}_1,\overline{\mathbf{G}}_2,\widetilde{\mathbf{G}}] = \left(\mathbf{I}_{NT} + \sum_{k=1}^{\infty}\left(\beta_1\overline{\mathbf{G}}_1 + \beta_2\overline{\mathbf{G}}_2\right)^k\right)(\mathbf{X}\theta + \mathbf{N}\gamma + \widetilde{\mathbf{G}}\mathbf{X}\widetilde{\theta}) \tag{4.5}$$

To obtain instruments for $\overline{\mathbf{G}}_1\mathbf{y}, \overline{\mathbf{G}}_2\mathbf{y}$, we pre-multiply (4.5) by $\overline{\mathbf{G}}_1$ and $\overline{\mathbf{G}}_2$. If $\theta \neq \mathbf{0}$, suitable instruments are $\overline{\mathbf{G}}_1\mathbf{X}, \overline{\mathbf{G}}_2\mathbf{X}$. We use $\mathbf{Z} = (\mathbf{N},\mathbf{X},\widetilde{\mathbf{G}}\mathbf{X},\overline{\mathbf{G}}_1\mathbf{X},\overline{\mathbf{G}}_2\mathbf{X})$, or equivalently

$$\mathbf{z}_{it} = \left(degree_{it} \quad pioprox1_{it} \quad pioprox2_{it} \quad \mathbf{x}'_{it} \quad \widetilde{\mathbf{x}}'_{it} \quad \overline{\mathbf{x}}'_{it} \quad \overline{\mathbf{x}}'_{i,00\to t-1}\right)' \tag{4.6}$$

Mobility implies $\widetilde{\mathbf{G}} \neq \overline{\mathbf{G}}_1$ and $\mathbf{Z}$ has full column rank.

An advantage of our identification strategy is that it avoids weak identification that may arise when the network structure is close to one of intra-group interactions, in which individuals interact intra-group but not inter-group (Lee, 2007). Due to mobility, the network $\overline{\mathbf{A}}$ is not exactly characterised by intra-group interactions, though it depends on the intra-hospital network $\widetilde{\mathbf{A}}$, which is. This implies that $\overline{\mathbf{A}}$ has structure closer to intra-group interactions than is typical for a social network. In contrast to our approach, the benchmark identification strategy for peer-effects in social networks (Bramoullé et al. 2009) includes peer characteristics on the right hand side of (4.4) (i.e. replacing $\widetilde{\mathbf{G}}\mathbf{X}$ with $\overline{\mathbf{G}}_1\mathbf{X}$), and uses characteristics of peers-of-peers ($\overline{\mathbf{G}}_1^2\mathbf{X}$) as excluded instruments. If the network has structure close to intra-group interactions, there is little distinction between peers and peers-of-peers, hence identification can be weak.[21] This is because $\mathbf{Z} = (\mathbf{N},\mathbf{X},\overline{\mathbf{G}}_1\mathbf{X},\overline{\mathbf{G}}_1^2\mathbf{X},\overline{\mathbf{G}}_2\mathbf{X})$ and the columns of $(\overline{\mathbf{G}}_1\mathbf{X},\overline{\mathbf{G}}_1^2\mathbf{X})$ are close to collinear. Our approach avoids this problem by exploiting the fact that contextual effects need only be included for intra-hospital peers, rather than all peers. Since we have seven excluded instruments and two endogenous variables, our baseline specifications are overidentified.

4.2. Baseline Results

Table 4 presents results for two-stage least squares (TSLS) and ordinary least squares (OLS) estimation of (4.1). TSLS estimates use different subsets of instruments. To interpret the relative magnitudes of the effects, Table 4 reports standardised parameter estimates. For continuous covariates, we report the effect of a standard deviation increase on take-up, also measured in standard deviations. For binary covariates (age and pioneer proximity), we report the effect of a unit increase. We use the 2014 cross-section to compute the standard deviations, hence the interpretation is based on between consultant variation in 2014. Table 6 in the appendix presents full non-standardised results, including tests for weak identification and overidentifying restrictions.

We find positive contemporaneous peer-effects in all models. A standard deviation increase in peer take-up is associated with a 0.07 standard deviation increase in take-up based on OLS and leads to around a 0.12 increase for TSLS. The standardised effect based

[21] Weak identification is more pronounced when there is limited variation in group sizes and groups are large (Lee, 2007)

Table 4: *Baseline results: Standardised effects*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
	Peer take-up				
$\bar{y}_{it}$	0.073***	0.145*	0.114**	0.126***	0.121**
$\bar{y}_{i,00\to t-1}$	0.096***	-0.023	-0.042	-0.075	-0.088
	Network characteristics				
$degree_{it}$	0.108	0.131	0.152*	0.162**	0.170**
$pioprox1_{it}$	0.154	0.113	0.123	0.114	0.115
$pioprox2_{it}$	0.133	0.093	0.104	0.097	0.097
	Consultant characteristics				
$age_{it}^{<40}$	0.002	0.021	0.016	0.020	0.020
age_{it}^{40-44}	0.125	0.150*	0.140*	0.144*	0.143*
age_{it}^{45-49}	0.149**	0.164***	0.157***	0.159***	0.158***
age_{it}^{50-54}	0.097***	0.100***	0.098***	0.098***	0.097**
$expkey_{it}$	0.137***	0.142***	0.142***	0.144***	0.144***
$expcolosur_{it}$	0.351***	0.350***	0.351***	0.350***	0.350***
$patientscore_{it}$	0.055***	0.055***	0.054***	0.054***	0.053***
	Intra-hospital peer characteristics				
$\widetilde{age}_{it}^{<40}$	0.011	0.010	0.014	0.015	0.016
$\widetilde{age}_{it}^{40-44}$	0.008	0.011	0.014	0.016	0.017
$\widetilde{age}_{it}^{45-49}$	-0.001	0.002	0.003	0.005	0.005
$\widetilde{age}_{it}^{50-54}$	-0.006	-0.007	-0.006	-0.006	-0.006
$\widetilde{expkey}_{it}$	0.000	0.000	0.000	0.001*	0.001*
$\widetilde{expcolosur}_{it}$	0.000	0.000	0.000	0.000	0.000
$\widetilde{patientscore}_{it}$	-0.011*	-0.011*	-0.011*	-0.011*	-0.011*
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Score instruments	-	Yes	Yes	No	Yes
Age instruments	-	Yes	No	Yes	Yes
Experience instruments	-	No	Yes	Yes	Yes

Notes: We report standardised estimated coefficients from Table 6, for which standard errors clustered by consultant and hospital-year. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. For continuous covariates we report the effect of a standard deviation increase in terms of standard deviations of the proportion of keyhole surgeries. For binary variables we report the effect of a unit increase. We use 2014 standard deviations (see Table 2).

on TSLS is relatively large. Indeed, it is twice as large as that of patient suitability (0.06). The OLS results also suggest a positive effect of cumulative peer take-up, though this is not borne out by the TSLS, for which the effect is negative, though small and not statistically distinguishable from zero. We find positive network effects in all models. The TSLS effect size for the degree is around 0.15, which is comparatively large. Relative to having never worked with a pioneer nor another consultant who has, having worked with a pioneer is estimated to increase take-up by 0.11-0.15 standard deviations, and having worked with a consultant who has worked with a pioneer by 0.1-0.13. Though not statistically distinguishable from zero, these suggest a positive effect of pioneer proximity.

Consultant characteristics also have an impact. The age profile peaks at 44-49, and is lowest amongst those aged under 40 and over 55. Experience plays an important role. Both experience variables have a statistically significant effect at the 0.01 level. Experience in colorectal cancer surgery has the largest effect size of all covariates, at around 0.35. This is more than double the next largest.

We find a small, positive and marginally statistically significant (at the 0.1 level) effect of intra-hospital peers' experience in keyhole surgery for conditions other than colorectal cancer but no effect of their experience in colorectal cancer surgery. We also find a small negative effect of intra-hospital peers' patient suitability, which is statistically significant at the 0.1 level. This suggests that both patient suitability and its difference with intra-hospital peer patient suitability play a role. A small difference effect could be indicative of limited congestion effects and/or sorting of patients to high take-up consultants. Most subsets of instruments are relatively strong (see Table 6), though one cannot rule out weak instruments when peer experience is not used.

4.3. Extensions and Robustness

4.3.1 Heterogeneous Peer-effects

Our baseline results impose a homogeneous peer-effect. It might be that some consultants are more susceptible to peer influence than others. We adapt the baseline model to allow for heterogeneity in peer-effects over the course of a consultant's career. We do this by including interaction terms between experience and peer-effects. To limit the number of endogenous covariates we focus on the contemporaneous peer-effect, which our baseline results suggest plays a more prominent role than the cumulative peer-effect. We use both experience in keyhole surgery for conditions other than colorectal cancer and experience in colorectal cancer surgery, hence we augment the covariates to include $\overline{y}_{it} \times expkey_{it}$ and $\overline{y}_{it} \times expcolosur_{it}$. In TSLS specifications we augment the instruments based on contemporaneous peer patient suitability, age and experience to include their interactions with $expkey_{it}$ and $expcolosur_{it}$.

Results are reported in Table 7. Our estimates are consistent with experienced consultants placing greater weight on their own knowledge than on the take-up of their peers. Relative to our baseline results, the estimated coefficient on the contemporaneous peer-effect and both experience measures increase whilst the coefficients on the interaction terms are negative. For a consultant with no post-2000 experience in colorectal cancer surgery nor in keyhole surgery ($expkey_{it} = expcolosur_{it} = 0$), our TSLS results suggest that a standard deviation increase in contemporaneous peer take-up leads to around a 0.17 standard deviation increase in take-up.[22] For a consultant of mean experience in 2014 ($expkey_{it} = 5.01, expcolosur_{it} = 2.33$, see Table 2), the corresponding figure is 0.14, and at the maximum observed values in 2014 ($expkey_{it} = 47.56, expcolosur_{it} = 9.37$), it is 0.04. Our baseline estimates suggest a value of 0.12, which is similar to the effect on a consultant of average experience.

There is tentative but inconclusive statistical evidence of heterogeneity in peer-effects by experience. The coefficient on the interaction term on experience in keyhole surgery for conditions other than colorectal cancer is statistically significant at the 0.05 level for OLS and for TSLS with peer patient suitability and age based instruments. The coefficient on the

[22] Standard deviations are from the 2014 cross-section of consultants, see Table 2.

interaction with experience in colorectal surgery is not significant at the 0.05 level in any specification. The interaction terms are marginally jointly significant (p-values smaller than 0.12) in all but one specification.

4.3.2 Endogeneity of Patient Suitability

Using the years 2012-2014 to construct patient suitability and the years 2000-2014 for our main analysis could lead to limited endogeneity due to the overlapping windows. This is because for $t = 12, 13, 14$, $patientscore_{it}$ depends on y_{it} through the estimated Logit parameters (see the Appendix for details on cunstruction of $patientscore_{it}$). Endogeneity is likely limited since all consultants are used to fit the Logit model, and so the take-up of an individual consultant will have a small impact on the Logit estimates. As a robustness check, we repeat out main analysis using only the years 2000-2011, which mitigates this concern. The results are reported in Table 8. Our findings related to the role of the network are similar to the baseline specifications. The only notable difference is that the coefficient on patient suitability falls in magnitude, and the p-values for the Hansen test of overidentifying restrictions increase. The decrease in the coefficient on patient suitability may be due to endogeneity of patient suitability in our baseline results, but could also be explained by omitting the last three years of the data, during which time we would expect consultants' response to patient suitability to be strongest.

4.3.3 Time-varying Patient Suitability

Patient suitability is constructed so that a given patient is as suitable for keyhole surgery in 2000 as in 2014. It could be argued that this does not truly reflect suitability since best practice may evolve over time as more information becomes available. As a robustness check, we re-compute patient suitability using the years 2000-2014 to fit the Logit model and interacting patient characteristics (though not the constant) with a quadratic trend in date of surgery, measured in days from 01/01/2000 to 31/12/2014. This allows the response of consultant to a given set of patient characteristics to evolve smoothly over time. Table 9 repeats our main analysis using this alternative measure. Our findings related to the role of the network are not affected, though the coefficient on patient suitability becomes much larger. This is likely because constructing patient suitability in this way captures some aspects of consultant behaviour in the early years of the sample which were omitted from the baseline measure.

