

2022-03

Technology adoption by primary care physicians

T. Iversen, C.-T.A. Ma. 2022. "Technology adoption by primary care physicians.." Health Econ, Volume 31, Issue 3, pp. 443 - 465. <https://doi.org/10.1002/hec.4447>

<https://hdl.handle.net/2144/44132>

"Downloaded from OpenBU. Boston University's institutional repository."

Technology adoption by primary care physicians

Tor Iversen¹ | Ching-to Albert Ma² 

¹Department of Health Management and Health Economics, University of Oslo, Oslo, Norway

²Department of Economics, Boston University, Boston, Massachusetts, USA

Correspondence

Ching-to Albert Ma, Department of Economics, Boston University, 270 Bay State Rd, Boston, MA, USA.

Email: ma@bu.edu

Funding information

Norges Forskningsråd, Grant/Award Number: 204677

Abstract

We study primary care physicians' prevention and monitoring technology adoption. Physicians' adoption decisions are based on benefits and costs, which depend on payment incentives, educational assistance, and market characteristics. The empirical study uses national Norwegian register and physician claims data between 2009 and 2014. In 2006, a new annual comprehensive checkup for Type 2 diabetic patients was introduced. A physician collects a fee for each checkup. In 2013, an education assistance program was introduced in two Norwegian counties. We estimate adoption decisions by fixed-effect regressions, and two-part and hazard models. We use a difference-in-difference model to estimate the education program impact. Fixed-effect estimations and separate analyses of physicians who have moved between municipalities support a peer effect. The education program has a strongly positive effect, which is positively associated with a physician's number of diabetic patients, and the fraction of physician-adopters in the same market.

KEYWORDS

education program, incentives, monitoring, primary care, technology

JEL CLASSIFICATION

I11, I18, O31

1 | INTRODUCTION

We study physicians' adoption of innovative treatment programs. Healthcare stake holders such as insurers, government, and sponsors would like to motivate physicians to adopt best practices. However, physician practices vary, and often variations have not been associated with better health outcomes or efficient resource uses (Skinner, 2012). Motivating the adoption of effective protocols may yield higher efficiency.

The best ways to motivate adoption are seldom agreed upon. The extant economics literature has concentrated on financial incentives and competition. The health and medicine literature, however, has exhibited a wider perspective (see, e.g., Gawande, 2010). Paying physicians for adopting certain procedures or treatments, and pay-for-performance contracts are examples of financial mechanisms, whereas information dissemination, peer reinforcement, educational programs, and explicit enforcement of new protocols are examples of nonfinancial mechanisms.

In this paper, we study mechanisms for the adoption of new information system and treatment guides for preventive care. The study setting is the monitoring of Type 2 Diabetes (T2D) in Norway between 2009 and 2014; we use primary care

This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial-NoDerivs](https://creativecommons.org/licenses/by-nc-nd/4.0/) License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2021 The Authors. Health Economics published by John Wiley & Sons Ltd.

physician claims and register data in this time period. The Norwegian Directorate of Health (2009, 2016) publishes medical guidelines for T2D prevention, diagnostics and treatment. Patients with T2D may benefit from monitoring and prevention from deterioration, so should have a structured annual check-up with their primary care physicians.¹ After the annual check-up, physicians submit data to a national quality register, which is maintained by a center called NOKLUS.²

The financial aspect of the Norwegian Directorate guideline works through a fee-for-service module. From 2008, the structured annual check-up has entitled a physician to a payment, in addition to the office visit fee. This additional charge is called Fee 109, which was about NOK 110 in 2012 (equivalent to about US \$20 in 2012). Fee 109 has been a national policy. There has also been a regional education program to promote the adoption since 2013. In two west coast counties, Rogaland and Hordaland, diabetes nurses have been installing software, and providing training to physicians. Both financial and educational policies are thought to promote adoptions. Although Fee 109 and the education program were not set up for comparing their relative effectiveness, the selective education implementation can be regarded as a quasi-experiment.

Using Norwegian physician panel data, we study financial and educational mechanisms in multiple steps. First, we use fixed-effect models to study how physician and municipality characteristics affect Fee 109 adoption. We identify a peer effect; those physicians who practice in municipalities with more adopters tend to adopt Fee 109 and use the check-up more often; peer effects show up in the extensive margin. We find that physician competition has a negligible effect on adoption. A separate analysis on 230 physicians who have moved between municipalities supports the identification. Second, to assess education, we use a difference-in-difference regression for the program that started in 2013; we find a strong causal effect on Fee 109 use. The program has a greater effect in municipalities where many physicians already have adopted, again confirming that education programs' adoption effects are contingent on local adoption shares. Having peers who have already adopted strengthens the education program effect. Third, we use two-part models and hazard models to verify robustness of the fixed-effect models.

We are unaware of research that uses national micro data to study primary care medical technology adoption, which we believe is an important issue. First, primary care plays a crucial role in an aging population because of the prevalence of chronic illnesses such as T2D and chronic obstructive pulmonary disease among the elderly. As well, primary care physicians provide the crucial lead in care coordination between generalist and specialists. Second, technology in primary care technology is less sophisticated than technology in hospitals and specialty care. Lowbrow technology and protocols such as surveillance and monitoring have probably escaped researchers' attention, but actually deserve more investigation because they can be cost effective. Third, primary care is decentralized as single or small-group practices, so very different from hospitals. Results on hospital technology adoption cannot be expected to apply to primary care.

The structure of the paper is as follows. The next subsection is a literature review. Section 2 describes the institutional setting of Norwegian health care. Section 3 presents a theory of optimal adoption decisions and derives hypotheses. Data and descriptive statistics are in Section 4. Our main empirical results are in Section 5, where we present fixed-effect estimation to assess peer effects, and difference-in-difference estimation to assess the effectiveness of education programs. Robustness checks are in Section 6, where we present estimation results from two-part models and hazard-rate estimations from survival models. Finally, Section 7 draws some conclusions.

1.1 | Literature review

Encouraging physicians to adopt technology and treatment guidelines has received attention in the literature. However, according to Grol and Grimshaw (2003), many physicians are slow to adopt. The economics literature and the medical literature seem to have looked at different perspectives on adoption. Whereas the economics literature focuses on financial incentives and competition, the medical literature focuses on audits, peer reviews and educational programs.

Grol (1992) suggests that physicians' reluctance to adopt stems from competence, attitude, and personal characteristics such as age and training. Indeed, continuing medical education, face-to-face instruction, audit and feedback can encourage adoption. Wensing et al. (1998) find that social influence and management support can improve information transfer, but performance information or ratings do not. Ivers et al. (2012) find that audit and feedback improve professional practice and patient outcomes, although the effect can be small. Our paper fits into this literature. The education program for physicians in specific Norwegian counties served as a quasi-experiment on T2D prevention and monitoring technology adoption.

Economists' recent interest on social network builds a bridge between the medical and economics literature. A recent review, Miraldo et al. (2019), documents the role of peers and networks on technology diffusion: evidence shows that

physician characteristics and network collaboration improve information dissemination, especially when best practice is not agreed upon. Molitor (2018) makes use of cardiologists' migration to study the role of practice environment on physician behavior. He finds that physician behavior in the first year after the move changes 0.6–0.8 percentage points for each percentage point change in practice environment. Our finding is in-line with Molitor's: where peers have adopted, physicians tend to adopt more often.

Most of the economics empirical literature on technology adoption is about hospitals and specialty care. Baker (2001) examines the relationship between Health Maintenance Organization (HMO) market share and magnetic resonance imaging (MRI) diffusion. Across markets, higher HMO market shares are associated with slower MRI diffusion, and markedly lower MRI uses. Horwitz et al. (2017) study the adoption of three invasive cardiac services from 1996 to 2014 (diagnostic angiography, percutaneous coronary interventions, and coronary artery bypass grafting). Using proportional hazard models, they find that hospitals are more likely to adopt an invasive service if hospitals within an hour of driving distance also adopt new services. Karaca-Mandic et al. (2017) find that drug-eluting stent diffusion is faster where cardiology practices face more competition. In our study, competition seems to have played little role. First, we have no exogenous competition policy changes in the data period. Second, Fee 109 does not require a huge capital investment, and the market demand has not responded to adoption.

Our study is related to the literature on factors that affect physicians' new drug adoption. Liu and Gupta (2012) use a micro-level diffusion model and find that marketing efforts, patients' requests, and contagion effects of nearby physicians have shown positive adoption influence. In Kremer et al. (2008), a meta-analysis shows significant and positive adoption effects by promotional expenditures, but these are modest and vary across diseases. Blankart and Stargardt (2020) document that German Health Technology Assessment agencies' information dissemination in the form of published favorable assessments leads to quicker adoption as well as favorable negotiation and pricing.

Studies of technology diffusion in primary care is quite scarce. Scott et al. (2009) evaluate the impact of an incentive program in primary care in Australia on diabetic care quality, measured by the probability of ordering an Hemoglobin-A1c blood sugar test. The study finds that the incentive program increases the probability of an HbA1c test by 20 percentage points. Klausen et al. (1992) study the diffusion of dry-chemistry equipment in Norwegian primary care practices. Based on the maximization of future net revenue of a practice, the adoption probability at a certain date should be positively related to incremental income, practice consultations, and dry-chemistry analysis reimbursement, but negatively related to wet-chemistry reimbursement, and dry-chemistry equipment prices. Their empirical work finds support that diffusion is affected by profits. These papers have generally adopted a benefit-cost approach, to which we have subscribed here.

