Technology Adoption in Primary Health Care

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Abstract

We study primary care physicians' prevention and monitoring technology adoption. Physicians are assumed to decide to adopt 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 two-part and fixed-effect regressions, and hazard models. We use a difference-in-difference model to estimate the education program impact. Adoptions are positively associated with a physician's number of diabetic patients, and the fraction of physician-adopters in the same market. Fixed-effect estimations and separate analyses of physicians who have moved between municipalities causally support a peer effect. The education program has a strongly positive effect.

Keywords: primary care, technology, monitoring, incentives, education program

JEL: I11, I18, O31

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1 Introduction

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

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

In this paper, we study financial and nonfinancial 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 physician claims and registrar 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] In addition, physicians submit data obtained at check-ups to a national register, which is maintained by a center called NOKLUS.[2]

[1] The check-up should include suitable blood tests, inspection of feet and eyes, referrals to an ophthalmologist, and recommendation of life-style changes.

[2] http://www.noklus.no/Diabetesregisterforvoksne/Diabetesregisterforvoksne.aspx

First, the financial aspect of the Norwegian Directorate guideline works through a fee-for-service module. From 2008, the structured annual check-up has entitled the 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. Second, 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 used 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 two-part models to correlate physician and municipality characteristics with Fee 109 adoption. We find that a physician's adoption is positively associated with the number of T2D patients in her practice, and to the lagged number of municipality physicians who have already adopted. Fee 109 adoption is negatively associated with municipality access to specialty care. We do not find an association between the lagged number of physicians with open practices, a measure of competition, and Fee 109 use.

Second, we use fixed-effect models to identify a peer effect; those physicians who practice in municipalities with more adopters tend to adopt Fee 109 and use the technology more often. A separate analysis on 230 physicians who have moved between municipalities supports the identification. Third, we use hazard models to verify robustness in association in two-part models and peer effects in fixed-effect models. Finally, to assess education, we use a difference-in-difference regression for the program that started in 2013, and find a strong causal effect on Fee 109 use. The program has a greater effect in municipalities where many physicians already have adopted, so again confirming that education programs' adoption effects are contingent on local adoption shares.

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, followed by the econometric methods and results in Section 5. Finally, Section 6 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 potentially 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) make 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 adoption has been chosen by peers, 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 much more likely to adopt an invasive service if nearby 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 seemed to respond to adoption.

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 quality of care in diabetes, as measured by the probability of ordering an Haemoglobin-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 profit diversity. These papers have generally adopted a benefit-cost approach, which we have subscribed to 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 had improved substantially from the previous registration, 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.

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

In Norway, a 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 4,100 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; this fee was NOK 386 in 2012, at which time the exchange rate was about US $1 to NOK 6. A physician had, on average, 1,200 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 calender 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 and 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 1,980 and any excess was paid for by the National Health Insurance.

2.2 Type 2 Diabetes and Fee 109

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 U.S., 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. 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 Registry 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.

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. 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 registry. 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. 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.

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. 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 due to 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. Chronically ill patients may regard a physician's adoption as her offering higher care quality. 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 (ICPC2). 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 six

