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Peer and network effects in medical innovation: the case of laparoscopic surgery in the English NHS*

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Abstract

This paper examines the effect of peers and networks on the uptake of innovation in surgery. Using a rich matched patient-surgeon data set covering all relevant surgeons, we construct a wide set of time varying measures of peer behaviour and network effects. Our estimates allow for simultaneity bias and treatment of the network as partially unknown. The findings show the importance of multiple channels in affecting the diffusion of innovative behaviour across individual surgeons.

JEL codes:

Key words: innovation, peer effects, unknown networks

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1. Introduction

Networks have been shown to be important determinants of behaviour in many areas of the economy, including education (Calvó-Armengol et al, 2009; Sacerdote, 2011), risky-behaviours (Powell et al, 2005, Ali and Dwyer, 2009), programme participation (Banerjee et al, 2013), risk-sharing (Fafchamps and Lund, 2005), knowledge spillovers (Bloom et al, 2013; König et al, 2014), trade (Chaney, 2014) and systemic risk (Acemoglu et al, 2015). The aim of the present paper is to examine the effect of networks and peer effects on the adoption of innovation in medical practice. Despite the fact that the health care sector is characterised by high levels of innovation (for example, Newhouse, 1992; U.S. CBO, 2008; Smith, Newhouse, and Freeland, 2009) there is little robust evidence on the effect of peer behaviour on adoption of innovation in this sector (Agha and Molitor 2018). However, the healthcare context, in which individuals train for long periods, become highly specialised and work in teams is one where peer and network effects would be expected to operate.

We study the extent to which the adoption of an important innovation in surgical practice is associated with the characteristics of senior physicians, their experience, their work networks and the behaviour of their peers. As our "test bed" we use the English National Health Service (NHS) and exploit a novel database which matches all NHS treated patients, physicians and hospitals over 14 years. The innovation we study is laparoscopic resection for colorectal cancer patients. Our choice of innovation and setting is motivated by the following reasons. First, colorectal cancer is the third most common cancer worldwide. There are 1.4 million new cases and almost 700,000 deaths annually (Arnold et al, 2017). In England, colorectal cancer accounts for around 10 percent of all cancer deaths annually and is the most expensive cancer to treat for the NHS, costing around $90m per annum (Laudicella et al, 2016). Second, laparoscopic resection is an important innovation that is associated with improved survival for colon cancer and better short-term outcomes including reduced pain and blood loss, faster recovery time, and shorter length of hospital stay relative to the alternative procedure of open resection (for example, Lacy et al., 2002, Nelson et al., 2004). Third, we observe the take-up of this procedure from its first introduction in the NHS in 2000 so we can examine the impact of network and peer behaviour from the beginning of the diffusion process. Fourth, laparoscopy is almost exclusively undertaken by senior physicians who also perform the alternative procedure, so all physicians we examine could, if they wished, adopt the innovation. Finally, in this single payer setting where almost all surgeons are employees of a single hospital and healthcare is free at the point of use, surgeons and hospitals all operate within the same centrally governed system with the same financial incentives. Furthermore there is a common and centrally driven laparoscopy training system for physicians. This allows us to isolate the role of the physician and their peers, abstracting from drivers of variation that arise from responses to different payment regimes, patient selection based on insurance status, defensive medicine and differences in hospital organization.[1]

We exploit the richness of our data to construct a dynamic network based on common workplaces of surgeons from 1992 to 2014. The network thus evolves as surgeons move posts between hospitals. We use this network to decompose each surgeon's peers into present peers (i.e. those with whom a

[1]Our analyses control for hospital and time effects to capture any common time shocks and persistent differences across hospitals.

surgeon currently works in the same hospital) and past peers (i.e. those with whom a surgeon has worked in the past but does not currently work, and also to decompose peer laparoscopic behaviour into present behaviour (i.e. behaviour in the same year) and past behaviour (i.e. behaviour in past years whilst working together). Our empirical model thus incorporates four endogenous peer effects allowing for heterogeneous effects of present/past behaviour of present/past peers.

Surgeons' behaviour may be affected by the behaviour of leaders in their profession who are not part of their workplace network. So in addition to workplace peer effects, we also seek to establish the existence and identities of 'leaders' in the diffusion process. We thus suppose there are two networks through which peer effects operate: an observable workplace network, and an unobservable leaders network, which we estimate together with the associated peer effects.[2] Our approach is motivated by Rose, (2018), which considers a setting in which a static peer network is unobserved yet sparse (i.e. each surgeon has only a few peers relative to the number of surgeons). We apply the same ideas to a setting in which we have an observed workplace network that may not capture peer effects arising from leaders. Specifically, we suppose that there exists a group of potential leaders who perform high annual volumes of colorectal cancer surgery early on in the diffusion process(we take the top 5%). We apply the STIV estimator of Gautier et al, (2018) to simultaneously estimate leader identities and their effect on behaviour. We also explore the extent to which the number of peers (present and past) and distance in the network to the nearest pioneer affect laparoscopic behaviour.

Contemporaneous peer behaviour is endogenous by construction due to simultaneity and exposure to common shocks.[3] This implies that two of the workplace peer effects variables (those based on contemporaneous behaviour) and leader behaviour are endogenous in our model. For this reason, we use an instrumental variables strategy to identify the parameters (as studied in in Manski (1993); Moffitt et al, 2001; Lee 2007; Davezies et al, 2009; Bramoullé et al, 2009; Blume et al, 2015 among others). The basic idea is to use exogenous characteristics of peers as instrumental variables for contemporaneous peer behaviour.[4] Our identification strategy is based on the fact that certain patients are more suitable for laparoscopic surgery than others. For each patient we predict this suitability based on the detailed data we have on their exogenous characteristics (following an approach adopted by Currie et al. 2016). Our empirical model includes a measure of each surgeon's own patients suitability scores in a particular year as a regressor. To construct instruments for the endogenous peer effects, we replace the observed laparoscopic behaviour of peers with the predicted laparoscopic behaviour of peers based on the suitability of their patients. The identifying assumption is that the suitability of peers' patients does not directly determine a surgeon's laparoscopic behaviour, conditional on their own patient suitability and individual, year and hospital fixed effects.

Our results show that peer behaviour and the networks to which a surgeon belongs have quantitatively important effects on uptake of the innovation we study. We show that there are several channels that operate to increase the diffusion of innovation. Current peer effects, how well connected the individual is, proximity to pioneers (early adopters) and one high volume leader in

[2]We restrict the leaders network to comprise of a 'star' structure, in which there is a link from each leader to all other surgeons.

[3]To be more precise, due to differential exposure to common shocks, since we include year effects in our specifications.

[4]If peer characteristics enter directly into the structural equation, the researcher instead uses the exogenous characteristics of peers-of-peers as instruments, and so on.

the field all influence the individual surgeon's use of the innovation for their patients. In addition, we demonstrate that estimates that do not control for simultaneity and exposure to common shocks are upwardly biased.

We make a contribution to two distinct literatures. The first is that on variation in medical practice. It is well established that there are large differences in healthcare spending and utilization across and within regions in the U.S. and elsewhere (Finkelstein et al. (2016); Skinner (2012); IOM (2013)), with medical outcomes largely unassociated with utilization (Doyle et al. (2017); IOM (2013); Fisher et al. (2003)). These differences cannot be fully explained by random fluctuations, differences in prices across regions, income, health status (Finkelstein et al. (2016)) and preferences of patients (Barnato et al. (2007)). Recent studies have instead pointed to the fact that these differences are in part related to persistent productivity differentials across providers of care within regions (Skinner and Staiger (2015)).[5] While variations are well-established, there is much less understanding of why these persistent productivity differentials exist. Recent research has focused on the behaviour of physicians (e.g. Epstein and Nicholson (2009), Currie et al. (2016), Currie and Macleod (2018), Cutler et al (2019)). A small number of recent studies have focused on peer and work environment effects and have shown the importance of peers in determining behaviour with respect to well established medical procedures (Molitor, 2018, Chan, 2018, Silver, 2016. None of these studies have, to our knowledge, examined the role of peers in the uptake of innovation.

