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Marianne Simonsen, Lars Skipper, Niels Skipper and Peter Rønø Thingholm

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This paper investigates consequences of practice closures among primary care providers on subsequent patient health care utilization and health. Critically, the analysis relies on population-level administrative Danish data that facilitate a unique link between all Danes and their family doctor. We start by characterizing the nature of a practice closure, including the change in provider characteristics that occurs when patients change provider. Practice closure leads patients to choose a systematically younger and less experienced primary care provider. Using a difference-in-differences strategy that compares individuals who experience a practice closing with similar individuals enrolled in similar practices that do not close until later, we next investigate consequences for patient health care utilization and health outcomes. We find that a change in provider due to practice closure increases detection of chronic illness but does not lead to concurrent changes in primary care utilization. We do detect a considerable increase in the use of emergency care, however. A decomposition exercise shows that both physician practice style and the disruption itself plays a role for the total effects but that the direction of their relative influence varies across outcome domains. Importantly, disruption is not always negative from the perspective of the patient.

JEL: I11, I12, I18

Keywords: Physician practice closure; disruption; practice styles

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1. Introduction

There are widespread concerns that the stock of physicians is growing older. In 2016, for example, it was estimated that 29% or nearly 279,000 of all actively licensed physicians in the United States were older than 60 years (Young et al, 2017). The bulge of baby boomers among European doctors is of such a magnitude that already by 2009 around 30% of doctors were above 55 years of age and by 2020 3.2% of all European doctors are expected to retire *annually* (European Commission, 2012). This trend is expected to lead to practice closures, particularly in areas with relatively socio-economically disadvantaged groups (Young et al., 2017). In this paper, we study practice closures among primary care providers (henceforth PCPs), or family doctors, who are usually the first to see patients and who serve as gatekeepers for specialized medical treatment and care. All individuals affected by closures will surely experience a discontinuity in care. Moreover, the disruption of a practice closure may lead to lack of care, at least for some period, as well as changes in the quality of care. This paper asks two key questions. Firstly, what are the consequences of practice closures, if any, for patient health care utilization and health outcomes? And secondly, to what extent are effects driven by variation in physician practice styles, and thus at least partly susceptible to policy, or by the disruption itself?

To answer these questions, we employ population-level administrative Danish data. The data cover the period 1998-2015 and facilitate a unique link between all Danes and their PCP. We start out by unpacking the anatomy of a practice closure. To do this, we first describe patient behavior leading up to a closure and next characterize the change in provider characteristics that occurs when patients change from a closing PCP to another. Using a difference-in-differences strategy where we compare individuals who experience a practice closure with similar individuals enrolled in practices that do not close until later, we formally investigate consequences for patient health care utilization and health outcomes. We study three types of outcomes: Primary care utilization, detection of illness, and substitution into other types of health care. We complete our empirical analysis with a decomposition of the overall effects of practice closure into changes in provider practice style and discontinuity of care. To operationalize this, we first follow a recent literature using patient mobility to infer practice style for closing as well as destination providers from a two-way patient and physician fixed effects model (Abowd et al, 1999; Finkelstein et al, 2016; Markussen and Roed, 2017) using data prior to practice closure to avoid contamination. Next, we use the results from this two-way fixed-effects model to decompose our estimated practice-closure effects into the share explained by changes in practice style and the share explained by the disruption.

We show that the patients do not react to closures long in advance, yet practice closures lead patients to be matched with a systematically younger and less experienced PCP. This is hardly surprising given the fact that 52% of our closures are due to doctors retiring. We observe that the majority of patients enrolled in one closing practice typically switch to the same, new health care provider. Importantly, a change in provider due to practice closure leads to a 30 to 60% increase in detection of chronic illness (hypertension, hyperlipidemia, and diabetes) immediately following a closure. This corresponds to somewhere between 25 and 100 additional patients initiating treatment for these illnesses for every 10,000 patients experiencing a closure. We do not find that closure leads to any concurrent changes in primary care utilization and we only detect small and opposing effects on substitution into use of PCPs outside of normal office hours and use of specialists. We do see a slight increase in emergency care of between 5 to 10% relative to the mean during the first two years following the disruption.

Since we do not see any drop in primary care utilization, i.e. *coverage*, supervening the closure and because we are empirically unable to detect any changes in either practice size or distance between patient residence and the new practice compared to the closing, we argue that our main results stem from a combination of discontinuity of care and differences in practice style. Our decomposition analysis shows, in fact, that both physician practice style but also the disruption itself plays a role for the overall effects. In terms of primary care utilization, the two channels are of the same magnitude but pulling in opposite directions: destination physicians typically induce more activity (6% increase relative to pre-closure mean), whereas the disruption is associated with a decline in utilization (6% decrease relative to pre-closure mean). Results on detection of chronic illness, in contrast, indicate that both the shift in physician practice style, and to an even greater extent the disruption – a fresh perspective, maybe – are beneficial to the patient. For example, the take-up of statins (targeting hyperlipidemia) increases by 24% relative to the pre-closure mean with about 20 percentage points explained by the disruption itself. Finally, we find that practice styles of the destination physicians induce an increase in the use of other types of health care, primarily in the use of other specialists that increases with 11% relative to the pre-closure mean. This effect is completely offset, however, by the disruption itself that also fully explains the increasing use of emergency services. Put differently, the receiving PCPs appear to have a higher propensity to refer patients to specialists but at the same time, the closure in and of itself disturbs or *disrupts* the use of referrals.

Our paper contributes to several strands of literature. First and foremost, our paper provides the first evidence of the consequences of the imminent wave of PCP practice closures across several crucial outcome domains. Kwok (2018) studies effects of involuntary PCP switches, including switches that are driven by retirement, on primary care utilization among Medicare recipients above the age of 65 and finds increases in take-up around the switch. To the best of our knowledge, however, no one has yet analyzed outcomes more closely associated with health or studied utilization in a population-wide setting. Secondly, our paper provides new evidence to the literature concerned with the, typically negative, consequences of disruption, or fragmentation, of care (Cebul et al, 2008; Agha et al, 2017; Schwab, 2018) by showing that, for some outcomes, a mere change in provider may not necessarily work to the patient's disadvantage. Finally, we shed new light on the importance of practice style heterogeneity among PCPs (Koulayev et al, 2017; Kwok, 2018) and among physicians more generally (e.g. Doyle et al, 2010; Silver, 2016).

The paper is organized as follows: Section 2 provides relevant background information; Section 3 describes our data and present descriptive statistics; while Section 4 explains our formal identification strategy. Section 5 shows our main results, while Section 6 investigates channels and performs heterogeneity analyses. Finally, Section 7 concludes.

2. Background

2.1 The link between practice closure and patient outcomes

Little is known about consequences of PCP practice closures for patient outcomes. As discussed above, Kwok (2018) analyzes effects of involuntary PCP switches on primary care utilization and finds upticks around the switch. A few Norwegian studies provide evidence that a shift in primary care physician, for example due to physician retirement, leads to changes in claims for sick pay and disability benefits (Markussen et al, 2013) as well as in work absenteeism (Dale-Olsen and Godøy, 2016). Yet to the best of our knowledge, we know less about health consequences associated with closures among primary care physicians.

In contrast, there exist a few studies of the consequences of hospital closures for patient health. One example is Buchmueller et al (2006) who show that in a US setting, an increased distance to the closest hospital increases deaths from heart attacks and unintentional injuries. A Swedish study by Avdic (2016) links the geographical distance from an emergency hospital to the probability of surviving an acute myocardial infarction. Recently, papers have studied consequences of limited access to specialized clinics such as abortion clinics in Texas that also provide other types of women's preventive care. In line with expectations, these types of clinic closures lead to fewer abortions

(Cunningham et al, 2017) but also fewer clinical breast exams, mammograms, and Pap tests (Lu and Slusky, 2016).

Practice closure among PCPs may affect patient outcomes through a variety of channels and it will, without doubt, lead to discontinuity in care; an issue that has received much attention in the medical literature (van Walraven et al, 2010). Several papers argue that such disruption increases utilization.[1] Schwab (2018) provides compelling evidence of the phenomenon by exploiting that, in the military, physicians are often withdrawn from their practices to be deployed oversees.

Following Haggerty et al (2003), continuity in care covers both information continuity, management continuity (consistency of patient care), and interpersonal continuity (the relationship between the patient and the provider). In our context, while some types of information like patient files could, because of the institutional set-up, naturally flow from one PCP to the next, private information about treatment response and adherence is unlikely to transfer fully – and interpersonal discontinuity is of course complete with a practice closure.

Practice closure may also lead to periods without access to care and it may change the quality of care, or cause management discontinuity, for example via changes in distance to care, practice size, or provider characteristics and practice style. It is well-known that physicians vary in their practice style (Chandra et al, 2011), just as it has been shown that physicians adapt their practice style to the practice environment when they move (Molitor, 2018). Practice style among PCPs has in a few studies been shown to be of major importance for patient outcomes. Koulayev et al (2017) document this in their study of the role of PCP in drug adherence, while Laird & Nielsen is concerned with PCPs' propensity to prescribe prescription drugs and the subsequent link to labor supply. Kwok (2018), on the other hand, focuses on primary care utilization. More evidence exist for physicians more broadly. Doyle et al (2010), for example, study a setting in which patients arriving at a large medical center are randomly assigned to one of two medical groups. One of the groups is affiliated with a prestigious medical school while the other is not. They find that providers from the higher-ranked medical schools systematically conduct fewer tests and have lower costs even though both groups have similar patient outcomes. Currie et al (2015) instead investigate emergency room practice style and patient outcomes and document that patients assigned to providers who are more likely to use invasive

[1] A version of this is fragmentation where patients are exposed to several physicians or types of specialists. Agha et al (2017), for example, exploit Medicare enrollees who move across regions with variation in care fragmentation and find that increases in regional fragmentation is associated with a corresponding increases in care utilization.

procedures have consistently higher costs and better outcomes. Silver (2016) similarly studies emergency departments and shows that physicians exogenously exposed to fast-paced team environments ration care and cause increases in mortality in several patient groups.

In our analysis below, we will combine knowledge about institutional features as well as access to comprehensive register data informative about providers as well as patients to shed light on which channels appear more important in our context. Importantly, the extent to which results are driven by changes in practice and provider characteristics is testable with our data.

2.2 Institutional setting: health care and primary care physicians in Denmark

The Danish public health insurance provides visits and services at the primary care physician free of charge. PCPs engage in primary disease prevention and health maintenance as well as diagnosis and treatment of minor acute and chronic illnesses. In Denmark, PCPs additionally serve as gatekeepers to the rest of the health care system in the sense that they refer to specialists and hospital admissions. There are approximately 3,500 PCPs in Denmark who serve about 1,800 patients each. Of these PCPs, around 2,200 are organized in single-physician practices. PCPs are self-employed, but in order to get reimbursed by the national insurance, the physician needs to acquire a practice authorization number (*ydernummer*). The number of practice authorizations is controlled by the government, based on factors such as the population density in a given area.

Physician income is generated from a mixed payment system from the government: a fixed capitation fee per patient listed with them (DKK 445 or around USD 70 in 2018), and fee-for-service payments. Around one third of the income stems from the fixed capitation and two thirds from fee-for-service. The fees are negotiated yearly between the Danish Medical Association and the government. Importantly, the physician receives no fee in connection with outpatient prescriptions. Still, PCPs are responsible for approximately 90% of all outpatient prescriptions. Variation in this domain of practice style may therefore have important implications for both take-up, adherence, and subsequent patient health.

Continued training of primary care physicians

Another important dimension when it comes to (changes in) practice style is access to and use of research-based knowledge dissemination and continued education of PCPs. PCPs were not obliged to participate in continued training programs during the period we study below and this may, in itself, induce differences in practice style across providers, most obviously between younger and older physicians.[2] However, a variety of short courses on topics within general medicine were offered through the organization of private practicing doctors. In addition to this, a monthly journal (*Månedsskriftet for Almen Praksis*) is distributed to all primary care physicians. The main focus of the journal is to keep physicians up to date on advances in treatments and research in all areas of medicine. As in most other countries, primary care physicians are targeted by detailing from pharmaceutical companies.

Patient allocation

Patients are listed with a specific practice and can only visit the practice they are listed with. It is possible to change practice for a smaller fee of DKK 150 (roughly USD 20). Patients are free to choose among physicians open for intake as long as the practice is located within 15 km from the patient's home. Physicians cannot turn away individual patients selectively; however, they can close their lists for general intake when the list-size reaches 1,600 patients (per physician in the practice). If a physician closes the practice for intake, she cannot discretionarily add a patient. Under some circumstances a physician can terminate the physician-patient relationship: if the patient does not comply with treatment, or if the patients is violent or aggressive towards the physician. In either case the relationship is terminated by application to the authorities.[3]

The local government is by law required to assist patients when a practice closes (e.g. in the event that the physician retires). When a practice closes one of two things can happen: 1) the patient list is either sold by the retiring physician in a private market (often in conjunction with the physical practice), or 2) patients are distributed randomly to nearby practices with available capacity. If two (or more) physicians work in the same practice and one of them retire, the remaining physician(s) can continue operating the practice. If they want to reduce the number of patients listed, *all* patients are dismissed from the practice and need to apply to be listed with the practice again on a first-come, first-served basis. Importantly, a new physician cannot selectively turn away patients in either case. Patients are informed that they are allowed to choose a new practice within their choice set (without paying the token fee), and it is the responsibility of the local government to make sure that each patient has at least two different practices with open lists within the 15 km travel distance. The closing

[2] Mandatory continued training was introduced as part of the collective agreement made between the local governments and the primary care physicians in 2014 which is after the period under consideration in this study.
[3] This is a rare outcome with a total of 458 reported cases in 2017.

physician has no obligation to communicate the upcoming closing to her patient. In the scenario where a new physician only acquires the patient list and not the physical practice, the acquiring physician cannot freely determine the location of the new practice. Instead, location is negotiated on a case-by-case basis with the local government. Traveling distances not being adversely affected for the listed patients as well as the concentration of other practices are two of the considerations weighing in.

It is crucial to stress that no patients in Denmark will lose access to primary care as a consequence of a practice closure – even in areas with a sparse supply of (open) practices. The local governments are obligated by law (the Danish Health Act, Chapter 13) to guarantee that all citizens have access to care. If no practices are open for intake the local government itself can establish a practice and contract with physicians to see the patients.[4] Of course, to the extent that the quality of the service received is lower after experiencing a practice closure, this will comprise part of the effects we estimate in our analyses below.

Information transfer

When a patient-physician relationship is terminated, vital information about the patient's health status is at risk of being lost. To mitigate this information discontinuity, formally recorded information in terms of patient records are automatically transferred from the old to the new physician. Patients can choose *not* to have their records transferred, but they need actively to do so (a patient has a 14-day window after being listed with the new physician to do this[5]). However, tacit knowledge about patient preferences and the like is less easily transferrable between physicians.