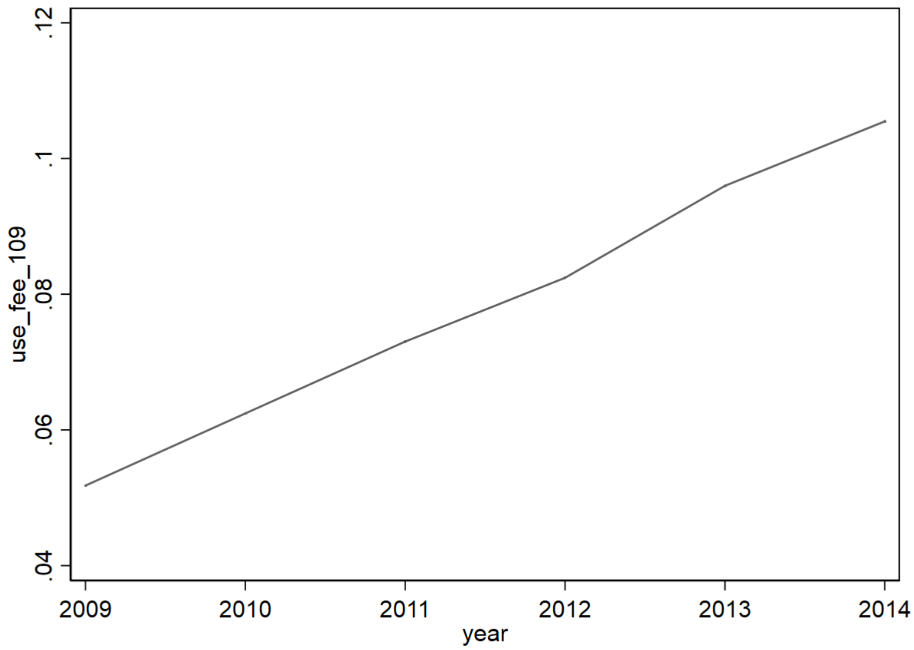

Figure 1: Time trend of physicians adopting Fee 109

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 he or she makes use of Fee 109 at least 10 times in one 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 descriptives of adopters and non-adopters. 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 nonadopters. Adopters have a longer patient list, and are less likely to experience patient shortage than nonadopters.

On average adopters are located in smaller municipalities than non-adopters. Adopters' smaller municipalities have fewer open lists than non-adopters' municipalities, but when population size is normalized, adopters and adopters seem to have the same percentage of practices with open lists. Table 1 also describes the number of physicians in the municipalities who have adopted the comprehensive annual check-up (#adopters). Adoptions seem to be more likely when there are more adopters in the municipality in the previous years. 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 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 1: Physician descriptive statistics in 2009

Variable Definition	Non-adopters			Adopters		
Physician level	mean	st dev		mean	st dev	
#T2D Number patients with T2D	48	28	min 10 max 307	66	33	min 26 max 305
Proportion T2D Proportion patients with T2D	0.04	0.02	min 0.01 max 0.17	0.05	0.02	min 0.02 max 0.25
#comorbidities Number comorbidities	18	12	min 1 max 143	25	19	min 4 max 185
Specialist Primary care specialist	0.60	0.49	min 0 max 1	0.74	0.44	min 0 max 1
Age Physician age	48	10	min 26 max 80	48	10	min 28 max 67
Maxlist Maximum list size	1,192	441	min 0 max 2,500	1,245	350	min 0 max 2,400
List Actual list size	1,219	380	min 157 max 2,720	1,317	326	min 541 max 2,396
Shortage List < (Maxlist - 100)	0.20	0.40	min 0 max 1	0.15	0.36	min 0 max 1
Municipality level						
Total_listed Listed patients (in 1,000)	111	190	min 0.1 max 612	88	153	min 0.7 max 612
#openlists Number open lists	30	56	min 0 max 183	21	43	min 0 max 183
#open_per_cap 1000*#openlists/Total_listed	0.40	0.41	min 0.00 max 8.26	0.40	0.31	min 0.00 max 1.55
#adopters Total number of adopters	5.6	8.4	min 0 max 33	7.1	9.2	min 1 max 33
Access private specialist Private specialist access index	0.68	1.11	min -1.54 max 2.21	0.46	1.09	min -1.33 max 2.21
Access hospital Hospital access index	1.72	3.66	min -2.09 max 11.78	1.19	2.79	min -1.26 max 11.78
Observations	3,669			201		