Our setting of T2D monitor recommendation has been in a number of descriptive studies. Using records of patients identified with diabetes mellitus, Claudi et al. (2008) present cross-sectional results from four Norwegian geographical areas. About 90% of the study population had HbA1c tests, and blood pressure and lipids measurements annually. More than 70% of patients with T2D were referred for eye examinations; albumin levels were recorded in 40% of patients. The authors concluded that care quality improved substantially, but potential improvements were possible. Bakke et al. (2017) compare the results in Claudi et al. (2008) with those in a 2014 survey among physicians. They find moderate improvements during the previous decade, which confirms a worldwide trend. Perhaps more pertinent for our work, Bakke et al. (2018) find that performance varies substantially between physicians; physicians with a higher workload tend to order fewer procedures. They conclude that performance of screening procedures was suboptimal overall, and that the use of a structured diabetes form should be mandatory.

What are potential benefits and costs to patients and society from more annual check-ups? The potential health benefits and reduced costs are considerable if check-ups avert chronic decline and complications. For Sweden, Andersson et al. (2020) find substantial economic burden due to T2D complications. Key cost drivers are the macrovascular complications angina pectoris, heart failure and stroke; and the microvascular eye diseases, including retinopathy, kidney disease and neuropathy. Early mortality in working ages contributes to a substantial production loss in addition to the health care costs.

Can systematic check-ups result in fewer late disease complications? In a literature review of the association between GPs recording clinical data and T2D mortality and morbidity, Larun et al. (2016) conclude that current published data provide ambiguous answers, but form use in diabetic patient follow-ups in general practice may lower mortality and morbidity. An important question is whether a regular check-up may associate with recommended procedure uses. Nøkleby et al. (2020) find large variations in T2D patient care delivered by physicians, who performed on average 63.4% of the recommended procedures (with 46% in the lowest quintile and 81% in the highest). The structured follow-up was associated with GPs being in the top three quintiles. In Nøkleby et al. (2021), the authors explore the association between recommended procedure uses and patients' cardiovascular risk. They find that patients treated by the 20% worst-performing

physicians have a 75% higher modifiable cardiovascular risk compared with patients of the 20% best-performing physicians. Hence, altogether the potential benefits and averted costs to patients and society from increased use of the annual check-up may be substantial.

In summary, the health economics literature finds that economic incentives have an impact on technology adoption. The evidence has come from hospital and specialty care, but not from primary care. The medical literature finds that education programs, audits and feedback may have positive effects on adoption although magnitudes differ across studies.

2 | STUDY SETTING

2.1 | Norwegian health services and primary care physicians

Norwegian National Health Service provides health care for more than 5 million residents. Since 2001 each resident has been offered to list with a primary care physician, who provides primary care and serves as a gatekeeper for specialty care. By 2010 over 95% of the population participated in the list system. In 2010, over 95% of more than 4100 Norwegian primary care physicians were private practitioners who contracted with municipalities (For brevity, from now on, the term physician means primary care physician.) The remaining physicians were salaried municipality employees. Physician employees usually work in sparsely populated areas; a fixed salary serves to shield physicians from financial risks due to service demand fluctuations in low-population areas. In the present paper, we consider only private-practice physicians, and all descriptions and analyses apply to them only.

The list system comes with the following financial arrangements for physicians. First, the physician receives a capitation fee from the municipality for each patient in her list; in 2012, this fee was NOK 386 per year, at which time the exchange rate was about US \$1 to NOK 6. A physician had, on average, 1200 patients listed in his practice. Second, a physician receives fee-for-service payments, set by the National Insurance Scheme, when health services are provided to patients. Third, the physician also receives a patient copayment at the time of service; the copayment is decided by the Norwegian Parliament as part of the National Insurance Scheme. Each revenue component constitutes about one third of a physician's practice income.

In a calendar year, a patient may switch physicians up to two times, and each year approximately 3% of the patients do switch. Characteristics of patients who switch vary considerably. Patients who are male or older, and who have good health but only basic education tend to stay with their physicians. Switching patients form a kind of market demand. In the supply side, a physician sets the maximum practice list size. A practice may actually be closed when a physician has enough patients. Whether a practice is open or closed is public information, available on the Internet or from the municipality. A physician may have fewer patients than the declared maximum. In the empirical work, a physician is said to experience shortage if the actual list falls short of the stated maximum by more than 100 patients. Patient shortage and not being a specialist in general medicine make it more likely that physicians experience patients switching into or out of their practices (Iversen & Lurås, 2011).

Whereas patients receive general care from physicians, they receive specialty care from specialists, who may be private practitioners or work in public hospitals. Most private specialists contract with Regional Health Authorities, which are responsible for hospitals in their regions. A private specialist receives a practice allowance from a Regional Health Authority, and fee-for-service payments from National Insurance Scheme. Most private specialists are in urban areas, and they provide about one third of all outpatient consultations. In 2012, a patient's copayments for an outpatient visit with a physician and a specialist were about NOK 180 and NOK 307, respectively, but a patient's copayment within a year was capped at NOK 1980 and any excess was paid for by the National Health Insurance.

2.2 | Type 2 diabetes and the annual comprehensive check-up

We consider technology adoption for Type 2 diabetes (or T2D) management. Diagnostic and treatment guidelines have been developed in countries with different health systems for this common chronic illness. For instance, in the United States, Kaiser Permanente (2017) presents detailed guidelines for monitoring T2D patients. The monitoring includes glycemic control target, microalbumin assessments and regular retinal and foot screening. Similar guidelines have been worked out by Socialstyrelsen (2018) for Sweden. A recent study in France (Andrade et al., 2018) shows that adherence to

four guidelines (quarterly determination of HbA1c, complete lipid profile, microalbuminuria and influenza vaccination) is associated with monitored patients having up to 30% fewer annual hospital admissions.

The Norwegian Directorate of Health (2009, 2016) publishes medical guidelines for diabetes prevention, diagnosis, and treatment. National medical experts work out the guidelines. T2D is included in the guidelines together with Type 1 Diabetes (T1D). The guidelines prescribe that T2D patients should have physician check-ups. For patients with poorly regulated diabetes or complications, physicians and specialists should share care responsibility to coordinate treatment.

From 2006, Norwegian Quality Improvement of Primary Health Care Laboratories (NOKLUS) has initiated a national quality register, The Norwegian Diabetes Register for Adults. The Register was approved by the Norwegian Data Inspectorate in 2005. The goal is to develop a T2D patient database. Medical personnel submit data to the Register on a voluntary basis, subject to patients' written consent. For data submission, physicians have to install computer software that links to patient electronic records. The software also assists the physician with organizing the annual check-up to include all required components. The Register issues annual quality reports to participating medical centers and individual doctors. Hence, the technology we study contains two components. The first is an annual check-up according to medical guidelines. The second is a software, supplemental to patient electronic records, assisting the physician to implement the annual check-up, and transferring data to the national quality register.

Each time a physician uses the annual checkup for T2D patients and submits data to the Register, she can, in addition to the consultation fee, file a fee-for-service claim, the Fee 109, which was about NOK 110 in 2012. To mitigate coding errors, we conservatively define physician adoption by her claiming Fee 109 at least 10 times annually. Despite the recommendation of NOKLUS by the Directorate of Health and the Fee 109 reimbursement, only a minority of physicians have chosen to participate. Accordingly, there has been an interest in identifying participating physicians' characteristics. Furthermore, to encourage participation, since 2013, physicians in Rogaland and Hordaland, two counties on the Norwegian west coast, have been offered assistance. A diabetes nurse would install software for the comprehensive annual check-up and launch data submission to the national register. The assistance also includes an education session to demonstrate the working and the benefit from the checkup software. These counties were chosen because they obtained project funding. Also, one diabetes nurse was already based at the Register in Hordaland, and a physician had both a position at the Register and at Stavanger University Hospital in Rogaland.

Patient associations have often an important role in the education of patients with chronic disease. In Norway, the Norwegian Diabetes Association is an influential patient association with 33,000 members (in 2018). This accounts for about 15% of the patients with T1D and T2D. We do not have access to the distribution of members according to counties. We do know the number of local organizations by counties. Adjusted for population size, Hordaland has an above-median number of local organizations, whereas Rogaland has a below-median number.

The second part of our empirical work studies whether this educational effort has increased adoption. In effect, we regard the efforts for Rogaland and Hordaland as a quasi-experiment.

3 | ADOPTION DECISION AND HYPOTHESES

We focus on a physician's decision on the adoption of the technology for monitoring patients who have chronic illnesses, so abstract from other such decisions as practice size, amount of fee-for-service treatments, referrals, etc. We simply posit that the physician's adoption decision is based on a benefit-cost comparison. We then hypothesize how the adoption benefit and cost depend on a physician's personal characteristics and prevailing market conditions.

Consider the adoption decision to be made by a physician in a municipality at a certain point in time. We use a binary variable α to represent the adoption decision; α takes the value 0 if the physician does not adopt, and the value 1 if she adopts. We use a vector θ to denote the physician's personal characteristics, and another vector ϕ to denote market conditions. We let the function $B(\alpha; \theta, \phi)$ denote benefits, and the function $C(\alpha; \theta, \phi)$ denote costs; these functions may well be indexed by physicians, municipalities, and time, but we will gloss over these indexes for a simpler exposition.³ Benefits and costs can be financial and nonfinancial, and represent discounted values. Adoption may change the patient list and service demand, which, in turn, change revenues and job satisfaction; likewise, service and time cost may change due to adoption. Due to list size and service demand uncertainty, the benefit and cost functions are to be regarded as the expected benefits and expected costs that arise from the adoption decision.