Agha and Molitor (2018) examine the role local opinion leaders play in easing information frictions associated with technology adoption. The paper analyzes the influence of physician investigators who lead clinical trials for new cancer drugs. By comparing diffusion patterns across 21 new cancer 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 percent more likely to receive the new drug, but utilization 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, whilst the topic studied in Agha and Molitor (2018) is related, the setting is rather different, taking place within the US system in which financial incentives for adoption are potentially stronger. More importantly, Agha and Molitor (2018) do not directly examine the effect of peers on physicians behaviour, nor deal with endogenous peers and unknown pioneers. In contrast, we address these issues directly.

This paper also makes a contribution to the literature on spatial models and identification of endogenous peer effects. Our empirical model is an extension of the Panel Spatial Autoregression model studied by Lee and Yu (2010, 2012), among others. We extend the panel SAR model in two dimensions, both of which, to the best of our knowledge, are entirely novel. First, through decomposing peers and their behaviours into present and past, and second, through introducing an unobserved leaders network.

[5] The magnitudes that are similar to those found in the manufacturing sector (Chandra et al. (2016)

2. Data and Methodology

2.1. Data

Data was linked from three main sources: the patient level hospital discharge dataset (Hospital Episodes Statistics, HES) for all patients treated by the NHS in England for financial years 2000-2014[6]; consultant level demographic and employment data from NHS Workforce Statistics for 1992-2014; and consultant-level demographic and medical education data from the General Medical Council (GMC) register, the national body that determines clinicians' qualification to practice in England.

HES contains information on patients' use of hospital care in all NHS Hospitals (known as hospital trusts but referred to here as hospitals). This information includes date and method of admission and discharge, clinical information on diagnoses and care provided. All clinicians registered to practice in England have a unique GMC code, which is recorded in each dataset, allowing the three data sources to be matched at the consultant level. In HES this code relates to the consultant who led the surgical team that undertook the procedure. The GMC data provides information on all clinicians 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. Medical registration dates are also available post-1998. NHS Workforce Statistics provide information on the surgeon's career path between 1992 and 2014, both pre- and post-becoming a senior clinician (known as a consultant in the UK), including hospital (trust) of practice, job title (career position), and grade.

Using HES data, those colorectal cancer patients for which there was a choice for surgical treatment between open and laparoscopic surgeries were identified using the Office of Population Censuses and Surveys Classification of Surgical Operations and Procedures (OPCS) (NHS Digital, 2018).[7] This produced a dataset of 276,073 patients uniquely linked to a consultant (anonymised) code. The data were then collapsed to create a single observation at consultant-year-hospital combination.[8] 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). 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 in the years prior to 2000 (the year when laparoscopic surgery for colon cancer was first used in the NHS and our HES data starts) in order to create peer and network variables (described below) and to

[6]Laparoscopic colectomy was introduced to the NHS in 2000.

[7]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, HartmannâĂŹs procedure). Laparoscopic surgeries were identified with the additional secondary OPCS codes Y75, Y50.8 or Y71.4. Only the patientsâĂŹ first colorectal surgery was included, as subsequent surgeries are less likely to offer a clinical choice of resection (Burns et al., 2014; 2013). We code any laparoscopic surgery converted into open resection (OPCS: Y71.4) as laparoscopic surgery to capture intention-to-treat laparoscopically.

[8]Only consultants with clinical expertise in performing colorectal cancer surgery and classified as in one of the following four primary specialties: general surgery, geriatric medicine, gastroenterology, and urology were included to ensure we focused on individuals for whom this kind of surgery was a normal part of their work.

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.[9] Consequently, we construct a panel of 3,522 consultants from 1992-2014, though our estimation sample is restricted to 2000-2014 due to availability of HES data.

2.1.1 Dependent variable

The dependent variable for our analysis is the proportion of colorectal cancer surgeries which were performed laparoscopically, defined as $y_{it} = lap_{it}/sur_{it}$, where lap_{it} is the number of laparoscopic colorectal cancer surgeries and sur_{it} is the number of colorectal cancer surgeries. We compute this for $t = 2000, 2001, ..., 2014$ using the HES data.

2.1.2 Surgeon characteristics

To control for surgeon characteristics, in addition to surgeon fixed effects, we use the GMC register and HES data to construct surgeon age in bands, ($age_{it}^{<40}, age_{it}^{40-44}, age_{it}^{45-49}, age_{it}^{50-54}, age_{it}^{\geq 55}$), number of laparoscopic surgeries performed in areas other than colorectal cancer surgery in year t ($olap_{it}$), surgeon experience, measured by cumulative colorectal cancer surgeries performed up to and including year t, divided by years since becoming a consultant ($exper_{it}$).[10] Each of these variables are constructed for the years $t = 2000, 2001, ..., 2014$. In addition to these consultant characteristics, we also created an index of patient suitability score for laparoscopic surgery (sco_{it} for $t = 2000, 2001, ..., 2014$). Details of the construction of this variable are in Appendix A. The basic idea is to predict patient suitability for laparoscopic surgery on the basis of a wide number of observed patient characteristics only at the end of the period we observe in HES (in the years 2012-14). This period is after the initial diffusion phase and after the issuance of national guidance in 2006 on use of laparoscopic surgery for colorectomy and a training programme aimed at training colorectal surgeons in laparoscopic surgery in 2009. Thus which patients are selected for laparoscopy should reflect good practice rather than surgeon taste. The index of patient suitability (sco_{it}) is then the mean of the suitability scores over all patients of surgeon i in year t patient suitability score.

There are a total of 3,522 surgeons in our unbalanced panel, but many of these perform very few colorectal cancer surgeries. Between 2000 and 2014 the median surgeon performs just 4.5 colorectal cancer surgeries per year on average, whilst the tenth percentile is 1.75. For this reason, we restrict our estimation sample to those surgeons at or above the 0.6 percentile of cancer surgeries per year on average (i.e. total colorectal surgeries divided by number of years in the sample between 2000 and 2014), which corresponds to 1,466 surgeons with average annual volumes at least equal to 6.

Tables 1 and 2 respectively summarise the data for all consultants and the estimation sample in the first and last years of the estimation sample (2000 and 2014). There are no clear differences between the two samples in terms of age composition, patient suitability scores nor number of laparoscopic surgeries for conditions other than colorectal cancer. The estimation sample comprises

[9] This results in a dataset of 65,366 consultant-hospital-year observations covering 1992-2014 and contains data on surgeons prior to their appointment as consultants.

[10] Additional time varying variables at the consultant-year level that were calculated included a mortality indicator (the ratio of patients discharged dead to all colorectal cancer surgery patients) and a binary indicator of moving hospital.

more experienced consultants, who perform more colorectal cancer surgeries on average. Surgeons in the estimation sample also perform a higher proportion of laparoscopic colorectal cancer surgeries in 2014 (mean of 0.486) compared with all surgeons (mean of 0.416), though there is no difference in 2000.