Table 2: Physician descriptive statistics in 2014

Variable	Non-adopters			Adopters		
Physician level	mean	st dev		mean	st dev	
#T2D	37	22	min 10 max 252	51	23	min 15 max 227
Proportion T2D	0.03	0.02	min 0.00 max 0.14	0.04	0.02	min 0.01 max 0.19
#comorbidities	14	9	min 0 max 106	19	12	min 2 max 130
Specialist	0.60	0.49	min 0 max 1	0.70	0.46	min 0 max 1
Age	48	11	min 26 max 74	49	11	min 27 max 68
Maxlist	1,167	395	min 0 max 2,500	1,297	363	min 0 max 2,500
List	1,181	355	min 147 max 3,080	1,319	347	min 484 max 2,898
Shortage	0.15	0.35	min 0 max 1	0.09	0.29	min 0 max 1
Municipality level						
Total_listed	125	221	min 0.5 max 715	129	196	min 0.5 max 715
#openlists	36	65	min 0 max 215	35	57	min 0 max 215
#open_per_cap	0.42	0.39	min 0.00 max 6.45	0.34	0.25	min 0.00 max 2.3
#adopters	17.5	28.9	min 0 max 109	25.7	35.2	min 1 max 109
Access private specialist	0.66	1.13	min -1.54 max 2.21	0.62	0.99	min -1.50 max 2.21
Access hospital	1.71	3.66	min -2.09 max 11.78	1.46	3.10	min -1.99 max 11.78
Observations	3,720			445		

Table 2 shows descriptives 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: Physician descriptive statistics by counties in 2012

	Counties without program			Rogaland, Hordaland		
Physician level	mean	st dev		mean	st dev	
#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	1,142	445	min 0 max 2500	1,268	372	min 0 max 2500
List	1,199	359	min 144 max 2,707	1,292	380	min 312 max 2,502
Shortage	0.17	0.38		0.15	0.35	
Municipality level	mean	st dev		mean	st dev	
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		3,333			725	

Table 3 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 other counties. Both Rogaland and Hordaland have lower access to specialized care compared to other counties.

5 Econometric methods and results

We estimate factors that contribute to physicians adopting a structured annual check-up for T2D patients. Four different estimations are used. First, we use a two-part model. Here, we consider the extensive and intensive margins: whether or not physicians have used Fee 109 ten times or more, and, given any use, physicians' frequency of using Fee 109 above nine times. Second, we estimate two sets of fixed-effect models. The first set adjusts 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 enable us to identify peer effects. Third, using a flexible parametric survival model, we estimate the adoption hazard rate, the probability of adoption given that the physician has not adopted before. Fourth, with the Rogaland and 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 may depend on physician and municipality characteristics. and we examine these heterogenous effects by additional difference-in-difference models.

5.1 Two-part estimation

In the two-part model (Deb, Norton and Manning, 2017, p106), the density g_{it} of dependent variable y_{it} conditional on independent variables $\mathbf{x}_{it}$ is

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

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 Akaike information (AIC) and Bayesian information criteria (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, which are displayed in the following footnote.[3] Error terms are clustered at the physician level. We take into account Duan's (1983) smearing factor when calculating expected values.

[3] Akaike and Bayesian information criteria:

Model	N	loglik	AIC	BIC
logit, linear	18,902	-11,862.24	23,776.47	23,980.50
logit, loglinear	18,902	-6,362.67	12,777.34	12,981.36
probit, loglinear	18,902	-23,044.06	46,140.12	46,344.14
logit, glm (log, gamma)	18,902	-12,016.17	24,084.33	24,288.35
negative binomial regression	18,902	-13,188.89	26405.77	26515.63

Table 4: Logit then logged dependent variable OLS two-part model

	First part	Second part	Marginal effects
#T2D	0.018^{***}	0.010^{***}	0.395^{***}
	(0.003)	(0.001)	(0.051)
#comorbidities	0.007	-0.004	0.028
	(0.006)	(0.003)	(0.094)
Age	-0.023^{***}	0.001	-0.298^{***}
	(0.005)	0.002	0.070
Specialist	0.300^{**}	0.065	5.046^{***}
	(0.100)	(0.039)	(1.508)
L.Shortage	-0.048	-0.017	-0.912
	(0.108)	(0.044)	(1.605)
L.adopters	0.013^{***}	-0.003^{***}	0.128^{***}
	(0.002)	(0.001)	(0.027)
L.#open_per_cap	-0.159	0.122	-0.143
	(0.125)	(0.069)	(1.997)
Access private	-0.126^{*}	-0.011	-1.848^{*}
	(0.052)	(0.020)	(0.765)
Access hospital	-0.052^{**}	0.021^{**}	-0.357
	(0.018)	(0.008)	(0.264)
Constant	-3.618^{***}	2.365^{***}	
	(0.129)	(0.091)	
N	18,902	18,902	18,902
Years fixed effects	×	×	×
Errors clustered at physician level	×	×	×
Standard errors in parentheses			
* p<0.05; **p<0.01 ***p<0.001			