4.3.4 Different Peer Weights

The measures of peer take-up in (3.4)-(3.9) give equal weight to intra and inter hospital peers. One might argue that intra-hospital peers should be given more weight, since their take-up is likely more salient. We repeat our analysis, re-weighting the peer-effect by the number of years since last having worked in the same hospital. A natural way to achieve this is to suppose that weights depreciate geometrically. We use

$$\mathbf{W}_{ijt} = \frac{\delta^{t-\tilde{t}(i,j)} colosur_{jt}}{\sum_{k=1}^{N} \overline{\mathbf{A}}_{ikt} \delta^{t-\tilde{t}(i,k)} colosur_{kt}} \tag{4.7}$$

where $\delta \in (0, 1]$ and $\tilde{t}(i, j) \leq t$ denotes the most recent year in which i and j worked in the same hospital. This reduces the relative weight on inter-hospital peers. We modify $\mathbf{V}_{ijt}$ in the same way. Table 9 reports results for $\delta = 0.5$, which lies in the middle of its range.[23] Relative to our baseline TSLS results (corresponding to $\delta = 1$), the signs of the estimated peer-effects are unchanged except for when using patient and age based instruments, which changes the contemporaneous peer-effect from positive and significant at the 0.1 level to marginally negative and insignificant. This is likely due to the instruments being weaker than for $\delta = 1$. For this specification the Kleibergen-Paap F-Statistic falls from to 6.66 with $\delta = 1$ to 3.34 with $\delta = 0.5$. The reason for the decrease is that, as δ falls, our measures of peer take-up become more heavily weighted towards intra-hospital peers, weakening their partial correlation with the characteristics of inter-hospital peers. In the extreme case of $\delta = 0$, we have $\bar{\mathbf{x}}_{it} = \tilde{\mathbf{x}}_{it}$, hence the excluded instruments are collinear with the included exogenous covariates. For $\delta = 0.5$, all estimates other than the peer-effects are similar to the baseline results. Results for other values of $0.25 \leq \delta < 1$ are comparable to $\delta = 0.5$, though for $\delta < 0.25$ the peer-effects estimates become imprecise.

4.3.5 Dynamic Model

Our baseline specification allows for temporal dependence in take-up through consultant, hospital and community-year fixed effects, cumulative peer take-up, consultant experience, age, degree, and proximity to a pioneer. However, it does not allow for direct dependence of take-up on past take-up. To allow for this we include take-up in the previous year (y_{it-1}) as an additional covariate, augment the instruments to include take-up two years ago (y_{it-2}), and estimate the model in first differences.[24] Table 11 reports the results. The OLS coefficient on lagged take-up is large, negative, and statistically significant. This is expected because first-differenced lagged take-up ($y_{it-1} - y_{it-2}$) is negatively correlated with the first-differenced error ($\epsilon_{it} - \epsilon_{it-1}$) by construction. In all TSLS models the coefficient on lagged take-up is positive but smaller than 0.01 and statistically insignificant at any conventional level. All other parameters remain similar to our baseline estimates, apart from experience in keyhole surgery for conditions other than colorectal cancer, which has an insignificant coefficient which is close to zero. This could be due to consultants' increasing keyhole surgery in the previous year both for colorectal cancer and for other conditions, inducing positive correlation between lagged take-up and experience.

[23] We do not estimate δ as it requires estimation of a nonlinear panel model with fixed effects. Instead, we show that our baseline results are not sensitive to intermediate values.

[24] Our baseline results use the within-consultant transformation.

4.3.6 Non-linear Peer-effects

Our baseline specification supposes that peer-effects are linear. To verify this, we add the square of contemporaneous peer take-up ($\overline{y}_{it}^2$) as an additional covariate and augment the instruments based on contemporaneous peer patient suitability, age and experience to include their squared values. To avoid too many endogenous covariates, we focus on non-linearity in the contemporaneous peer-effect. Table 12 reports the results. The coefficient on $\overline{y}_{it}^2$ is positive for every specification, but it is statistically insignificant for every TSLS model. It is also imprecisely estimated due to the instruments being collectively weak. The Kelibergen-Paap F-statistic is smaller than five in every model. Since we do not find compelling evidence of non-linear peer-effects, and to avoid weak identification, we favour our baseline linear model.

5. Key Players

We now turn our attention to identifying 'key players'. For the moment we loosely define key players to be consultants, the proximity to whom impacts upon take-up above and beyond their contribution to the peer and network effects in our baseline model. A formal definition is given below. Key players play particularly influential roles in the diffusion process. They could, for example, be well respected in the profession, or contribute to others' training. As explained below, we are agnostic as to which consultants are key players. We jointly estimate their identities and effects on others and compare their observables with other consultants'.

Key players are differentiated from pioneers because the latter are defined based on their own take-up, rather than their impact on others' take-up. Similarly, we do not define key player status based on experience, nor do we consider peer weights which depend on experience and/or pioneer status. This is because it is not clear which types of physicians exert the greatest influence over their peers (Burke et al, 2009; Husch 2009), nor that experience and/or pioneer status alone determine the extent of influence on peers.[25] In our empirical results below, though there is evidence to suggest that pioneer status and experience play a role, we also find that take-up, age, hospital type and region matter.

We aim to capture peer-effects and information transmission emanating from key players. To capture peer-effects, we define $N = 1,466$ covariates, given by

$$\overline{y}_{it}^{j} = \mathbf{1}\{colosur_{jt} > 0\}\overline{\mathbf{A}}_{ijt}y_{jt}, \quad j = 1, ..., N \tag{5.1}$$

where $\mathbf{1}\{colosur_{jt} > 0\}$ is an indicator equal to one if consultant j conducts at least one colorectal cancer surgery in year t, which we include so that inactive (e.g. retired) consultants cease to have an effect. If i and j are peers, these covariates capture the effect of consultant j's contemporaneous take-up on consultant i's take-up above and beyond consultant j's

[25] Even if this were the case, we would require additional restrictions either on cut-off values to determine key player status or on the functional form of peer weights.

contribution to $\overline{y}_{it}$. To capture information transmission, we define

$$keyprox1^j_{it} = \mathbf{1}\{colosur_{jt} > 0\}\overline{\mathbf{A}}_{ijt}, \quad j = 1, ..., N \tag{5.2}$$

which is an indicator for being a peer in years in which j conducts at least one colorectal cancer surgery. For parsimony, and since our baseline results show that they play secondary roles, we do not include a cumulative peer-effect nor an effect of being a second order peer of a key player. We augment our baseline specification in (4.1) to include the term

$$\sum_{j=1}^{N} \left(\beta_{3,j}\overline{y}^j_{it} + \beta_{4,j} keyprox1^j_{it}\right), \tag{5.3}$$

resulting in an additional $2N = 2,932$ parameters. The covariates $\overline{y}^1_{it}, \overline{y}^2_{it}, ..., \overline{y}^N_{it}$ are endogenous. To obtain instruments for $\overline{y}^j_{it}$, we can use patient suitability, experience and age. The patient suitability based instrument is defined by replacing y_{jt} with $patientscore_{jt}$ in (5.1). We define age and experience based instruments in the same way, yielding (up to) $7N = 10,262$ additional instrumental variables relative to our baseline models.

Augmenting the covariates and instruments results in a high-dimensional instrumental variables model, in which the number of parameters and/or number of instruments is large relative to the sample size. In this setting, standard instrumental variables based estimators such as TSLS or GMM are not appropriate. This is because the linear systems on which they are based are close to rank deficient. To reduce the dimensionality, we suppose that the parameter vectors β_3 and β_4 are sparse. Sparsity means that the vectors have many entries equal to zero, though we do not specify which ones. Equivalently, it means that there are relatively few key players compared to the total number of consultants, but we do not know their identities. In this way, we formally define key players as $j \in \{1, 2, ..., N\}$ such that at least one of $\beta_{3,j}, \beta_{4,j}$ is not equal to zero.

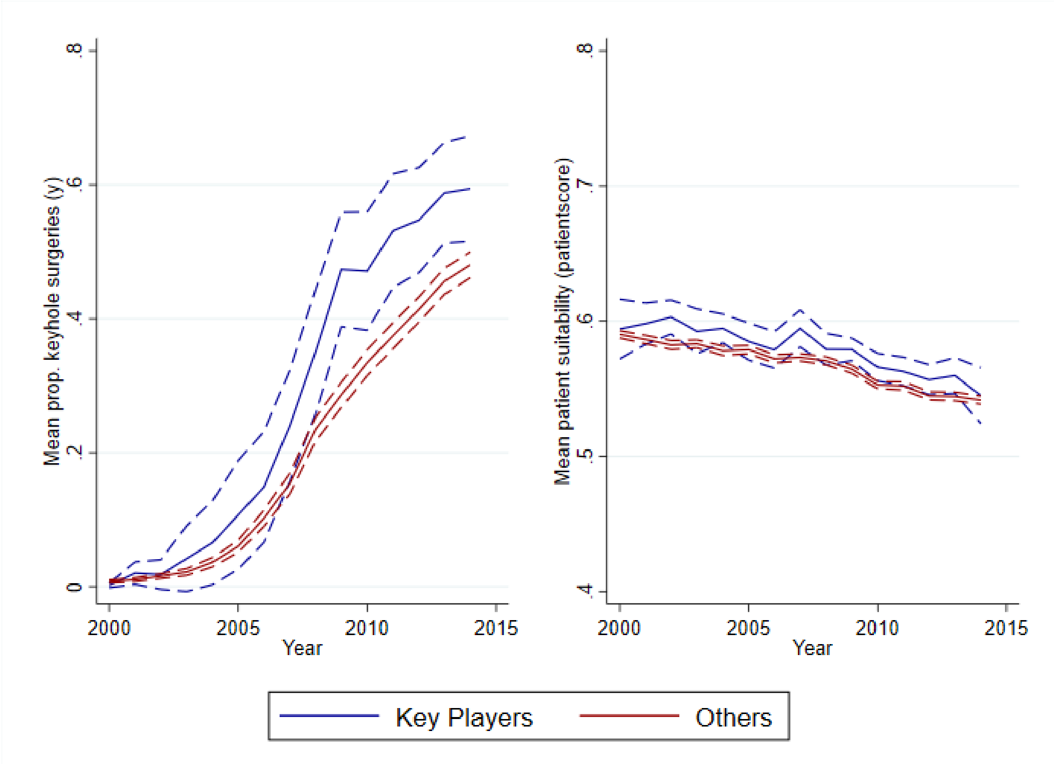
To estimate the parameters we apply the STIV estimator of Gautier and Rose (2019). Given an $n \times d_R$ matrix of covariates $\mathbf{R}$, an $n \times d_Z$ matrix of instrumental variables $\mathbf{Z}$ and an $n \times 1$ vector of outcomes $\mathbf{y}$, STIV is defined as a solution $(\widehat{b}, \widehat{\sigma})$ of the convex program

$$\min_{\substack{\widehat{\sigma}(b) \le \sigma, \\ |\mathbf{D_Z}\mathbf{Z}^\top(\mathbf{y}-\mathbf{R}b)/n|_\infty \le \widehat{r}\sigma}} |\mathbf{D_R}^{-1} b|_1 + c\sigma \tag{5.4}$$

where $\widehat{\sigma}(b) = |\mathbf{y} - \mathbf{R}b|_2/\sqrt{n}$, $\mathbf{D_R}, \mathbf{D_Z}$ are diagonal scaling matrices which ensure invariance to the units of measurement of the covariates and instruments,[26] $|\cdot|_p$ is the ℓ_p norm for $p \in [1, \infty]$, $c > 0$ controls the sparsity and $\widehat{r} > 0$ is computed from the data.

In the high-dimensional setting, even with exact identification it does not make sense to search for an estimator which exactly satisfies the sample moment conditions, and doing so induces a very large estimation error. STIV searches instead for a parameter vector which approximately satisfies the sample moment conditions, which is imposed through

[26] The diagonal entries of $\mathbf{D_R}^{-1}$ are $\left(\sqrt{\sum_{i=1}^n \mathbf{R}^2_{ik}/n}\right)_{k=1}^{d_R}$, and $\mathbf{D_Z}$ is equivalently defined.