2.1.3 Networks

We use the NHS Workforce Statistics to define networks based on the hospital in which a surgeon practices for the years 1992-2014. This period overlaps with the HES data (from 2000 onwards) but also gives us additional information on surgeon's work histories prior to 2000 (but not their surgical activity). In a given year we say that there exists a link between two surgeons if they practice in the same hospital. This permits us to define three networks, which we characterize by the time-varying, symmetric $N \times N$ adjacency matrices $\mathbf{A}_t^n$, $\mathbf{A}_t^p$ and $\mathbf{A}_t$ for $t = 1992, 1993, ..., 2014$. The entries are defined as:

$$\mathbf{A}_{ijt}^n = \begin{cases} 1 & \text{if i and j work in the same hospital in year t and } j \neq i \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

$$\mathbf{A}_{ijt}^p = \begin{cases} 1 & \text{if } \sum_{s=1992}^{t-1} \mathbf{A}_{ijt}^n > 0 \text{ and } \mathbf{A}_{ijt}^n = 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

$$\mathbf{A}_{ijt} = \mathbf{A}_{ijt}^p + \mathbf{A}_{ijt}^n \tag{2.3}$$

These undirected (i.e. symmetric) networks keep track of each surgeon's present links ($\mathbf{A}_t^n$), past links ($\mathbf{A}_t^p$) and combined present and past links ($\mathbf{A}_t$). The networks evolve over time as surgeons move between hospitals. The networks are constructed such that a link between j and i in year t may exist either in the present network, or the past network, but not both simultaneously. Hence, if i works in the same hospital as j in year t, and has also previously worked in the same hospital as j we would say that j is a current link of i ($\mathbf{A}_{ijt}^n = 1$) but not a past link ($\mathbf{A}_{ijt}^p = 0$). We do this to avoid double counting the behaviour of j when constructing our peer effects variables below. We now proceed to describe the network-related covariates to be included in our analysis.

2.1.4 Diffusion over networks

The heat maps below show the diffusion over the network. To read these heatmaps: *white* $\rightarrow y_{it} = 0$, *red* $\rightarrow y_{it} = 1$. The diagrams are constructed using a spring algorithm, so as to place surgeons close to other surgeons with whom they are linked. To make the figure less noisy, each surgeon is shaded by the average y_{it} among the 10 closest surgeons (according to their location on the diagram, and including themselves). This 'smoothing' allows us to get an idea of heteroegeneity in diffusion over different parts of the network (it can be thought of as similar to a non-parametric smoother e.g. nearest neighbours regression). Broadly speaking, the heat maps show evidence of heterogeneity in diffusion over the network. This could be due to peer effects, information flows etc. of the kind we investigate here. It could, of course, also be due to other sources of heterogeneity (age, individual effects, hospital effects etc.) and therefore we need to condition on these, which we do in the formal analysis.

2.1.5 Peer effects

To examine how the laparoscopic behaviour of a surgeon i's peers determines their own laparoscopic behaviour we exploit the richness of our panel data. We decompose peers into present and past using the networks defined above, and peer laparoscopic behaviour into present and past. This allows us to study peer effects in a dynamic setting. We study four possible peer effects on surgeon i in year t, defined below. To construct the peer effects variables, we combine our networks with the HES data to define the following peer effects covariates for $t = 2000, 2001, ..., 2014$.[11]

- 'Now-now' peer effects ($\overline{y}_{it}^{nn}$): The proportion of laparoscopic surgeries in year t among other surgeons in the same hospital as surgeon i in year t. This measures the impact of current behaviour among i's current peers. It is defined as:

$$\overline{y}_{it}^{nn} = \sum_{j=1}^{N} w_{ijt}^{nn} \mathbf{A}_{ijt}^{n} y_{jt} \tag{2.4}$$

$$w_{ijt}^{nn} = \frac{sur_{jt}}{\sum_{k=1}^{N} \mathbf{A}_{ikt}^{n} sur_{kt}} \tag{2.5}$$

  where w_{ijt} weights each peer of i by the number of colorectal cancer surgeries performed, and the weights are normalised to sum to 1. Weighting in this way implies that the behaviour of i is equally influenced by each colorectal cancer surgery performed by a peer. Consequently, an equivalent definition is:

$$\overline{y}_{it}^{nn} = \frac{\sum_{j=1}^{N} \mathbf{A}_{ijt}^{n} lap_{jt}}{\sum_{j=1}^{N} \mathbf{A}_{ijt}^{n} sur_{jt}} \tag{2.6}$$

  which is the proportion of laproscopic surgeries among all surgeries conducted by other surgeons in the same hospital. A similar interpretation applies to the remaining peer effects.

  The above definition cannot be applied to construct the peer effect for surgeons with no peers (i.e. $\mathbf{A}_{ijt}^{n} = 0$ for $j = 1, ..., N$). In this event we set $\overline{y}_{it}^{nn} = 0$, which means that having no peers is equivalent to having peers which do zero laparoscopic surgeries.[12] We adopt the same convention for the remaining peer effects.

- 'Past-now' peer effects ($\overline{y}_{it}^{pn}$): The proportion of laparoscopic surgeries in year t among other surgeons with which surgeon i has worked with in years $1992, 1993..., t-1$ but does not work

[11]Peer effects are constructed for laproscopic surgery, which is recorded in HES and starts in t=2000. The networks are defined from 1992.

[12]Our analysis also conditions on number of peers, see Section 2.1.8

with in year t. This measures the impact of current behaviour among i's past peers. It is defined identically to $\overline{y}_{it}^{nn}$, replacing $\mathbf{A}^n$ with $\mathbf{A}^p$.

- 'Now-past' peer effects ($\overline{y}_{it}^{np}$): The proportion of laparoscopic surgeries in years $2000, 2001, ..., t-1$ for surgeons in the same hospital as surgeon i in year t. In constructing this variable, we only consider surgeries by surgeon j in years in which i and j worked together. That is, we only consider peer laparoscopic behaviour to which surgeon i was exposed. This measures the impact of past behaviour among i's current peers. For $t = 2001, 2002, ..., 2014$ it is defined as:

$$\overline{y}_{it}^{np} = \sum_{s=2000}^{t-1} \sum_{j=1}^{N} w_{ijs}^{np} \mathbf{A}_{ijt}^n \mathbf{A}_{ijs}^n y_{js} \tag{2.7}$$

$$w_{ijs}^{np} = \frac{sur_{js}}{\sum_{r=2000}^{t-1} \sum_{k=1}^{N} \mathbf{A}_{ikt}^n \mathbf{A}_{ikr}^n sur_{kr}} \tag{2.8}$$

For $t = 2000$, we set $\overline{y}_{it}^{np} = 0$ for all i, since laparoscopic colorectal cancer surgery did not take place prior to 2000.

- 'Past-past' peer effects ($\overline{y}_{it}^{pp}$): The proportion of laparoscopic surgeries in years $1992, 1993, ..., t-1$ among other surgeons with which surgeon i has worked with in years $2000, 2001, ..., t-1$ but does not work with in year t. In constructing this variable, we only consider surgeries by surgeon j in years in which i and j worked together. That is, we only consider peer laparoscopic behaviour to which surgeon i was exposed. This measures the impact of past behaviour among i's past peers. It is defined identically to $\overline{y}_{it}^{np}$, replacing $\mathbf{A}_{ijt}^n$ and $\mathbf{A}_{ikt}^n$ with $\mathbf{A}_{ijt}^p$ and $\mathbf{A}_{ikt}^p$ respectively.

2.1.6 Leaders

We also consider peer effects arising from 'leaders', the identities of which we treat as unknown and seek to estimate. We suppose that the year t behaviour of a few particular surgeons ('leaders') determines the year t behaviour of all other surgeons. This is equivalent to introducing additional covariates, one for each potential leader. When estimating the model, we assume that there are only a few leaders and we treat their identities as unknown. This is equivalent to assuming that the parameter vector associated with the leader variables defined below is sparse (i.e. it has many entries equal exactly to zero). To achieve this, we apply the high-dimensional instrumental variables (STIV) estimator of Gautier et al, (2018).