Two-part model estimation results are in Table 4. Columns 2 and 3 show the first and second part estimated coefficients. Column 4 shows the marginal effect estimated at the variables' mean values. An "L." before a variable name denotes that the variable takes on the value one period before (lagged). 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 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.

5.2 Fixed-effect estimation

Some municipality explanatory variables in the two-part regressions in Table 4 may be endogenous or missing. For instance, tourism and seasonal sports may lead some physicians in some municipalities to leave their practices open for tourists and seasonal residents. These physicians are unlikely to perform comprehensive annual check-ups on visitors. Municipalities in remote areas with lower physician densities may need to use part-time physicians or other practitioners; again, these providers may be less likely to perform checkups. However, these unobserved municipality characteristics should remain constant over time in our relatively short data period. In fact, we can correct for these omitted variables or endogeneity by fixed effects. In Table 5, the dependent variable is #Fee109, which is the number of Fee 109 claims when they are at least ten times within a calender year, and the regression has physician, municipality and year fixed effects. There are now less data variations because we can only exploit the within-physician and within-municipality variations. From Table 5, the number of adopters in the previous year becomes the only statistically significant effect. Our interpretation is that the peer effect seems robust.

Table 5: Linear model with physician, municipality and year fixed effects

	#Fee 109
#T2D	0.011
	(0.015)
#comorbidities	0.005
	(0.034)
Age	−0.086
	(0.122)
Specialist	−0.466
	(0.261)
L.Shortage	−0.202
	(0.168)
L.adopters	0.018**
	(0.006)
L.#open_per_cap	0.365
	(0.217)
Access private	−0.468
	(0.685)
Access hospital	−0.002
	(0.117)
N (484 singleton obs. dropped)	18,418
Years fixed effects	×
Municipalities fixed effects	×
Physicians fixed effects	×
Errors clustered at physician level	×
Standard errors in parentheses	
* p<0.05; **p<0.01 ***p<0.001	

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 porbably many magnitude higher than adoption cost. Focusing on these movers and 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 1,133 data points (an unbalanced sample of six 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 Δadopters as follows. For each mover, we note the origin and destination municipalities. We then compare the number of adopters in both municipalities. The Δadopters 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, Δadopters measures an increased exposure of peer adoption after the move. For the 16 physicians who have moved more than once, Δadopters is updated in each move. In the following Table 6, the dependent variable Fee 109 is equal to one if Fee 109 is used at least ten 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, 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 $*$ Δadopters.

Table 6: Linear model for movers with physician and year fixed effects

	Fee 109	#Fee 109
After	-0.033	-1.161*
	(0.025)	(0.622)
After * Δadopters	0.066*	1.300
	(0.032)	0.727
N	1,133	1,133
Covariates	×	×
Years fixed effects	×	×
Physicians fixed effects	×	×
Errors clustered at physician level	×	×
Standard errors in parentheses		
* p<0.05; **p<0.01 ***p<0.001		

According to Table 6, 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 is insignificant at 5% but significant at 10%. The results support a peer effect.

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 7 shows the result of linear regressions with fixed effects for physicians, municipalities and 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 likely 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.