3. Data, samples and descriptive statistics

To investigate how practice closures affect patient outcomes we leverage Danish administrative register data that covers the entire adult (18+) population and made available through Statistics Denmark. Focal to this study is the fee-for-services data covering the entire universe of reimbursements paid out to all PCPs active in Denmark. Crucially, these data are informative about physician as well as patient identity: for each reimbursement we observe the exact time of the interaction and the provider. This enables us to observe the evolution of patient-provider links over

[4] In the timeframe of this study this is a rare event: The first clinic established directly by a local government was in 2008. This has since increase such that now 53 government-run clinics exits with an average of 2,200 patients listed in each.

[5] Personal communication with both the organization of private practicing doctors (PLO) and Local Government Denmark (KL) reveals that this is sufficiently rare such that no information on this is systematically collected.

time. We augment these data with socio-economic information describing demographics, income, and education, just as we exploit information about health-care service use and diagnoses associated with hospital interactions (ICD10). Finally, for the period 2004-2010, we also have access to a unique dataset containing information on distances between individuals and physicians in Denmark. Based on address-specific geocodes, Statistics Denmark has calculated distances between the home addresses of all individuals and the (up to) 50 closest physicians within a 20 km travel distance of residence (using public roads).

We use patient-physician interactions to infer the identity of the primary physician, in line with Kjærsgaard et al (2016). Their algorithm successfully links individuals to their primary care physician in as many as 98.6% of all cases.[6] Our starting point is a dataset that contains patient-physician spells covering the period 1998-2015.

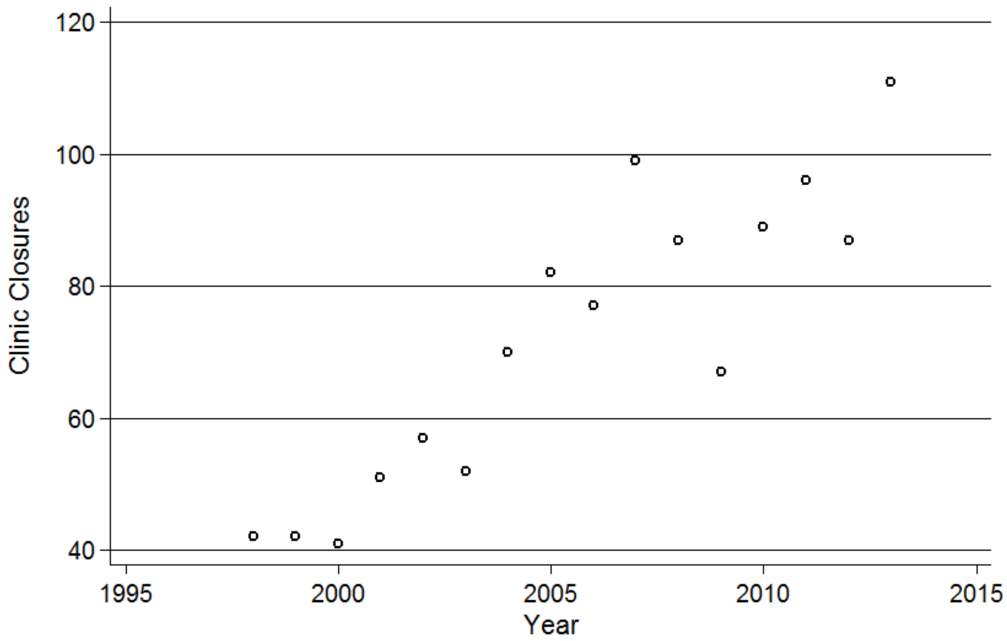
The next step is to determine the exact date of a practice closure. Having established patient-physician links, we define a practice as closing in the last month in which we observe a contact between a patient and the practice.[7] Figure 1 illustrates that practice closures are common and that rates are increasing over time. Thus, potential consequences of closures are a real concern, also in our context.

[6] Kjærsgaard et al (2016) train and evaluate their algorithm on a list of actual switching dates for a subset of years. The details of our implementation are described in Appendix B.

[7] Figure A1 shows corresponding reductions in practice level reimbursement from national insurance leading up to the closure.

FIGURE 1

CLOSURES ACROSS TIME



Notes: This figure shows the number of primary physician practice closures across calendar year. A practice is defined to be closed in the first month in which no services are provided. In comparison, at the start of the estimation period (1998-2000), 2,401 practices operate in Denmark.

Combining the closure dates with the physician-patient spell data, we construct a balanced panel of patients exposed to a practice closure, where we observe individuals for two years prior to and after the practice closure. 811,649 individuals or about 20% of the adult population experience a practice closure at least once during our observation period. These individuals are distributed across 770 closing practices. 6.5% of the individuals experiences several practice closures across the four years. Our analyses always consider the effects of the first practice closure.

To characterize individuals listed at closing practices, and for the purpose of our formal analyses below, we follow Guryan (2004) and match individuals exposed to a closure to a comparison group consisting of the 877,547 individuals (distributed across 915 practices) who experience a practice closure *three years into the future*. Our comparison is based on a rich set of patient demographics, health behaviors and health outcomes as well as the demographics of origin and destination physician around the time of practice closure. The comparison group is assigned a synthetic (random) closing data in the year of the match. Synthetic closing dates are drawn from a distribution that mimics the actual observed distribution of closing dates. [8] We do this as not to conflate any seasonal variation in PCP utilization with behavioral responses to the actual practice closure.

We study three types of outcomes related to primary care utilization, start-up of prescription drug treatment targeted chronic diseases, and substitution into other – and more expensive – types of health care (or offset effects). Primary care utilization is measured via indicators for physician visits and total government reimbursement associated with primary physician services. Detection of illness is measured as take-up of ACE inhibitors, statins, and metformin. These medications are considered first-line[9] treatments targeting the major chronic conditions hypertension (ACE-inhibitors), hyperlipidemia (statins), and diabetes (metformin). It is well-established that these conditions are significant risk-factors for cardiovascular morbidity and mortality; Scandinavian Simvastatin Survival Study Group (1994), DCCT (1993). Further, the prevalence of these conditions is high (especially among the elderly) and there is a general consensus that they are underdiagnosed in many populations. Among the adult US population, it is estimated that 13% had two of these conditions, and that 1 in 7 (15%) adults had one or more of the conditions undiagnosed; Fryar et al (2010). Finally, substitution into other types of health care is measured as use of emergency doctor services outside of regular office hours, practicing specialists, and hospital-related out-patient care.

Table 1 shows that the group exposed to practice closure resembles the comparison groups in terms of our observed characteristics but are slightly less well-educated and slightly younger than the overall population. In terms of health care usage, there is no economically significant differences between the three groups across any of the measures.

[8] Of the 1338 practices that close in the period 1998-2014 50.15% close in December and 17.15% closes in the last week of the year.

[9] Danish national prescription drug recommendation list: https://www.sst.dk/da/rationel-farmakoterapi/rekommandationsliste

TABLE 1

MEAN PATIENT CHARACTERISTICS OF COMPARISON AND TREATMENT GROUP, 6 MONTHS PRIOR TO (SYNTHETIC) PRACTICE CLOSURE

Variable		Clinic closure:		Overall Population
		Comparison	Exposed	2004
Health capital:				
Predicted health index quartile (0/1)	1st Quartile	0.291	0.259	0.25
	2nd Quartile	0.244	0.247	0.25
	3rd Quartile	0.241	0.249	0.25
	4th Quartile	0.215	0.237	0.25
Use of chronic medication (0/1)		.314	.351	.334
Socio-economic status:				
Gross income (0/1)	1st Quartile	0.243	0.25	0.25
	2nd Quartile	0.247	0.248	0.25
	3rd Quartile	0.25	0.246	0.25
	4th Quartile	0.259	0.256	0.25
Male (0/1)		0.475	0.495	0.491
Education (0/1)	Some Primary	0.448	0.458	0.351
	Secondary	0.072	0.069	0.076
	Vocational	0.312	0.306	0.334
	Short tertiary	0.104	0.103	0.163
	Medium tertiary	0.012	0.012	0.014
	Long tertiary	0.052	0.052	0.061
Age (0/1)	<30	0.186	0.174	0.177
	30-65	0.596	0.611	0.623
	>65	0.218	0.215	0.2
Outcomes:				
Any PCP visit (0/1)		0.568	0.561	0.59
PCP reimbursement (DKK)		45.6	44.3	45.2
		(65.2)	(61.7)	(59.9)
Any pharmacy claim (0/1)		0.534	0.536	0.550
Drug initiation (0/1)	ACE inhibitors	0.003	0.003	0.003
	Statins	0.003	0.003	0.004
	Metformin	0.001	0.001	0.001
Any out-patient care (0/1)		0.085	0.084	0.082
Any use of practicing specialists (0/1)		0.135	0.135	0.126
Any use of emergency doctor service (0/1)		0.023	0.024	0.015
# Individuals		877,547	811,649	3,191,232

Notes: This table shows descriptive statistics for individuals who experience a practice closure and compares these with corresponding characteristics of a matched comparison group that consists of individuals who experience a practice closure three years into the future. The comparison group is assigned a synthetic closing data in the year of the match. The averages are calculated over the six to three months prior to the (synthetic) closure. The predicted health index is the predicted expenditures on prescription drugs in the calendar year of the closure based on demographics, health care expenditures, and other medical service use in the previous calendar year (see Appendix C for details). The higher the index, the higher the predicted expenditures. The overall population means exclude individuals who experience a practice closure and are measured in the final quarter of 2004.

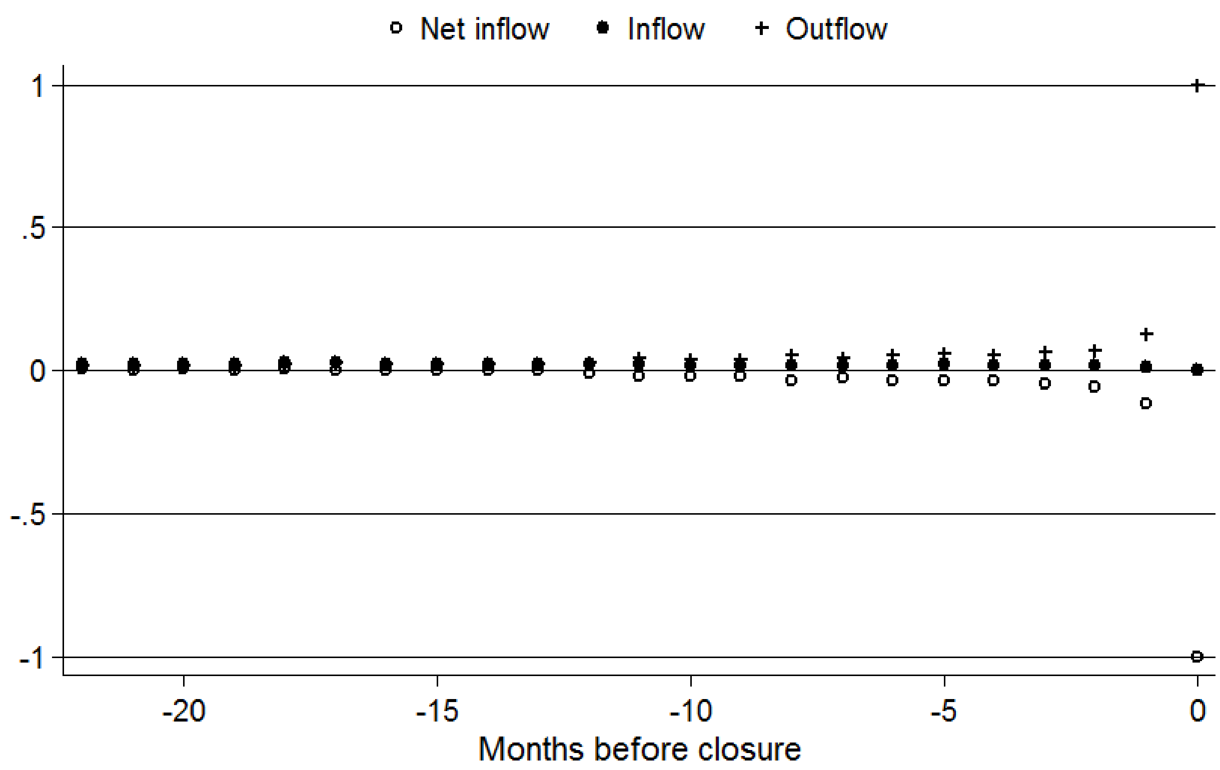
3.1 Patient behavior leading up to closure

To properly design our formal analyses, particularly in terms of defining an uncontaminated pre-period, it is important to gauge *when* patients react to the future closing. To this end, Figure 2 first plots the net patient flow leading up to practice closure. We observe that slightly more patients leave (i.e. interact with a new physician) than enter a practice as early as 10 months prior to the actual closure but practice size is roughly constant up until six months before the closing. The vast majority of patients are not observed to visit a new physician in the months before practice closure. An alternative of depicting these dynamics is by showing the fraction shifting from one PCP to another in the time period leading up to and after a closure; see Figure A2.

As seen in Figure 3, those who leave early are slightly more likely to be women; have lower income; worse predicted health score; and more likely purchase drugs targeted chronic disease.