Notes: Dashed lines are 0.95 confidence intervals.

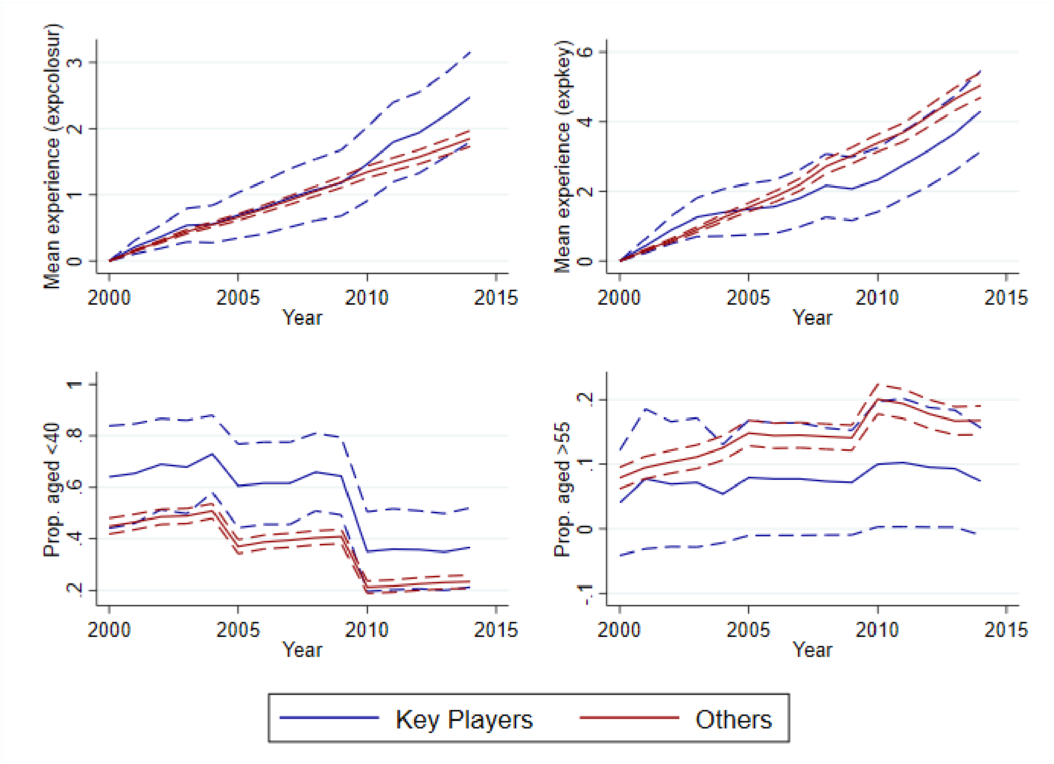
Figure 3: *Key Players: take-up of keyhole colorectal cancer surgery and patient suitability*

the constraint

$$|\mathbf{D_Z Z}^\top(\mathbf{y} - \mathbf{R}b)/n|_\infty \leq \widehat{r}\sigma. \tag{5.5}$$

in (5.4). The left-hand side of (5.5) is the largest absolute deviation of the rescaled sample moment conditions from zero. The right hand side ensures that this deviation is small. This is because $\widehat{r}$ is typically of the order $\sqrt{\ln d_Z/n}$.[27] The first term in the objective function implies that STIV searches for a parameter vector of small ℓ_1 norm among all parameters which approximately satisfy the sample moment condition, inducing sparsity on $\widehat{b}$. The constraint $\widehat{\sigma}(b) \leq \sigma$ and the second term in the objective are necessary because the scale of the errors is not known. Under homoskedasticty, both $\widehat{\sigma}^2$ and $\widehat{\sigma}(\widehat{b})^2$ estimate the error variance. The value of $c > 0$ controls the sparsity. Increasing c tightens the constraint (5.5) and reduces the sparsity. In our implementation we use $\alpha = 0.05$, $\widehat{r} = -1.1n^{-1/2}\Phi^{-1}(\alpha/(2d_Z)) \approx 0.05$ and choose c using the rule of thumb in Section 7.1 of Gautier and Rose (2019). We also modify the first term in the objective function in (5.4) so as to induce sparsity only on the high-dimensional component of the parameter vector, given by β_3, β_4. This is achieved by replacing b with the sub-vector corresponding to β_3, β_4, and is covered by the theory of Gautier and Rose (2019). We apply STIV to both the low-dimensional (without key players) and high-dimensional models. Results are presented in Table 13 in the Appendix. We use

[27]In our application, $\sqrt{\ln d_Z/n} \approx 0.03$.



Notes: Dashed lines are 0.95 confidence intervals. Experience is measured in hundreds.

Figure 4: *Key Players: Experience and age*

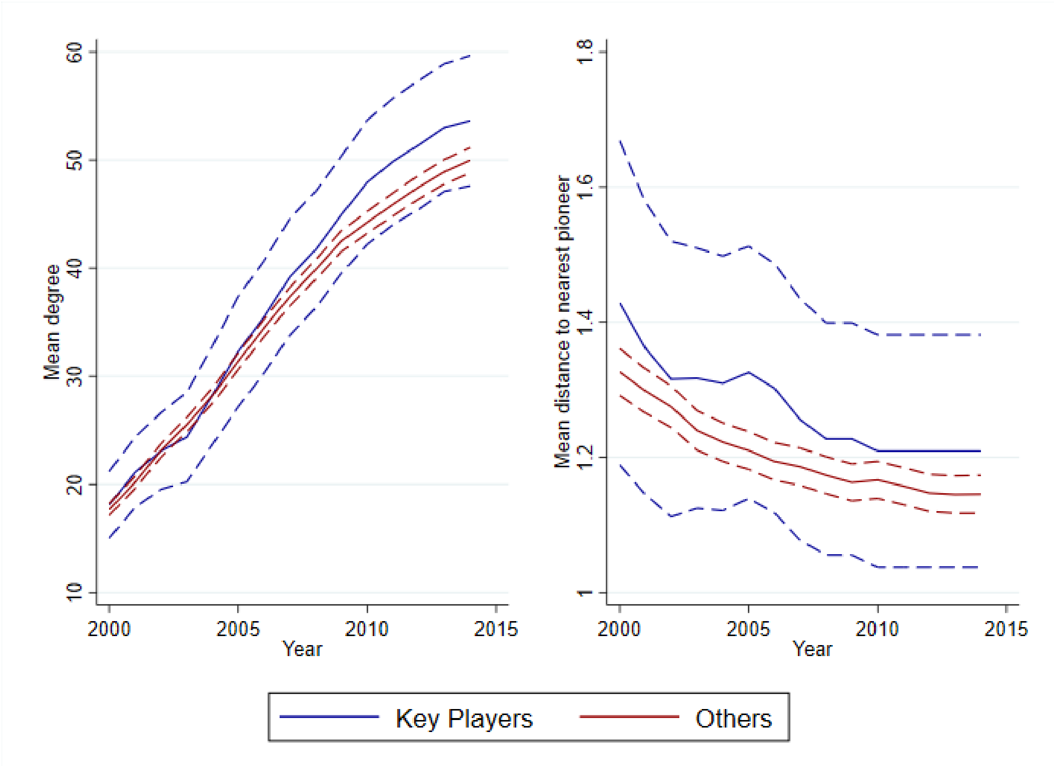
peer age and experience as instrumental variables, hence the results are comparable to the penultimate TSLS column in Table 6. We focus on this choice of instruments since they perform well both in terms of strength (Kleibergen-Paap F Statistic = 17.79) and tests of overidentifying restrictions (Hansen p-value=0.24).[28] STIV is a shrinkage based estimator hence 'biased' towards zero. For this reason, we also report a bias-corrected STIV estimator.[29]

The estimated baseline peer-effects, network effects and consultant and patient characteristics for the bias-corrected STIV estimator are similar to our baseline results. There are two differences of note. First, the estimate of the cumulative peer-effect is positive and statistically significant rather than marginally negative and insignificant. This is likely due to STIV trading off OLS with instrumental variables, which is a desirable property with possibly weak instruments (see page 7 of Gautier and Rose (2019) for a discussion). In practice, this can result in STIV estimates similar to OLS estimates, as we observe here. Second, the standard errors are smaller.[30] This is at least in part because they do not account for clustering at the consultant and trust-year levels, and so statistical significance ought to be interpreted cautiously.

[28]For brevity, we do not report STIV results for other instrument choices, which are available upon request.

[29]Bias-correction is based on Section 8.2 of Gautier et al. (2018).

[30]The bias-corrected STIV reports confidence intervals rather than standard errors. To obtain 'standard errors' as comparable as possible to those from low-dimensional estimators, we report value of $\widehat{SE}(\widehat{b})$ which equates the 0.95 STIV confidence interval with $[\widehat{b} \pm 1.96\widehat{SE}(\widehat{b})]$.



Notes: Dashed lines are 0.95 confidence intervals. Mean distance to nearest pioneer is computed using only consultants with finite distance to a pioneer.

Figure 5: *Key Players: Degree and proximity to pioneers*

We now turn our attention to key players. Beginning with the peer-effect, STIV returns 35 nonzero parameter estimates, implying 35 key players from a possible $N = 1,466$. The mean of the bias-corrected estimates for these 35 parameters is 0.11. For the subset of 13 which are statistically significant at the 0.05 level, the mean is 0.26. On average, the estimated peer-effect from a key player is positive but of smaller magnitude than the baseline peer-effects. For the proximity effect, STIV returns 10 nonzero parameter estimates, implying 10 key players, one of which is also a key player through their peer-effect. The mean of the bias-corrected estimates is 0.07, which implies a 7 percentage points increase in take-up for those which have worked concurrently in the same hospital as the average key player. This is of comparable magnitude to having worked concurrently in the same hospital as a pioneer, which we find to have an effect of 3-5 percentage points.

Combining the peer and proximity effects, STIV finds 44 key players from a possible $N = 1,466$. We now compare these 44 to the remaining 1,422 consultants. Figure 3 plots mean take-up and patient suitability. On average, key players' take-up began earlier and was faster. We find that 6.82% of key players are pioneers, relative to 4.92% of the remaining consultants. This difference is not statistically significant. By 2014, key players' mean take-up was 60%, relative to 45% for other consultants. There is also some evidence to suggest that key players' patients were marginally more suitable, though the 0.95 confidence intervals overlap in almost all years.

Figure 4 plots mean age and experience for key players and other consultants. There is little difference in experience prior to 2008. There is some evidence to suggest that key players performed more colorectal cancer operations after 2008, which, combined with higher take-up, suggests higher specialisation. Key players are also younger than others. Figure 5 plots the mean degree and proximity to the nearest pioneer. Prior to 2008, the mean degrees are similar, with some evidence that key players acquired more connections post 2008, though the difference is not statistically significant. We do not find statistically significant differences in proximity to pioneers.

We find that key players tend to be located in teaching hospitals (47.1% of consultant-year observations vs 41.8%), Foundation Trusts (53.5% vs 29.7%) and Specialist hospitals (2.2% vs 0.4%).[31] Each of these differences is statistically significant at the 0.05 level. We also find heterogeneity in the communities of key players (left panel of Figure 1). The most notable differences are that relatively few key players are part of the South-East community (27.2% of key players vs 39.0% of others) and relatively more are in North-East (27.2% vs 22.7%) and North West (22.7% vs 13%). There are no notable differences for South-West ($\approx$ 14%) and Midlands ($\approx$ 9%). This suggests that key players tend to be located in smaller, more regional and lower take-up communities.

In sum, we find that, key players' positively influence the take-up of their peers. They typically have earlier and faster take-up than others, are more likely to be pioneers, are younger, and tend to be located in teaching, Foundation Trust and Specialist hospitals in smaller, regional communities with lower average take-up.

6. Policy and Conclusion

We use our STIV estimates (final column of Table 13) to conduct counterfactual analysis with a view to providing policy recommendations. We consider the impact of two counterfactual policies implemented in 2001, and show how they could have been most effectively targeted using data from 1992-2000.