Table 7: Demand OLS with physician, municipality and year fixed effects

	Δlist	Δ#T2D
L.Adoption	4.208	0.323
	(6.229)	(0.322)
L.Shortage	108.400^{***}	4.437^{***}
	(20.839)	(0.865)
L.Adoption*L.Shortage	11.510	-0.610
	(20.910)	(0.869)
Constant	-22.470^{***}	-2.632^{***}
	(5.852)	(0.294)
N (492 singleton obs. dropped)	18,725	18,725
r2	0.349	0.294
Years fixed effects	×	×
Municipality fixed effects	×	×
Errors clustered at physician level	×	×
Standard errors in parentheses		
* p<0.05; **p<0.01 ***p<0.001		

5.3 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

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

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 modelled 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 2 shows a plot of negative log cumulative hazard rates for municipalities with above-median and

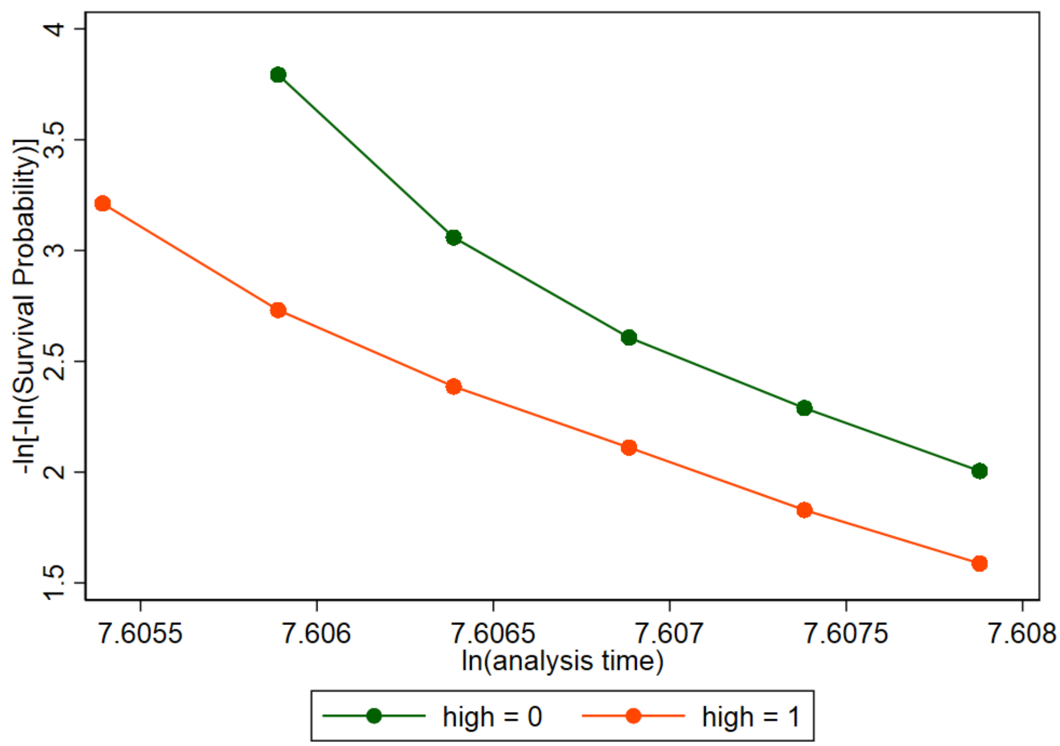

Figure 2: Negative log municipality cumulative hazards

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:

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

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 8: 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***	0.012***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
#comorbidities	0.008	0.009	0.008	0.009
	(0.005)	(0.005	(0.005)	(0.005)
Specialist	−0.013	−0.015	−0.013	−0.015
	(0.094)	(0.094)	(0.095)	(0.095)
Age	−0.025***	−0.025***	−0.025***	−0.025***
	(0.005)	(0.005)	(0.005)	(0.005)
Shortage	0.185	0.193	0.185	0.193
	(0.110)	(0.110)	(0.104)	(0.104)
L.adopters	0.010***	0.009***	0.010***	0.009***
	(0.002)	(0.002)	(0.001)	(0.002)
L.#open_per_cap	−0.422***	−0.466***	−0.422**	−0.466**
	(0.164)	(0.103)	(0.133)	(0.137)
Access private	−0.090	−0.091	−0.090	−0.091
	(0.047)	(0.047)	(0.058)	(0.058)
Access hospital	−0.029	−0.027	−0.029	−0.027
	(0.016)	(0.016)	(0.010)	(0.010)
Constant	−1.876***	−2.157***	−1.876***	−2.157***
	(0.221)	(0.159)	(0.189)	(0.183)
AIC	−3,905.370	−3,944.626	−3,905.370	−3,944.626
BIC	−3,812.554	−3,836.340	−3,812.554	−3,836.340
N	16,894	16,894	16,894	16,894