We assume that adoption results in a benefit increment: $B(1; \theta, \phi) > B(0; \theta, \phi)$. The new monitoring technology would be valuable to patients with a chronic illness, so may yield financial or altruistic benefits. We naturally assume that adoption is costly: $C(1; \theta, \phi) > C(0; \theta, \phi)$. A physician's adoption decision is now described by the choice of $\alpha \in \{0, 1\}$ that

maximizes $B(\alpha; \theta, \phi) - C(\alpha; \theta, \phi)$. Equivalently, a physician adopts whenever the benefit increment is higher than the cost increment: $B(1; \theta, \phi) - B(0; \theta, \phi) > C(1; \theta, \phi) - C(0; \theta, \phi)$.

Obviously, a physician's adoption decision depends on her personal characteristics, those represented in θ . In the empirical study, we have information about such physician characteristics as (i) age, (ii) medical specialty, (iii) the percentage of patients with a chronic illness in the practice, and (iv) other factors. The decision may also depend on market conditions, those represented in ϕ , such as (i) number or percentage of other physicians who have adopted, (ii) population density and access to specialty care, and (iii) competition, which we take to be the numbers of other physicians who accept new patients.

How do a physician's personal characteristics affect adoption benefits and costs? The physician likely enjoys higher adoption benefits (i) when she is younger, so has a longer career horizon, (ii) when she is a specialist in primary care, and (iii) when her practice has more patients who suffer from T2D. In a symmetric way, the physician likely has a higher adoption cost (i) when she is older, (ii) when she does not specialize in primary care, and (iii) when few patients in the practice suffer from T2D.

How do current adoption levels and market conditions affect adoption decisions? Within a market, (i) when more physicians have adopted the technology, a peer effect may develop, so learning may be easier and conforming with the norm may be preferred. We predict that when a market has more physicians who already have adopted the technology, it is more likely that a physician adopts. Also, within a market, (ii) when consumers have better access to specialty care, the demand for monitoring may be less, so the adoption benefit is reduced. Finally, (iii) competition as measured by the number of open practices, either in nominal or in per-capita terms, may have an ambiguous effect on benefits. Through word of mouth chronically ill patients may learn about a physician using the structured checkup; this practice style may be perceived as a quality increase. However, adoption may not be so attractive to those who are not chronically ill. Overall, it is ambiguous how competition intensity may change the benefits from adoption.

4 | DATA AND DESCRIPTIVES

Data for this paper come from two sources. The first one is primary care physicians' claims to the National Insurance Scheme. This database is called KUHR. The second source is the regular primary care physician register that contains information on physicians' characteristics, as well as identifies physicians' patient lists. Data are aggregated to the physician level, and supplemented with patients' residential municipality data.

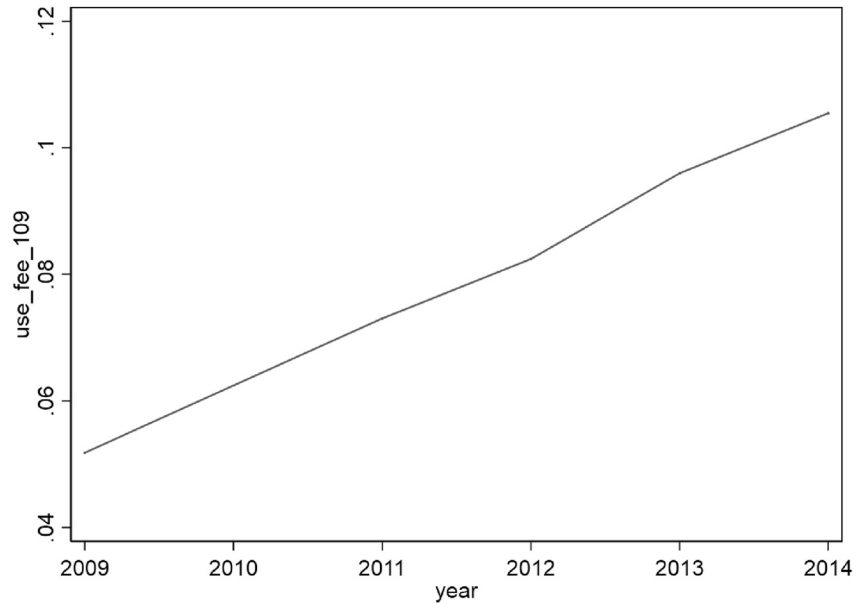
Patients who have chronic diseases are identified from KUHR. Claims data contained diagnoses at each contact. We identified patients with T2D from the diagnosis code T90 in International Classification of Primary Care. Patients with T2D were those who received the diagnosis code T90 in at least one consultation between 2006 and 2009. The two data sources cover the 6 years between 2009 and 2014, and are merged at the level of the individual patient's physician.

We define a physician as an adopter if she makes use of Fee 109 at least 10 times in 1 year. The 10-time use criterion is to avoid counting as adopters those physicians who have filed claims by mistake. Our definition also yields adoption-percentage figures that are consistent with those in NOKLUS. We drop from the data set those physicians who have had less than 10 T2D patients. Figure 1 shows that the proportion of physicians using Fee 109 has increased from 5% in 2009 to just above 10% in 2014. These percentages are approximately equal to the proportions of physicians who submitted data to The Norwegian Diabetes Register for Adults in 2009 and 2014.

Table 1 presents 2009 descriptive of adopters and non-adopters. Where appropriate, in all tables standard errors are in parentheses, and significance levels are indicated by the usual convention of * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$. On average adopters have more patients with T2D than non-adopters; adopters' patients tend to have more comorbidities. Adopters are more likely to be specialists in primary care, but have the same average age as non-adopters. Physicians report to the National Insurance Administration the maximum number of patients allowed in their practices (the maximum list or Maxlist). Adopters have longer patient and maximum lists, and are less likely to experience patient shortage than non-adopters.

On average adopters are located in smaller municipalities than non-adopters. Adopters' smaller municipalities have fewer open lists than non-adopters' municipalities. However, adopters and non-adopters seem to have the same percentage of practices with open lists per 100,000 inhabitants. Table 1 also describes the number of physicians in the municipalities who have adopted the comprehensive annual check-up (#adopters). Adoption seems to be more likely when there are more adopters in the previous years in the same municipality. The variable "Access private specialists" is an indicator for access to private specialists; it weighs the number of specialists by patients' travel time from the listing physician's

FIGURE 1 Time trend of physicians adopting Fee 109



practice municipality. The variable “Access hospital” is a similar variable for physician specialists located in hospitals. From Table 1 access to private and hospital specialists is better in non-adopters’ municipalities than adopters’.

Table 2 shows descriptive in 2014. The number of adopters has increased from 201 in 2009 to 445 in 2014. Nevertheless, differences between adopter and non-adopter profiles, both at the physician level and at the municipality levels, have not changed much between 2009 and 2014.

Table 3 compares characteristics of movers and non-movers. We record physician information in the first year of a physician’s appearance in the data. Because we have an unbalanced panel, the total number of physicians in Table 3 is larger than numbers of observations in previous tables for 2009 and 2014. We find that movers tend to be younger; this is consistent with Molitor (2018) who shows that younger cardiologists in the U.S. are more likely to move than older ones. The other variables therefore exhibit properties that are more prevalent with younger physicians: fewer being general-medicine specialists, having shorter lists, and experiencing patient shortage more often.

Table 4 presents 2012 physicians’ descriptive statistics for the two counties where the educational program was implemented since 2013, and also for remaining counties. At the physician level, the average list size is higher in Rogaland and Hordaland than in other counties. At the municipality level, there are fewer open lists in Rogaland and Hordaland, but the number of adopters tends to be much higher than in other counties. Both Rogaland and Hordaland have lower access to specialized care compared to other counties.

Table 5 provides some balancing tests for the treatment counties relative to the remaining counties. Column (1) shows

the standardized differences in covariate j , $d^j \equiv \frac{\overline{X_1^j} - \overline{X_0^j}}{\sqrt{\frac{1}{2}[(s_1^j)^2 + (s_0^j)^2]}}$, where $\overline{X_1^j}$ and $\overline{X_0^j}$ are covariates in the treatment

(subscript 1) and control (subscript 0) groups in 2012 and $(s_1^j)^2$ and $(s_0^j)^2$ are their corresponding sample variances. The standardized differences are independent of sample sizes and covariate measurement units. We also perform balancing tests by a fixed-effects estimation to compare how treatment and control group covariates evolve over time:

$$X_{it}^j = \mu_i + \lambda_t + \tau (EDU_i \times Post_t) + \varepsilon_{it},$$

where μ_i is the physician fixed effect; λ_t , time fixed effect; EDU_i , equals one if the physician is located in a treatment municipality and zero otherwise; $Post_t$, equals one from the start of treatment and zero otherwise, and ε_{it} is an error term. We estimate first, the fixed effects models separately (estimated coefficients for τ in column (2)) and second, account for multiple testing by providing adjusted p values (column (3)), as suggested by Clarke et al. (2019).