For each potential leader j, we define for $t = 2000, 2001, ..., 2014$:

$$\tilde{y}_{it}^{j} = \mathbf{1}_{\{j \neq i\}} \mathbf{1}_{\{sur_{jt} > 0\}} (1 - \mathbf{A}_{ijt}) y_{jt} \tag{2.9}$$

where $\mathbf{1}_{\{c\}}$ is the indicator for condition c. We include the $(1 - \mathbf{A}_{ijt})$ so that a leader is presumed to influence surgeon i in year t through this channel only if they are unknown to one another (in the sense that they have never worked in the same hospital at the same time). We do this to avoid double counting of behaviour, since if $\mathbf{A}_{ijt} = 1$ then the behaviour of j is captured by the peer effects covariates described in the previous section. It is also important for identification, since if we were to omit $(1 - \mathbf{A}_{ijt})$ then the leader variables would be almost collinear with year fixed effects, which we also include in our specification.[13]

We define $\widetilde{y}_{it}^{j}$ for each j in a set of potential leaders. We suppose that potential leaders are those with high average annual volumes of colorectal cancer surgery. We consider the set of potential leaders to be those surgeons in the top 5% of the average annual volume of colorectal cancer surgeries over 2000-2014. That is, for each surgeon, we divide the the total number of colorectal cancer surgeries between 2000 and 2014 and divide by the number of years observed in the data over the same period. We then take the top 5% of surgeons in this measure as our potential leaders. This yields 73 potential leaders, which we denote by $J \subseteq \{1, 2, ..., N\}$.

2.1.7 Endogeneity and instrumental variables

In a cross-section setting, endogeneity of the peer effects covariates is well known due to simultaneity of behaviour and exposure to common shocks. In our longitudinal setting, this implies that all peer effects variables based on year t behaviour $(\overline{y}_{it}^{nn}, \overline{y}_{it}^{pn}, \widetilde{y}_{it}^{j})$ are endogenous by construction. Consequently, our identification strategy follows an instrumental variables approach. To construct instruments, we replace y_{jt} in the definitions of each endogenous covariate listed above with the suitability score sco_{jt}, which yields the instrumental variables $\overline{sco}_{it}^{nn}, \overline{sco}_{it}^{pn}, \widetilde{sco}_{it}^{j}$. The instruments depend on only the networks, patient characteristics and volumes of colorectal cancer surgeries, and are thus plausibly exogenous in our model.

The exclusion restrictions thus require that the suitability scores of other surgeons' patients do not directly influence surgeon i's laparoscopic behaviour conditional on the score of i's patients, individual and year fixed effects and the other exogenous covariates listed in this section.

We treat peer effects based on past behaviour $(\overline{y}_{it}^{np}, \overline{y}_{it}^{pp})$ as exogenous, since simultaneity is broken by the temporal lag.

2.1.8 Network location

In addition to peer effects, we consider the role of i's position in the networks. Specifically, we consider:

- The number of other surgeons with which surgeon i works in year t. This measures the number of current connections, and is referred to as the degree. We define:

$$deg_{it}^{n} = \sum_{j=1}^{N} \mathbf{A}_{ijt}^{n} \tag{2.10}$$

[13] Omitting $(1 - \mathbf{A}_{ijt})$ yields $\widetilde{y}_{it}^{j} = \mathbf{1}_{\{j \neq i\}} \mathbf{1}_{\{sur_{jt} > 0\}} y_{jt}$. If our panel were balanced we would have $\mathbf{1}_{\{sur_{jt} > 0\}} = 1$, so that $\widetilde{y}_{it}^{j} = \mathbf{1}_{\{j \neq i\}} y_{jt}$. Consequently, $\widetilde{y}_{it}^{j}$ would take the same value for all $N - 1$ surgeons other than j, which would be almost collinear with an indicator for year t. Although our panel is not balanced, we observe most surgeons in most years, and so the above concerns still apply, though to a slightly lesser extent.

- The number of other surgeons with which i has worked in years 1992, , $t-1$ but does not work with in year t. This measures the number of past connections. We define:

$$deg_{it}^{p} = \sum_{j=1}^{N} \mathbf{A}_{ijt}^{p} \tag{2.11}$$

- The distance in the network to the nearest pioneer, defined as a surgeon who has performed at least 15 laparoscopic surgeries up to and including 2005.[14] We construct $dispio_{it}$ as the number of links traversed in the network represented by $\mathbf{A}_t$ (i.e. there exists a link between two surgeons if they have ever worked together, up to and including year t) to the nearest pioneer. Distance has range $0, 1, 2, ..., \infty$. A value of 0 means that i is a pioneer, 1 means that i has worked in the same trust as a pioneer up to and including year t (but i is not a pioneer), 2 means that i has worked in the same trust as a surgeon who has worked in the same trust as a pioneer (but i is not a pioneer and has not worked in the same trust as a pioneer up to and including year t), and so on. A value of ∞ means that i is not a pioneer and cannot reach a pioneer by traversing links in the network. This could arise if i has never worked in the same trust as another surgeon in our sample.

  We then construct indicators for $dispio_{it} = 1$ ($dispio1_{it}$) and $dispio_{it} = 2$ ($dispio2_{it}$) to include in our regressions. The excluded group are those surgeons with $dispio_{it} > 2$.[15]

[14] We define pioneer status as a time invariant characteristic of a surgeon. That is, we say that a surgeon is a pioneer in all years if they reach 15 laparoscopic surgeries by the end of 2005.

[15] The indicator for $dispio_{it} = 0$ is not time-varying, and so is absorbed into the surgeon fixed effect.

Table 1: *Summary statistics for all 3,522 surgeons*

	Mean	SD	Min	Max	n	Mean	SD	Min	Max	n
			2000					2014		
Dependent variable										
y_{it}	0.01	0.062	0	1	1093	0.416	0.346	0	1	1446
lap_{it}	0.167	0.737	0	10	1093	8.584	10.618	0	66	1446
sur_{it}	18.357	18.659	1	112	1093	16.211	14.929	1	71	1446
Peer effects										
$\overline{y}_{it}^{nn}$	0.009	0.02	0	0.4	1093	0.527	0.151	0.043	0.922	1446
$\overline{y}_{it}^{pn}$	0.009	0.03	0	0.5	1093	0.545	0.085	0	0.842	1446
$\overline{y}_{it}^{np}$	0	0	0	0	1093	0.326	0.165	0	0.832	1446
$\overline{y}_{it}^{pp}$	0	0	0	0	1093	0.125	0.119	0	0.765	1446
$\overline{sco}_{it}^{nn}$	0.488	0.055	0	0.571	1093	0.502	0.023	0.373	0.572	1446
$\overline{sco}_{it}^{pn}$	0.43	0.165	0	0.592	1093	0.5	0.044	0	0.56	1446
Network location										
deg_{it}^{n}	16.32	10.28	0	56	1093	22.44	9.69	5	45	1446
deg_{it}^{p}	26.36	19.28	0	98	1093	109.49	51.95	0	282	1446
$dispio1_{it}$	0.57	0.50	0	1	1093	0.791	0.401	0	1	1446
$dispio2_{it}$	0.378	0.485	0	1	1093	0.168	0.374	0	1	1446
Surgeon characteristics										
$age_{it}^{<40}$	0.181	0.385	0	1	1090	0.295	0.456	0	1	1442
age_{it}^{40-44}	0.277	0.448	0	1	1090	0.281	0.45	0	1	1442
age_{it}^{45-49}	0.248	0.432	0	1	1090	0.205	0.404	0	1	1442
age_{it}^{50-54}	0.18	0.384	0	1	1090	0.139	0.346	0	1	1442
$olap_{it}$	30.732	36.84	0	307	1093	85.596	71.507	0	746	1446
$exper_{it}$	5.387	9.221	0.125	77	943	19.795	17.255	0.05	114	1368
sco_{it}	0.466	0.087	0.059	0.701	1090	0.461	0.119	0.037	0.817	1442