FIGURE 2

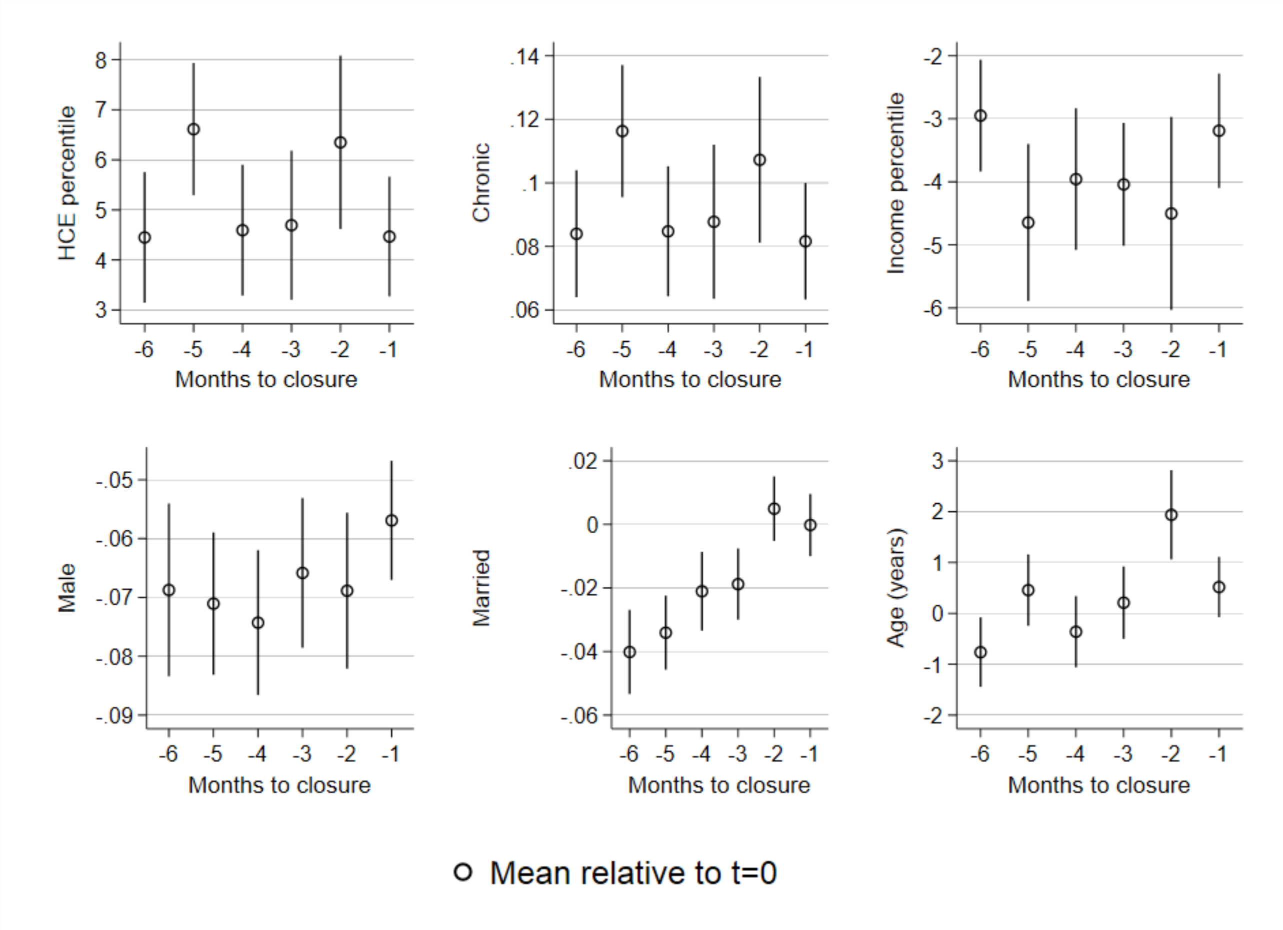
NET PATIENT FLOWS LEADING UP TO PRACTICE CLOSURE



Notes: This figure show net inflow, inflow, and outflow relative to the previous month.

FIGURE 3

CHARACTERISTICS OF PATIENTS LEAVING THE PRACTICE IN MONTH, RELATIVE TO CHARACTERISTICS OF PATIENTS WHO STAY UNTIL ACTUAL CLOSURE



Notes: This figure shows mean characteristics of patients who leave a practice prior to closure relative to those who stay until the actual closure. Bars represent 95% CI. Predicted health care expenditure is the predicted spending of prescription drugs in the calendar year of the closure based on demographics, prescription drugs consumption, and other medical service use in the previous calendar year (see Appendix C for details).

3.2 The destination physician

We define the destination physician as the first physician a patient interacts with after leaving a closing practice, and we describe the characteristics of the destination physician to get a sense of what being assigned to a new PCP entail. As seen in Table 2, and further explored in Figure 4, while closing physicians are similar to those who close their practice in the near future, they are clearly older than the destination physicians. This is natural since a closing is often associated with retirement, but as is evident by the peak in the age distribution around age 50 for closing physicians (Panel B, Figure 4), retirement is not the sole driver of practice closures. We formally explore the role of physician retirement in our analyses below. Moreover, the vast majority of patients have long-lasting relationships with the closing physician (see panel C, Figure 4). Figure A3 shows that a substantial share of patients leaves for the same new clinic. This is driven by cases where the destination practice is a completely new practice with no patients listed previously. Receiving practices that are already up and running typically only experience smaller increases in the size of their patient pools.

TABLE 2

CHARACTERISTICS OF PHYSICIANS BY CLOSURE STATUS

		Closing physician	Destination physician	Comparison physician
Male (0/1)		0.73	0.68	0.75
Married (0/1)		0.75	0.81	0.80
Immigrant (0/1)		0.10	0.06	0.04
Age	-40	0.08	0.07	0.03
	40-50	0.11	0.25	0.09
	50-60	0.23	0.45	0.35
	60+	0.58	0.22	0.53
Number of physicians in practice	1	0.78	0.55	0.78
	2	0.15	0.14	0.17
	3	0.04	0.10	0.03
	4+	0.03	0.07	0.01
Experience (years)		30.3	24.8	29.6
		(8.6)	(8.2)	(7.95)
Number of patients per physician, previous year		1,792	1,115	1,820
		(1.109)	(726)	(986)
Number of patients, subsequent year		0	1,166	1,793
		(0)	(765)	(1013)
Number of practices		770	2,826	915

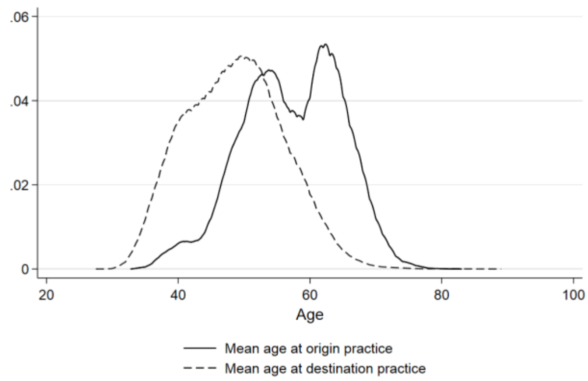
Notes: This table shows descriptive statistics for physicians who choose to close their practices, the practices that patients from closing practices disseminate to, and a matched comparison group that consists of practices that close three years into the future. The characteristics for the closing and destination practices are measured in the year of the closure, while the comparison practice is measured 3 years later.

FIGURE 4

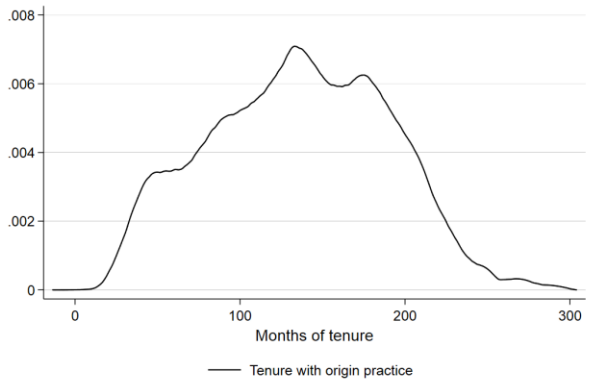
DISTRIBUTIONS, SELECTED PHYSICIAN CHARACTERISTICS

Panel A: Mean experience at origin and destination practice

Panel B: Mean age at origin and destination practice



Panel C: Tenure with original physician



Notes: This figure show the distribution of physician characteristics for origin and destination physicians. Panel A shows experience, panel B shows age, and panel C shows tenure with origin physician at closure. The distributions are weighted by the number of patients at the practice at the time of its closing.

4. Detecting consequences of practice closure for patient outcomes

The overarching goal of our paper is to estimate consequences of practice closures for patient-level outcomes. Obviously, the key challenge inherent in such an analysis is to estimate outcomes in the absence of practice closure. One might worry that patients enrolled in practices that close comprise a different population compared to the population of patients enrolled in practices that continue to operate.

To address this concern, we implement a difference-in-differences strategy using individual-level panel data, corresponding to a fixed-effects analysis. Our preferred strategy first compares one individual's outcomes *after* practice closure with that same individual's outcomes *prior* to practice closure. This first difference implicitly controls for time-invariant individual health. However, it is highly likely that underlying individual-level health changes with age, particularly for elderly patients. To account for this, we compare with a group of similar individuals enrolled in similar family practices *that continue to operate* for three more years beyond the point of comparison. The comparison group is subsequently assigned a random 'closure' date in the year of the treatment group based on the empirical distribution function of observed closing dates.

For computational and expositional reasons, we conduct our analysis on quarterly data instead of monthly data. We choose quarter *t-2* and earlier as the pre-closure quarters in our formal analyses and drop *t-1* completely from the main formal analyses.[10] *t-2* is sufficiently close to the timing of practice closure to ensure that patient health is not markedly different. At the same time, it lies sufficiently early to minimize contamination due to patient anticipation of practice closure: as shown above, the vast majority of patients remain listed with a practice up to six months before a closing.[11]

Our analyses rely on following regression:

$$Y_{it} = \alpha_i + \beta_1 1(post)_i + \beta_2 closure_i \cdot 1(post)_i + \beta_3 closure_i + \varepsilon_{it} \qquad (1)$$

where Y is the outcome of interest, $closure$ indicates that the patient belongs to the group exposed to practice closure, $1(post)$ indicates post-closure periods, ε is an error term, i indexes individuals, and t indexes time in quarters relative to the closure. β_2 is the parameter of interest. All background variables are measured prior to practice closure and thus do not vary across time. The effect of these

[10] Remember from above that we observe individuals in our sample during a symmetric four-year window around (synthetic) clinic closure.
[11] Below, we show that conclusions are robust to instead choosing quarter *t-1* and *t-4* as pre-closure points.

variables, along with *closure*, will therefore be cancelled out along with the individual level fixed effect, α_i.

The key identifying assumption in our difference-in-differences set-up is that there can be no differential trends between the treatment and control groups in the absence of practice closure. Below, we investigate the validity of this assumption graphically, by testing the robustness of our results to varying the choice of reference period, and by performing placebo analyses prior to closures.[12]

5. Results

5.1 Effects of closure on individual level health outcomes

We start out by analyzing effects on primary care utilization. Figure 5 shows mean de-trended utilization outcomes by quarter for the group of patients affect by closure as well as the comparison group, before and after the actual shutdown.[13] Critically, outcomes for the affected and comparison groups move in parallel before the closure. Note that slight differences do appear in the months just prior to the closure, consistent with the systematic differences observed above between those who remain listed until the time of closure and those who leave earlier. This (anticipatory) reaction is the main reason for using *t-2* and earlier as pre-closure points in the formal analyses. In appendix Table A1, Panel A we show the corresponding formal difference-in-difference results. Columns (1)-(3) show the results for PCP utilization using a gradually richer specification. In line with the descriptive evidence from Figure 5, regardless of the specification, we detect no statistically or economically significant effects on indicators for PCP visits and pharmacy claims. One might have worried about supplier-induced demand among the many destination PCPs who face financial constraints after having opened up an entirely new practice; we find no evidence of this. Another worry might have been that destination PCPs were capacity constrained and unable to deliver services on par with the closing physicians. This does not seem to be the case either; again at least on average.[14]

[12] Changing the choice of reference period is inherently also a placebo test; if this generates substantial differences in estimated effects, it implies that there are systematically different trends in pre-closure outcomes across treatment and comparison individuals that are not captured by our regression model.

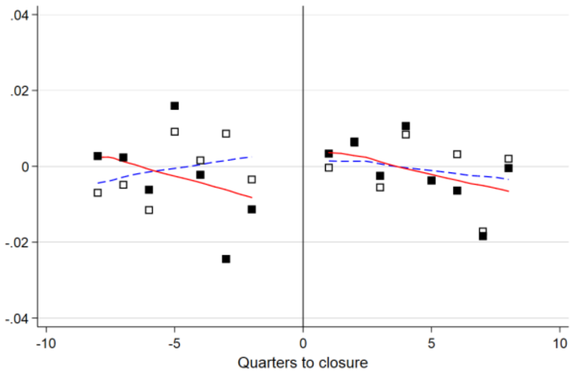
[13] We de-trend to purge away the upward-sloping trends reflecting that the population age in our sample window.

[14] Analyses not included in the paper show that existing patients at destination PCPs are unaffected by the influx of new patients. I.e. there appear to be no negative spillovers on the existing patient pool. This is not surprising since the increase relative to the stock of patients is often minor as discussed above. Results are available upon request.

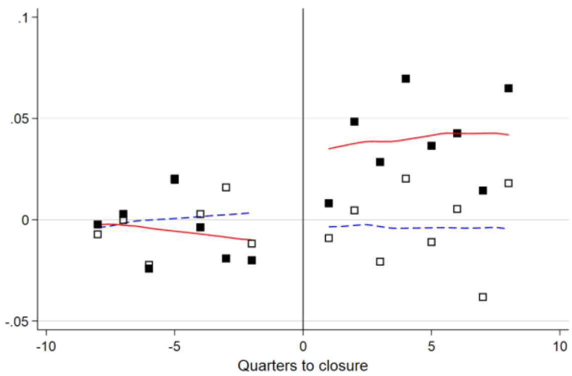
We do find evidence of destination physicians conducting procedures associated with statistically significantly higher government reimbursement but the effect sizes are minuscule: we observe an increase in fee-for-service on the part of the physician corresponding to DKK 2 per quarter (€ .25).

FIGURE 5: PRACTICE CLOSURE AND PRIMARY CARE UTILIZATION

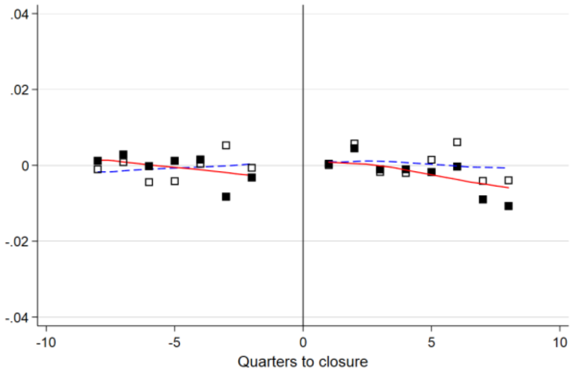
Panel A: Any PCP visit



Panel B: Total government reimbursement associated with PCP visit



Panel C: Any pharmacy claim

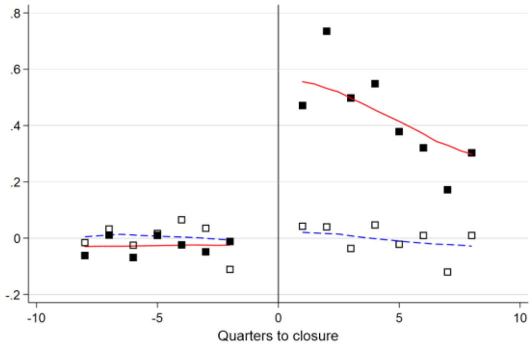


Notes: This figure shows the mean utilization primary care of a treated group (solid; red if read in color) and a comparison group (hollow; blue if read in color) relative to the time of (synthetic) closure. Each point is the quarterly average demeaned relative to the quarters $q \in (-8, -4)$. Lines are calculated using local linear regressions. Outcomes are a dummy variable for any consultation (panel A), total government reimbursement associated with PCP visit (panel B), and a dummy variable for any pharmacy claim (panel C).