Column (1) in Table 5 shows that there are some standardized differences between the intervention group and the control group for number and proportion of patients with T2D, list size, number of open list places, and access to specialized health care. Columns (2) and (3) show that these differences do not change during the intervention period compared

TABLE 1 Physician descriptive statistics in 2009

Variable definition	Non-adopters		Adopters		Mean difference		
	Mean	SD	Mean	SD			
Physician level							
#T2D			min 10		min 26		
Number patients with T2D	48	28	max 307	66	33	max 305	−18***
Proportion T2D			min 0.01			min 0.02	
Proportion patients with T2D	0.04	0.02	max 0.17	0.05	0.02	max 0.25	−0.01***
#comorbidities			min 1			min 4	
Number comorbidities	18	12	max 143	25	19	max 185	−7***
Specialist			min 0			min 0	
Primary care specialist	0.60	0.49	max 1	0.74	0.44	max 1	−0.14***
Age			min 26			min 28	
Physician age	48	10	max 80	48	10	max 67	0
Maxlist			min 0			min 0	
Maximum list size	1192	441	max 2500	1245	350	max 2400	−53
List			min 157			min 541	
Actual list size	1219	380	max 2720	1317	326	max 2396	−98***
Shortage			min 0			min 0	
List < (Maxlist − 100)	0.20	0.40	max 1	0.15	0.36	max 1	0.05*
Municipality level							
Total_listed			min 0.1			min 0.7	
Listed patients (in 1000)	111	190	max 612	88	153	max 612	23
#openlists			min 0			min 0	
Number open lists	30	56	max 183	21	43	max 183	9*
#open_per_cap 1000*#openlists			min 0.00			min 0.00	
Total_listed #adopters	0.40	0.41	max 8.26	0.40	0.31	max 1.55	0
Total number of adopters	5.6	8.4	min 0	7.1	9.2	max 33	−1.5*
Access private specialist			min −1.54			min −1.33	
Private specialist access index	0.68	1.11	max 2.21	0.46	1.09	max 2.21	0.22**
Access hospital			min −2.09			min −1.26	
Hospital access index	1.72	3.66	max 11.78	1.19	2.79	max 11.78	0.53**
Observations	3669			201			

with the pre-intervention period. This is in particular the case when we control for multiple testing. We conclude that the differences in covariates between the intervention group and the control group are not influenced by the intervention.

5 | FIXED-EFFECT AND DIFFERENCE-IN-DIFFERENCE ESTIMATIONS

In this section, we present our main estimation results for factors that contribute to physicians adopting a structured annual check-up for T2D patients. First, we estimate two sets of fixed-effect models. The first set studies the extensive and total margins of adoption, and controls for physician and municipality time invariant observable and unobservable characteristics. The second set focuses on a subset of physicians who have moved between municipalities. Such movers may experience a change in municipality adoption levels, so we may identify peer effects. Second, with the Rogaland and

TABLE 2 Physician descriptive statistics in 2014

Variable definition	Non-adopters			Adopters			Mean difference
	Mean	SD		Mean	SD		
Physician level							
#T2D	37	22	min 10 max 252	51	23	min 15 max 227	-14***
Proportion T2D	0.03	0.02	min 0.00 max 0.14	0.04	0.02	min 0.01 max 0.19	-0.01***
#comorbidities	14	9	min 0 max 106	19	12	min 2 max 130	-5***
Specialist	0.60	0.49	min 0 max 1	0.70	0.46	min 0 max 1	-0.1***
Age	48	11	min 26 max 74	49	11	min 27 max 68	-1
Maxlist	1167	395	min 0 max 2500	1297	363	min 0 max 2500	-130***
List	1181	355	min 147 max 3080	1319	347	min 484 max 2898	-138***
Shortage	0.15	0.35	min 0 max 1	0.09	0.29	min 0 max 1	0.06**
Municipality level							
Total_listed	125	221	min 0.5 max 715	129	196	min 0.5 max 715	-4
#openlists	36	65	min 0 max 215	35	57	min 0 max 215	1
#open_per_cap	0.42	0.39	min 0.00 max 6.45	0.34	0.25	min 0.00 max 2.3	0.08***
#adopters	17.5	28.9	min 0 max 109	25.7	35.2	min 1 max 109	-8.2***
Access private specialist	0.66	1.13	min -1.54 max 2.21	0.62	0.99	min -1.50 max 2.21	0.04
Access hospital	1.71	3.66	min -2.09 max 11.78	1.46	3.10	min -1.99 max 11.78	0.25
Observations	3720			445			

Hordaland educational program as a quasi-experiment, we estimate the causal effect of the program on adoption by a difference-in-difference model. Effects of the education program also may depend on physician and municipality characteristics, and we examine these heterogenous effects by additional difference-in-difference models.

5.1 | Fixed-effect estimation

The fixed effect estimation equation is:

$$y_{it}^k = \lambda_i + \mu_k + \rho_t + \sum_{j=1}^m \beta_j z_{ij} + \epsilon_{itk}, \quad \text{for } i = 1, \dots, n, k = 1, 2, \dots, \text{ and } t = 2009, \dots, 2016.$$

TABLE 3 Movers and non-movers statistics

Variable definition	Non-movers			Movers		
	Mean	SD		Mean	SD	
Physician level						
#T2D	44	28	min 10 max 307	38	22	min 10 max 129
Proportion T2D	0.04	0.02	min 0.01 max 0.25	0.04	0.02	min 0.01 max 0.10
#comorbidities	16	13	min 0 max 185	15	10	min 1 max 60
Specialist	0.48	0.50	min 0 max 1	0.27	0.44	min 0 max 1
Age	46	11	min 25 Max 80	38	9	min 26 max 69
Maxlist	1167	411	min 0 max 2500	971	528	min 0 max 2500
List	1165	378	min 157 max 2537	1063	379	min 281 max 2720
Shortage	0.25	0.43	min 0 max 1	0.37	0.48	min 0 max 1
Municipality level						
Total_listed	107	186	min 0.2 max 715	41	116	min 0.1 max 715
#openlists	29	57	min 0 max 251	12	34	min 0 max 183
#open_per_cap	0.41	0.39	min 0.00 max 5.94	0.63	0.71	min 0.00 max 8.3
#adopters	7.1	13.2	min 0 max 109	2.6	6.2	min 0 max 59
Access private specialist	0.62	1.12	min -1.54 max 2.21	0.12	1.08	min -1.54 max 2.21
Access hospital	1.59	3.54	min -2.09 max 11.78	0.44	2.34	min -2.07 max 11.78
Observations	4946			230		

We run two fixed-effect regressions with the above specification.⁴ In the first, the left-hand side variable y_{it}^k is a dummy variable (Fee 109); it takes the value 1 when the number of Fee 109 claims by physician i in municipality k in year t is at least 10; otherwise it is set at 0. This specification measures the extensive margin, or the likelihood that physicians adopt. In the second, y_{it}^k is the actual number of Fee 109 claims (#Fee 109) made by physician i in municipality k in year t when that number is at least 10, and y_{it}^k is set at zero for less than 10 claims. This specification measures the total margin, or how many actual claims. Fixed effects for physician i , municipality k and year t are denoted by λ_i , μ_k and ρ_t , respectively. We include a set of m covariates, z_{ijt} ; in particular, we take into account of patient population differences by including #T2D as a variable on the right-hand side. An “L.” before a variable name denotes that the variable takes on the value one period before (lagged). The coefficients β 's are parameters to be estimated. There are now less data variations because we can only exploit the within-physician and within-municipality variations. Finally, the normally distributed error terms, ϵ_{ikt} , are clustered at the physician level.⁵

The regression results for the extensive and total margins are in Table 6. In the first regression, the dependent variable is the dummy Fee 109; in the second, the dependent variable is the actual number of Fee 109 claims #Fee109. From

TABLE 4 Physician descriptive statistics by counties in 2012

	Counties without program			Rogaland, Hordaland		
	Mean	SD		Mean	SD	
Physician level						
#T2D	44	25	min 10 max 278	41	25	min 10 max 174
Proportion T2D	0.04	0.02	min 0.01 max 0.24	0.03	0.02	min 0.01 max 0.15
#comorbidities	16	11	min 0 max 163	16	11	min 1 max 86
Specialist	0.62	0.49		0.64	0.48	
Age	48	10	min 27 max 73	49	11	min 28 max 83
Maxlist	1142	445	min 0 max 2500	1268	372	min 0 max 2500
List	1199	359	min 144 max 2707	1292	380	min 312 max 2502
Shortage	0.17	0.38		0.15	0.35	
Municipality level						
Total_listed	119	216	min 0.4 max 653	107	113	min 0.1 max 277
#openlists	36	71	min 0 max 213	24	25	min 0 max 60
#adopters	5.23	7.69	min 0 max 23	10.47	12.04	min 0 max 29
Access private specialist	0.76	1.20	min -1.54 max 2.21	0.19	0.27	min -0.47 max 0.71
Access hospital	1.93	3.97	min -2.09 max 11.78	0.66	0.63	min -0.94 max 1.44
Observations	3333			725		

Table 6, the prior-year number of adopters (L_{t-1}) is the only statistically significant effect in both regressions. An increase of one adopter in the municipality in the previous year, increases the probability of adoption by 0.2 percentage point. With 10% of the GPs performing the annual check-up in 2014, one more adopter in the previous year implies a 2% increase in the probability of another adopter in this period (extensive margin). The regression of the total margin shows that an increase of one adopter in the municipality in the previous year, increases the number of check-ups above 10 by 0.03, which corresponds to a 1.5% increase.⁶

During the data period there has been a change in the municipality population composition. Urban municipalities have grown at the expense of rural ones. To account for this change we introduce municipality population as an additional right-hand side variable. We run a robustness check where we replace L_{t-1} with the lagged *proportion* of adopters in a municipality. We find that the estimated coefficient of proportion adopters is positive and statistically significant. We conclude that the peer effect is robust.