Table 2: *Summary statistics for estimation sample of 1,466 surgeons*

	Mean	SD	Min	Max	n	Mean	SD	Min	Max	n
			2000					2014		
Dependent variable										
y_{it}	0.008	0.03	0	0.256	650	0.486	0.29	0	1	923
lap_{it}	0.24	0.897	0	10	650	12.966	11.079	0	66	923
sur_{it}	27.409	19.334	1	112	650	23.629	13.953	1	71	923
Peer effects										
$\overline{y}_{it}^{nn}$	0.008	0.02	0	0.208	650	0.543	0.162	0	0.952	923
$\overline{y}_{it}^{pn}$	0.008	0.021	0	0.25	650	0.562	0.085	0	0.929	923
$\overline{y}_{it}^{np}$	0	0	0	0	650	0.338	0.17	0	0.819	923
$\overline{y}_{it}^{pp}$	0	0	0	0	650	0.125	0.127	0	1	923
$\overline{sco}_{it}^{nn}$	0.482	0.095	0	0.577	650	0.51	0.028	0	0.577	923
$\overline{sco}_{it}^{pn}$	0.415	0.188	0	0.586	650	0.508	0.039	0	0.566	923
Network location										
deg_{it}^{n}	6.491	3.862	0	19	650	8.472	3.758	0	17	923
deg_{it}^{p}	10.272	7.484	0	38	650	44.391	19.473	0	102	923
$dispio1_{it}$	0.52	0.5	0	1	650	0.764	0.425	0	1	923
$dispio2_{it}$	0.385	0.487	0	1	650	0.172	0.378	0	1	923
Surgeon characteristics										
$age_{it}^{<40}$	0.177	0.382	0	1	648	0.284	0.451	0	1	920
age_{it}^{40-44}	0.276	0.447	0	1	648	0.279	0.449	0	1	920
age_{it}^{45-49}	0.225	0.418	0	1	648	0.207	0.405	0	1	920
age_{it}^{50-54}	0.191	0.394	0	1	648	0.15	0.357	0	1	920
$olap_{it}$	33.502	36.808	0	307	650	82.436	62.583	0	746	923
$exper_{it}$	8.044	11.108	0.333	77	558	29.105	14.652	0.545	114	883
sco_{it}	0.487	0.062	0.103	0.701	650	0.491	0.08	0.043	0.686	923

3. Estimation

Our baseline specification for surgeon $i = 1, 2, ..., N$ in year $t = 2000, 2001, ..., 2014$ in hospital $h(i,t)$ is:

$$y_{it} = \alpha_i + \mu_t + \gamma_{h(i,t)} + \sum_{(a,b)\in\{n,p\}^2} \beta_{ab}\overline{y}_{it}^{ab} + \sum_{j\in J} \beta_j \widetilde{y}_{it}^{j} + \mathbf{x}_{it}'\delta + \epsilon_{it} \tag{3.1}$$

where α_i, μ_t and $\gamma_{h(i,t)}$ are respectively surgeon, year and hospital fixed effects, $\sum_{(a,b)\in\{n,p\}^2} \beta_{ab}\overline{y}_{it}^{ab}$ captures workplace peer effects, $\sum_{j\in J} \beta_j \widetilde{y}_{it}^{j}$ captures leader effects, $\mathbf{x}_{it}$ stacks network location covariates and consultant characteristics and ϵ_{it} is the disturbance. For specifications restricting $\beta_j = 0$ for $j \in J$, we apply OLS to estimate the parameters. Otherwise, we apply the STIV estimator of Gautier et al, (2018).

The STIV estimator is an instrumental variables estimator designed for a 'high-dimensional' setting. In particular, it does not restrict the relative magnitudes of the sample size, number of parameters and number of instruments. For instance, the number of parameters can be larger than the sample size, or the number of instruments can be fewer than the number of parameters. In our application, the number of instruments is equal to the number of parameters (=88: 4 peer effects, 73 leaders, 4 network location covariates, and 7 surgeon characteristics), which is relatively large compared to the sample size. Gautier et al, 2018 (Section 8.2) also derive confidence intervals, which we apply here. To facilitate comparison of OLS and STIV, we report confidence intervals as opposed to standard errors, since the confidence intervals for the STIV estimator are not constructed in the conventional way (i.e. by inverting a t-test).[16]

The STIV estimator yields sparse solutions (i.e. many of the parameters are estimated to be precisely zero). Sparsity is achieved through the addition of a penalty term in the objective function, which penalizes the sum of absolute values of the entries of the parameter vector or a subset of the parameter vector. In our application, we apply the penalty to the 77 entries of β_j for $j \in J$. This approach is well suited to our assumption that there are relatively few leaders among the set of potential leaders, but that their identities are unknown. Further details and performance guarantees for the STIV estimator are available in Gautier et al, (2018).

4. Results

Table 3 presents our results. Throughout this section, to interpret the magnitudes of the effects we present the effect of a year 2014 standard deviation change in the covariates (see Table 2) measured in year 2014 standard deviations of the proportion of laparoscopic surgeries.

In the 'OLS' column, we apply the least squares estimator to (3.1) under the restriction $\beta^j = 0$ for $j \in J$ (i.e. no leader effects). We find a positive and statistically significant peer effect based on current behaviour among current links ($\overline{y}_{it}^{nn}$). The effect is quite large: a standard deviation increase in $\overline{y}_{it}^{nn}$ is associated with a 0.16 standard deviation increase in the proportion of laparoscopic surgeries.

[16] We modify slightly the sample splitting procedure to fit our panel data setting. Instead of taking a random sample of observations, we take a random sample of consultants, keeping all of their observations together.

However, much of this effect is likely due to positive bias arising from simultaneity of behaviour and exposure of a surgeon and her peers to common shocks. The effect of the past behaviour of a surgeon's current links (y_{it}^{np}) is positive and statistically significant at the 0.1 level, though it is small in magnitude. The other peer effects are close to zero and statistically insignificant.

All of the network location variables have a positive sign, though only the number of past links (deg_{it}^{p}) is statistically significant at the 0.05 level. Each additional past connection is associated with an increase of 0.3 percentage points in the proportion of laparoscopic colorectal cancer surgeries. Whilst each additional connection has only a small impact, a standard deviation increase in the number of past connections is associated with a 0.20 standard deviation increase in the proportion of laparscopic surgeries.

The coefficients on the age dummies suggest an inverted-U association between uptake of laparoscopic surgery and consultant age. All else equal, consultants aged under 40 are similar to those 55 and over, with the highest uptake occurring between 44 and 49. The number of laparoscopic surgeries performed for diseases other than colorectal cancer and consultant experience are both positively and statistically significantly associated with the proportion of laparscopic surgeries (y_{it}). A standard deviation increase in the number of laparscopic surgeries for diseases other than colorectal cancer ($olap_{it}$) is associated with a 0.18 standard deviation increase in the proportion of laparscopic surgeries. For experience the effect of a standard deviation increase is smaller, with a standard deviation increase of 0.03.

The patient suitability score has a large, positive and statistically significant coefficient. The coefficient suggests that moving from a mean patient suitability of 0 to 1 is associated with an increase in the proportion of laparoscopic surgeries by around 0.5. Whilst this might appear large, a reasonable benchmark for this effect would be 1, which lies outside the confidence interval. This suggests that surgeons' behaviour is substantially influenced by factors other than patient suitability. Indeed, a standard deviation increase in the suitability score is associated with only a 0.14 standard deviation increase in the proportion of laparoscopic surgeries.

We now relax the restriction of no leader effects. This increases substantially the number of parameters to be estimated relative to OLS. To enable us to examine the effect of changing both the assumption of exogeneity of peer effects and the number of peer effects that are estimated, we report two sets of estimation results for the STIV estimator, the first under exogeneity (STOLS) and the second under endogeneity of contemporaneous peer effects (STIV).

The 'STOLS' column reports estimation results for the STIV estimator applied to (3.1) treating all covariates as exogenous. Relative to OLS, we find that all of the peer effects increase in magnitude. Moreover, the effect of proximity to an pioneer ($dispio1_{it}$,$dispio2_{it}$) increase in magnitude, and the coefficient on $dispio1_{it}$ is statistically significant at the 0.1 level. The estimator returns five non-zero coefficients, corresponding to five leaders. All of the coefficients are positive and all but one are statistically significant at the 0.05 level. However, as with the other peer effects, we expect positive bias due to simultaneity and exposure to common shocks.