6.1. Early Take-up Policy

We adapt the framework of Rose (2019) to study which consultants ought to have been targeted for early intervention so as to lead to the largest aggregate increase in take-up by 2014. We consider an intervention which targeted one consultant in 2001, the effect of which was to increase their residual take-up by 0.05 in years 2001-2014. That is, if i was the targeted consultant, we replace the STIV residual $\widehat{\epsilon}_{it}$ with $\widehat{\epsilon}_{it} + 0.05$ for $t = 01, ..., 14$. An example of such an intervention could be an individual training program. All other residuals, exogenous variables and the network were unchanged. We then solve the resulting linear system to obtain the implied take-up of all consultants in all years. This yields one counterfactual data-set for each consultant observed in 2000. We denote the mean take-up in year t under counterfactual i by $early_{it}$.

[31] A teaching hospital either serves a medical school as its main NHS partner, or is a member of the group of UK University Hospitals, or has University or Teaching hospital status. An NHS Foundation Trust has more financial and operational freedom than others. Specialist hospitals specialise in diseases and/or population sub-groups.

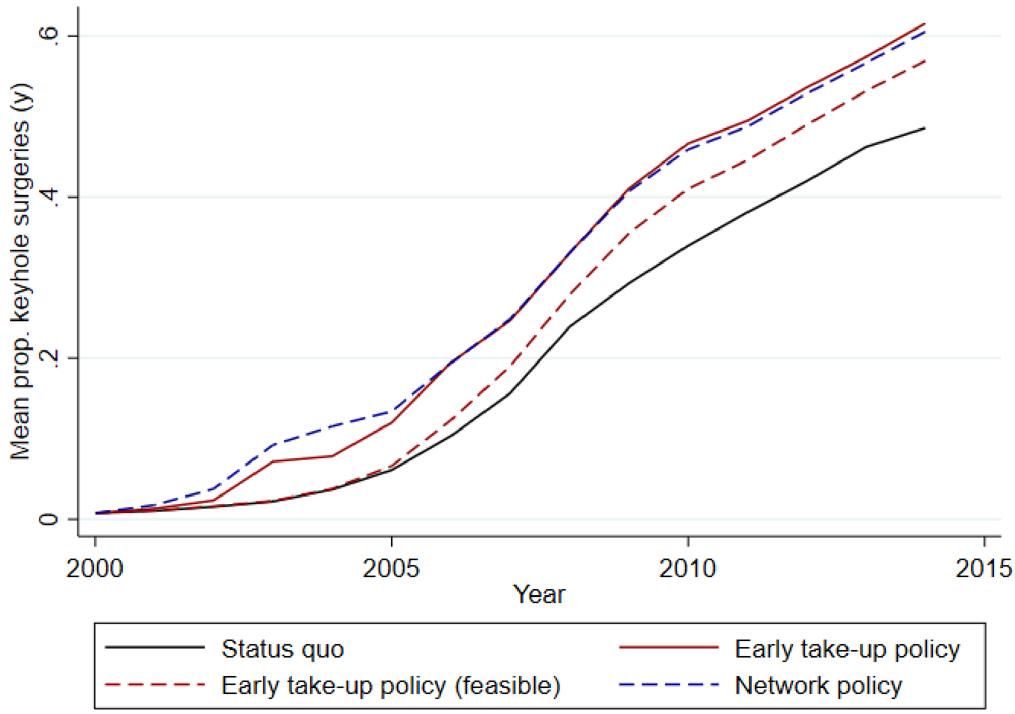


Figure 6: *Impact of early take-up and network policies*

Figure 6 depicts the results of this exercise. The solid red line plots the most effective intervention (that with largest $early_{i,14}$), which we estimate would have increased average take-up in 2014 by 13 percentage points relative to no intervention. Of course, this intervention could not have been implemented in 2001 because the identity of the optimal consultant is determined by data from 2000 to 2014. To address this, and with a view to informing future policy, we now consider which types of consultant would best have been targeted. We take the cross-section of consultants observed in 2000 and regress $early_{i,14}$ on their 2000 observables, including dummy variables for pioneer and key player status (pio_i, key_i). The results in Table 5 show that take-up, peer take-up, number of colorectal cancer surgeries performed, degree, pioneer status, proximity to pioneers and being 49 or younger are all positively and statistically significantly associated with more effective early intervention. The coefficient on key player status is close to zero and insignificant, which is likely due to its strong correlation with take-up, pioneer status and age.

The second column in Table 5 omits covariates which could not have been constructed using data up to and including 2000. It can be used to predict for which consultants intervention would have been most effective based on data available prior to the intervention in 2001. The dashed red line in Figure 6 depicts the impact of the most effective early intervention computed in this way. Had the regression coefficients been known, this intervention would have been feasible. We estimate that it would have lead to a 8 percentage point increase by 2014 relative to no intervention. To inform future policy, our results suggest that early intervention to increase take-up be targeted at young consultants with

Table 5: *Effectiveness of early intervention by 2014 & observables in 2000*

Dep. var. $early_{i,14}$ (range $[0.46, 0.62]$)				
Take-up & peer take-up				
$y_{i,00}$	0.113***	0.113***	0.116***	0.114***
	(0.0266)	(0.0267)	(0.0296)	(0.0292)
$colosur_{i,00}$	0.000386***	0.000367***	0.000400***	0.000376***
	(0.0000461)	(0.0000512)	(0.0000463)	(0.0000512)
$colokey_{i,00}$	-0.00122	-0.000878	-0.00148	-0.00124
	(0.00111)	(0.00105)	(0.00117)	(0.00108)
$\overline{y}_{i,00}$	0.277***	0.288***	0.279***	0.282***
	(0.0745)	(0.0719)	(0.0716)	(0.0686)
Network characteristics				
$deg_{i,00}$	0.000627***	0.000674***	0.000715***	0.000744***
	(0.0000984)	(0.0000978)	(0.0000979)	(0.0000948)
$pioprox1_{i,00}$	0.0347***		0.0298***	
	(0.0108)		(0.00905)	
$pioprox2_{i,00}$	0.0349***		0.0309***	
	(0.0107)		(0.00904)	
Consultant characteristics				
$age^{<40}_{i,00}$	0.0142***	0.0146***	0.0126***	0.0127***
	(0.00362)	(0.00360)	(0.00360)	(0.00363)
$age^{40-44}_{i,00}$	0.0126***	0.0134***	0.0123***	0.0130***
	(0.00348)	(0.00351)	(0.00345)	(0.00348)
$age^{45-49}_{i,00}$	0.0140***	0.0143***	0.0122***	0.0125***
	(0.00361)	(0.00368)	(0.00352)	(0.00361)
$age^{50-54}_{i,00}$	0.00682*	0.00787**	0.00574	0.00669*
	(0.00367)	(0.00372)	(0.00368)	(0.00372)
$patientscore_{i,00}$	0.00298	0.00650	0.0231	0.0249
	(0.0215)	(0.0216)	(0.0280)	(0.0278)
Intra-hospital peer characteristics				
$\widetilde{age}^{<40}_{i,00}$	-0.00684	-0.00398		
	(0.00505)	(0.00553)		
$\widetilde{age}^{40-44}_{i,00}$	-0.00230	0.000877		
	(0.00488)	(0.00546)		
$\widetilde{age}^{45-49}_{i,00}$	0.00887*	0.0108*		
	(0.00489)	(0.00564)		
$\widetilde{age}^{50-54}_{i,00}$	-0.0107**	-0.00797		
	(0.00521)	(0.00588)		
$\widetilde{patientscore}_{i,00}$	0.0115	0.00908		
	(0.0117)	(0.0116)		
pio_i	0.0361***		0.0299***	
	(0.0112)		(0.00963)	
key_i	-0.0192		-0.0203	
	(0.0144)		(0.0150)	
constant	0.456***	0.485***	0.465***	0.493***
	(0.0200)	(0.0176)	(0.0183)	(0.0168)
n	631	631	631	631
R^2	0.332	0.305	0.299	0.274

Notes: Heteroskedasticity robust standard errors in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. $colokey_{i,00}$ is the number of keyhole colorectal cancer surgeries performed in 2000 and $colosur_{i,00}$ is the number of colorectal cancer surgeries performed in 2000.

high take-up, number of surgeries performed and degree.

6.2. Network Policy

We consider a counterfactual in which links were added to the network in 2001. This could have been achieved, for example, through a secondment program. Our findings so far suggest linking low take-up consultants with limited network exposure (i.e. low degree) to young consultants with relatively high take-up, number of surgeries performed and degree.[32] For the low take-up group, we used the 153 consultants observed in 2000, who in that year did not perform a keyhole colorectal cancer surgery ($y_{i,00} = colokey_{i,00} = 0$) and had degree at most 10. For the high take-up group, we used the 10 consultants observed in 2000 with the largest fitted values of $early_{i,14}$ using the second column in Table 5. For each member of the low take-up group, if one did not already exist, we added a link to the nearest member of the high take-up group in the 2001 network.[33] This would have resulted in 147 additional links, a 1.1% increase. Our counterfactual accounts for the effect of adding links on all other network related variables such as the degree, which are modified accordingly. Other exogenous variables and residual take-up were unchanged. The dashed blue line in Figure 6 depicts the impact of the network policy. We estimate that it would have increased 2014 take-up by 11 percentage points relative to no intervention. This is due to positive peer-effects and the increased exposure of low take-up consultants to high take-up consultants. To inform future policy, our results suggest fostering links between these two groups.

6.3. Conclusion

We use novel matched patient-physician-hospital panel data to examine the effect of a physician network on the take-up of innovation in medical practice. We propose and implement a new identification strategy for peer and network effects, and identify key physicians in the diffusion process. Though our data do not permit identification of the underlying mechanisms, our results are commensurate with peer learning and/or imitation, and information transmission due to mobility of physicians between hospitals. Our findings suggest that physician networks can be leveraged for policy. We estimate that carefully targeted early intervention on just one physician in 2001 could have increased average take-up in 2014 by from 48% to 56%. Since only one physician need be trained, this represents a cost-effective means of improving take-up. A more ambitious (and likely more costly) policy to foster links between high and low take-up physicians could have increased average take-up to 60%.

[32] Another approach would be to fix the number of links to be added and to search for the most effective among all possible combinations. We do not do this because it is computationally intractable.

[33] We used the year 2000 network to determine proximity. In the event of a tie, the link goes to the consultant with the highest take-up in 2000.

References

Agha L, Molitor D. The local influence of pioneer investigators on technology adoption: evidence from new cancer drugs. Review of Economics and Statistics. 2018;100(1):29-44.

Arnold M, Sierra MS, Laversanne M, Soerjomataram I, Jemal A, Bray F. Global patterns and trends in colorectal cancer incidence and mortality. Gut 2017;66(4):683-91.

Arrow, K.J., Bilir, K. and Sorensen, A.T., 2017. The impact of information technology on the diffusion of new pharmaceuticals (No. w23257). National Bureau of Economic Research.

Barnato, A. E. M. B. Herndon, D. L. Anthony, P. M. Gallagher, J. S. Skinner, J. P. Bynum & E. S. Fisher (2007). Are regional variations in end-of-life care intensity explained by patient preferences?: A Study of the US Medicare Population. Med Care 45(5): 386-393.

Blondel, V.D. Renaud Lambiotte J.G. and Lefebvre E. 2008. Fast unfolding of communities in large networks. Journal of Statistical Mechanics: Theory and Experiment, 10

Braga, M., Frasson, M., Vignali, A., Zuliani, W., Civelli, V. and Di Carlo, V., 2005. Laparoscopic vs. open colectomy in cancer patients: long-term complications, quality of life, and survival. Diseases of the colon & rectum, 48(12), pp.2217-2223.

Bramoullé, Y. Djebbari, H. and Fortin, B. 2009. Identification of peer-effects through social networks. Journal of econometrics, 150(1), pp.41-55.

Braunerhjelm, P., Ding, D. and Thulin, P., 2020. Labour market mobility, knowledge diffusion and innovation. European Economic Review, 123, p.103386.

Burke, M.A., Fournier, G. and Prasad, K., 2003. Physician social networks and geographical variation in medical care. Washington, DC: Center on Social and Economic Dynamics.

Burke, M.A., Fournier, G.M. and Prasad, K., 2007. The diffusion of a medical innovation: is success in the stars?. Southern Economic Journal, pp.588-603.