We now turn to a second set of fixed-effect regressions to analyze peer effect further. A compelling way to account for endogeneity of lagged adoption is to find an exogenous event, one that is uncorrelated to adoption but one that exposes physicians to different municipality adoption levels. Inspired by Molitor (2018), we choose 230 physicians who have moved from one municipality to another municipality during the data period, between 2009 and 2014. The identifying assumption is that factors affecting a physician's move are uncorrelated to those affecting the physician's adoption of Fee 109. A move results from multiple considerations, which are likely uncorrelated with software and hardware upgrades and visit protocols. Moving cost is probably many magnitude higher than adoption cost. Focusing on these movers and

TABLE 5 Balancing tests

	Std.Diff. (1)	DID-FE (2)	DID-FE MT <i>p</i> value (3)
#T2D	0.1160	-0.1995 (0.3422)	0.9163
Proportion T2D	0.3384	0.0003 (0.0002)	0.3785
#comorbidities	0.0120	-0.3331* (0.1633)	0.1036
Specialist	-0.0389	0.0012 (0.0109)	0.9402
Age	-0.0590	-0.0000 (0.1129)	0.9442
Maxlist	-0.3020	23.3505** (7.1614)	0.0159
List	-0.2497	-8.6570 (6.0186)	0.2629
Shortage	0.0630	0.0181 (0.0109)	0.2629
Municipality level			
Total_listed	0.0655	-1980.892 (1218.728)	0.4143
#open_per_cap	0.2089	-0.0127 (0.0096)	0.3227
Access private specialist	0.6579	-0.0146** (0.0049)	0.2629
Access hospital	0.4456	-0.0337* (0.0143)	0.6892

their exposure to adoption is a credible way to account for endogeneity. The drawback of course is that we work with a sample of only 1133 data points (an unbalanced sample of 6 years for a total of 230 physicians).

We construct a new variable *After*. For each mover, we record the year in which a move has occurred, and for that and later years, the variable *After* takes the value 1, and for years before the move, *After* takes the value 0. Sixteen of the 230 physicians have moved more than once, and the variable *After* continues to assume the value one after the first move. Next, we define another new variable Δ adopters as follows. For each mover, we note the origin and destination municipalities. We then compare the number of adopters in both municipalities. The Δ adopters variable takes the value 1 if there are more adopters in the destination municipality than the origin municipality; it is set to zero otherwise. Thus, Δ adopters measures an increased exposure of peer adoption after the move. For the 16 physicians who have moved more than once, Δ adopters is updated in each move. In the following Table 7, the dependent variable *Fee 109* is equal to one if *Fee 109* is used at least 10 times in a year; it is set at zero otherwise. The included covariates are #T2D, #comorbidities, Age, Specialist, L.Shortage, L.#open_per_cap, Access private, Access hospital, Total_listed, and these variables are used in later regressions where Covariates are indicated. Peer effect is measured by the estimated coefficient of the interaction term of *After* * Δ adopters.

According to Table 7, physicians who have moved to a municipality with more adopters are more likely to adopt, and the effect is significant at 5%. There is also a positive effect on the number of *Fee 109* uses. However, the *p* value is 0.08, so the effect is insignificant at 5% but significant at 10%. The results support a peer effect. The magnitude of the effect is considerable. A physician who moves to a municipality with more adopters is estimated to increase adoption by 6.6 percentage points than if he moves to a municipality with fewer adopters. As we have seen in Table 3, physicians who have

TABLE 6 Linear model with physician, municipality and year fixed effects

	Fee 109	#Fee 109
#T2D	0.001 (0.001)	0.010 (0.015)
#comorbidities	-0.001 (0.001)	0.006 (0.034)
Age	-0.002 (0.006)	-0.085 (0.122)
Specialist	-0.012 (0.011)	-0.475 (0.261)
L.Shortage	0.011 (0.010)	-0.187 (0.169)
L.adopters	0.002*** (0.000)	0.027* (0.008)
L.#open_per_cap	0.006 (0.014)	0.350 (0.217)
Access private	-0.040 (0.070)	-0.538 (0.691)
Access hospital	-0.004 (0.010)	-0.002 (0.116)
Total_listed	-0.000*** (0.000)	-0.000 (0.000)
N (484 singleton obs. dropped)	18,413	18,413
Years fixed effects	×	×
Municipalities fixed effects	×	×
Physicians fixed effects	×	×
Errors clustered at physician level	×	×

Note: Standard errors in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 7 Linear model for movers with physician and year fixed effects

	Fee 109	#Fee 109
After	-0.033 (0.026)	-1.223* (0.604)
After * Δ adopters	0.066* (0.033)	1.490 (0.790)
N	1133	1133
Covariates	×	×
Years fixed effects	×	×
Physicians fixed effects	×	×
Errors clustered at physician level	×	×

Note: Standard errors in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

moved tend to be younger. Younger professionals likely are more eager to learn from peers. However, a move to a different location is a necessary condition for someone to be exposed to peer effects, so our regressions must capture exposure effects rather than only differences between younger movers and older non-movers.

Despite the lack of a competition effect, we would like to examine if the listing demand for physicians is associated with adoption. We use actual list size changes, and number of T2D patients changes in the list to proxy for the unobserved demand. Table 8 shows the result of linear regressions with fixed effects for physicians, municipalities and

	Δlist	$\Delta\#\text{T2D}$
L.Adoption	4.208 (6.229)	0.323 (0.322)
L.Shortage	108.400*** (20.839)	4.437*** (0.865)
L.Adoption*L.Shortage	11.510 (20.910)	-0.610 (0.869)
Constant	-22.470*** (5.852)	-2.632*** (0.294)
N (492 singleton obs. dropped)	18,725	18,725
r^2	0.349	0.387
Years fixed effects	×	×
Municipality fixed effects	×	×
Physicians fixed effects	×	×
Errors clustered at physician level	×	×

Note: Standard errors in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 8 Demand OLS with physician, municipality and year fixed effects

years. Standard errors are clustered at the physician level. The estimated coefficients of lagged adoption are positive, but insignificant. The estimated coefficients of lagged Shortage is positive; this is reasonable because physicians who have shortage would like to accept new patients. For the interaction between lagged Adoption and lagged Shortage, the two coefficients have different signs but neither of them is significant. We conclude that an adoption of a comprehensive annual check-up does not seem to result in additional patients in the physician's list. We do not find any evidence that adoption expands demand.

5.2 | Education program effect from difference-in-difference estimation

Physicians in Rogaland and Hordaland, two counties on the Norwegian west coast, were offered assistance in the form of education program since 2013. We estimate the effect of the education program by a difference-in-difference (DiD) regression:

$$y_{it}^{\gamma} = \alpha_0 + \alpha_1 \gamma + \alpha_2 \tau_t + \alpha_3 [\tau_t \times \gamma] + \sum_{j=1}^m \beta_j z_{ij} + v_{it}, \text{ for } i = 1, \dots, n, \text{ and } t = 2009, \dots, 2016.$$

Here y_{it}^{γ} describes the number of Fee 109 claims (when they are above 9) made by physician i in county γ in year t , where the county dummy γ is set to 1 for Rogaland and Hordaland, and 0 for other counties. For physicians who use Fee 109 fewer than 10 times, y_{it}^{γ} is set at zero. The treatment (education program) pre-post variable is τ_t , set to 0 for years $t = 2009, \dots, 2012$, and 1 for $t = 2013, 2014$. The effect of interest is the interaction term $\tau_t \times \gamma$, its coefficient α_3 measuring the difference in adoptions between physicians who have been assisted and who have not. We include a set of m covariates, z_{ij} . The coefficients α 's and β 's are parameters to be estimated. The normally distributed error terms, v_{it} , are clustered at the physician level.

We run a DiD regression and a regression with physician fixed effects. Results are in Table 9. The fixed-effect model did have smaller Akaike information (AIC) and Bayesian information criteria (BIC) values than OLS. In the basic DiD model, the interaction effect coefficient α_3 is 0.776 and significant at the 1% level. In the physician fixed-effect regression, the interaction coefficient is 1.027, also significant at the 1% level. Consider the average of the estimated interaction effects, $(0.776 + 1.027) / 2 = 0.902$. In 2012 the mean number of Fee 109 uses that were above 9 was 1.86. Hence, the average of the DiD and fixed-effect impact of 0.902 is about 50% that of the mean of 1.86 in 2012. This is evidence that the education program has a strong causal effect on adoption.

TABLE 9 Difference-in-difference and fixed-effect estimations of education effects

	Difference in difference	Fixed-effect regression	Matched, weighted difference in difference
Treat (α_1)	-0.312 (0.270)		-0.402 (0.234)
Post (α_2)	0.901*** (0.167)	0.947 (0.515)	1.052*** (0.381)
Treat \times Post (α_3)	0.776*** (0.242)	1.027*** (0.230)	0.816* (0.364)
<i>N</i>	18,897	18,897	16,746
Years fixed effects	×	×	×
Physician fixed effects		×	
Covariates	×	×	×
Physician level clustered errors	×	×	×
Mean #Fee109 above 9 in 2012 in treatment counties	1.86	1.86	1.79

Note: Standard errors in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Descriptive in Table 4 shows that physicians in Rogaland and Hordaland are different from those in other counties, and obviously, Rogaland and Hordaland are different from other counties. Balancing tests in Table 5 show that covariate magnitude changes during the treatment period do not depend on treatment status. Hence, changes in covariates seem balanced and we run the regressions with the entire sample as our main specification. Still, as a robustness check, we select a subsample of similar physicians in the treatment and control counties by a standard matching model (Rosenbaum & Rubin, 1983). We use a probit model to predict the probability of a physician being located in Rogaland or Hordaland by physician practice characteristics. Then we match physicians in the treatment (those in Rogaland or Hordaland) with those in the control (those in other counties) when differences in their estimated probabilities are below a threshold. Accordingly, we delete those physicians in the treatment group whose estimated probabilities are either higher than or lower than all estimated probabilities in the other group; this “common support” requirement reduces the number of physicians in the treatment group by 193 and the total number of observations from 18,902 to 16,747. Finally, we weigh each physician's observations with the inverse probability of being in the treatment group.

The matched-weighted DiD regression results are in the last column of Table 9. The interaction term has about the same magnitude as for the regressions in columns 2 and 3. This indicates that our results are robust.