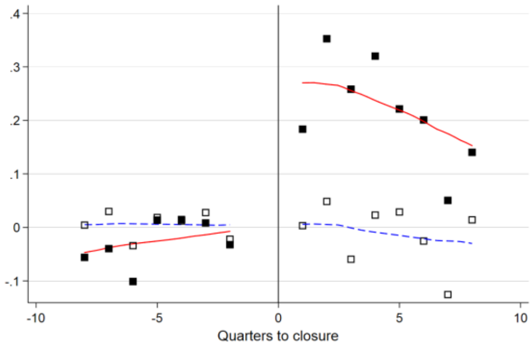
Figure 6 and Table A1, Panel B continues to explore effects on detection of illness. As mentioned above, we consider initiation rates of three of the most very important drugs targeted chronic ailments, namely hypertension (ACE inhibitors), hyperlipidemia (statins), and diabetes (metformin). These results stand in sharp contrast to the results on PCP utilization: shifting from a closing PCP leads to considerable *upticks* in start-ups with drugs that target severe diseases that are treatable yet to a high degree underdiagnosed in the overall population. Relative to the pre-closure sample mean, treatment initiations with ACE inhibitors increase by approximately 50%, statins by 20%, and metformin by 25%. Remarkably, these effects on start-ups persist throughout our data window.

FIGURE 6: PRACTICE CLOSURE AND INITIATION WITH CHRONIC MEDICATIONS

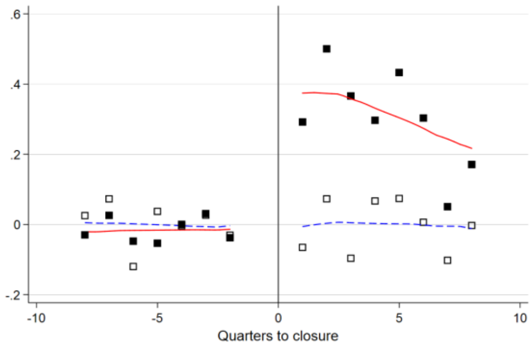
Panel A: Initiation with ACE inhibitor



Panel B: Initiation with Statin



Panel C: Initiation with Metformin

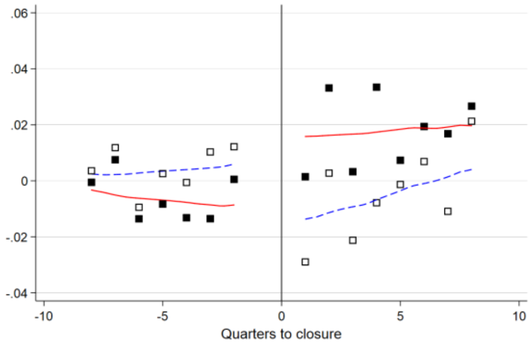


Notes: This figure shows the mean utilization primary care of a treated group (solid; red if read in color) and a comparison group (hollow; blue if read in color) relative to the time of (synthetic) closure. Each point is the quarterly average demeaned relative to the quarters $q \in (-8, -4)$. Lines are calculated using local linear regressions. Outcomes are dummy variables indicating initiation with ACE inhibitors (panel A), Statins (panel B), and Metformin (panel C).

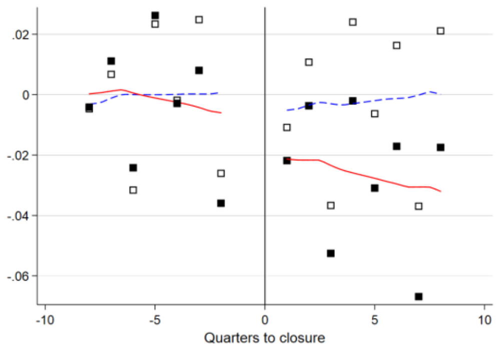
Finally, Figure 7 and Table A1, Panel C show results for use of additional, and typically more expensive, modes of care. We observe numerically small increases in hospital outpatient care of around 3% relative to the pre-closure sample mean but a corresponding drop of 3% in the use of practicing specialists. Though we do not want to read too much into these small effects at this stage, it could in line with an interpretation where the destination physicians are more likely to follow the official government guidelines that recommend the use of outpatient care at hospitals over private specialists to secure a higher degree of continuity of care and access to modern facilities and treatments. Finally, take-up of emergency services increases by as much as 5-10% relative to the pre-closure sample mean. This might be interpreted as a response to the disruption of the interpersonal continuity in the relationship between the patient and the physician.

FIGURE 7: PRACTICE CLOSURE AND SECONDARY AND OUTPATIENT CARE

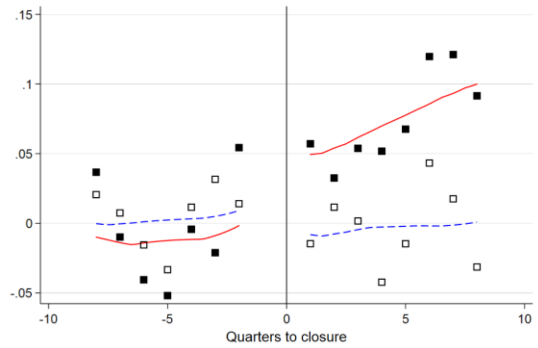
Panel A: Any outpatient care



Panel B: Any practicing specialist



Panel C: Any use of emergency doctor services



Notes: This figure shows the mean utilization primary care of a treated group (solid; red if read in color) and a comparison group (hollow; blue if read in color) relative to the time of (synthetic) closure. Each point is the quarterly average demeaned relative to the quarters $q \in (-8, -4)$. Lines are calculated using local linear regressions. Outcomes are dummy variables indicating any outpatient interaction (panel A), any specialist care (panel B), and any use of emergency care (panel C).

To sum up, we find little evidence of changes in primary care utilization, large effects on initiation of chronic medication, and some evidence of changes to referral patterns, possibly reflecting a more modern approach among destination physicians. To learn more about the degree to which the uptick in initiation rates of chronic medication reflect improved detection rates among the receiving physicians, Table A3 shows results on inpatient care associated with the most common, debilitating diseases; cardiovascular disease, diabetes, and cancer. Although rare events – between .1 and .5% of the population are hospitalized in each quarter because of these diseases – we are still able to detect large and highly statistically significant increases in inpatient care. The effects on the incidence of hospitalization associated with cardiovascular disease and diabetes amount to around 9% relative to the mean, while the effects on cancer are as large as 30% compared to the mean. As none of these ailments are in any way likely to be caused by the immediate change in provider, we ascribe these effects to improved detection skills of the destination physician. [15]

Of course, a deeper understanding of our findings requires us to delve into the roles of practice features and patient background. And even more fundamentally, we also need to clarify whether

[15] All main findings are robust to changing the pre-closure period from *t-2* to earlier points in time and excluding the time interval in between this reference point and actual closure. Similarly, we find no "effects" of practice closure in placebo analyses that consider outcomes measured *prior* to the actual closing. As expected with more than 11 million observations, some estimates are statistically significant but all are diminutive. Results are shown in Tables A3-A4.

effects arise because of provider practice style or merely because of the disruption itself. The next section explores these issues further.

6. Explicating effects on patient outcomes

6.1 Practice features

As explained in Section 2.2, government agencies bear the responsibility of assigning patients who experience a practice closure to new, nearby physicians – and in reality, as explained above and in line with our findings on PCP utilization, patients do not go uncovered in our period of investigation. Still, as discussed above, patients may experience some changes in the quality of care, for example via changes in distance to care and the patient load with the new provider. This section empirically explores these margins. In practice, we model distance to PCP and practice size as outcomes in our difference-in-difference set-up.

To learn about effects on distance to PCP, we augment our main data with auxiliary data containing information about the distance between individuals' residence and the (up to) 50 closest PCPs within a 20 km radius. Our data allow us to identify changes in distance for 261,166 out of 530,594 individuals who experience a practice closure from 2005 to 2010. Table A5 shows how this sample (henceforth the distance-sample), compares to the original estimation sample in terms of observable characteristics and Table A6 replicates our main findings on the distance-sample.

Table 3 shows the formal results on changes in distance to physician based on the distance-sample and practice size based on the full sample. Though statistically significant, we find no economically important increases in distance arising from practice closure. On average, patients travel .5 km longer. We observe no statistically significant effects on patients per physician; the estimate lies around 20 patients, which should be compared to a mean of just above 1,000 patients.

TABLE 3: DIFFERENCE-IN-DIFFERENCE RESULTS

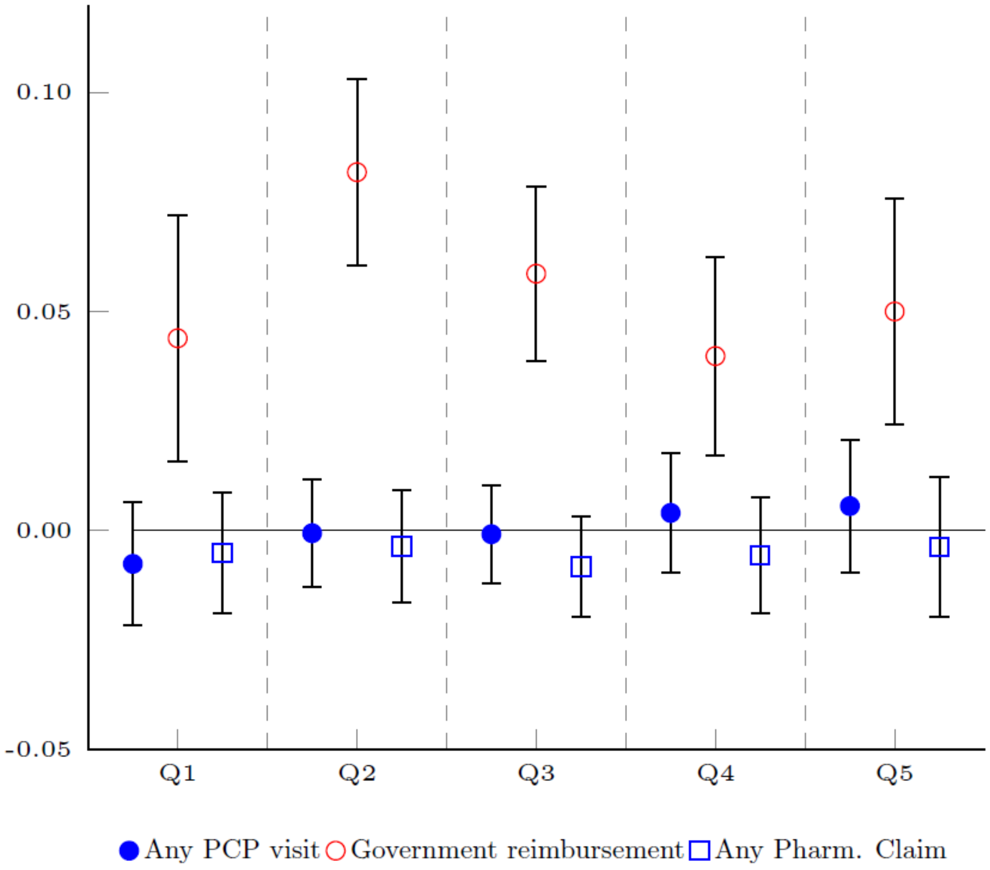
	(1) Distance to physician	(2) Distance to physician	(3) Distance to physician	(4) Patients per physician	(5) Patients per physician	(6) Patients per physician
Closure	3.46***	3.46***		-63.06***	-64.63***	
	(0.08)	(0.08)		(9.25)	(9.29)	
Closure X Post	0.47***	0.47***	0.47***	19.71	20.06	17.26
	(0.13)	(0.13)	(0.06)	(18.63)	(18.63)	(11.50)
# Observations	18,262,557	18,262,557	18,262,556	24,844,530	24,844,530	24,844,530
R-squared	0.449	0.451	0.913	0.003	0.005	0.274
Mean outcome	3.4	3.4	3.4	1,083	1,083	1,083
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes

Notes: This table shows individual level difference-in-difference results for distance to physician measured in km (columns (1)-(3) using the distance-sample) and patients per physician (columns (4)-(6) using the full estimation sample). Standard errors are clustered on physician level. ***p<0.01, **p<0.05, *p<0.10.

While neither distance nor patients per physician appears to be barriers to maintaining access, the availability of physicians can still be constrained if nearby physicians are closed for take-up. If a patient experiences a practice closure in an area with fewer existing practices, it might be relatively more difficult for the governmental authorities to assign patients to physicians.

To investigate this dimension, we use the distance-data to calculate the fraction of physicians in each patient choice set that are closed for intake of patients. We approximate a practice as being closed for intake of patients if the patients to physician ratio is larger than 1,600 (see Section 2.2). We define *patient density* as the ratio of practices in the choice set that is closed for intake of new patients. If the effect on primary care utilization varies across this dimension it would indicate that some areas have problems with access. We estimate effects of practice closures for each quintile in the share of practices closed for intake distribution and present these in Figure 8. We find no evidence that effects on PCP utilization – the probability of having a visit, the extent of government reimbursement, and the number of pharmacy claims – decrease with patient density.

FIGURE 8: EFFECTS OF PRACTICE CLOSURE ON PRIMARY CARE UTILIZATION BY QUINTILES OF PATIENT DENSITY



Notes: This figure shows how a practice closure affects the probability of any PCP visit (solid blue circles), total government reimbursement associated with PCP visit(hollow red circles), and having any prescription claim (open square) by quintile of share of practices in a patient choice set that is closed for intake.

We interpret this latter finding as evidence that practice closures are not associated with differential access to care afterwards. Our finding of large increases in the take-up of drugs targeting major chronic diseases plausibly stem from different sources. For example, detection of these chronic conditions is potentially related to differences in provider characteristics and practice styles between closing physicians and the comparison group. If physicians generally upon seeing a new patient do routine check-ups, and hence detect these conditions, we can interpret it as a positive effect of care discontinuity or *disruption*. While some information may be lost in the transfer from one PCP to the next, any negative consequences from this are not large enough to counterbalance the gains from meeting a new provider.