The 'STIV' column reports estimation results for the STIV estimator applied to (3.1) treating the covariates based on the contemporaneous laparoscopic behaviour of other surgeons ($\overline{y}_{it}^{nn}$, $\overline{y}_{it}^{pn}$, $\widetilde{y}_{it}^{j}$) as endogenous. As discussed in Section 2.1.7, our identification strategy is based on instruments

($\overline{sco}_{it}^{nn}, \overline{sco}_{it}^{pn}, \widetilde{sco}_{it}^{j}$) which replace y_{jt} with the suitability score sco_{jt} in the definition of the endogenous covariates.

Relative to the 'STOLS' estimator, the instrumental variables approach reduces the magnitudes of all of the peer effects, though the effect of current peers' current behaviour remains positive and statistically significant. The reduction in magnitudes of the endogenous peer effects variables can be attributed to a reduction in positive bias due to simultaneity and common shocks. Additionally, the estimator returns only one non-zero leader parameter, which is a subset of the five leaders suggested by the STOLS estimator. The associated parameter has decreased in magnitude by a factor of a around a half. As with the other peer effects, this change is likely due to a reduction in positive bias. With regard to finding one (as opposed to five) leaders, there are two possible explanations. The first is that the STOLS estimator spuriously yields non-zero coefficients for four of the leaders due to upwards bias, which is corrected by the STIV estimator. The second is that the STIV estimator has lower precision than STOLS (as does the IV estimator relative to OLS), and so it is more conservative in setting the parameters equal to zero.

These two explanations would apply equally if we had applied OLS and IV and compared t-statistics for the null hypothesis of equality to zero. We would fail to reject the null with higher probability with the IV estimator than with the OLS estimator for two reasons. First, because the IV coefficient will typically be smaller in magnitude than the OLS coefficient, and second because it will typically be less precisely estimated. Thus, the numerator of the t-statistic is smaller, and the denominator larger, and so the t-statistic is smaller under IV than OLS.

Parameter estimates for three of the network location covariates are larger in magnitude for STIV than STOLS/OLS. The effect of the number of current links (deg_{it}^{p}) remains close to zero and statistically insignificant, whilst the number of past links maintains a positive and significant coefficient close to those of OLS and STOLS. There is, however, an increase in the effect size of pioneer proximity, with the parameter estimates for the indicators of having worked at the same hospital as a pioneer ($dispio1_{it}$) and having worked at the same hospital as a surgeon who has worked at the same hospital as a pioneer ($dispio2_{it}$) both increasing in magnitude. The former is statistically significant at the 0.05 level. Having worked in the same hospital as a pioneer increases the proportion of laparoscopic surgeries by 6.5 percentage points relative to surgeons who have never worked with a pioneer nor with another surgeon who has worked with a pioneer. This effect size corresponds to a 0.22 standard deviation increase in the proportion of laparoscopic surgeries.

The STIV estimator suggests a similar inverted-U age profile to OLS/STOLS. The coefficient on the number of laparoscopic surgeries for diseases other than colorectal cancer also remains similar, though the coefficient on experience is smaller in magnitude and not statistically significant.

We now consider the relative importance of determinants of laparoscopic behaviour. To do this, we use our STIV results to compare the relative effect sizes of year 2014 standard deviation changes in determinants, measured in year 2014 standard deviations of the proportion of laparoscopic surgeries. For dummy variables, we consider instead a change from 0 to 1.

In decreasing effect size, the determinants which induce more than a 0.1 standard deviation change in laparoscopic behaviour are: the number of laparoscopic surgeries for diseases other than

Table 3: *Estimation Results*

Dep. var. y_{it} (range $[0,1]$)	OLS	STOLS	STIV
Peer effects			
$\overline{y}_{it}^{nn}$	0.283^{**}	0.452^{**}	0.206^{**}
	[0.251,0.315]	[0.406,0.499]	[0.130,0.282]
$\overline{y}_{it}^{pn}$	0.0296	0.115^{**}	0.110
	[-0.020,0.079]	[0.012,0.217]	[-0.038,0.259]
$\overline{y}_{it}^{np}$	0.0496^{*}	0.191^{**}	0.004
	[-0.001,0.100]	[0.114,0.269]	[-0.131,0.140]
$\overline{y}_{it}^{pp}$	-0.0265	-0.2346^{**}	0.031
	[-0.087,0.034]	[-0.348,-0.121]	[-0.117,0.179]
$\widetilde{y}_{it}^{11}$		0.403^{**}	
		[0.161,0.645]	
$\widetilde{y}_{it}^{28}$		0.008	
		[-0.238,0.255]	
$\widetilde{y}_{it}^{43}$		0.260^{*}	
		[-0.044,0.565]	
$\widetilde{y}_{it}^{64}$		0.143	
		[-0.029,0.315]	
$\widetilde{y}_{it}^{72}$		0.341^{**}	0.164
		[0.201,0.481]	[-0.053,0.382]
Network location			
deg_{it}^{n}	0.00177^{*}	-0.00115	0.00139
	[-0.00015,0.00369]	[-0.00458,0.00227]	[-0.00234,0.00512]
deg_{it}^{p}	0.00301^{**}	0.00346^{**}	0.00359^{**}
	[0.0018,0.0042]	[0.0021,0.0048]	[0.0017,0.0054]
$dispio1_{it}$	0.0273	0.0466^{*}	0.0650^{**}
	[-0.079,0.134]	[-0.004,0.097]	[0.011,0.119]
$dispio2_{it}$	0.0281	0.0288	0.0394
	[-0.074,0.130]	[-0.021,0.079]	[-0.014,0.093]
Surgeon characteristics			
$age_{it}^{<40}$	-0.00574	-0.0467^{**}	-0.0327^{**}
	[-0.053,0.041]	[-0.066,-0.027]	[-0.060,-0.005]
age_{it}^{40-44}	0.0270	0.0564^{**}	0.0235^{**}
	[-0.010,0.063]	[0.0448,0.0680]	[0.0075,0.0393]
age_{it}^{44-49}	0.0356^{**}	0.0158^{**}	0.0435^{**}
	[0.010,0.062]	[0.003,0.028]	[0.025,0.062]
age_{it}^{50-54}	0.0212^{**}	0.0110	-0.0091
	[0.005,0.038]	[-0.003,0.025]	[-0.030,0.012]
$olap_{it}$	0.000830^{**}	0.00112^{**}	0.00118^{**}
	[0.00072,0.00094]	[0.00092,0.00134]	[0.00087,0.00148]
$exper_{it}$	0.000675^{**}	0.001286^{**}	0.00008
	[0.00015,0.00120]	[0.00053,0.00205]	[-0.00112,0.00127]
sco_{it}	0.505^{**}	0.623^{**}	0.572^{**}
	[0.459,0.550]	[0.517,0.729]	[0.429,0.715]
Consultant FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes
Leaders	No	Yes	Yes
Sample size	11,266	11,259	11,259

Notes: 95% confidence intervals in brackets. $**$: significant at the 0.05 level, $*$: significant at 0.1 level. The STOLS column applies the estimator of Gautier et al, (2018) treating all covariates as exogenous. The STIV column applies the estimator of Gautier et al, (2018) treating contemporaneous peer effects ($\overline{y}_{it}^{nn}$, $\overline{y}_{it}^{pn}$, $\widetilde{y}_{it}^{j}$) as endogenous, with corresponding instruments ($\overline{sco}_{it}^{nn}$, $\overline{sco}_{it}^{pn}$, $\widetilde{sco}_{it}^{j}$). Only non-zero estimates of β^{j} are reported in models with Leaders.

colorectal cancer ($olap_{it}$, 0.25), the number of past links (deg^{p}_{it}, 0.24), having worked in the same hospital as a pioneer ($dispio1_{it}$, 0.22), patient suitability (sco_{it}, 0.16), being aged 44-49 (age^{44-49}_{it}, 0.15), having worked in the same hospital as a surgeon who has worked with a pioneer ($dispio2_{it}$, 0.14), the laparoscopic behaviour of other surgeons in the same hospital in the same year ($\overline{y}^{nn}_{it}$, 0.12) and leader laparoscopic behaviour ($\widetilde{y}^{72}_{it}$, 0.10).