We next study if the education program has heterogenous effects on adoption depending on physician and municipality characteristics. In the following Table 10, High age refers to those physicians whose ages are above the 75th percentile; Many T2D means that the physician's number of T2D patients in the list is above the median, and Many adopters means the a practice is in municipality whose proportion of adopters is above the median. Table 10 presents the interactions between the education program and physician age, number of listed patients with T2D, and proportion of adopters in the municipality. We do not find an additional effect of age, but both many patients with T2D in the practice and municipalities with an above-median adopters do add to the education effect, supporting the peer effect.

We performed two validation-placebo tests. First, we set 2011, instead of 2013, as the start year of the program, and rerun the regressions. Indeed, from Table 11, the estimated coefficient of the interaction term of the first placebo test is statistically insignificant.

Second, we replaced the intervention counties with two sets of other counties with similar total inhabitants. In Table 12, Placebo counties 1 are Akershus and Buskerud, and Placebo counties 2 are Oslo and Sor-Trondelag. Both sets of placebo counties produce similar and validating results as the year placebo.

The difference-in-difference method is valid when treatment and control groups have similar Fee 109 use time trends before intervention. Figure 2 presents Event Study Graphs for Fee 109 uses for the entire sample period. We calculate the average frequencies of physicians who have used Fee 109 at least 10 times in a year. Then we subtract average frequencies of physicians in counties other than Rogaland and Hordaland from those in Rogaland and Hordaland. The year 2012 is the reference. The dots show the mean Fee 109 use difference between treatment and control physicians in each year. The

	High age		Many T2D		Many adopters	
	DiD	FE	DiD	FE	DiD	FE
Treat (α_1)	-0.311 (0.270)		-0.314 (0.270)		-0.277 (0.273)	
Post (α_2)	0.901*** (0.167)	0.947 (0.515)	0.896*** (0.167)	1.007 (0.515)	0.923*** (0.169)	0.947 (0.515)
Treat \times Post (α_3)	0.675* (0.308)	1.031*** (0.275)	0.022 (0.286)	0.275 (0.200)	0.125 (0.413)	0.485 (0.292)
Treat \times Post \times Subgroup	0.341 (0.628)	-0.012 (0.442)	1.921*** (0.637)	1.827*** (0.461)	0.912 (0.516)	0.763* (0.322)
N	18,897	18,897	18,897	18,897	18,897	18,897
Year fixed effects	\times	\times	\times	\times	\times	\times
Physician fixed effects		\times		\times		\times
Covariates	\times	\times	\times	\times	\times	\times
Physician level clustered errors	\times	\times	\times	\times	\times	\times

Note: Standard errors in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 10 Heterogeneous education effects by difference-in-difference and fixed-effect models

	OLS	Physician fixed effects
Treat (α_1)	-0.130 (0.315)	
Post (α_2)	0.991** (0.172)	1.025 (0.516)
Treat \times After (α_3)	0.139 (0.242)	0.309 (0.220)
N	18,897	18,897
Year fixed effects	\times	\times
Physician fixed effects		\times
Covariates	\times	\times

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 11 Placebo test with 2011 set as treatment start

spread over the dots is the 95% confidence interval. There is no difference between treatment and nontreatment counties before 2012; this validates our common-trend assumption.

6 | TWO-PART AND HAZARD ESTIMATIONS

We present two sets of alternative estimations for robustness. The two-part model uses more conventional methods. We again consider the extensive and total margins: whether or not physicians have used Fee 109 at least 10 times, and, physicians' actual claims of Fee 109 (for at least 10 times). The second, hazard rate in survival, uses a dynamic approach. The fixed effects and two-part models do not estimate the adoption time path. As a check, we use a flexible parametric survival model, similar to Horwitz et al. (2017) to estimate the adoption hazard rate, the probability of adoption given that the physician has not adopted before.

6.1 | Two-part estimation

In the two-part model (Deb et al., 2017, p. 106), the density g_{it} of dependent variable y_{it} conditional on independent variables \mathbf{x}_{it} is

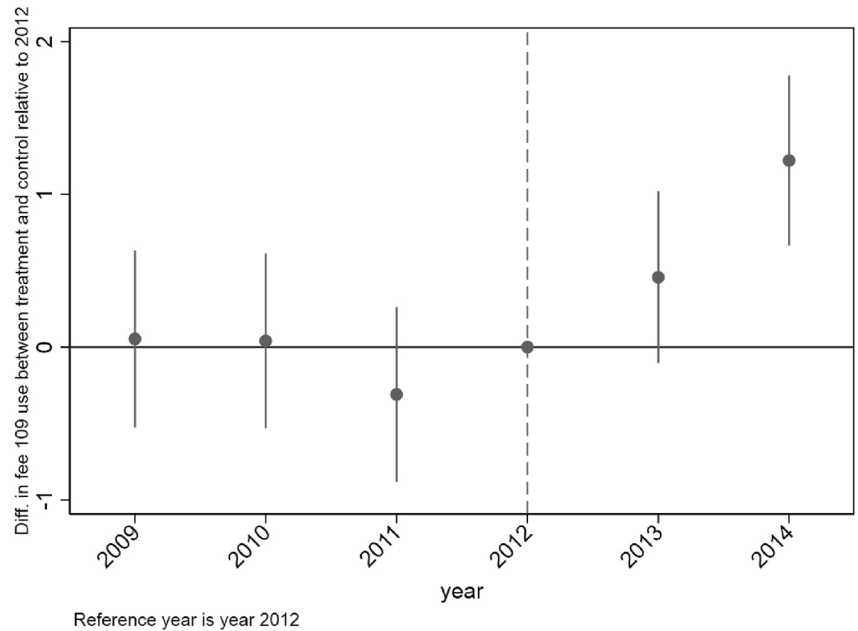
$$g_{it}(y_{it} | \mathbf{x}_{it}) = \begin{cases} [1 - \Pr(y_{it} > 0 | \mathbf{x}_{it})] \times f_0(0 | \mathbf{x}_{it}) & \text{if } y_{it} = 0 \\ \Pr(y_{it} > 0 | \mathbf{x}_{it}) \times f_+(y_{it} | \mathbf{x}_{it}) & \text{if } y_{it} > 0 \\ \text{for } i = 1, \dots, n, \text{ and } t = 2009, \dots, 2016 \end{cases}$$

TABLE 12 Placebo test with alternate treatment counties

	Placebo counties 1		Placebo counties 2	
	OLS	Physician fixed effects	OLS	Physician fixed effects
Treat (α_1)	0.591 (0.394)		-2.749 (1.946)	
Post (α_2)	1.016*** (0.169)	1.060* (0.517)	1.131*** (0.172)	1.037* (0.515)
Treat \times After (α_3)	-0.035 (0.284)	-0.094 0.228	-0.401 (0.286)	-0.541 (0.319)
N	18,897	18,897	18,897	18,897
Year fixed effects	\times	\times	\times	\times
Physician fixed effects		\times		\times
Covariates	\times	\times	\times	\times

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

FIGURE 2 Event study: Change in fee 109 use between treatment and control groups relative to year 2012



Here, y_{it} is the number of Fee 109 uses by physician i in year t . We distinguish between $y_{it} = 0$ and $y_{it} > 0$. The “first part” refers to conditional density f_0 for $y_{it} = 0$ given the independent variables \mathbf{x}_{it} , and the “second part” refers to conditional density f_+ for $y_{it} > 0$ given the independent variables \mathbf{x}_{it} .

We evaluated several functional forms for g_{it} by AIC and BIC, for the first and second parts. As a robustness check we also evaluated a negative binomial regression model because we used count data. A model with logit in the first part and OLS with $\ln(y_{it})$ as the dependent variable for the second part was chosen due to lowest AIC and BIC scores. Error terms are clustered at the physician level. We take into account Duan’s (1983) smearing factor when calculating expected values.

Two-part model estimation results are in Table 13. Columns 2 and 3 show the first and second part estimated coefficients. Column 4 shows the marginal effect estimated at the variables’ mean values. Numbers of T2D patients, #T2D, are positively associated with the adoption decision. Conditional on the program having been adopted, #T2D is positively associated with frequencies of Fee 109 use. In total, the marginal effect of #T2D is positive. Age is negatively associated with the adoption decision and has also a negative marginal effect. Being a specialist is positively associated with adoption decision. In total, being a specialist has a positive marginal effect. The lagged number of

	First part	Second part	Marginal effects
#T2D	0.018*** (0.003)	0.010*** (0.001)	0.395*** (0.051)
#comorbidities	0.007 (0.006)	-0.004 (0.003)	0.028 (0.094)
Age	-0.023*** (0.005)	0.001 0.002	-0.298*** 0.070
Specialist	0.300** (0.100)	0.068 (0.040)	5.046*** (1.508)
L.Shortage	-0.047 (0.108)	-0.015 (0.043)	-0.912 (1.605)
L.adopters	0.016*** (0.003)	-0.002 (0.001)	0.128*** (0.027)
L.#open_per_cap	-0.160 (0.124)	0.117 (0.068)	-0.143 (1.997)
Access private	-0.134* (0.053)	-0.013 (0.020)	-1.848* (0.765)
Access hospital	-0.015 (0.050)	0.039* (0.018)	-0.357 (0.264)
Total_listed	-0.000 (0.000)	0.000 (0.000)	-0.357 (0.264)
Constant	-2.689*** (0.216)	2.381*** (0.091)	
N	18,897	18,897	18,897
Years fixed effects	×	×	×
Errors clustered at physician level	×	×	×

Note: Standard errors in parentheses.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 13 Logit then logged dependent variable OLS two-part model