Burke, M.A., Fournier, G.M. and Prasad, K., 2009. The diffusion of a medical innovation: is success in the stars? Further evidence. Southern Economic Journal, pp.1274-1278.

Burns, E.M., Currie, A., Bottle, A., Aylin, P., Darzi, A. and Faiz, O., 2013. Minimal-access colorectal surgery is associated with fewer adhesion-related admissions than open surgery. Br J Surg, 100(1), pp.152-159.

Chan, D.C., 2016. Teamwork and moral hazard: evidence from the emergency department. Journal of Political Economy, 124(3), pp.734-770.

Chan, D.C., Forthcoming. Influence and Information in Team Decisions: Evidence from Medical Residency. American Economic Journal: Economic Policy .

Charlson ME, Pompei P, Ales KL, et al. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis. 1987;40(5):373–383.

Currie, J. MacLeod, W. B. & Van Parys, J. (2016). Provider practice style and patient health outcomes: the case of heart attacks. Journal of health economics, 47, 64-80.

Currie, J. M. & MacLeod, W. B. (2018). Understanding Physician Decision Making: The Case of Depression (No. w24955). National Bureau of Economic Research.

Cutler, D. Skinner, J. Stern, A. D. & Wennberg, D. (2019). Physician beliefs and patient preferences: a new look at regional variation in health care spending. American Economic Journal: Economic Policy, 11 (1): 192-221.

de Groot V, Beckerman H, Lankhorst GJ, et al. How to measure comorbidity: a critical review of available methods. J Clin Epidemiol. 2003;56(3):221–229.

Epstein AJ, Nicholson S. The formation and evolution of physician treatment styles: an application to cesarean sections. Journal of Health Economics. 2009;28(6):1126-40.

Finkelstein A, Gentzkow M, Williams H. Sources of Geographic Variation in Health Care: Evidence From Patient Migration. The Quarterly Journal of Economics. 2016;131(4):1681-726.

Fisher, E. S., Wennberg, D. E., Stukel, T. A., Gottlieb, D. J., Lucas, F. L., and Pinder, E. L. (2003). The implications of regional variations in Medicare spending. Part 1: the content, quality, and accessibility of care. Annals of Internal Medicine, 138(4), 273–287.

Fox, J., Gross, C.P., Longo, W. and Reddy, V., 2012. Laparoscopic colectomy for the treatment of cancer has been widely adopted in the United States. Diseases of the colon & rectum, 55(5), pp.501-508.

Gautier, E., Rose, C. and Tsybakov, A. 2018. High-dimensional instrumental variables regression and confidence sets. arXiv preprint arXiv:1105.2454v5.

Gautier, E. and Rose, C. 2019. High-dimensional instrumental variables regression and confidence sets. arXiv preprint arXiv:1105.2454v6.

General Medical Council Register, 2014, General Medical Council, London, UK

Goldacre, M. Davidson, J. Maisonneuve, J. and Lambert, T. 2013. Geographical movement of doctors from education to training and eventual career post: UK cohort studies. Journal of the Royal Society of Medicine, 106(3), pp.96-104.

Graham, B.S. 2008. Identifying social interactions through conditional variance restrictions. Econometrica, 76(3), pp.643-660.

Green, C.J., Maxwell, R., Verne, J., Martin, R.M. and Blazeby, J.M., 2009. The influence of NICE guidance on the uptake of laparoscopic surgery for colorectal cancer. Journal of public health, 31(4), pp.541-545.

Hall, B.H., 2006. Innovation and Diffusion. In The Oxford Handbook of Innovation.

Hospital Episodes Statistics 2000-2014, 2014, NHS Digital, Leeds, UK

Huesch, M.D., 2009. Comment on" the diffusion of a medical innovation: is success in the stars?". Southern Economic Journal, 75(4), pp.1270-1273.

IOM (2013). Variation in Healthcare Spending. Target Decision Making, Not Geography, Institute of Medicine.

Jackson, M.O., Rogers, B.W. and Zenou, Y., 2017. The economic consequences of social-network structure. Journal of Economic Literature, 55(1), pp.49-95.

Jayne DG, Thorpe HC, Copeland J, Quirke P, Brown JM, Guillou PJ. Five-year follow-up of the Medical Research Council CLASICC trial of laparoscopically assisted versus open surgery for colorectal cancer. British Journal of Surgery 2010;97(11):1638-45.

Kaiser, U., Kongsted, H.C. and Rønde, T., 2015. Does the mobility of R&D labor increase innovation?. Journal of Economic Behavior & Organization, 110, pp.91-105.

Kemp, J.A. and Finlayson, S.R., 2008. Nationwide trends in laparoscopic colectomy from 2000 to 2004. Surgical endoscopy, 22(5), pp.1181-1187.

Lacy AM, Garcia-Valdecasas JC, Delgado S, Castells A, Taura P, Pique JM, et al. Laparoscopy-assisted colectomy versus open colectomy for treatment of non-metastatic colon cancer: a randomised trial.

The Lancet 2002;359(9325):2224-9.

Lamiraud, K. and Lhuillery, S., 2016. Endogenous technology adoption and medical costs. Health economics, 25(9), pp.1123-1147.

Laudicella M, Walsh B, Burns E, Smith PC. Cost of care for cancer patients in England: evidence from population-based patient-level data. British Journal of Cancer 2016;114(11):1286-92.

Lee, L.F. 2007. Identification and estimation of econometric models with intra-group interactions, contextual factors and fixed effects. Journal of Econometrics, 140(2), pp.333-374.

Lee, L.F. and Yu, J. 2010. Estimation of spatial autoregressive panel data models with fixed effects. Journal of Econometrics, 154(2), pp.165-185.

Lee, L.F. and Yu, J. 2012. QML estimation of spatial dynamic panel data models with time varying spatial weights matrices. Spatial Economic Analysis, 7(1), pp.31-74.

Manski, C.F. 1993. Identification of endogenous social effects: The reflection problem. The review of economic studies, 60(3), pp.531-542.

Molitor D. The evolution of physician practice styles: evidence from cardiologist migration. American Economic Journal: Economic Policy. 2018;10(1):326-56.

Moloo, H., Haggar, F., Martel, G., Grimshaw, J., Coyle, D., Graham, I.D., Sabri, E., Poulin, E.C., Mamazza, J., Balaa, F.K. and Boushey, R.P., 2009. The adoption of laparoscopic colorectal surgery: a national survey of general surgeons. Canadian Journal of Surgery, 52(6), p.455.

National Institute for Health and Care Excellence (NICE). Keyhole surgery for colorectal cancer. Technology appraisal guidance TA105, 2006.

Nelson H, Sargent DJ, Wieand HS, Fleshman J, Anvari M, Stryker SJ, et al. A comparison of laparoscopically assisted and open colectomy for colon cancer. New England Journal of Medicine 2004;350(20):2050-9.

NHS Workforce Statistics 1992-2014, 2014, NHS Digital, Leeds, UK

Peng, S. 2019. Heterogeneous endogenous effects in networks. arXiv preprint arXiv:1908.00663.

Pollack, C.E., Weissman, G., Bekelman, J., Liao, K. and Armstrong, K., 2012. Physician social networks and variation in prostate cancer treatment in three cities. Health services research, 47(1pt2), pp.380-403.

Robinson, C.N., Chen, G.J., Balentine, C.J., Sansgiry, S., Marshall, C.L., Anaya, D.A., Artinyan, A., Albo, D. and Berger, D.H., 2011. Minimally invasive surgery is underutilized for colon cancer. Annals of surgical oncology, 18(5), pp.1412-1418.

Rose, C.D. 2017. Identification of peer-effects through social networks using variance restrictions. The Econometrics Journal, 20(3), pp.S47-S60.

Rose, C.D. Identification of Spillover Effects using Panel Data (2018). Working paper.

Rose, C.D. 2019. Optimal injection points for information diffusion. Economics Letters, 175, pp.67-70.

Safiri, S. Sepanlou, S.G. Ikuta, K.S. Bisignano, C. Salimzadeh, H. Delavari, A. Ansari, R. Roshandel, G. Merat, S. Fitzmaurice, C. and Force, L.M. 2019. The global, regional, and national burden of colorectal cancer and its attributable risk factors in 195 countries and territories, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. The Lancet Gastroenterology & Hepatology, 4(12), pp.913-933.

Saia, M., Buja, A., Mantoan, D., Sartor, G., Agresta, F. and Baldo, V., 2017. Isolated rectal cancer surgery: a 2007–2014 population study based on a large administrative database. Updates in Surgery, 69(3), pp.367-373.

Silver, D. (2016). Haste or waste? Peer pressure and the distribution of marginal returns to health care. Mimeo: UC Berkeley.

Skinner, J. (2012). Causes and Consequences of Geographic Variation in Health Care. Handbook of Health Economics Vol. 2. M. P. T. McGuire, and P. Pita Barros North Holland.

Skinner, J. & D. Staiger (2015). "Technology Diffusion and Productivity Growth in Health Care." Rev Econ Stat 97(5): 951-964.

Smith, S., Newhouse, J.P. and Freeland, M.S., 2009. Income, insurance, and technology: why does health spending outpace economic growth?. Health Affairs, 28(5), pp.1276-1284.

Staats, B.R., Kc, D.S. and Gino, F., 2018. Maintaining beliefs in the face of negative news: The moderating role of experience. Management Science, 64(2), pp.804-824.

Taylor, E.F., Thomas, J.D., Whitehouse, L.E., Quirke, P., Jayne, D., Finan, P.J., Forman, D., Wilkinson, J.R. and Morris, E.J.A., 2013. Population-based study of laparoscopic colorectal cancer surgery 2006–2008. The British journal of surgery, 100(4), p.553.

Thompson, B.S., Coory, M.D. and Lumley, J.W., 2011. National trends in the uptake of laparoscopic resection for colorectal cancer, 2000–2008. Medical journal of Australia, 194(9), pp.443-447.

Congressional Budget Office (2008). Technological Change and the Growth of Health Care Spending.

Wheelock, A. Miraldo, M. Barrenho, E. and Propper C. (2017). Determinants of adoption and diffusion of innovation: a qualitative study. Mimeo.