6.2 Patient characteristics

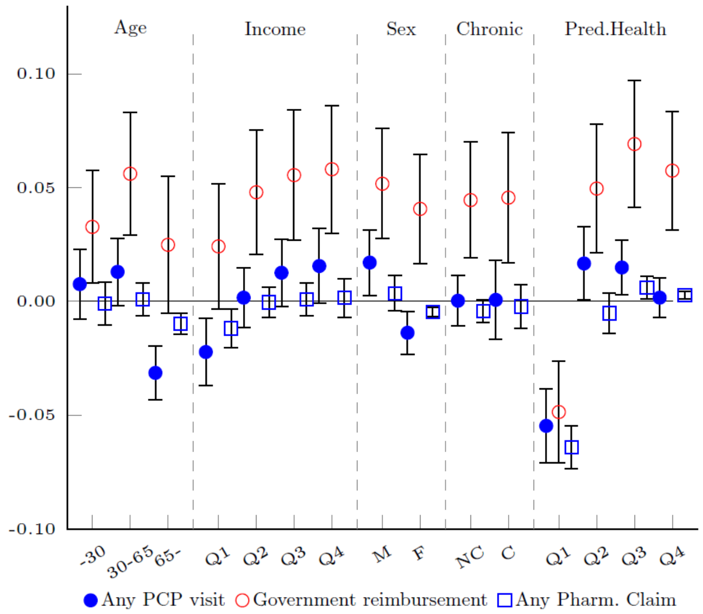
We next assess the degree to which effects of practice closure vary across individuals. Though we see little change in utilization, for example, there could be variation across patient groups – and there is certainly political focus on disadvantaged groups and inequality in health. Moreover, evidence from the medical literature shows that patients with chronic diseases in particular value relationship continuity with their physicians (Guthrie et al, 2008); this is likely because continuous monitoring and assistance in complying with treatment regiments plays a crucial in this population. Accordingly, they may be disproportionally affected by closures.

To investigate heterogeneity in effects of being exposed to a practice closure across background characteristics, we extend our baseline model to include interactions between these characteristics and the indicator for practice closure.

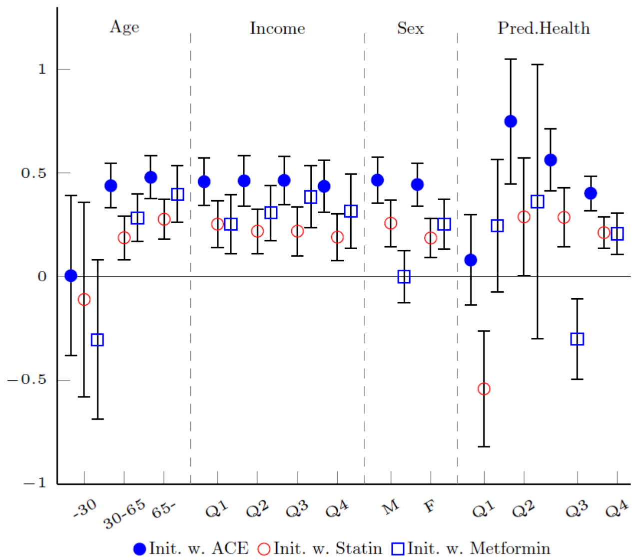
Results are presented in Figure 8. Panel A shows results for primary care utilization panel B chronic medication initiation, and panel C secondary care utilization. To ease comparability across subgroups, each panel presents the estimated effect for a subgroup relative to the within-group mean outcome prior to (synthetic) closure. While the sign of the effects tend to align across subgroups, the most striking finding is that those in better health (1^{st} quartile of health score) in fact experience reductions in primary care utilization, lower initiations, and lower secondary care utilization, pointing to more targeted service provision from destination physicians. Moreover, except for use of practicing specialists, effects on secondary care utilization increase monotonously in health quartiles.

FIGURE 9: HETEROGENOUS TREATMENT EFFECTS

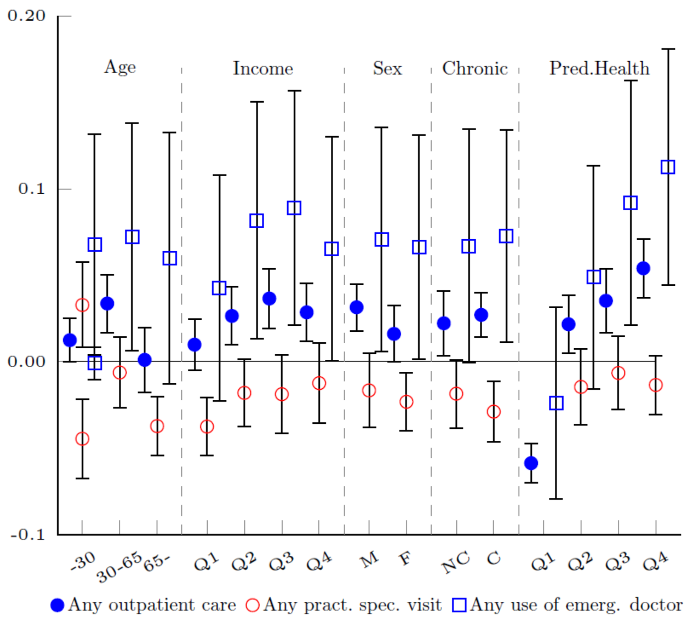
Panel A: Primary care utilization



Panel B: Initiation with chronic medications



Panel C: Secondary and outpatient care utilization



Notes: This figure shows the average quarterly effects over the first two years following closure by subgroups. The graph reports the effects relative to the within group outcome mean 2 quarters before the practice closes. Panel A shows the results of primary care, panel B show the results for medication initiation and panel C shows the results for secondary utilization. Standard errors are clustered at the physician level. The corresponding 95%-confidence bounds are shown as bars.

6.3 Physician practice styles and disruption effects

So far, our results indicate that practice closures may differentially affect patients with varying background characteristics. Distance to as well as practice size, in contrast, do not appear to serve as mechanisms behind our overall findings. Of course, this does not rule out that physician characteristics matter. Figure 4 above, for example, provides initial evidence that the destination physicians are considerably younger and less experienced than origin physicians on average. As these characteristics have been shown to correlate with practice style (see Currie et al, 2016; Epstein & Nichols, 2009; Koulayev et al, 2017), a natural question is to which degree the increases in treatment for chronic disease reflect changes in physician composition (or practice style) versus a pure disruption effect. On one hand, if the observed difference between the comparison and treatment groups are solely due to the change in provider, then the estimated effect would equal the difference in practice styles. On the other hand, if the observed difference on average has nothing to do with the physician, the change in physician practice style would not influence the estimates. This will offer an important insight, as the relative weights of these dimensions are crucial for fully understanding the impacts of practice closures on patient outcomes.

As a first indication that practice styles do indeed matter, we explore whether experiencing a closure driven by physician retirement differs from other types of closures: individuals moving from a retired physician are precisely expected to get a younger and less experienced physician (who is also more often female) relative to their origin physician, than would be the case for individuals experiencing a practice closure due to other reasons.[16] Individuals experiencing closures classified as retirements, for example, face a much larger reduction in physician age (16 years reduction vs. 3.5 years) and a larger increase in the occurrence of female physicians (14 vs. 0.4 percentage points).

We find that while the differences in effects are miniscule for the primary care utilization and secondary care,[17] the effects on initiation with chronic medication are significantly lower (by a factor 3) for the sample of individuals who experience a closure due to non-retirement. Results are shown in Tables A7 (retirees) and A8 (non-retirees). These findings confirm that individuals exposed to larger changes in observed physician characteristics that are associated with practice style, experience relatively larger effects. We interpret this as preliminary evidence that distinct practice styles matter for outcomes, and that the documented changes in health care utilization are not driven solely by disruption.

Equipped with this insight, we proceed to shed light on the relative importance of physician practice styles more generally. First, we estimate practice styles via physician fixed effects from an auxiliary regression that relies on data prior to practice closures. To do this, we follow a recent literature using patient mobility to infer practice style from a *two-way fixed effects model* (Abowd et al, 1999; Finkelstein et al, 2016, 2018; Markussen and Roed, 2017). We estimate this model on the group exposed to practice closure before they experience the closure ($q < -1$) and our comparison group. The two-way fixed effects model is then

[16] As the reason for closure is not available from the data, we impute (Hastie et al, 2001)) an age threshold from the ages of the closing physician, and classify physicians older than this threshold are classified as retirees, and younger are classified as closing due to other reasons. We identify a threshold of 60.3 years, which is illustrated in appendix Figure A4.

[17] Table A7 show the results for the retirees and Table A8 the results for the non-retirees.

$$y_{it} = \alpha_i + \gamma_{j(i,t)} + \sum_{\tau \in (-2,2)} \delta_t q(i,\tau) + \tau_t + \varepsilon_{it}, \quad (3)$$

where y_{it} denote the outcome of interest, $q(i,\tau)$ is a dummy for quarter relative to the separation, and $\gamma_{j(i,t)}$ measure practice fixed effects, or practice style. As in Finkelstein et al (2016), the inclusion of $q(i,\tau)$ allows outcomes at the end of an existing relationship with a physician and at the beginning of a new relationship to be different from outcomes in stable periods. We do this to facilitate the possibility that patients differ in their health care utilization around physician switches, as the reason – e.g. residential relocation - for the switch might affect the outcome.

Since α_i, the patient fixed-effect, and $\gamma_{j(i,t)}$, the practice fixed effect, can be arbitrarily correlated in our estimation set-up, we consequently allow for certain patient types to select into certain practices; or sorting between patients and practices. Following Finkelstein et al (2016), we do assume away selection into a practice based on unobserved but time-varying patient characteristics, ε_{it}. Contemporaneous health shocks, for instance, cannot lead patients to seek out physicians with certain practice styles. Formally, $E[\gamma_{j(i,t)}\varepsilon_{it}|\alpha_i] = 0$. For a detailed discussion see Abowd et al (1999) or Abowd et al (2002).

We proxy practice style of the first assigned destination practice via a standard leave-one-out strategy to accommodate the possibility of patient sorting into destination practices in connection with practice closure. We do this by predicting the practice fixed effect by a weighted average of destination practice fixed effects for the subset of all the *other* patients from the *same* closing practice who leave in the period just prior to the closure. Formally, let D_o denote the set of destination practices that patients from the origin practice *o* switches to in last period we observe *o*. We weigh the destination practices by the fraction of movers from origin practice *o* to each destination practice d, θ_{od}.[18] That is, let

$$\bar{\gamma}_{j(i,t)} = \sum\nolimits_{d \in D_o} \gamma_d \frac{\theta_{od}}{\sum_{d \in D_o} \theta_{od}}$$

be the average physician practice style of physicians who receive patients from the closing practice *o*. We then define the *predicted* practice fixed effect by

[18] As there is variation in how many destination practices each closure produces, we show that the general case, where we weigh every destination practice produces similar results to choose the modal destination practices or the weighted average of the up to three, five, and ten destination practices. Results are available upon request.

$$\gamma^*_{j(i,t)} = \begin{cases} \bar{\gamma}_{j(i,t)} & if\ closure_i = 1\ , post_{i,t} = 1\ , F_{j(i,t)} = 1 \\ \gamma_{j(i,t)} & else \end{cases}$$

where $close_i$ is an indicator for being in the treatment group, $post_{i,t}$ is an indicator for having experienced a practice closure and $F_{j(i,t)}$ is an indicator if the physician is the first visited after a practice closure.

After obtaining $\gamma^*{}_{j(i,t)}$, we finally decompose the differences between the treated and the comparisons before and after the (synthetic) closure of the practice in the spirit of Finkelstein et al. (2016). Under (3), we can decompose the change in outcome into a share explained by changes in physician practice style and a share that is not.[19] We interpret the latter residual as the share of the effect that is due to the disruption, and hence assume that e.g. any behavioral changes of individuals unrelated to practice affiliation is part of the disruption effect.

TABLE 4: DECOMPOSITION OF EFFECTS ACROSS OUTCOMES

	Primary care utilization			Initiation with chronic medications			Secondary and outpatient care		
Outcome	Any visit	Gov. reimb.	Any pharm. claim	ACE inhib.	Statins	Metformin	Any outpat. Care	Any prac. spec.	Any emerg. care
Total effect variation	1	1	1	1	1	1	1	1	1
Share physician	0.51	0.74	0.47	0.07	0.21	0.36	0.61	0.48	0.04
Share disruption	0.49	0.26	0.53	0.93	0.79	0.64	0.39	0.52	0.96
Total effect (relative to mean)	0%	5%	0%	48%	24%	31%	3%	-1%	7%
Rel. effect phys	6%	7%	2%	3%	5%	11%	2%	11%	0%
Rel. effect disruption	-6%	-3%	-3%	44%	19%	20%	1%	-12%	7%

Notes: This table shows the decompositions for each outcome. The top three rows show how much of the variation in the change in outcome is due to changes in physician practice style and what is due to disruption. The bottom three rows show the total effect relative to the mean and how much is due to physicians and what is due to disruptions.

Table 4 presents our decomposition results. The main take-away is that disruption effects are present, and they are not unambiguously harmful to patient outcomes. Importantly, we do find a negative disruption effect in primary care utilization. However, gains in practice style offsets the negative disruption effects, such that the total impact on PCP utilization of the practice closure is modest at most. The total effect on the probability of seeing a PCP, for example, is 0.2 percentage points or

[19] As unconditional and conditional estimated effect sizes in table A1 are very similar, we decompose the detrended but otherwise unconditional outcome.

0.4% relative to the mean (compared to Table A1). However, the estimated disruption effect constitutes a 6% reduction relative to the mean that is offset by a 6% *increase* attributable to the physicians' practice style. Results are more or less similar for the other primary care outcomes; disruption causes a reduction in utilization, which to varying extents are offset by (more aggressive) physician practice styles.

Turning to start up in chronic medication the lesson is slightly different. While the physician still has a positive effect, the disruption effect is also positive and vastly dominates that of the physician. The total effect of closure on statin initiations, for example, is a 24% increase relative to the mean. Here, the disruption effect constitutes 19 percentage points of this increase and the change in physician practice style constitutes the remaining 5 percentage points. This suggests that the large increases in drug treatment initiations are by no means solely driven by differential practice styles of the physicians but pertain to an effect of seeing a new provider.

For the remaining utilization measures the size and sign of the disruption effect varies across outcomes. Regarding outpatient care effects are similar in direction and magnitude, while for emergency care visits the disruption effects dominate completely. Finally, the effects on specialist visits that stems from increases in physician effects is large (11% relative to the mean), but offset by a large negative disruption effect of -12% relative to the mean.

The findings in this section reveal two important insights: firstly, practice styles among the destination physicians uniformly increase care utilization and detection of chronic illness. Secondly, and contrary to much common belief, disruption is not *per se* negative from the point of view of the patient; disruption in and of itself does reduce primary care provision as well as referrals to practicing specialists, but at the same time it clearly supports the initiation of medications targeted chronic disease.

7. Conclusion

We study how discontinuity in primary care provision affects health care utilization in Denmark. We do this by utilizing that over time, primary care practices close for business, and patients are subsequently met with new providers. Using a difference-in-differences setup, we compare utilization patterns among those who experience a practice closure to those who only experience a practice closure later.