Table 8 displays estimation results of the flexible parametric survival model in four versions. 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 clusterings, 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 9 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 9: Flexible parametric survival estimated hazard for movers' Fee 109 adoption

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

5.4 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:

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

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 $t = 2009, ..., 2012$, 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_{itj}. 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 10. The fixed-effect model did have the smaller AIC and BIC values than OLS. In the basic DiD model, the interaction effect coefficient α_3 is 0.867 and significant at the 1% level. In the physician fixed-effect regression, the interaction coefficient is 1.041, also significant at the 1% level. Consider the average of the estimated interaction effects, $(0.867+1.041)/2 = 0.954$. 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 0.954 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.

According to Table 3, physicians in Rogaland and Hordaland are different from those in other counties, and obviously, Rogaland and Hordaland are different from other counties. To make the treatment and control groups more similar, we select a subsample of similar physicians in the treatment and control counties by a standard matching model (Rosenbaum and 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 10. The interaction term has about the same magnitude as for the regressions in columns 2 and 3. This indicates that our results are robust.

Table 10: Difference-in-difference and fixed-effect estimations of education effects

	Difference in difference	Fixed-effect regression	Matched, weighted Difference in difference
Treat (α_1)	-0.328		-0.425
	(0.271)		(0.255)
Post (α_2)	0.959***	0.941	0.983***
	(0.163)	(0.514)	(0.276)
Treat × Post (α_3)	0.867***	1.041***	0.820**
	(0.236)	(0.230)	(0.358)
N	18,902	18,902	16,747
Years fixed effects	×	×	×
Physician fixed effects		×	
Covariates	×	×	×
Physician level clustered errors	×	×	×
Standard errors in parentheses			
* p<0.05; **p<0.01 ***p<0.001			
Mean #Fee109 above 9 in 2012 in treatment counties	1.86	1.86	1.79

We next study if the education program has heterogenous effects on adoption depending on physician and municipality characteristics. In the following Table 11, 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 11 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. The last effect supports the peer effect.

Table 11: Heterogeneous education effects by Difference-in-difference and Fixed-effect models

	High age		Many T2D		Many adopters	
	DiD	FE	DiD	FE	DiD	FE
Treat (α_1)	-0.326		-0.329		-0.277	
	(0.272)		(0.272)		(0.273)	
Post (α_2)	0.959***	0.940	0.953***	1.002	0.923***	0.947
	(0.163)	(0.514)	(0.163)	(0.514)	(0.169)	(0.515)
Treat × Post (α_3)	0.765**	1.043***	0.113	0.256	0.125	0.485
	(0.311)	(0.273)	(0.290)	(0.198)	(0.413)	(0.292)
Treat × Post × Subgroup	0.345	-0.008	1.922***	1.829***	0.912	0.763*
	(0.626)	(0.443)	(0.637)	(0.461)	(0.516)	(0.322)
N	18,902	18,902	18,902	18,902	18,902	18,902
Year fixed effects	×	×	×	×	×	×
Physician fixed effects		×		×		×
Covariates	×	×	×	×	×	×
Physician level clustered errors	×	×	×	×	×	×
Standard errors in parentheses						
* p<0.05; **p<0.01 ***p<0.001						

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 12, the estimated coefficient of the interaction term of the first placebo test is statistically insignificant.

Table 12: Placebo test with 2011 set as treatment start

	OLS	Physician fixed effects
Treat (α_1)	-0.161	
	(0.318)	
Post (α_2)	1.064***	1.045
	(0.167)	(0.513)
Treat × After (α_3)	0.205	0.308
	(0.242)	(0.220)
N	18,902	18,902
Year fixed effects	×	×
Physician fixed effects		×
Covariates	×	×

Second, we replaced the intervention counties with two sets of other counties with similar total inhabitants. In Table 13, 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.