Table 6: *Baseline results*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
			Peer take-up		
$\overline{y}_{it}$	0.311***	0.619*	0.487**	0.536***	0.517**
	(0.0545)	(0.351)	(0.205)	(0.202)	(0.202)
$\overline{y}_{i,00\to t-1}$	0.252***	-0.0590	-0.109	-0.197	-0.229
	(0.0757)	(0.199)	(0.209)	(0.153)	(0.154)
			Network characteristics		
$degree_{it}$	0.00156	0.00188	0.00219*	0.00233**	0.00244**
	(0.00104)	(0.00122)	(0.00121)	(0.00115)	(0.00115)
$pioprox1_{it}$	0.0447	0.0327	0.0356	0.0332	0.0333
	(0.0309)	(0.0310)	(0.0307)	(0.0304)	(0.0305)
$pioprox2_{it}$	0.0385*	0.0269	0.0302	0.0280	0.0282
	(0.0198)	(0.0211)	(0.0203)	(0.0201)	(0.0203)
			Consultant characteristics		
$age_{it}^{<40}$	0.000475	0.00617	0.00474	0.00586	0.00579
	(0.0282)	(0.0294)	(0.0291)	(0.0293)	(0.0294)
age_{it}^{40-44}	0.0363	0.0434*	0.0407*	0.0419*	0.0416*
	(0.0222)	(0.0240)	(0.0232)	(0.0234)	(0.0234)
age_{it}^{45-49}	0.0431**	0.0475***	0.0455***	0.0462***	0.0459***
	(0.0168)	(0.0179)	(0.0173)	(0.0174)	(0.0174)
age_{it}^{50-54}	0.0280**	0.0289***	0.0283***	0.0284***	0.0282**
	(0.0109)	(0.0111)	(0.0110)	(0.0110)	(0.0110)
$expkey_{it}$	0.00750***	0.00780***	0.00782***	0.00789***	0.00792***
	(0.00163)	(0.00163)	(0.00162)	(0.00163)	(0.00163)
$expcolosur_{it}$	0.0499***	0.0498***	0.0499***	0.0498***	0.0498***
	(0.00525)	(0.00533)	(0.00533)	(0.00536)	(0.00538)
$patientscore_{it}$	0.346***	0.346***	0.340***	0.339***	0.337***
	(0.0601)	(0.0624)	(0.0617)	(0.0616)	(0.0616)
			Intra-hospital peer characteristics		
$\widetilde{age}_{it}^{<40}$	0.0147	0.0133	0.0190	0.0199	0.0214
	(0.0249)	(0.0261)	(0.0271)	(0.0263)	(0.0263)
$\widetilde{age}_{it}^{40-44}$	0.00979	0.0136	0.0179	0.0197	0.0211
	(0.0218)	(0.0219)	(0.0241)	(0.0229)	(0.0230)
$\widetilde{age}_{it}^{45-49}$	-0.00134	0.00253	0.00521	0.00673	0.00771
	(0.0203)	(0.0204)	(0.0218)	(0.0212)	(0.0212)
$\widetilde{age}_{it}^{50-54}$	-0.0111	-0.0123	-0.0108	-0.0108	-0.0105
	(0.0152)	(0.0153)	(0.0156)	(0.0157)	(0.0157)
$\widetilde{expkey}_{it}$	0.00101	0.00510	0.00639	0.00768*	0.00828*
	(0.00383)	(0.00474)	(0.00495)	(0.00435)	(0.00436)
$\widetilde{expcolosur}_{it}$	-0.000808	-0.00128	-0.00253	-0.00290	-0.00328
	(0.00744)	(0.00802)	(0.00797)	(0.00798)	(0.00802)
$\widetilde{patientscore}_{it}$	-0.122*	-0.113*	-0.118*	-0.117*	-0.118*
	(0.0663)	(0.0637)	(0.0623)	(0.0614)	(0.0611)
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Sample size	11932	11932	11932	11932	11932
Score instruments	-	Yes	Yes	No	Yes
Age instruments	-	Yes	No	Yes	Yes
Experience instruments	-	No	Yes	Yes	Yes
Hansen p-value	-	0.25	0.05	0.24	0.09
Kleibergen-Paap F-statistic	-	6.66	27.00	17.79	15.36

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. TSLS results are provided for different subsets of excluded instruments for the peer-effects, which use the suitability score, age dummies and experience of peers.

Table 7: *Heterogeneous peer-effects*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
	Peer take-up				
$\overline{y}_{it}$	0.397***	0.698**	0.705***	0.716***	0.721***
	(0.0598)	(0.322)	(0.194)	(0.189)	(0.187)
$\overline{y}_{it} \times expkey_{it}$	-0.0175***	-0.0211**	-0.00660	-0.00709	-0.0120
	(0.00598)	(0.00923)	(0.00832)	(0.00959)	(0.00815)
$\overline{y}_{it} \times expcolosur_{it}$	-0.0176	-0.00791	-0.0171	-0.0357*	-0.0238
	(0.0130)	(0.0226)	(0.0186)	(0.0194)	(0.0173)
$\overline{y}_{i,00\to t-1}$	0.280***	-0.0962	0.162	-0.140	-0.103
	(0.0751)	(0.203)	(0.203)	(0.147)	(0.148)
	Network characteristics				
$degree_{it}$	0.00165	0.00213*	0.00137	0.00217*	0.00208*
	(0.00104)	(0.00118)	(0.00120)	(0.00113)	(0.00113)
$pioprox1_{it}$	0.0438	0.0316	0.0334	0.0291	0.0300
	(0.0302)	(0.0310)	(0.0292)	(0.0293)	(0.0293)
$pioprox2_{it}$	0.0369**	0.0257	0.0263	0.0223	0.0235
	(0.0187)	(0.0209)	(0.0182)	(0.0188)	(0.0187)
	Consultant characteristics				
$age_{it}^{<40}$	-0.00566	0.00158	0.00125	-0.000836	0.000470
	(0.0278)	(0.0292)	(0.0287)	(0.0292)	(0.0291)
age_{it}^{40-44}	0.0268	0.0356	0.0373	0.0323	0.0343
	(0.0219)	(0.0238)	(0.0232)	(0.0235)	(0.0234)
age_{it}^{45-49}	0.0355**	0.0408**	0.0432**	0.0389**	0.0402**
	(0.0165)	(0.0178)	(0.0175)	(0.0176)	(0.0175)
age_{it}^{50-54}	0.0249**	0.0261**	0.0273**	0.0252**	0.0258**
	(0.0109)	(0.0112)	(0.0110)	(0.0110)	(0.0111)
$expkey_{it}$	0.0172***	0.0195***	0.0113**	0.0117**	0.0144***
	(0.00349)	(0.00538)	(0.00480)	(0.00535)	(0.00464)
$expcolosur_{it}$	0.0595***	0.0542***	0.0589***	0.0690***	0.0626***
	(0.00777)	(0.0126)	(0.0106)	(0.0108)	(0.00983)
$patientscore_{it}$	0.342***	0.339***	0.352***	0.340***	0.341***
	(0.0599)	(0.0617)	(0.0610)	(0.0612)	(0.0611)
	Intra-hospital peer characteristics				
$\widetilde{age}_{it}^{<40}$	0.0154	0.0164	0.00621	0.0150	0.0145
	(0.0249)	(0.0265)	(0.0265)	(0.0262)	(0.0261)
$\widetilde{age}_{it}^{40-44}$	0.0108	0.0174	0.00642	0.0163	0.0158
	(0.0218)	(0.0226)	(0.0235)	(0.0229)	(0.0228)
$\widetilde{age}_{it}^{45-49}$	-0.000239	0.00563	-0.00248	0.00485	0.00446
	(0.0203)	(0.0208)	(0.0214)	(0.0212)	(0.0211)
$\widetilde{age}_{it}^{50-54}$	-0.00950	-0.01000	-0.0131	-0.0112	-0.0110
	(0.0151)	(0.0155)	(0.0153)	(0.0156)	(0.0155)
$\widetilde{expkey}_{it}$	0.00107	0.00632	0.00155	0.00670	0.00615
	(0.00381)	(0.00467)	(0.00474)	(0.00422)	(0.00417)
$\widetilde{expcolosur}_{it}$	-0.00124	-0.00248	0.000522	-0.00187	-0.00184
	(0.00745)	(0.00794)	(0.00773)	(0.00787)	(0.00784)
$\widetilde{patientscore}_{it}$	-0.127*	-0.117*	-0.115*	-0.121*	-0.119*
	(0.0666)	(0.0631)	(0.0664)	(0.0627)	(0.0630)
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Sample size	11932	11932	11932	11932	11932
Peer score instruments	-	Yes	Yes	No	Yes
Peer age instruments	-	Yes	No	Yes	Yes
Peer experience instruments	-	No	Yes	Yes	Yes
Hansen p-value	-	0.49	0.00	0.00	0.00
Kleibergen-Paap F-statistic	-	5.21	17.16	13.31	11.47
$H_0 : \overline{y}_{it} \times expkey_{it} = \overline{y}_{it} \times expcolosur_{it} = 0$	0.00	0.07	0.48	0.11	0.12

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. TSLS results are provided for different subsets of excluded instruments for the peer-effects, which use the suitability score, age dummies and experience of peers. These instruments are also interacted with $expkey_{it}$ and $expcolosur_{it}$.

Table 8: *2000-2011 subsample*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
			Peer take-up		
$\overline{y}_{it}$	0.253***	0.344	0.567***	0.601***	0.561***
	(0.0586)	(0.389)	(0.198)	(0.197)	(0.195)
$\overline{y}_{i,00\to t-1}$	0.308***	0.0600	-0.0795	-0.172	-0.187
	(0.0874)	(0.240)	(0.241)	(0.175)	(0.176)
			Network characteristics		
$degree_{it}$	0.00198*	0.00232*	0.00226*	0.00239**	0.00248**
	(0.00103)	(0.00119)	(0.00121)	(0.00114)	(0.00113)
$pioprox1_{it}$	0.0191	0.0155	0.00984	0.00851	0.00925
	(0.0252)	(0.0266)	(0.0245)	(0.0244)	(0.0246)
$pioprox2_{it}$	0.0421**	0.0377*	0.0310*	0.0294*	0.0302*
	(0.0165)	(0.0195)	(0.0164)	(0.0164)	(0.0166)
			Consultant characteristics		
$age_{it}^{<40}$	0.0185	0.0218	0.0254	0.0266	0.0263
	(0.0278)	(0.0286)	(0.0286)	(0.0288)	(0.0288)
age_{it}^{40-44}	0.0498**	0.0530**	0.0578**	0.0589***	0.0583**
	(0.0219)	(0.0232)	(0.0226)	(0.0228)	(0.0228)
age_{it}^{45-49}	0.0551***	0.0569***	0.0601***	0.0608***	0.0603***
	(0.0161)	(0.0170)	(0.0166)	(0.0167)	(0.0167)
age_{it}^{50-54}	0.0305***	0.0307***	0.0316***	0.0316***	0.0315***
	(0.0103)	(0.0104)	(0.0103)	(0.0104)	(0.0103)
$expkey_{it}$	0.00995***	0.0101***	0.0101***	0.0102***	0.0102***
	(0.00218)	(0.00220)	(0.00219)	(0.00220)	(0.00221)
$expcolosur_{it}$	0.0572***	0.0572***	0.0570***	0.0570***	0.0570***
	(0.00578)	(0.00587)	(0.00589)	(0.00592)	(0.00593)
$patientscore_{it}$	0.218***	0.213***	0.218***	0.217***	0.215***
	(0.0550)	(0.0571)	(0.0574)	(0.0569)	(0.0568)
			Intra-hospital peer characteristics		
$\widetilde{age}_{it}^{<40}$	0.00386	0.00750	0.00282	0.00419	0.00619
	(0.0237)	(0.0253)	(0.0271)	(0.0256)	(0.0255)
$\widetilde{age}_{it}^{40-44}$	-0.00772	-0.00165	-0.00330	-0.00103	0.000682
	(0.0211)	(0.0218)	(0.0249)	(0.0228)	(0.0227)
$\widetilde{age}_{it}^{45-49}$	-0.0179	-0.0137	-0.0152	-0.0136	-0.0123
	(0.0200)	(0.0203)	(0.0222)	(0.0211)	(0.0211)
$\widetilde{age}_{it}^{50-54}$	-0.0247*	-0.0248	-0.0274*	-0.0274*	-0.0268*
	(0.0150)	(0.0153)	(0.0156)	(0.0156)	(0.0156)
$\widetilde{expkey}_{it}$	0.00181	0.00576	0.00700	0.00847*	0.00897*
	(0.00464)	(0.00575)	(0.00594)	(0.00510)	(0.00513)
$\widetilde{expcolosur}_{it}$	-0.00519	-0.00686	-0.00656	-0.00719	-0.00762
	(0.00860)	(0.00927)	(0.00911)	(0.00912)	(0.00916)
$\widetilde{patientscore}_{it}$	-0.0664	-0.0673	-0.0584	-0.0588	-0.0613
	(0.0602)	(0.0594)	(0.0582)	(0.0566)	(0.0562)
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Sample size	9220	9220	9220	9220	9220
Peer score instruments	-	Yes	Yes	No	Yes
Peer age instruments	-	Yes	No	Yes	Yes
Peer experience instruments	-	No	Yes	Yes	Yes
Hansen p-value	-	0.55	0.31	0.88	0.46
Kleibergen-Paap F-statistic	-	4.38	14.73	12.69	11.16

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. TSLS results are provided for different subsets of excluded instruments for the peer-effects, which use the suitability score, age dummies and experience of peers.