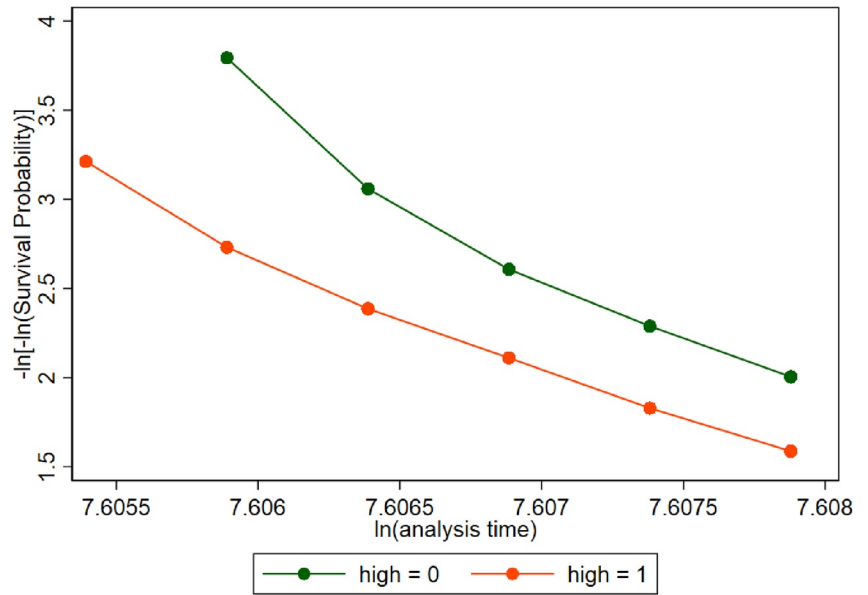
adopters in the municipality is positively associated with the adoption decision; this is interpreted as a peer effect, as we have mentioned before. Also, the marginal effect is positive. However, competition, as measured by the lagged per-capita number of open lists in the municipality, is not associated with adoption. Access to private specialists and hospitals are both negatively associated with the adoption decision. Access to private specialists also has a negative marginal effect.

6.2 | Hazard rate estimation in a survival model

Now we turn to a duration or survival model. The “hazard” of physician i adopting in period t is defined to be the probability of adoption in period t given that adoption has not occurred by period t . We estimate how hazard rates are associated with time and independent variables. Specifics on duration models are in Royston and Parmar (2002) and Royston and Lambert (2011). We start with the proportional hazard, or Cox model, whose hazard function is written as

$$h_i(t|\mathbf{x}_i) = h_0(t) \exp(\mathbf{x}_i\boldsymbol{\beta}),$$

FIGURE 3 Negative log municipality cumulative hazards



where $h_i(t|\mathbf{x}_i)$ is the hazard for individual i at time t conditional on covariates \mathbf{x}_i , $h_0(t)$ is the baseline hazard, and the effects of the covariates are modeled exponentially. The Cox model is estimated by partial likelihood estimation without estimating the baseline hazard.

An assumption in the Cox model is that hazard rates are proportional over time. Figure 3 shows a plot of negative log cumulative hazard rates for municipalities with above-median and below-median lagged adopters. Clearly, the plots are not parallel and the proportional hazard assumption does not seem to be valid.

In flexible parametric survival models, the baseline hazard also is estimated. The cumulative hazard function is expressed as:

$$\ln[H(t|\mathbf{x}_i)] = \ln[H_0(t)] + \mathbf{x}_i\boldsymbol{\beta}, \text{ for } i = 1, \dots, n, \text{ and } t = 2009, \dots, 2016,$$

where H is the cumulative hazard function, defined by $H(t|\cdot) = \sum_{t'=2009}^t h(t'|\cdot)$, and H_0 is the baseline cumulative hazard. The log baseline cumulative hazard is modeled as restricted cubic splines with knots. For example, with four knots, we have

$$\ln[H(t|\mathbf{x}_i)] = \gamma_0 + \gamma_1 z_{1i} + \gamma_2 z_{2i} + \gamma_3 z_{3i} + \mathbf{x}_i\boldsymbol{\beta}.$$

The log baseline hazard function is then estimated as a piecewise linear function.

Table 14 displays estimation results of the flexible parametric survival model in four versions.⁷ In the first two versions, error terms are clustered at the physician level. In version 1 there is one knot, and in version 2 there are three knots. Versions 3 and 4 have error terms clustered at the municipality level with one knot in version 3 and three knots in version 4. Signs of the estimated coefficients are correspondingly the same across the clustering and knot specifications. Across different clustering, estimated coefficients are the same given each knot specification. Also, statistical significance levels are more or less the same across clustering and knot specifications.

The adoption hazard rate is negatively associated with the lagged number of physicians with open lists per capita, and also access to private specialists. However, adoption hazard is positively associated with the number of patients with T2D in physician practice, the lagged number of adopters, which confirms a peer effect, but negatively associated with physician age. These are consistent with our benefit-cost consideration on adoption decisions.

As in the linear models, we have also analyzed movers' decisions in survival models. Table 15 shows a positive effect on the adoption hazard rate for those physicians who have moved to a municipality with more adopters; the result supports results in the fixed-effect models. Our sample drops to less than 800 because some physicians have already adopted when their first data appear.

TABLE 14 Flexible parametric survival estimated hazard for Fee 109 adoption

Clustering	Physician #knots: 1	Physician #knots: 3	Municipality #knots: 1	Municipality #knots: 3
#T2D	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)
#comorbidities	0.008 (0.005)	0.009 (0.005)	0.008 (0.005)	0.009 (0.005)
Specialist	-0.013 (0.094)	-0.015 (0.094)	-0.013 (0.095)	-0.015 (0.095)
Age	-0.025*** (0.005)	-0.025*** (0.005)	-0.025*** (0.005)	-0.025*** (0.005)
Shortage	0.185 (0.110)	0.193 (0.110)	0.185 (0.104)	0.193 (0.104)
L.adopters	0.010*** (0.002)	0.009*** (0.002)	0.010*** (0.001)	0.009*** (0.002)
L.#open_per_cap	-0.422*** (0.164)	-0.466*** (0.103)	-0.422** (0.133)	-0.466** (0.137)
Access private	-0.090 (0.047)	-0.091 (0.047)	-0.090 (0.058)	-0.091 (0.058)
Access hospital	-0.029 (0.016)	-0.027 (0.016)	-0.029 (0.010)	-0.027 (0.010)
Constant	-1.876*** (0.221)	-2.157*** (0.159)	-1.876*** (0.189)	-2.157*** (0.183)
AIC	-3905.370	-3944.626	-3905.370	-3944.626
BIC	-3812.554	-3836.340	-3812.554	-3836.340
N	16,894	16,894	16,894	16,894

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Clustering	Physician	Municipality
After	-1 (0.762)	-1.931* (0.819)
After * Δ adopters	1.213* (0.561)	1.213* (0.574)
Covariates	×	×
#knots	1	1
N	789	789

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

TABLE 15 Flexible parametric survival estimated hazard for movers' Fee 109 adoption

7 | CONCLUDING REMARKS

We have studied primary care physicians' adoption of monitoring and prevention technology for Type 2 Diabetes patients. In Norway, the adoption of the technology has been meager. Up till 2019, only about 25% of physicians have adopted. In the study, we use a physician panel register data between 2009 and 2014. We identify a peer effect by means of fixed-effect models and by studying physicians who have moved between municipalities: adoption is encouraged by the proportion of municipality adopters. Two-part models and hazard models lend support to robustness of these effects. Finally, the introduction of an education program in two counties in 2013 has had a strong impact on adoption. The education-program effect varies positively according to proportion of municipality adopters, again a peer effect.

Our analysis and results make a number of points. First, our model posits a natural benefit and cost comparison to guide adoption. Broadly, physician and municipality characteristics yield their expected effects. Factors that raise benefits and reduce costs have encouraged adoption. Thus, physicians who have more T2D patients, who are younger and specialists, and who practice in municipalities with many adopters tend to adopt. Second, the last factor points to a peer effect, which may correspond to physician network and collaboration identified in earlier studies (Miraldo et al., 2019). The strong impact of the education program also may have fostered the network effect.

Third, the low adoption may have been due to the low financial rewards. Fee 109 was not a significant amount, but our data would not allow us to test such a hypothesis because the level has not changed. Finally, and somewhat unexpectedly, market conditions have not been associated with adoption. This is in contrast with studies on technology adoption in hospitals. Possibly, T2D patients may not be aware of the benefit of the structured annual check-up, so do not particularly demand physicians who have introduced the procedure. Without a demand threat, physicians lack an incentive to adopt the program. Furthermore, fees for treating T2D patients may not be financially attractive, and having other patients may be more profitable. Our work therefore points to the risk of borrowing results of hospital technology adoption to primary care settings.

ACKNOWLEDGMENTS

We are grateful to the Research Council of Norway for financial support through the Health Economics Research Program at the University of Oslo (HERO). Part of the research was carried out when Ma was a visiting professor of economics at the University of Oslo. For their comments, we thank discussant Brigitte Dormont and participants at the iHEA World Congress in Boston, participants at the EuHEA Conference in Maastricht, discussant Dorte Gyrð Hansen and participants at the 39th NHESG Meeting in Tromsø, and seminar participants in University of Melbourne, Peking University, and Taiwan Economic Association Conference. We also thank coeditor Rosella Levaggi, and two referees for their comments and suggestions. This study was funded by Norges Forskningsråd (Grant No. 204677). The project was approved by the Norwegian Regional Committee for Medical and Health Research Ethics with registration number 2011/1708/REK sør-øst B

CONFLICT OF INTEREST

Tor Iversen and Ching-to Albert Ma declare that they have no conflict of interest regarding this research.

DATA AVAILABILITY STATEMENT

Data availability subject to the Regional Committee for Medical and Health Research Ethics and Norway Health Insurance Administration approval.