Table 13: Placebo test with alternate treatment counties

	Placebo counties 1		Placebo counties 2	
	OLS	Physician fixed effects	OLS	Physician fixed effects
Treat (α_1)	0.617		-3.089	
	(0.398)		(1.699)	
Post (α_2)	1.101^{***}	1.044^{*}	1.151^{***}	1.034^{*}
	(0.165)	(0.516)	(0.162)	(0.514)
Treat × After (α_3)	-0.067	-0.084	-0.391	-0.574
	(0.285)	0.228	(0.287)	(0.302)
N	18,902	18,902	18,902	18,902
Year fixed effects	×	×	×	×
Physician fixed effects		×		×
Covariates	×	×	×	×

The difference-in-difference method is valid when treatment and control groups have similar Fee 109 use time trends before intervention. Figure 3 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 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 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

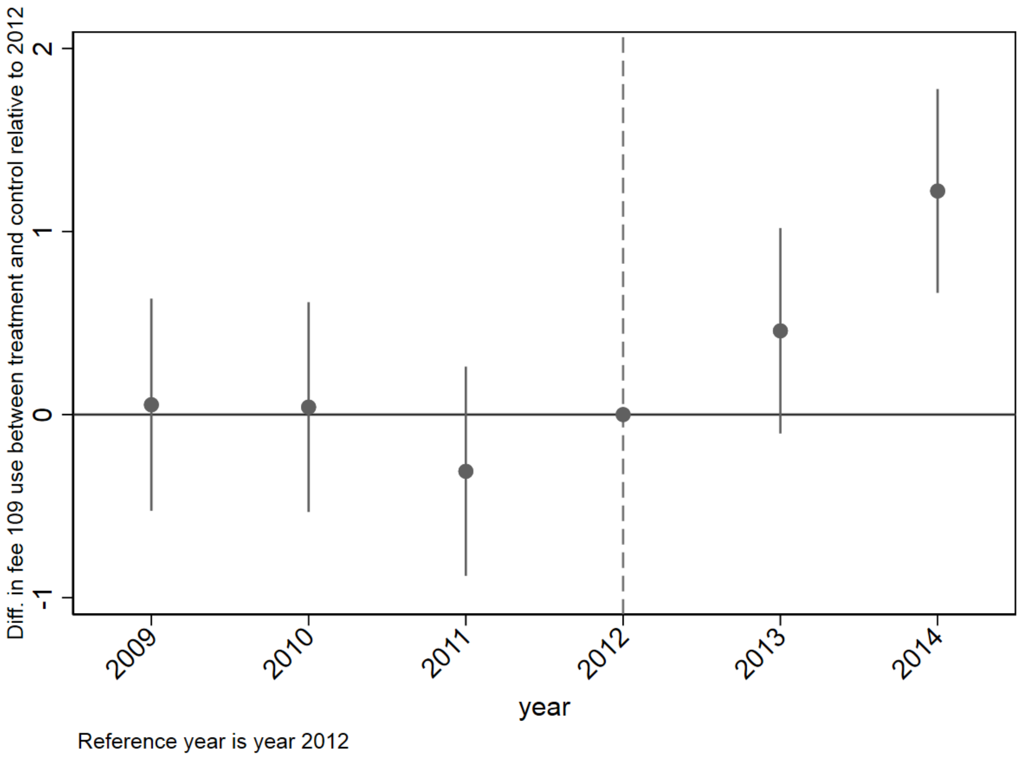

Figure 3: Event study

2019, only about 25% of physicians have adopted. Using two-part models, we have examined factors that are associated with adoption using physician panel and register data between 2009 and 2014. By means of fixed-effect models and by studying physicians who have moved between municipalities, we identify a peer effect: adoption is encouraged by the proportion of municipality adopters. 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 perhaps has 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.

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