Table 9: *Time-varying patient suitability*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
			Peer take-up		
$\overline{y}_{it}$	0.318***	0.404	0.390**	0.557***	0.429**
	(0.0540)	(0.283)	(0.189)	(0.200)	(0.187)
$\overline{y}_{i,00\to t-1}$	0.263***	-0.157	-0.123	-0.167	-0.125
	(0.0754)	(0.128)	(0.130)	(0.152)	(0.120)
			Network characteristics		
$degree_{it}$	0.00151	0.00241**	0.00235**	0.00222*	0.00230**
	(0.00102)	(0.00118)	(0.00110)	(0.00114)	(0.00110)
$pioprox1_{it}$	0.0506	0.0430	0.0438	0.0387	0.0428
	(0.0314)	(0.0323)	(0.0318)	(0.0309)	(0.0315)
$pioprox2_{it}$	0.0430**	0.0366	0.0373*	0.0321	0.0362
	(0.0213)	(0.0231)	(0.0223)	(0.0213)	(0.0220)
			Consultant characteristics		
$age_{it}^{<40}$	0.00220	0.00552	0.00516	0.00765	0.00569
	(0.0280)	(0.0291)	(0.0288)	(0.0291)	(0.0288)
age_{it}^{40-44}	0.0374*	0.0398*	0.0395*	0.0431*	0.0403*
	(0.0220)	(0.0235)	(0.0229)	(0.0232)	(0.0229)
age_{it}^{45-49}	0.0442***	0.0451***	0.0449***	0.0473***	0.0454***
	(0.0166)	(0.0175)	(0.0171)	(0.0173)	(0.0171)
age_{it}^{50-54}	0.0284***	0.0282**	0.0282***	0.0288***	0.0283***
	(0.0108)	(0.0110)	(0.0109)	(0.0109)	(0.0109)
$expkey_{it}$	0.00784***	0.00818***	0.00815***	0.00822***	0.00816***
	(0.00161)	(0.00162)	(0.00162)	(0.00161)	(0.00161)
$expcolosur_{it}$	0.0452***	0.0453***	0.0453***	0.0452***	0.0453***
	(0.00527)	(0.00538)	(0.00536)	(0.00537)	(0.00536)
$patientscore_{it}$	0.743***	0.721***	0.722***	0.727***	0.724***
	(0.0929)	(0.0957)	(0.0945)	(0.0945)	(0.0943)
			Intra-hospital peer characteristics		
$\widetilde{age}_{it}^{<40}$	0.0153	0.0241	0.0236	0.0201	0.0226
	(0.0228)	(0.0239)	(0.0241)	(0.0237)	(0.0237)
$\widetilde{age}_{it}^{40-44}$	0.00909	0.0208	0.0199	0.0187	0.0194
	(0.0202)	(0.0211)	(0.0214)	(0.0208)	(0.0210)
$\widetilde{age}_{it}^{45-49}$	-0.00177	0.00701	0.00635	0.00606	0.00610
	(0.0188)	(0.0194)	(0.0196)	(0.0193)	(0.0194)
$\widetilde{age}_{it}^{50-54}$	-0.0114	-0.0100	-0.0101	-0.0109	-0.0103
	(0.0145)	(0.0148)	(0.0148)	(0.0147)	(0.0147)
$\widetilde{expkey}_{it}$	0.000816	0.00750*	0.00698	0.00715*	0.00689
	(0.00381)	(0.00450)	(0.00438)	(0.00431)	(0.00426)
$\widetilde{expcolosur}_{it}$	0.000297	-0.00247	-0.00229	-0.00146	-0.00203
	(0.00725)	(0.00789)	(0.00766)	(0.00777)	(0.00766)
$\widetilde{patientscore}_{it}$	-0.601***	-0.602***	-0.601***	-0.610***	-0.603***
	(0.144)	(0.142)	(0.142)	(0.143)	(0.143)
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Sample size	11926	11926	11926	11926	11926
Peer score instruments	-	Yes	Yes	No	Yes
Peer age instruments	-	Yes	No	Yes	Yes
Peer experience instruments	-	No	Yes	Yes	Yes
Hansen p-value	-	0.15	0.17	0.27	0.22
Kleibergen-Paap F-statistic	-	9.43	40.74	17.60	18.12

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. TSLS results are provided for different subsets of excluded instruments for the peer-effects, which use the suitability score, age dummies and experience of peers.

Table 10: *Unequal peer weighting*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
			Peer take-up		
$\overline{y}_{it}$	0.317***	-0.0310	0.441***	0.360**	0.303**
	(0.0290)	(0.263)	(0.159)	(0.145)	(0.142)
$\overline{y}_{i,00\to t-1}$	0.0983	0.00500	-0.0674	-0.193	-0.228
	(0.0714)	(0.211)	(0.185)	(0.143)	(0.143)
			Network characteristics		
$degree_{it}$	0.00139	0.00270**	0.00140	0.00196*	0.00222*
	(0.00101)	(0.00135)	(0.00122)	(0.00116)	(0.00115)
$pioprox1_{it}$	0.0446	0.0505	0.0400	0.0401	0.0408
	(0.0295)	(0.0348)	(0.0287)	(0.0292)	(0.0298)
$pioprox2_{it}$	0.0451**	0.0449*	0.0433**	0.0423**	0.0421**
	(0.0181)	(0.0240)	(0.0170)	(0.0181)	(0.0189)
			Consultant characteristics		
$age_{it}^{<40}$	0.00325	-0.00275	0.00650	0.00567	0.00479
	(0.0277)	(0.0295)	(0.0279)	(0.0283)	(0.0284)
age_{it}^{40-44}	0.0373*	0.0296	0.0404*	0.0388*	0.0376*
	(0.0218)	(0.0237)	(0.0220)	(0.0223)	(0.0225)
age_{it}^{45-49}	0.0446***	0.0379**	0.0469***	0.0452***	0.0441***
	(0.0165)	(0.0179)	(0.0168)	(0.0169)	(0.0170)
age_{it}^{50-54}	0.0297***	0.0260**	0.0307***	0.0297***	0.0291***
	(0.0108)	(0.0115)	(0.0109)	(0.0109)	(0.0109)
$expkey_{it}$	0.00732***	0.00767***	0.00735***	0.00752***	0.00759***
	(0.00160)	(0.00168)	(0.00159)	(0.00160)	(0.00162)
$expcolosur_{it}$	0.0494***	0.0502***	0.0491***	0.0493***	0.0495***
	(0.00521)	(0.00542)	(0.00522)	(0.00525)	(0.00528)
$patientscore_{it}$	0.355***	0.325***	0.359***	0.349***	0.343***
	(0.0600)	(0.0639)	(0.0624)	(0.0619)	(0.0619)
			Intra-hospital peer characteristics		
$\widetilde{age}_{it}^{<40}$	-0.00644	0.0354	-0.0158	-0.00310	0.00431
	(0.0237)	(0.0346)	(0.0293)	(0.0273)	(0.0271)
$\widetilde{age}_{it}^{40-44}$	-0.00726	0.0267	-0.0130	-0.00170	0.00449
	(0.0208)	(0.0284)	(0.0250)	(0.0229)	(0.0228)
$\widetilde{age}_{it}^{45-49}$	-0.0141	0.00997	-0.0180	-0.00992	-0.00551
	(0.0195)	(0.0242)	(0.0218)	(0.0207)	(0.0207)
$\widetilde{age}_{it}^{50-54}$	-0.0145	-0.00629	-0.0164	-0.0140	-0.0125
	(0.0145)	(0.0165)	(0.0147)	(0.0148)	(0.0149)
$\widetilde{expkey}_{it}$	-0.00120	0.00675	-0.000743	0.00284	0.00447
	(0.00366)	(0.00618)	(0.00550)	(0.00489)	(0.00484)
$\widetilde{expcolosur}_{it}$	0.00600	-0.00573	0.00863	0.00506	0.00298
	(0.00718)	(0.0118)	(0.00926)	(0.00913)	(0.00918)
$\widetilde{patientscore}_{it}$	-0.112*	-0.137**	-0.104	-0.110*	-0.114*
	(0.0669)	(0.0632)	(0.0671)	(0.0641)	(0.0627)
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Sample size	11932	11932	11932	11932	11932
Peer score instruments	-	Yes	Yes	No	Yes
Peer age instruments	-	Yes	No	Yes	Yes
Peer experience instruments	-	No	Yes	Yes	Yes
Hansen p-value	-	0.03	0.00	0.01	0.00
Kleibergen-Paap F-statistic	-	3.34	11.12	7.75	6.92

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. TSLS results are provided for different subsets of excluded instruments for the peer-effects, which use the suitability score, age dummies and experience of peers.

Table 11: *Lagged dependent variable*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
	Lagged dependent variable				
y_{it-1}	-0.379***	0.0101	0.00937	0.00859	0.00692
	(0.0195)	(0.0727)	(0.0735)	(0.0732)	(0.0730)
	Peer take-up				
$\bar{y}_{it}$	0.192***	0.361	0.456*	0.526**	0.480**
	(0.0547)	(0.259)	(0.261)	(0.226)	(0.224)
$\bar{y}_{i,00\to t-1}$	0.256**	-0.303	-0.340	-0.293	-0.390
	(0.119)	(0.445)	(0.396)	(0.305)	(0.297)
	Network characteristics				
$degree_{it}$	0.00213*	0.00335**	0.00322**	0.00307**	0.00321**
	(0.00123)	(0.00151)	(0.00151)	(0.00148)	(0.00149)
$pioprox1_{it}$	0.0122	0.0369	0.0338	0.0317	0.0328
	(0.0433)	(0.0476)	(0.0455)	(0.0458)	(0.0458)
$pioprox2_{it}$	0.00291	0.0343***	0.0305***	0.0278***	0.0295***
	(0.0268)	(0.0119)	(0.00880)	(0.00873)	(0.00815)
	Consultant characteristics				
$age_{it}^{<40}$	0.0204	0.0325	0.0335	0.0342	0.0338
	(0.0235)	(0.0297)	(0.0295)	(0.0296)	(0.0295)
age_{it}^{40-44}	0.0184	0.0254	0.0264	0.0270	0.0266
	(0.0189)	(0.0243)	(0.0241)	(0.0242)	(0.0242)
age_{it}^{45-49}	0.0292**	0.0361**	0.0367**	0.0373**	0.0368**
	(0.0133)	(0.0178)	(0.0178)	(0.0178)	(0.0178)
age_{it}^{50-54}	0.0203**	0.0213*	0.0215*	0.0216*	0.0215*
	(0.00947)	(0.0128)	(0.0128)	(0.0129)	(0.0128)
$expkey_{it}$	0.00322	-0.00186	-0.00174	-0.00176	-0.00160
	(0.00316)	(0.00325)	(0.00323)	(0.00317)	(0.00318)
$expcolosur_{it}$	0.0500***	0.0352***	0.0351***	0.0351***	0.0351***
	(0.00839)	(0.00941)	(0.00944)	(0.00940)	(0.00943)
$patientscore_{it}$	0.351***	0.419***	0.421***	0.423***	0.422***
	(0.0618)	(0.0854)	(0.0854)	(0.0855)	(0.0853)
	Intra-hospital peer characteristics				
$\widetilde{age}_{it}^{<40}$	0.0375**	0.0215	0.0195	0.0182	0.0190
	(0.0167)	(0.0213)	(0.0208)	(0.0207)	(0.0207)
$\widetilde{age}_{it}^{40-44}$	0.0259*	0.0201	0.0184	0.0174	0.0179
	(0.0155)	(0.0191)	(0.0189)	(0.0188)	(0.0188)
$\widetilde{age}_{it}^{45-49}$	0.00525	0.00528	0.00399	0.00332	0.00349
	(0.0157)	(0.0189)	(0.0190)	(0.0189)	(0.0188)
$\widetilde{age}_{it}^{50-54}$	0.00481	0.0109	0.00957	0.00876	0.00910
	(0.0134)	(0.0163)	(0.0165)	(0.0164)	(0.0163)
$\widetilde{expkey}_{it}$	0.00664*	0.00553	0.00553	0.00526	0.00570
	(0.00377)	(0.00432)	(0.00464)	(0.00444)	(0.00441)
$\widetilde{expcolosur}_{it}$	0.00520	0.00371	0.00468	0.00540	0.00496
	(0.00666)	(0.00771)	(0.00755)	(0.00749)	(0.00749)
$\widetilde{patientscore}_{it}$	-0.149***	-0.169**	-0.164**	-0.159**	-0.163**
	(0.0527)	(0.0753)	(0.0750)	(0.0748)	(0.0747)
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Sample size	8947	7658	7658	7658	7658
Peer score instruments	-	Yes	Yes	No	Yes
Peer age instruments	-	Yes	No	Yes	Yes
Peer experience instruments	-	No	Yes	Yes	Yes
Kleibergen-Paap F-statistic	-	5.63	17.44	10.91	9.67

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. TSLS results are provided for different subsets of excluded instruments for the peer-effects, which use the suitability score, age dummies and experience of peers. The instrument for y_{it-1} is y_{it-2} and the model is estimated in first-differences.