In sum, the results show that both the workplace network and peer effects play important roles in determining the uptake of laparoscopic surgery. In terms of networks, the number of past links that a surgeon has plays a large effect and workplace proximity to a pioneer is also important. With regard to peer effects, it seems that surgeons' behaviour depends to a much larger extent on the contemporaneous behaviour of others in the same hospital as opposed to the past behaviour of their direct colleagues. Finally, the laparoscopic behaviour of leaders also seems to play an important role.

5. Conclusion

The focus of this paper is the effect of work network and peer behaviour on the uptake of a highly cost-effective medical innovation. We use matched data on patient treatment and surgeon employment to create a rich panel data set that allows us to construct surgeons' networks (whom they worked with and when) and the behaviour of peers. Our model contains present and past peers and the behaviour of each types of peers in the present and past and a measure of distance to pioneers of the innovation. In our estimation, we treat these peer effects as endogenous. We also allow for two networks through which peer effects may operate: an observable workplace network and an unobservable network of 'leaders' in the innovation process.

Our results show the importance of multiple peer and network effects. We show uptake operates through several channels. We identify an effect of current behaviour of workplace colleagues (a peer effect), distance to pioneers (a network effect), number of connections (a network effect) and the effect of (one) leader in the field (a network effect). While we cannot identify exactly how these effects operate, our results are commensurate with information flows between surgeons and, for the peer effects, access to resources for such surgery in the hospital. We can however rule out the explanation of an absence of facilities for laparoscopic surgery at the hospital level as all the hospitals in our sample have these facilities.

More generally, our results show the importance of multiple channels influencing behaviour in this field. In terms of policy, our findings suggests first, that using multiple channels may be better than simply using one and, second, that focusing on individuals who have good networks may be less cost-effective that trying to identify those who are outside those networks and targeting efforts on providing them with better connections to leaders and early adopters.

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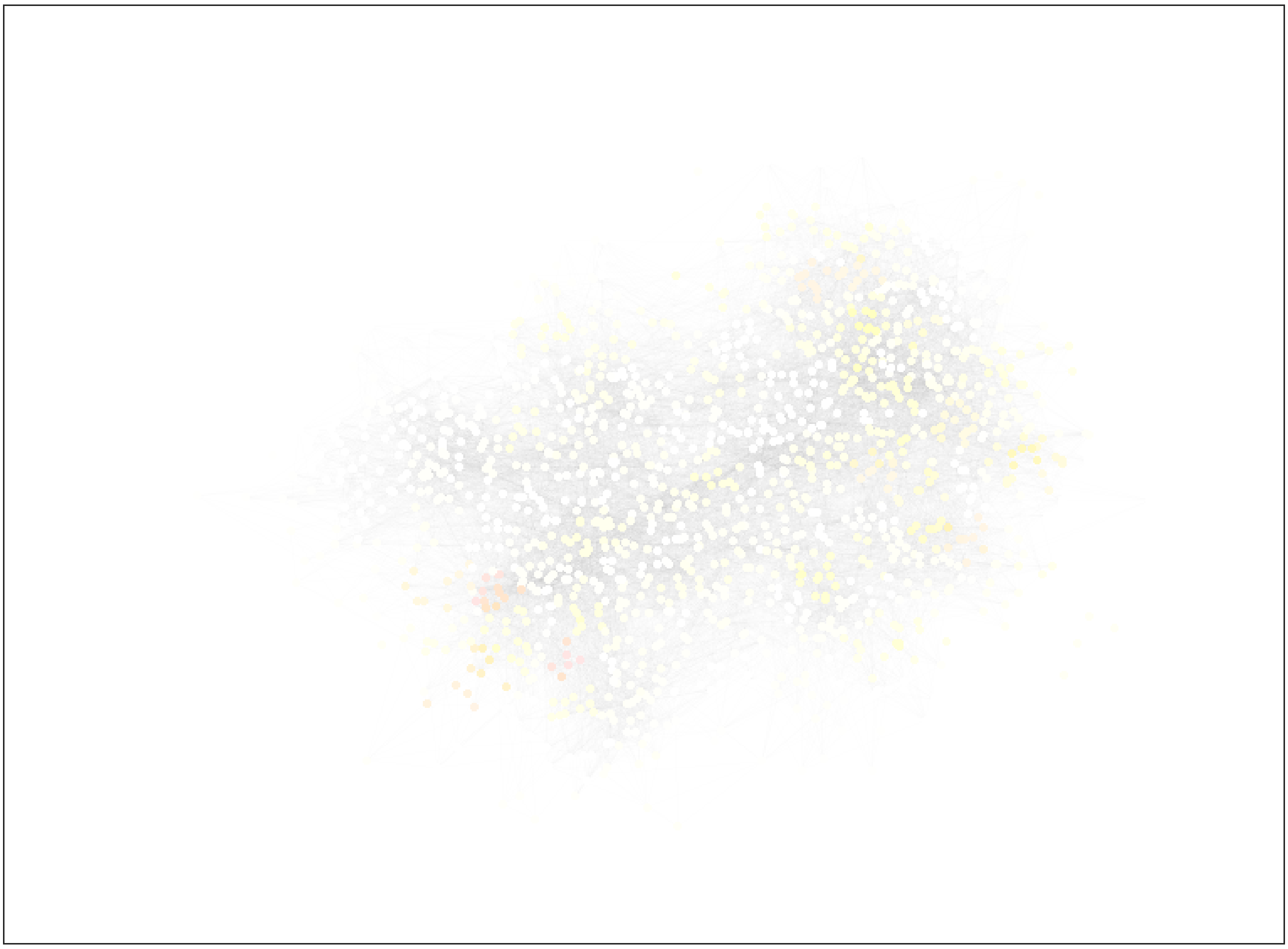