We find large, positive impacts on the take-up of prescription medications that target the three major chronic conditions hypertension, hyperlipidemia, and diabetes. It is well-established that these conditions are significant risk-factors for cardiovascular morbidity and mortality and is generally underdiagnosed; see for example Fryar et al (2010). We show, however, that the take-up of drugs targeted these chronic conditions is not driven by differential treatment styles across physicians but stems from a common disruption effect associated with seeing a new physician. We also find that the dissolution of patient-physician relationships induced by the practice closures have only modest effects on primary-care utilization as well as on the use of other specialists. The disruption of the relationship between the patient and his provider – the break in interpersonal continuity – leads, however, to an increase in the use of emergency services.

Overall, our findings are important for policy makers because they indicate that practice closures are not necessarily to the patient’s disadvantage. A change in provider may even, because it implicitly introduces a second option, lead to the detection and treatment of chronic disease and ultimately to higher patient well-being. Of course, our results are only valid in a context where the patient is not left entirely without access to primary care.

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Appendix A: Additional tables and figures

TABLE A1: DIFFERENCE-IN-DIFFERENCES RESULTS, EFFECTS OF CLOSURE ON QUARTERLY OUTCOMES

Panel A	(1) Any PCP visit	(2) Any PCP visit	(3) Any PCP visit	(4) Government reimbursement to PCP (DKK)	(5) Government reimbursement to PCP (DKK)	(6) Government reimbursement to PCP (DKK)	(7) Any pharmacy claim	(8) Any pharmacy claim	(9) Any pharmacy claim
Closure (x100)	0.160	0.0138		47.4	13.6		0.948***	0.424***	
	(0.232)	(0.185)		(42.5)	(40.2)		(0.220)	(0.137)	
Closure X Post (x100)	0.0977	0.0386	0.181	209.3***	204.9***	212.9***	-0.126	0.206	0.063
	(0.393)	(0.288)	(0.125)	(58.8)	(53.8)	(19.3)	(0.376)	(0.182)	(0.069)
# Observations	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768
R-squared	0.001	0.157	0.352	0.003	0.084	0.289	0.001	0.311	0.529
Mean outcome (x100)	56	56	56	4405	4405	4405	53	53	53
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B	(1) ACE	(2) ACE	(3) ACE	(4) Statins	(5) Statins	(6) Statins	(7) Metformin	(8) Metformin	(9) Metformin
Closure (x100)	0.0149*	0.00		0.0212**	0.000		0.000***	0.000***	
	(0.00)	(0.00)		(0.00)	(0.000)		(0.000)	(0.000)	
Closure X Post (x100)	0.122***	0.122***	0.124***	0.0825***	0.0824***	0.0831***	0.0261***	0.0259***	0.0266***
	(0.0136)	(0.0130)	(0.0103)	(0.0165)	(0.0155)	(0.0114)	(0.000)	(0.000)	(0.000)
# Observations	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768
R-squared	0.000	0.003	0.064	0.000	0.004	0.063	0.000	0.001	0.066
Mean outcome (x100)	.260	.260	.260	.327	.327	.327	.084	.084	.084
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel C	(1) Any outpatient care	(2) Any outpatient care	(3) Any outpatient care	(4) Any prac. specialist	(5) Any prac. specialist	(6) Any prac. specialist	(7) Any emergency care	(8) Any emergency care	(9) Any emergency care
Closure (x100)	0.147***	0.115**		0.570***	0.350***		0.177**	0.201**	
	(0.0604)	(0.0516)		(0.134)	(0.131)		(0.0845)	(0.0814)	
Closure X Post (x100)	0.255**	0.245**	0.293***	-0.304	-0.312	-0.300***	0.174	0.162	0.183***
	(0.127)	(0.117)	(0.0889)	(0.252)	(0.238)	(0.0569)	(0.147)	(0.145)	(0.0646)
# Observations	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768
R-squared	0.001	0.014	0.143	0.002	0.020	0.268	0.001	0.006	0.174
Mean outcome(x100)	8.3	8.3	8.3	8.6	8.6	8.6	2.3	2.3	2.3
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: This table shows difference-in-differences results for primary care utilization (panel A), initiation with chronic medication (panel B) and secondary care use (Panel C). For each outcome we run models sequentially adding quarter and region dummies. Standard errors are clustered on physician level. ***p<0.01, **p<0.05, *p<0.10.

TABLE A2: DIFFERENCE-IN-DIFFERENCES RESULTS, EFFECTS OF CLOSURE ON QUARTERLY OUTCOMES

Panel A	(1) Any CVD Hosp	(2) Any CVD Hosp	(3) Any CVD Hosp	(4) CVD Hosp >5 days	(5) CVD Hosp >5 days	(6) CVD Hosp >5 days	(7) CVD Hosp >10 days	(8) CVD Hosp >10 days	(9) CVD Hosp >10 days
Closure (x100)	0.0515***	0.0239***		0.0285***	0.0170***		0.0135***	0.008***	
	(0.006)	(0.005)		(0.003)	(0.003)		(0.002)	(0.002)	
Closure X Post (x100)	0.030**	0.0311***	0.040***	0.0002	0.001	0.005	0.0005	0.0001	0.002
	(0.011)	(0.009)	(0.007)	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)
# Observations	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768
R-squared	0.000	0.008	0.117	0.000	0.004	0.091	0.000	0.002	0.081
Mean outcome (x100)	.451	.451	.451	.16	.16	.16	.066	.066	.066
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B	(1) Any Diab Hosp	(2) Any Diab Hosp	(3) Any Diab Hosp	(4) Diab Hosp >5 days	(5) Diab Hosp >5 days	(6) Diab Hosp >5 days	(7) Diab Hosp >10 days	(8) Diab Hosp >10 days	(9) Diab Hosp >10 days
Closure (x100)	0.007**	0.004		5.41e-05**	0.004		0.003*	0.003	
	(0.003)	(0.003)		(0.002)	(0.002)		(0.002)	(0.002)	
Closure X Post (x100)	0.007	0.007	0.008**	0.001	0.001	0.002	0.002	0.002	0.001
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
# Observations	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768
R-squared	0.000	0.003	0.114	0.000	0.002	0.090	0.000	0.001	0.078
Mean outcome (x100)	.105	.105	.105	.06	.06	.06	.029	.029	.029
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel C	(1) Any Cancer Hosp	(2) Any Cancer Hosp	(3) Any Cancer Hosp	(4) Cancer Hosp >5 days	(5) Cancer Hosp >5 days	(6) Cancer Hosp >5 days	(7) Cancer Hosp >10 days	(8) Cancer Hosp >10 days	(9) Cancer Hosp >10 days
Closure (x100)	0.044***	0.033***		0.024***	0.019***		0.013***	0.010***	
	(0.004)	(0.005)		(0.002)	(0.002)		(0.002)	(0.002)	
Closure X Post (x100)	0.048***	0.049***	0.060***	0.021***	0.021***	0.027***	0.010***	0.011***	0.014***
	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
# Observations	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768	25,302,769	25,302,769	25,302,768
R-squared	0.000	0.002	0.138	0.000	0.001	0.102	0.000	0.000	0.088
Mean outcome (x100)	.199	.199	.199	.098	.098	.098	.055	.055	.055
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: This table shows difference-in-differences results for inpatient admissions with Cardio Vascular Diseases (panel A), inpatient admissions with diabetes related diseases (panel B) and inpatient admissions with cancer (Panel C). For each outcome we run models sequentially adding quarter and region dummies. Standard errors are clustered on physician level. ***p<0.01, **p<0.05, *p<0.10.

TABLE A3: DIFFERENCE-IN-DIFFERENCES RESULTS, EFFECTS OF CLOSURE ON QUARTERLY OUTCOMES. ROBUSTNESS TO COMPARISON QUARTER

Panel A	(1) Any PCP visit	(2) Any PCP visit	(3) Any PCP visit	(4) Government reimbursement to PCP (DKK)	(5) Government reimbursement to PCP (DKK)	(6) Government reimbursement to PCP (DKK)	(7) Any pharmacy claim	(8) Any pharmacy claim	(9) Any pharmacy claim
Closure X Post (x100)	0.126	0.244**	0.376***	211.1***	184.6***	175.1***	0.000	0.127*	0.140*
	(0.127)	(0.124)	(0.125)	(19.5)	(20.1)	(21.0)	(0.0703)	(0.0720)	(0.0734)
# Observations	23,613,572	21,924,371	20,235,167	23,613,572	21,924,371	20,235,167	23,613,572	21,924,371	20,235,167
R-squared	0.355	0.359	0.364	0.292	0.296	0.302	0.530	0.532	0.535
Mean outcome (x100)	56	56	56	4405	4405	4405	53	53	53
Reference Quarter	q=-3	q=-4	q=-5	q=-3	q=-4	q=-5	q=-3	q=-4	q=-5
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	(1) ACE	(2) ACE	(3) ACE	(4) Statins	(5) Statins	(6) Statins	(7) Metformin	(8) Metformin	(9) Metformin
Closure X Post (x100)	0.132***	0.130***	0.129***	0.0831***	0.0837***	0.0848***	0.0269***	0.0278***	0.0280***
	(0.0107)	(0.0112)	(0.0117)	(0.0119)	(0.0122)	(0.0127)	(0.000)	(0.000)	(0.000)
# Observations	23,613,572	21,924,371	20,235,167	23,613,572	21,924,371	20,235,167	23,613,572	21,924,371	20,235,167
R-squared	0.069	0.074	0.081	0.068	0.074	0.080	0.071	0.076	0.083
Mean outcome (x100)	.263	.263	.263	.327	.327	.327	.082	.082	.082
Reference Quarter	q=-3	q=-4	q=-5	q=-3	q=-4	q=-5	q=-3	q=-4	q=-5
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C	(1) Any outpatient care	(2) Any outpatient care	(3) Any outpatient care	(4) Any prac. specialist	(5) Any prac. specialist	(6) Any prac. specialist	(7) Any emergency care	(8) Any emergency care	(9) Any emergency care
Closure X Post (x100)	0.273***	0.249**	0.248**	-0.317***	-0.359***	-0.366***	0.193***	0.183**	0.182**
	(0.0930)	(0.0980)	(0.104)	(0.0595)	(0.0622)	(0.0644)	(0.0684)	(0.0709)	(0.0738)
# Observations	23,613,572	21,924,371	20,235,167	23,613,572	21,924,371	20,235,167	23,613,572	21,924,371	20,235,167
R-squared	0.147	0.153	0.160	0.290	0.294	0.300	0.181	0.186	0.192
Mean outcome (x100)	8.3	8.3	8.3	8.6	8.6	8.6	2.3	2.3	2.3
Reference Quarter	q=-3	q=-4	q=-5	q=-3	q=-4	q=-5	q=-3	q=-4	q=-5
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows difference-in-differences results for primary care utilization (panel A), initiation with chronic medication (panel B) and secondary care use (Panel C). For each outcomes the reference quarter is sequentially set to q=-3, -4, -5. All models include quarter dummies, individual background characteristics and individual FE. Coefficients are multiplied by 100. Standard errors are clustered on physician level. ***p<0.01, **p<0.05, *p<0.10.

TABLE A4: DIFFERENCE-IN-DIFFERENCES RESULTS, PLACEBO ANALYSES, QUARTERLY OUTCOMES

Panel A	(1) Any PCP visit	(2) Any PCP visit	(3) Any PCP visit	(4) Government reimbursement to PCP (DKK)	(5) Government reimbursement to PCP (DKK)	(6) Government reimbursement to PCP (DKK)	(7) Any pharmacy claim	(8) Any pharmacy claim	(9) Any pharmacy claim
Closure X Post (x100)	1.16***	-0.890***	-0.759***	-78.1***	-58.3***	-59.1***	-0.376***	-0.245***	-0.173**
	(0.178)	(0.145)	(0.137)	(20.0)	(17.1)	(18.7)	(0.0766)	(0.0737)	(0.0756)
# Observations	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736
R-squared	0.420	0.420	0.420	0.375	0.375	0.375	0.592	0.592	0.592
Mean outcome (x100)	56	56	56	4405	4405	4405	53	53	53
Pseudo Treatment	q=-4	q=-5	q=-6	q=-4	q=-5	q=-6	q=-4	q=-5	q=-6
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	(1) ACE	(2) ACE	(3) ACE	(4) Statins	(5) Statins	(6) Statins	(7) Metformin	(8) Metformin	(9) Metformin
Closure X Post (x100)	0.00255	0.00386	-0.001	0.009	0.016	0.017	0.005	0.001	0.000
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.004)	(0.004)	(0.004)
# Observations	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736
R-squared	0.141	0.141	0.141	0.140	0.140	0.140	0.142	0.142	0.142
Mean outcome (x100)	.263	.263	.263	.327	.327	.327	.082	.082	.082
Pseudo Treatment	q=-4	q=-5	q=-6	q=-4	q=-5	q=-6	q=-4	q=-5	q=-6
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel C	(1) Any outpatient care	(2) Any outpatient care	(3) Any outpatient care	(4) Any prac. specialist	(5) Any prac. specialist	(6) Any prac. specialist	(7) Any emergency care	(8) Any emergency care	(9) Any emergency care
Closure X Post (x100)	-0.0311	0.000	0.000	-0.128**	-0.0877*	-0.128**	0.0112	0.000	-0.0338
	(0.0694)	(0.0584)	(0.0549)	(0.0533)	(0.0522)	(0.0533)	(0.0421)	(0.0413)	(0.0413)
# Observations	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736	11,720,736
R-squared	0.224	0.224	0.224	0.374	0.374	0.374	0.253	0.253	0.253
Mean outcome (x100)	8.3	8.3	8.3	8.6	8.6	8.6	2.3	2.3	2.3
Pseudo Treatment	q=-4	q=-5	q=-6	q=-4	q=-5	q=-6	q=-4	q=-5	q=-6
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows difference-in-differences results for primary care utilization (panel A), initiation with chronic medication (panel B) and secondary care use (Panel C), while relying on pre-closure data only. For each outcome, the practice closure is artificially set to take place in q=-4, -5, -6. All models include quarter dummies, individual background characteristics and individual FE. Coefficients are multiplied by 100. Standard errors are clustered on physician level. ***p<0.01, **p<0.05, *p<0.10.