Table 12: *Non-linear peer-effects*

Dep. var. y_{it} (range $[0,1]$)					
	OLS	TSLS	TSLS	TSLS	TSLS
			Peer take-up		
$\overline{y}_{it}$	0.0565	-0.393	-0.515	-0.498	-0.475
	(0.0919)	(1.222)	(0.770)	(0.652)	(0.647)
$\overline{y}_{it}^2$	0.385***	1.284	1.260	1.436	1.290
	(0.138)	(1.680)	(1.074)	(0.897)	(0.884)
$\overline{y}_{i,00\to t-1}$	0.208***	-0.0350	-0.397*	-0.397**	-0.397**
	(0.0772)	(0.206)	(0.227)	(0.161)	(0.161)
			Network characteristics		
$degree_{it}$	0.00155	0.00166	0.00274**	0.00250**	0.00265**
	(0.00104)	(0.00121)	(0.00117)	(0.00113)	(0.00113)
$pioprox1_{it}$	0.0468	0.0462	0.0451	0.0429	0.0438
	(0.0304)	(0.0331)	(0.0322)	(0.0312)	(0.0315)
$pioprox2_{it}$	0.0393**	0.0359*	0.0362*	0.0331	0.0347*
	(0.0192)	(0.0213)	(0.0217)	(0.0206)	(0.0211)
			Consultant characteristics		
$age_{it}^{<40}$	0.000620	0.00361	0.00383	0.00551	0.00460
	(0.0282)	(0.0291)	(0.0295)	(0.0296)	(0.0296)
age_{it}^{40-44}	0.0367*	0.0408*	0.0385	0.0415*	0.0398*
	(0.0222)	(0.0238)	(0.0236)	(0.0236)	(0.0236)
age_{it}^{45-49}	0.0437***	0.0471***	0.0448**	0.0471***	0.0458***
	(0.0168)	(0.0179)	(0.0176)	(0.0176)	(0.0176)
age_{it}^{50-54}	0.0275**	0.0268**	0.0257**	0.0261**	0.0260**
	(0.0109)	(0.0113)	(0.0114)	(0.0113)	(0.0113)
$expkey_{it}$	0.00736***	0.00718***	0.00746***	0.00740***	0.00745***
	(0.00162)	(0.00183)	(0.00170)	(0.00168)	(0.00169)
$expcolosur_{it}$	0.0498***	0.0495***	0.0496***	0.0495***	0.0496***
	(0.00522)	(0.00529)	(0.00539)	(0.00535)	(0.00537)
$patientscore_{it}$	0.348***	0.354***	0.338***	0.344***	0.340***
	(0.0600)	(0.0621)	(0.0614)	(0.0613)	(0.0613)
			Intra-hospital peer characteristics		
$\widetilde{age}_{it}^{<40}$	0.0154	0.0160	0.0308	0.0261	0.0288
	(0.0249)	(0.0258)	(0.0277)	(0.0265)	(0.0265)
$\widetilde{age}_{it}^{40-44}$	0.0105	0.0140	0.0284	0.0255	0.0272
	(0.0218)	(0.0218)	(0.0249)	(0.0233)	(0.0233)
$\widetilde{age}_{it}^{45-49}$	-0.00140	0.000177	0.0104	0.00838	0.00962
	(0.0204)	(0.0206)	(0.0223)	(0.0216)	(0.0216)
$\widetilde{age}_{it}^{50-54}$	-0.0123	-0.0157	-0.0124	-0.0143	-0.0131
	(0.0152)	(0.0158)	(0.0162)	(0.0160)	(0.0160)
$\widetilde{expkey}_{it}$	0.000685	0.00177	0.00832*	0.00739*	0.00804*
	(0.00384)	(0.00589)	(0.00478)	(0.00444)	(0.00443)
$\widetilde{expcolosur}_{it}$	0.000153	0.00222	-0.00161	-0.000156	-0.00112
	(0.00744)	(0.00943)	(0.00818)	(0.00809)	(0.00811)
$\widetilde{patientscore}_{it}$	-0.119*	-0.106	-0.113*	-0.107*	-0.111*
	(0.0659)	(0.0664)	(0.0606)	(0.0612)	(0.0608)
Consultant FE	Yes	Yes	Yes	Yes	Yes
Community-Year FE	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes
Sample size	11932	11932	11932	11932	11932
Peer score instruments	-	Yes	Yes	No	Yes
Peer age instruments	-	Yes	No	Yes	Yes
Peer experience instruments	-	No	Yes	Yes	Yes
Hansen p-value	-	0.12	0.34	0.01	0.08
Kleibergen-Paap F-statistic	-	1.11	4.25	3.10	2.74

Notes: Standard errors clustered by consultant and hospital-year in parentheses. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. TSLS results are provided for different subsets of excluded instruments for the peer-effects, which use the suitability score, age dummies and experience of peers.

Table 13: *Key Players*

Dep. var. y_{it} (range $[0,1]$)						
	STIV (OLS)	BC-STIV (OLS)	STIV	BC-STIV	STIV	BC-STIV
	Peer take-up					
$\overline{y}_{it}$	0.308	0.381***	0.308	0.381***	0.297	0.427***
		(0.0484)		(0.063)		(0.0867)
$\overline{y}_{i,00\to t-1}$	0.215	0.22***	0.207	0.172***	0.203	0.296***
		(0.0346)		(0.0345)		(0.0571)
	Network characteristics					
$degree_{it}$	0.00115	0.00164**	0.00106	0.000229	0.00123	0.00234**
		(0.000721)		(0.000711)		(0.000947)
$pioprox1_{it}$	0.0418	0.0503***	0.0386	0.0543***	0.0428	0.0454***
		(0.0145)		(0.0173)		(0.0166)
$pioprox2_{it}$	0.038	0.0296**	0.0356	0.0201	0.0458	0.0121
		(0.0144)		(0.0172)		(0.0175)
	Consultant characteristics					
$age_{it}^{<40}$	0.00526	0.0121**	0.00374	0.00335	0.00050	0.00922
		(0.00604)		(0.00619)		(0.00957)
age_{it}^{40-44}	0.0449	0.0427***	0.0433	0.0414***	0.0419	0.0239***
		(0.00322)		(0.00344)		(0.00596)
age_{it}^{45-49}	0.0475	0.0459***	0.0462	0.0458***	0.0468	0.0584***
		(0.0035)		(0.00361)		(0.00552)
age_{it}^{50-54}	0.0268	0.0355***	0.0262	0.0366***	0.0272	0.04***
		(0.00432)		(0.00445)		(0.00856)
$expkey_{it}$	0.00665	0.00713***	0.00646	0.00586***	0.0074	0.00845***
		(0.00079)		(0.000746)		(0.00131)
$expcolosur_{it}$	0.0496	0.0492***	0.0494	0.0528***	0.0494	0.053***
		(0.00231)		(0.00274)		(0.00372)
$patientscore_{it}$	0.303	0.381***	0.301	0.319***	0.321	0.265**
		(0.0531)		(0.0594)		(0.11)
	Key Players: Peer-effect $(\overline{y}_{it}^{j})_{j=1}^{N}$					
					All	$p \leq 0.05$
Count $\neq 0$	-		-		35	13
Mean$\| \neq 0$	-		-		0.114	0.26
Median$\| \neq 0$	-		-		0.055	0.245
St.Dev.$\| \neq 0$	-		-		0.404	0.582
	Key Players: Proximity Effect $(keyprox1_{it}^{j})_{j=1}^{N}$					
					All	$p \leq 0.05$
Count $\neq 0$	-		-		10	2
Mean$\| \neq 0$	-		-		0.0723	0.222
Median$\| \neq 0$	-		-		0.102	0.222
St.Dev.$\| \neq 0$	-		-		0.172	0.111
Consultant FE	Yes		Yes		Yes	
Community-Year FE	Yes		Yes		Yes	
Hospital FE	Yes		Yes		Yes	
Key Players	No		No		Yes	
Sample size	11932		11932		11932	
Score instruments	-		No		No	
Age instruments	-		Yes		Yes	
Experience instruments	-		Yes		Yes	

Notes: BC-STIV corrects the shrinkage based bias of the STIV estimator in (5.4). STIV (OLS) is STIV with covariates serving as their own instruments. BC-STIV provides confidence intervals rather than standard errors. The 'standard errors' reported in parentheses are obtained by setting the BC-STIV 0.95 confidence intervals equal to the usual 0.95 confidence interval $[\widehat{b} \pm 1.96\widehat{SE}(\widehat{b})]$ and solving for $\widehat{SE}(\widehat{b})$. ***: significant at the 0.01 level, **: significant at the 0.05 level, *: significant at 0.1 level. All models control for characteristics of intra-hospital peers, but results are omitted for parsimony. Key players results report summary statistics for the estimate of the corresponding N dimensional parameter vector. 'Count $\neq 0$' is the number of nonzero entries in the STIV estimator. 'Mean$| \neq 0$', 'Median$| \neq 0$' and 'St.Dev.$| \neq 0$' summarise the distribution of the bias-corrected STIV estimator conditional on the STIV estimator being nonzero. 'All' provides summary statistics for all nonzero entries, whilst '$p \leq 0.05$' summarises the subset which are statistically significant at the 0.05 level.

Patient suitability

An index of patient suitability for keyhole surgery was constructed as follows. HES data contains a rich set of observable patient characteristics including the age, sex, detailed diagnosis code, comorbidities, cancer location, and socioeconomic characteristics of the patient's small geographical area of residence. To reduce these variables to a single index we follow the same methodology by Currie et al. (2016) using a Logit model for keyhole surgery as a function of a vector of patient characteristics. We use the sample of patients undergoing surgery between 2012 and 2014. This period is after the issuance of national guidelines and a training programme to promote the use of keyhole surgery for colon cancer (Coleman, 2009), so patient treatment reflects 'accepted and best practice' rather than the behaviour early in the diffusion process and the index reflects patient suitability rather than (unobserved) consultant attitudes towards the innovation. We estimate the following model for patient j:

$$Prob(keyhole_j = 1) = F(\mathbf{w}_j'\theta) \tag{6.1}$$

where $F(.)$ is the logistic cumulative distribution function, $Prob(keyhole_j = 1)$ is the probability that the patient j receives a keyhole procedure for colorectal cancer, $\mathbf{w}_j$ is a vector of patient characteristics defined below and θ is the parameter vector.

The vector of patient characteristics $\mathbf{w}_j$ comprises a constant, a gender dummy, dummies for age in groups (<50,50-59,60-69,70-79,80+), dummies for quintile of the income distribution in the small geographical area where the patient lives as reported in the 2001 Census, dummies for the three locations of colorectal cancer (i.e. colon, rectosigmoid junction, and rectum), dummies for the number of comorbidities diagnosed (ranging from 1,2,3,...,9+), and dummies for the comorbidities on which the Charlson index is based. We also include all pairwise interactions of the above covariates. Comorbidities are coexistent diseases to colorectal cancer, which may directly affect the prognosis the disease, or indirectly influence the choice of treatment. The Charlson comorbidity index is the most widely used comorbidity index for predicting the outcome and risk of death from many comorbid diseases (Charlson et al. 1987; de Groot et al. 2003). It contains 17 comorbidities including cardiac arrhythmia, congestive heart failure, peripheral vascular disease, cerebral vascular disease, dementia, coronary obstructive pulmonary disease, rheumatoid disease, ulcers, liver disease, diabetes, kidney disease, hemiplegia or paraplegia, leukaemia, lymphoma, dementia, metastatic cancer, and acquired immunodeficiency syndrome (AIDS). We do not include the index itself since it is a linear combination of the comorbidity dummies.

We predict the probability of keyhole surgery for each patient treated from 2000 to 2014 using the Logit estimates of θ (which use the 2012-2014 subsample of patients). To obtain the patient suitability index $patientscore_{it}$, we take the mean predicted probability of keyhole surgery over all patients of consultant i in year t.