Figure 1: *Diffusion by 2004*

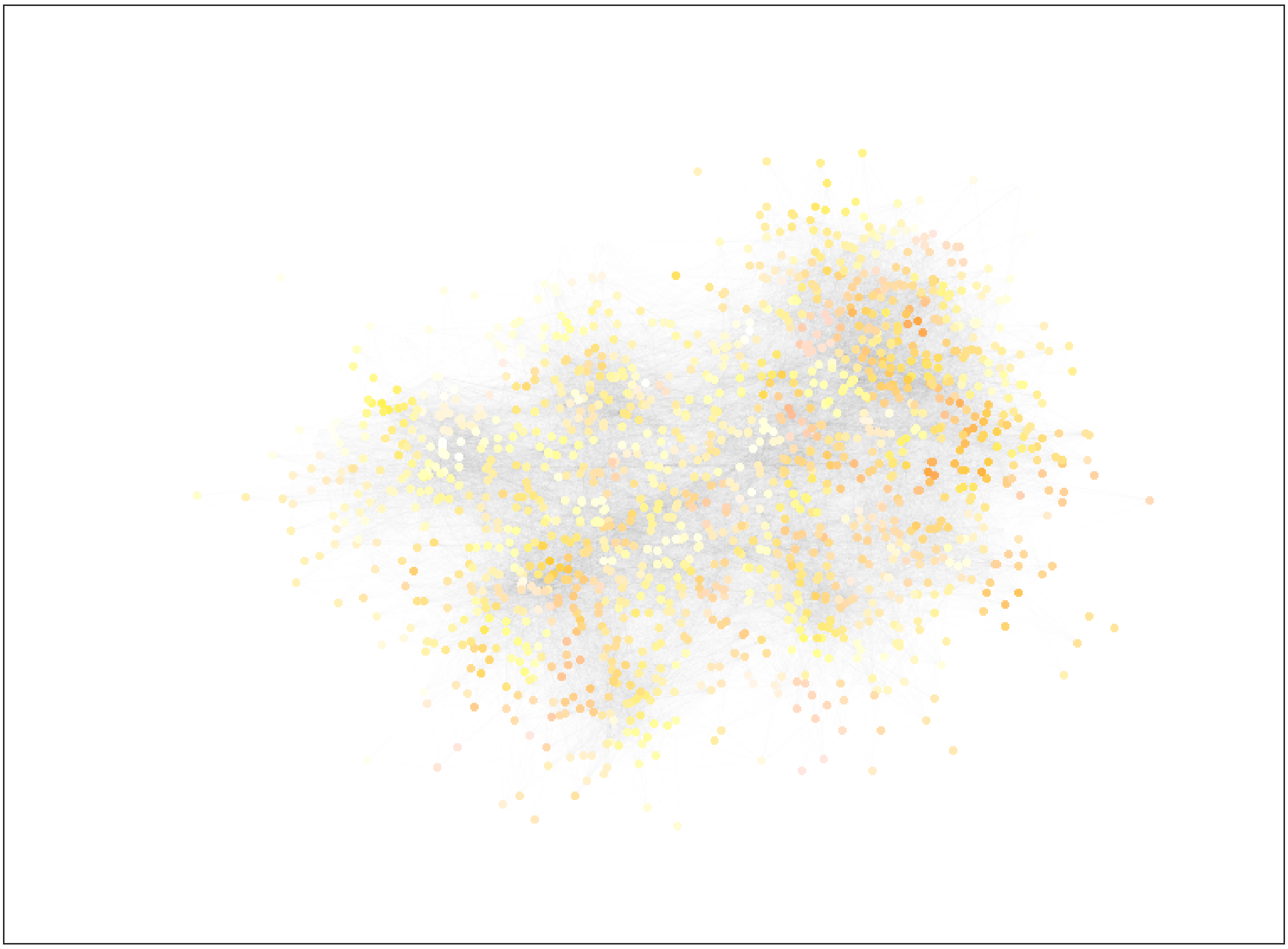

Figure 2: *Diffusion by 2009*

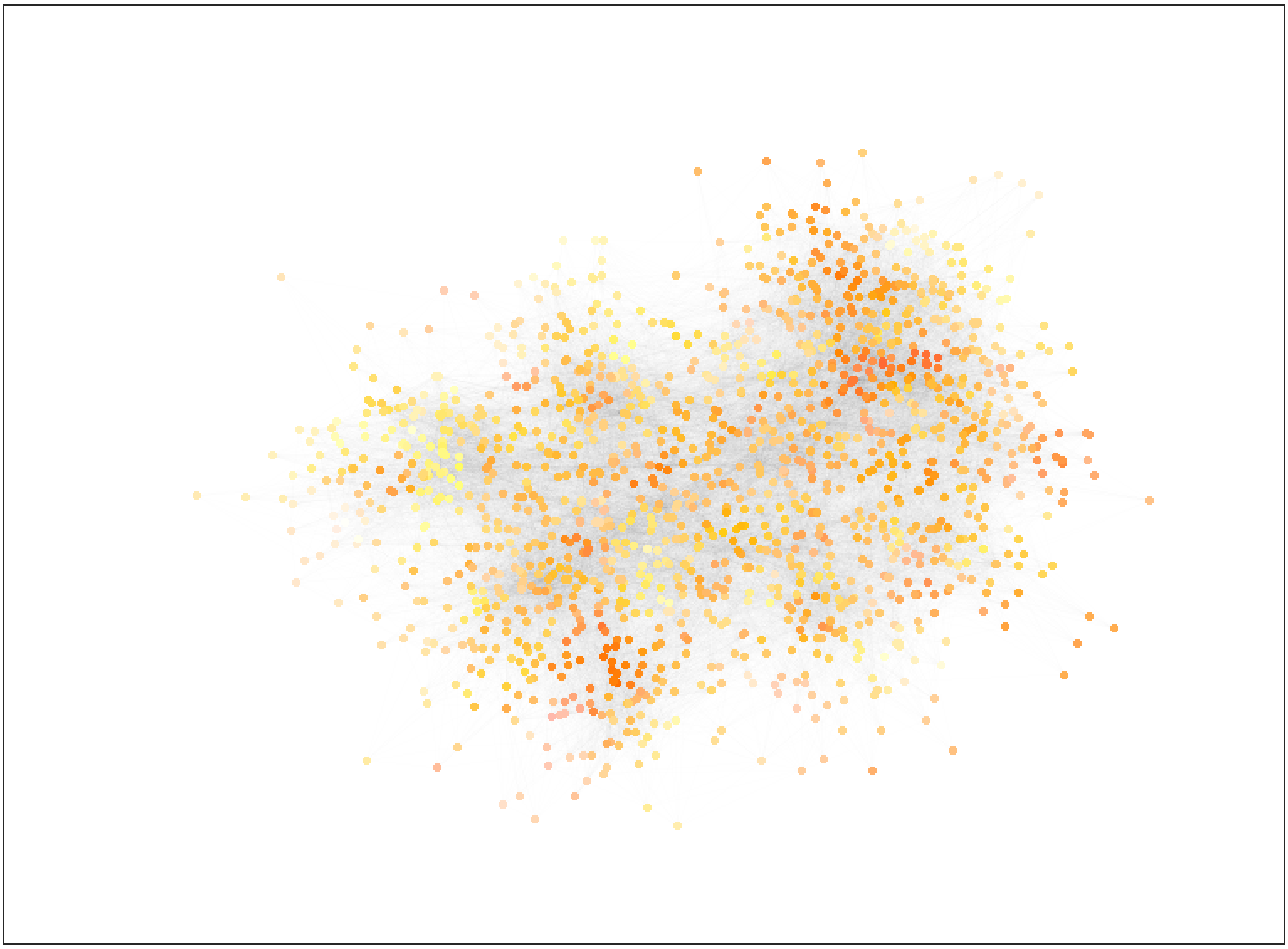

Figure 3: *Diffusion by 2014*

A. Construction of the patient score

An index of patient suitability for laparoscopic 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 (required as we use this as an instrument for peer behaviour) we follow the same methodology by Currie et al. (2016) and use a standard simple 'machine learning' algorithm that estimates a logit model of use of laparoscopy for the pool of patients undergoing surgery between 2012 and 2014 as a function of a vector of patient characteristics. This period is after the issuance of national guidelines and a training programme to promote the use of laparoscopic surgery for colon cancer (Coleman, 2009), so patient treatment reflects 'accepted and best practice' rather than the behavior early in the diffusion process and the index reflects patient suitability rather than physician (unobserved) attitudes towards innovation.

We estimate the following model for patient j:

$$Prob(laparoscopy_j = 1) = F(\mathbf{w}_j'\theta) \tag{A.1}$$

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

The vector of patient characteristics $\mathbf{w}_j$ is composed by gender, age in groups, $(page_j^{<50}, page_j^{50-59}, page_j^{60-69}, page_j^{70-79}, page_j^{>79})$, income distribution in quintiles of the small geographical area where the patient lives as reported in the 2001 Census, dummy variables for the three locations of colorectal cancer (i.e. colon, rectosigmoid junction, and rectum), number of comorbidities diagnosed (ranging from 1 to 7), and the Charlson comorbidity index in groups, $(charlson_j^{<2}, charlson_j^{3-4}, charlson_j^{>4})$. 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). Each comorbidity is weighted according to their potential influence on mortality and, because of that, is likely to identify poorer candidates for invasive procedures (i.e. better candidates for laparoscopic surgery).

We then predict the patient suitability score for each patient using the logit estimates of θ for the universe of patients treated between 2000 and 2014. To obtain the patient suitability index sco_{it}, we take the mean predicted probability of laparoscopic surgery over all patients of surgeon i in year t.