TABLE A5: REPRESENTATIVENESS OF DISTANCE-SAMPLE

Variable		Exposed to clinic closure: Distance not observed	Distance observed
Predicted health index quartile (0/1)	1st Quartile	0.29	0.24
	2nd Quartile	0.23	0.26
	3rd Quartile	0.24	0.25
	4th Quartile	0.23	0.24
Gross income (0/1)	1st Quartile	0.27	0.24
	2nd Quartile	0.25	0.25
	3rd Quartile	0.23	0.26
	4th Quartile	0.24	0.26
Male (0/1)		0.49	0.50
Education (0/1)	Some Primary	0.51	0.38
	Secondary	0.07	0.07
	Vocational	0.26	0.37
	Short tertiary	0.09	0.12
	Medium tertiary	0.02	0.01
	Long tertiary	0.06	0.05
Age (0/1)	<30	0.20	0.15
	30-65	0.59	0.64
	>65	0.21	0.21
Any PCP visit (0/1)		0.56	0.55
PCP reimbursement (DKK)		43.1	46.65
		(59.8)	*(65.4)*
Any Claim (0/1)		0.540	0.533
Drug initiation (0/1)	ACE inhib.	0.003	0.003
	Statins	0.003	0.004
	Metformin	0.001	0.001
Out-patient care		0.087	0.079
Practicing specialists		0.140	0.131
Emergency Doctor Service		0.025	0.021

Notes: This table show the descriptive statistics for those we observe in our distance sample conditional on experiencing a practice closer. The distance is measured as the change in kilometers between the closing physician and the destination physician.

TABLE A6: DIFFERENCE-IN-DIFFERENCES RESULTS, DISTANCE SAMPLE

Panel A	(1) Any PCP visit	(2) Any PCP visit	(3) Any PCP visit	(4) Government reimbursement to PCP (DKK)	(5) Government reimbursement to PCP (DKK)	(6) Government reimbursement to PCP (DKK)	(7) Any pharmacy claim	(8) Any pharmacy claim	(9) Any pharmacy claim
Closure X Post (x100)	0.335	0.324	0.371**	367.7***	367.1***	370.2***	0.185	0.17	0.250***
	(0.603)	(0.397)	(0.150)	(76.9)	(62.8)	(27.4)	(0.604)	(0.239)	(0.0848)
# Observations	17,120,906	17,120,906	17,120,905	17,120,906	17,120,906	17,120,905	17,120,906	17,120,906	17,120,905
R-squared	0.001	0.159	0.355	0.004	0.086	0.292	0.001	0.317	0.531
Mean outcome (x100)	55.86	55.86	55.86	4448.85	4448.85	4448.85	52.91	52.91	52.91
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B	(1) ACE	(2) ACE	(3) ACE	(4) Statins	(5) Statins	(6) Statins	(7) Metformin	(8) Metformin	(9) Metformin
Closure X Post (x100)	0.170***	0.171***	0.171***	0.0786***	0.0787***	0.0789***	0.0418***	0.0418***	0.0421***
	(0.0206)	(0.0194)	(0.0157)	(0.0239)	(0.0214)	(0.0160)	(0.006)	(0.006)	(0.005)
# Observations	17,120,906	17,120,906	17,120,905	17,120,906	17,120,906	17,120,905	17,120,906	17,120,906	17,120,905
R-squared	0.000	0.003	0.064	0.000	0.004	0.063	0.000	0.001	0.066
Mean outcome (x100)	0.267	0.267	0.267	0.341	0.341	0.341	0.078	0.078	0.078
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel C	(1) Any outpatient care	(2) Any outpatient care	(3) Any outpatient care	(4) Any prac. specialist	(5) Any prac. specialist	(6) Any prac. specialist	(7) Any emergency care	(8) Any emergency care	(9) Any emergency care
Closure X Post (x100)	0.848***	0.846***	0.862***	-0.115	-0.114	-0.112	0.682***	0.680***	0.686***
	(0.167)	(0.152)	(0.109)	(0.384)	(0.345)	(0.0716)	(0.197)	(0.197)	(0.0983)
# Observations	17,120,906	17,120,906	17,120,905	17,120,906	17,120,906	17,120,905	17,120,906	17,120,906	17,120,905
R-squared	0.001	0.014	0.142	0.000	0.044	0.287	0.001	0.006	0.173
Mean outcome (x100)	8.17	8.17	8.17	13.0	13.0	13.0	2.14	2.14	2.14
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: This table shows difference-in-differences results for primary care utilization (panel A), initiation with chronic medication (panel B) and secondary care use (Panel C), for the distance-sample. Standard errors are clustered on the physician level.

TABLE A7: DIFFERENCE-IN-DIFFERENCES RESULTS, EFFECTS OF CLOSURE ON QUARTERLY OUTCOMES, RETIRING PHYSICIANS

Panel A	(1) Any PCP visit	(2) Any PCP visit	(3) Any PCP visit	(4) Government reimbursement to PCP (DKK)	(5) Government reimbursement to PCP (DKK)	(6) Government reimbursement to PCP (DKK)	(7) Any pharmacy claim	(8) Any pharmacy claim	(9) Any pharmacy claim
Closure X Post (x100)	-0.119	-0.188	-0.0274	223.1***	218.0***	227.2***	-0.0743	-0.169	0.127
	(0.424)	(0.308)	(0.142)	(64.8)	(57.8)	(23.8)	(0.415)	(0.201)	(0.0802)
# Observations	20,156,712	20,156,712	20,156,711	20,156,712	20,156,712	20,156,711	20,156,712	20,156,712	20,156,711
R-squared	0.001	0.159	0.355	0.003	0.085	0.292	0.001	0.315	0.531
Mean outcome (x100)	56.3	56.3	56.3	4427.7	4427.7	4427.7	53.43	53.43	53.43
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B	(1) ACE	(2) ACE	(3) ACE	(4) Statins	(5) Statins	(6) Statins	(7) Metformin	(8) Metformin	(9) Metformin
Closure X Post (x100)	0.169***	0.170***	0.171***	0.112***	0.112***	0.113***	0.0370***	0.0367***	0.0375***
	(0.0163)	(0.0157)	(0.0129)	(0.0198)	(0.0187)	(0.0132)	(0.005)	(0.005)	(0.004)
# Observations	20,156,712	20,156,712	20,156,711	20,156,712	20,156,712	20,156,711	20,156,712	20,156,712	20,156,711
R-squared	0.000	0.003	0.064	0.000	0.004	0.063	0.000	0.001	0.066
Mean outcome (x100)	0.267	0.267	0.267	0.334	0.334	0.334	0.081	0.081	0.081
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel C	(1) Any outpatient care	(2) Any outpatient care	(3) Any outpatient care	(4) Any prac. specialist	(5) Any prac. specialist	(6) Any prac. specialist	(7) Any emergency care	(8) Any emergency care	(9) Any emergency care
Closure X Post (x100)	0.319**	0.307**	0.360***	-0.371	-0.381	-0.367***	0.0501	0.0428	0.060
	(0.137)	(0.124)	(0.0939)	(0.284)	(0.268)	(0.0680)	(0.166)	(0.163)	(0.0602)
# Observations	20,156,712	20,156,712	20,156,711	20,156,712	20,156,712	20,156,711	20,156,712	20,156,712	20,156,711
R-squared	0.001	0.014	0.143	0.000	0.044	0.287	0.001	0.006	0.177
Mean outcome (x100)	8.36	8.36	8.36	13.3	13.3	13.3	2.25	2.25	2.25
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: This table shows difference-in-differences results for primary care utilization (panel A), initiation with chronic medication (panel B) and secondary care use (Panel C) for individuals experiencing a closure due to retirement. Standard errors are clustered on the physician level.

TABLE A8: DIFFERENCE-IN-DIFFERENCES RESULTS, EFFECTS OF CLOSURE ON QUARTERLY OUTCOMES, NON-RETIRING PHYSICIANS

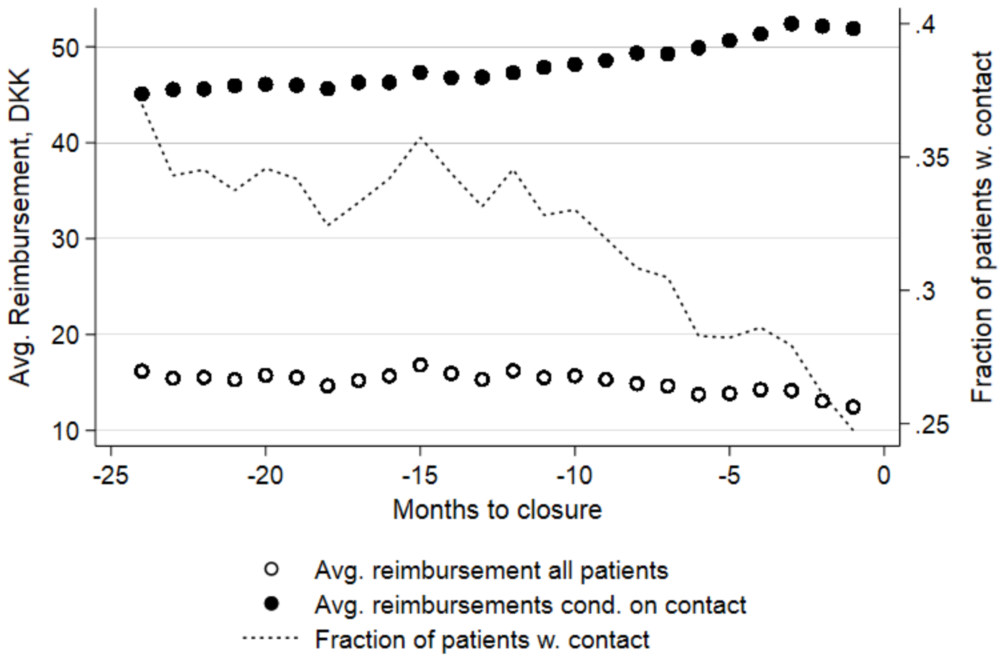
Panel A	(1) Any PCP visit	(2) Any PCP visit	(3) Any PCP visit	(4) Government reimbursement to PCP (DKK)	(5) Government reimbursement to PCP (DKK)	(6) Government reimbursement to PCP (DKK)	(7) Any pharmacy claim	(8) Any pharmacy claim	(9) Any pharmacy claim
Closure X Post (x100)	0.461	0.411	0.534***	183.6*	180.1*	186.5***	-0.221	-0.291	-0.0438
	(0.709)	(0.504)	(0.183)	(120.0)	(94.3)	(25.4)	(0.672)	(0.308)	(0.0932)
# Observations	17,761,015	17,761,015	17,761,014	17,761,015	17,761,015	17,761,014	17,761,015	17,761,015	17,761,014
R-squared	0.001	0.155	0.352	0.003	0.081	0.290	0.001	0.309	0.527
Mean outcome (x100)	55.8	55.8	55.8	4352.6	4352.6	4352.6	52.6	52.6	52.6
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel B	(1) ACE	(2) ACE	(3) ACE	(4) Statins	(5) Statins	(6) Statins	(7) Metformin	(8) Metformin	(9) Metformin
Closure X Post (x100)	0.0614***	0.0617***	0.0633***	0.0274	0.0274	0.0279**	0.0001*	0.0001*	0.0001***
	(0.0186)	(0.0171)	(0.0114)	(0.0206)	(0.020)	(0.012)	(0.00006)	(0.00006)	(0.00006)
# Observations	17,761,015	17,761,015	17,761,014	17,761,015	17,761,015	17,761,014	17,761,015	17,761,015	17,761,014
R-squared	0.000	0.003	0.064	0.000	0.004	0.064	0.000	0.001	0.066
Mean outcome (x100)	0.247	0.247	0.247	0.313	0.313	0.313	0.076	0.076	0.076
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Panel C	(1) Any outpatient care	(2) Any outpatient care	(3) Any outpatient care	(4) Any prac. specialist	(5) Any prac. specialist	(6) Any prac. specialist	(7) Any emergency care	(8) Any emergency care	(9) Any emergency care
Closure X Post (x100)	0.0837	0.000748	0.116	-0.216	-0.221	-0.211***	0.369	0.363	0.377***
	(0.204)	(0.185)	(0.118)	(0.429)	(0.402)	(0.070)	(0.239)	(0.238)	(0.110)
# Observations	17,761,015	17,761,015	17,761,014	17,761,015	17,761,015	17,761,014	17,761,015	17,761,015	17,761,014
R-squared	0.001	0.014	0.142	0.000	0.044	0.285	0.001	0.006	0.175
Mean outcome (x100)	8.25	8.25	8.25	12.9	12.9	12.9	2.20	2.20	2.20
Quarter dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual background chars	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Individual FE	No	No	Yes	No	No	Yes	No	No	Yes

Notes: This table shows difference-in-differences results for primary care utilization (panel A), initiation with chronic medication (panel B) and secondary care use (Panel C) for individuals experiencing a closure due to other reasons than retirement. Standard errors are clustered on the physician level.

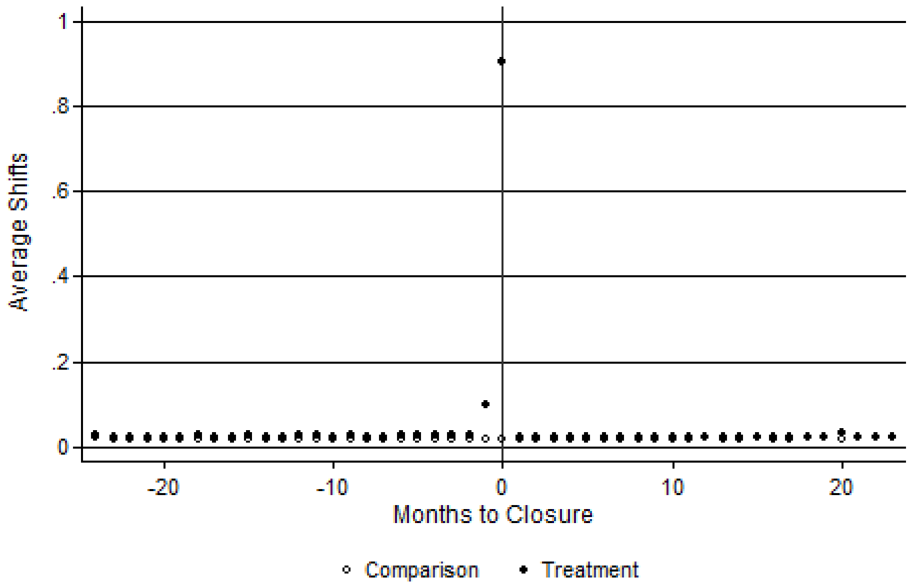
FIGURE A1: PRACTICE LEVEL ACTIVITY RELATIVE TO THE CLOSURE



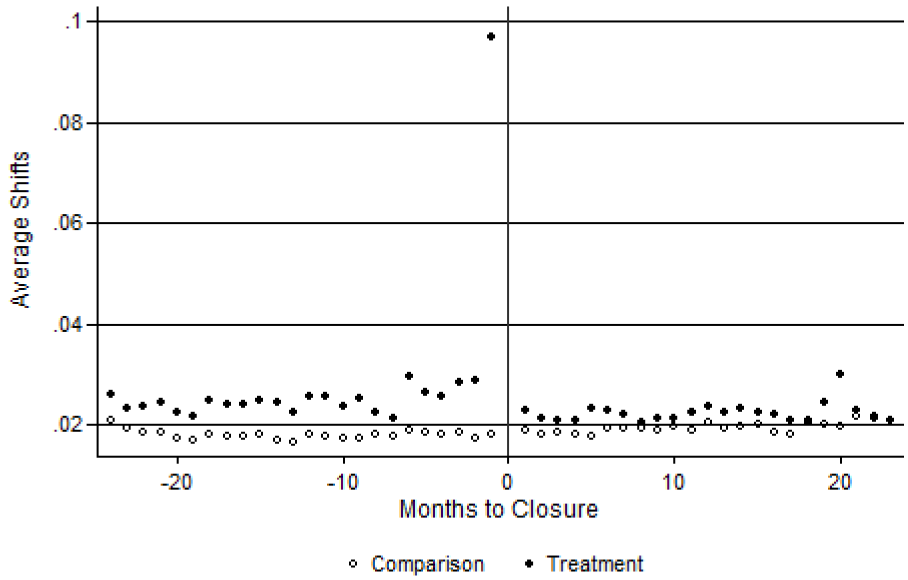
Notes: This figure show average practice level reimbursement for all and patients with a contact respectively for clinics closing relative to the month they close. On the right axis the figure depicts the fraction of patients who are affiliated with the practice who have any type of encounter with the practice in months relative to the closure.