ORCID

Ching-to Albert Ma  <https://orcid.org/0000-0002-8985-1594>

ENDNOTES

- ¹ The check-up should include suitable blood tests, inspection of feet and eyes, referrals to an ophthalmologist, and recommendation of lifestyle changes.
- ² <https://www.noklus.no/Diabetesregisterforvoksne/Diabetesregisterforvoksne.aspx>.
- ³ Our regressions with fixed effects explicitly allow adoption decisions to be specific to physicians in different municipalities and time periods. Vectors θ and ϕ capture those variables that do not stay constant with a physician or a municipality.
- ⁴ Numbers of physicians vary according to municipalities and time, so n should also depend on k and t ; we have glossed over those details to avoid a cluttered exposition.
- ⁵ As shown by Bertrand et al. (2004) and Cameron and Miller (2015), fixed-effect models generally do not control for all the within-cluster error-term correlations, so the cluster robust estimate of the variance matrix should be used. The usual question is at what level to cluster. Cameron and Miller (2015) observe that “In practice researchers often cluster at progressively higher (i.e., broader) levels and stop clustering when there is relatively little change in the standard errors. This seems to be a reasonable approach.” We have considered clustering both at the physician level and at the municipality level. Because the standard errors declined when we went from the physician level to the municipality level, we decided to cluster standard errors at the physician level.
- ⁶ In a separate regression (not presented here), we have also studied the number of Fee 109 claims, conditional on the use of Fee 109 (Fee 109 = 1). But we have not found a peer effect. The total effect we have found is likely the same as the extensive margin.
- ⁷ In these models, the variables Total_listed is dropped since the algorithm does not converge.

REFERENCES

- Andersson, E., Persson, S., Hallén, N., Ericsson, Å., Thielke, D., Lindgren, P., Steen Carlsson, K., & Jendle, J. (2020). Costs of diabetes complications: Hospital-based care and absence from work for 392,200 people with type 2 diabetes and matched control participants in Sweden. *Diabetologia*, *63*, 2582–2594.
- Andrade, L. F., Rapp, T., & Sevilla-Dedieu, C. (2018). Quality of diabetes follow-up care and hospital admissions. *International Journal of Health Economics and Management*, *18*, 153–167.
- Baker, L. C. (2001). Managed care and technology adoption in health care: Evidence from magnetic resonance imaging. *Journal of Health Economics*, *20*, 395–421.
- Bakke, Å., Cooper, J. G., Thue, G., Skeie, S., Carlsen, S., Dalen, I., Løvaas, K. F., Madsen, T. V., Oord, E. R., Berg, T. J., Claudi, T., Tran, A. T., Gjelsvik, B., Jennum, A. K., & Sandberg, S. (2017). Type 2 diabetes in general practice in Norway 2005–2014: Moderate improvements in risk factor control but still major gaps in complication screening. *British Medical Journal Open Diabetes Research & Care*, *5*, e000459. <https://doi.org/10.1136/bmjdr-2017-000459>
- Bakke, Å., Tran, A. T., Dalen, I., Bakke, Å., Tran, A. T., Dalen, I., Cooper, J. G., Løvaas, K. F., Jennum, A. K., Berg, T. J., Madsen, T. V., Nøkleby, K., Gjelsvik, B., & Claudi, T. (2018). Population, general practitioner and practice characteristics are associated with screening procedures for microvascular complications in type 2 diabetes care in Norway. *Diabetic Medicine*, *36*(11), 1431–1443.
- Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, *119*, 249–275.
- Blankart, K. E., & Stargardt, T. (2020). The impact of drug quality ratings from health technology assessments on the adoption of new drugs by physicians in Germany. *Health Economics*, *29*, 63–82. <https://doi.org/10.1002/hec.4108>
- Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, *50*, 317–372.
- Clarke, D., Romano, J. P., & Wolf, M. (2019). The Romano-Wolf multiple hypothesis correction in Stata. IZA DP No. 12845. IZA Institute of Labor Economics.
- Claudi, T., Ingskog, W., Cooper, J. G., Jennum, A. K., & Hausken, M. F. (2008). Kvaliteten på diabetesbehandlingen i allmennpraksis. *Tidsskrift for Den norske Legeforening*, *128*, 2570–2574.
- Deb, P., Norton, E. C., & Manning, W. G. (2017). *Health econometrics using Stata*. Stata Press.
- Duan, N. (1983). Smearing estimate: A nonparametric retransformation method. *Journal of the American Statistical Association*, *78*, 605–610.
- Gawande, A. (2010). *The checklist manifesto: How to get things right*. Metropolitan Books.
- Grol, R. (1992). Implementing guidelines in general practice care. *Quality in Health Care*, *1*, 184–191.
- Grol, R., & Grimshaw, J. (2003). From best evidence to best practice: Effective implementation of change in patients' care. *Lancet*, *362*, 1225–1230.
- Helsedirektoratet. (2009). *Nasjonal faglig retningslinje for forebygging, diagnostikk og behandling av diabetes*. IS-1674. Helsedirektoratet.
- Helsedirektoratet. (2016). *Nasjonal faglig retningslinje for diabetes*. Retrieved June 27, 2017, from <https://helsedirektoratet.no/retningslinjer/diabetes>
- Horwitz, J. R., Hsuan, C., & Nichols, A. (2017). *The role of hospital and market characteristics in invasive cardiac service diffusion*. NBER Working Paper No. 23530. National Bureau of Economic Research.
- Ivers, N., Jamtvedt, G., Flottorp, S., Young, J. M., Odgaard-Jensen, J., French, S. D., O'Brien, M. A., Johansen, M., Grimshaw, J., & Oxman, A. D. (2012). Audit and feedback: Effects on professional practice and healthcare outcomes. *Cochrane Database of Systematic Reviews*, *6*, CD000259. <https://doi.org/10.1002/14651858.CD000259.pub3>
- Iversen, T., & Lurås, H. (2011). Patient switching in general practice. *Journal of Health Economics*, *30*, 894–903.
- Kaiser Permanente. (2017). *Adult diabetes clinician guide*. Retrieved March 19, 2019, from <http://kpcmi.org/files/diabetes-clinician-guide.pdf>
- Karaca-Mandic, P. K., Town, R. J., & Wilcock, A. (2017). The effect of physician and hospital market structure on medical technology diffusion. *Health Services Research*, *52*, 579–598.
- Klausen, L. M., Olsen, T. E., & Risa, A. E. (1992). Technological diffusion in primary health care. *Journal of Health Economics*, *11*, 439–452.
- Kremer, S. T. M., Bijmolt, T. H. A., Leeflang, P. S. H., & Wieringa, J. E. (2008). Generalizations on the effectiveness of pharmaceutical promotional expenditures. *International Journal of Research in Marketing*, *25*, 234–246.
- Larun, L., Bjørner, T., Fretheim, A., & Brurberg, K. G. (2016). Use of forms for follow-up of diabetes in general practice. *Tidsskrift for den Norske Legeforening*, *136*, 417–422.
- Liu, Q., & Gupta, S. (2012). A micro-level diffusion model for new drug adoption. *Journal of Product Innovation Management*, *29*, 372–384.
- Miraldo, M., Hauck, K., Vernet, A., & Wheelock (2019). Variations in the adoption of healthcare innovation: A literature review. In J. H. Hamilton (Ed.), *Oxford research encyclopedia of economics and finance*. Oxford University Press. <https://doi.org/10.1093/acrefore/9780190625979.013.76>
- Molitor, D. (2018). The evolution of physician practice styles: Evidence from cardiologist migration. *American Economic Journal: Economic Policy*, *10*, 326–356.
- Nøkleby, K., Berg, T. J., Mdala, I., Tran, A. T., Bakke, Å., Gjelsvik, B., Claudi, T., Cooper, J. G., Løvaas, K. F., Thue, G., & Sandberg, S. (2020). Variation between general practitioners in type 2 diabetes processes of care. *Primary Care Diabetes*, *14*, S1751.

- Nøkleby, K., Berg, T. J., Mdala, I., Berg, T. J., Mdala, I., Buhl, E. S., Claudi, T., Cooper, J. G., Løvaas, K. F., Sandberg, S., & Jennum, A. K. (2021). High adherence to recommended diabetes follow-up procedures by general practitioners is associated with lower estimated cardiovascular risk. *Diabetic Medicine*, *38*(8), e14586.
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55.
- Royston, P., & Lambert, P. C. (2011). *Flexible parametric survival analysis using Stata: Beyond the Cox Model*. Stata Press.
- Royston, P., & Parmar, M. K. B. (2002). Flexible parametric proportional-hazards and proportional-odds models for censored survival data, with application to prognostic modelling and estimation of treatment effects. *Statistics in Medicine*, *21*, 2175–2197.
- Scott, A., Schurer, S., Jensen, P. H., & Sivey, P. (2009). The effects of an incentive program on quality of care in diabetes management. *Health Economics*, *18*, 1091–1108.
- Skinner, J. (2012). Causes and consequences of regional variations in health care. In M. V. Pauly, T. G. McGuire, & P. P. Barros (Eds.), *Handbook of health economics* (vol. 2, pp. 46–93). Elsevier.
- Socialstyrelsen (2018). *Nationella riktlinjer för diabetesvård. Stöd för styrning och ledning*. Socialstyrelsen.
- Wensing, M., van der Weijden, T., & Grol, R. (1998). Implementing guidelines and innovations in general practice: Which interventions are effective? *British Journal of General Practice*, *48*, 991–997.

How to cite this article: Iversen, T., & Ma, C.-t. A. (2021). Technology adoption by primary care physicians. *Health Economics*, 1–23. <https://doi.org/10.1002/hec.4447>