FIGURE A2: MONTHLY SHARE OF PATIENTS
WHO SHIFT PCP RELATIVE TO CLOSURE

Panel A: All months

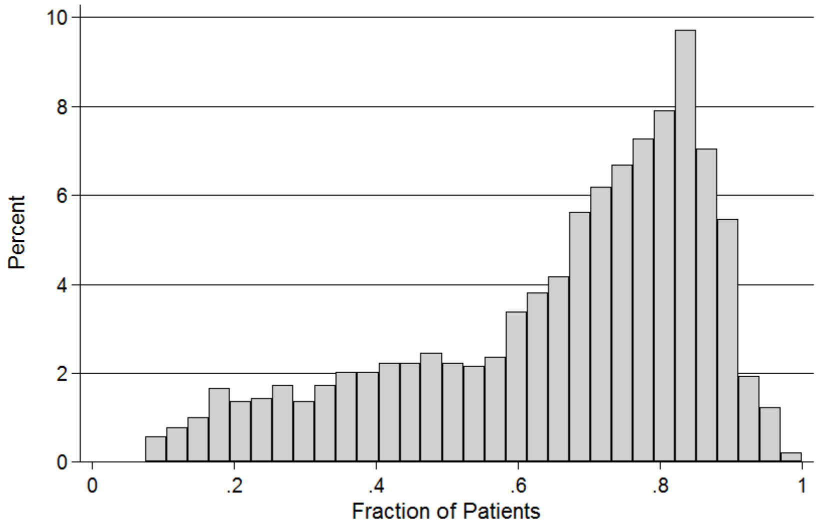


Panel B: Closing month (month 0) excluded



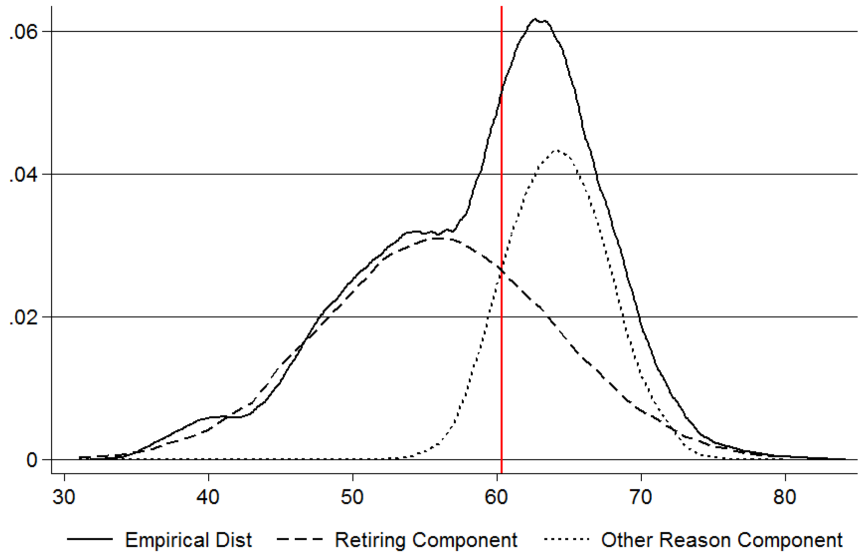
Notes: This figure shows average share of individuals who in a given month do not have the same primary care physician the following month. Panel A show all months and Panel B.

FIGURE A3: SHARE OF PATIENTS WHO MOVE
TO SAME NEW PRACTICE AFTER CLOSURE



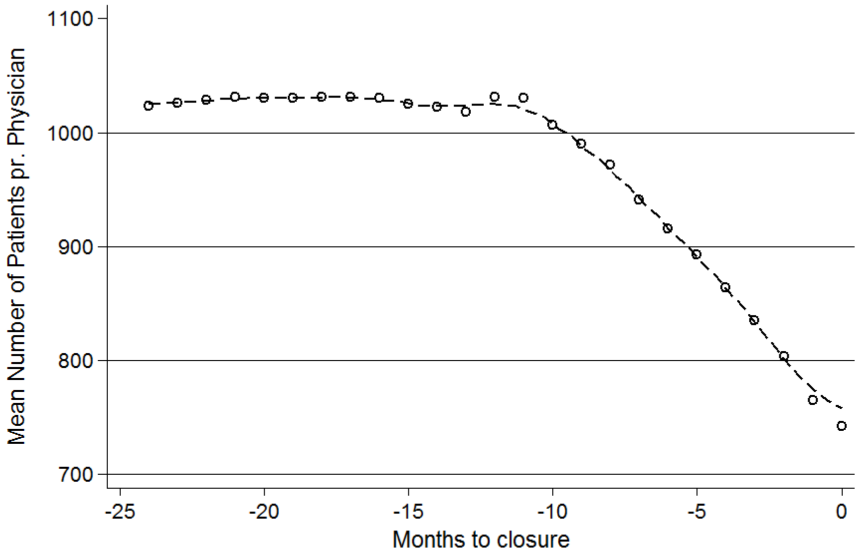
Notes: This figure shows the distribution of the share of patients who move to the same new practice after the closing of the old practice.

FIGURE A4: AGE DISTRIBUTION OF CLOSING PHYSICIANS AND ESTIMATED COMPONENTS



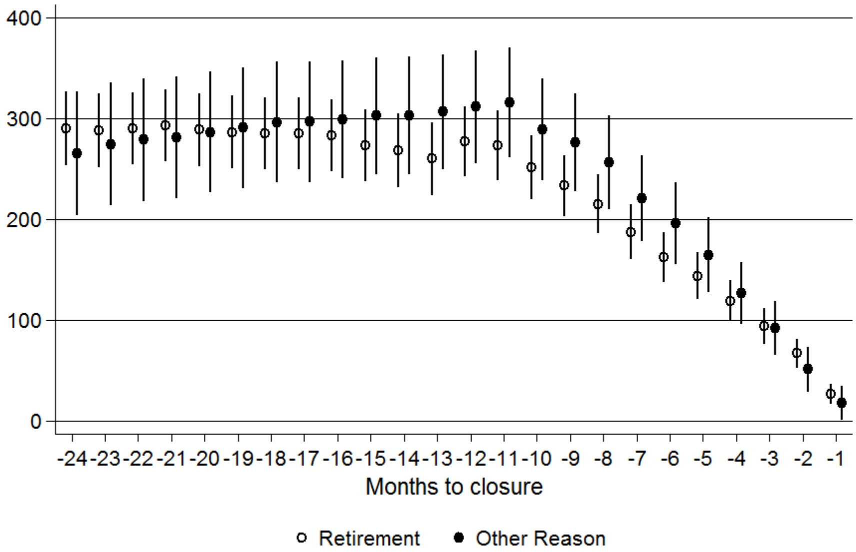
Notes: This figure show the empirical distribution of physician ages of closing physician. It also includes the posterior distributions of components from a two-component Gaussian finite mixture model.

FIGURE A5: AVERAGE NUMBER OF PATIENTS AT CLOSING PRACTICES



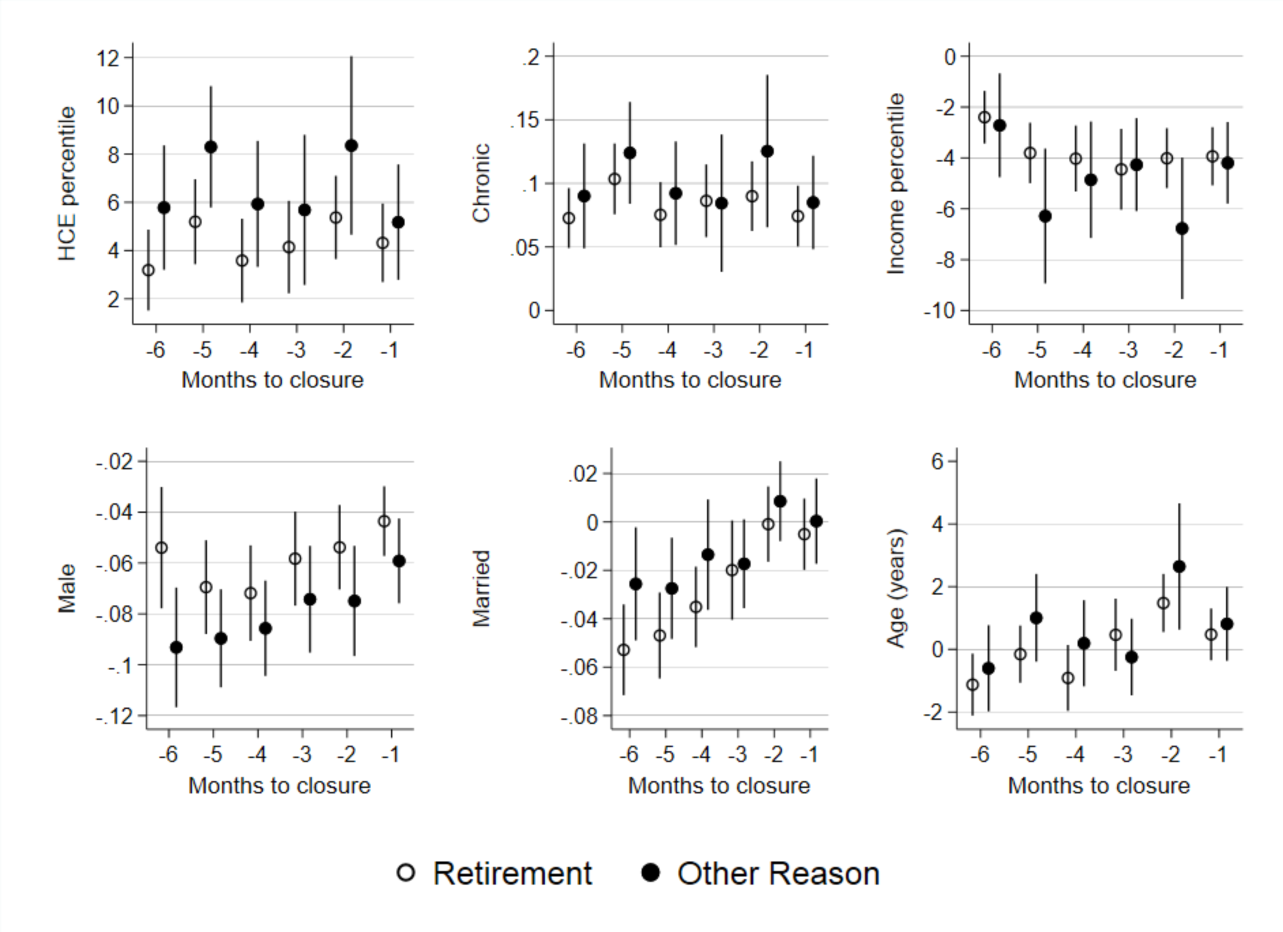
Notes: This figure show average number of patients per physician leading up to a practice closure in absolute numbers.

FIGURE A6: AVERAGE NUMBER OF PATIENTS AT CLOSING PRACTICES BY CLOSING STATUS



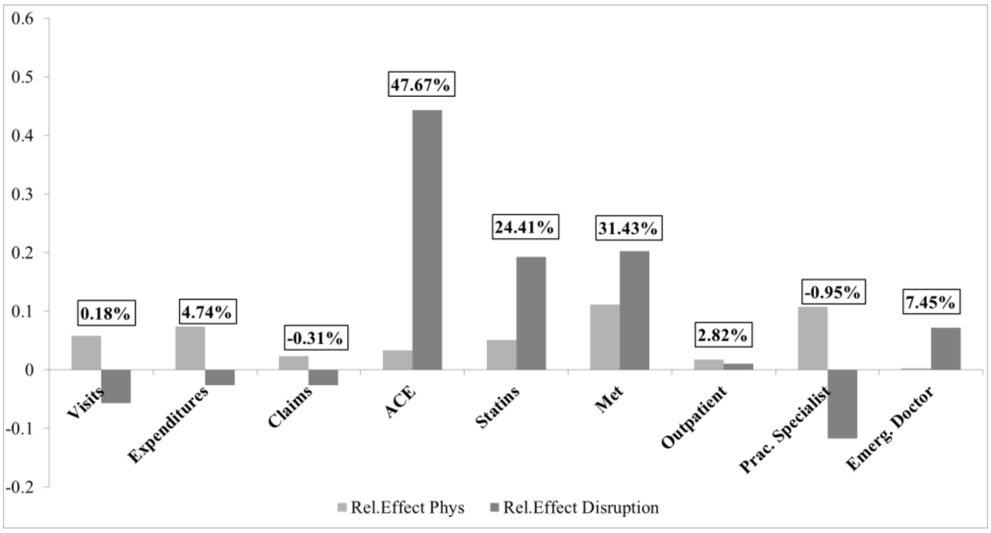
Notes: This figure show average number of patients per physician leading up to a practice closure in relative to the closing months (month 0), by retirement status of the closing practice. Standard errors are clustered at the practice level.

FIGURE A7: PATIENT CHARACTERISTICS OF MOVERS BY RETIREMENT STATUS



Notes: This figure show the characteristics of individuals leaving relative to the closure month by retirement status of the closing practice. Standard errors are clustered at the practice level.

FIGURE A8: DECOMPOSITION OF EFFECTS OF CLOSURE



Notes: This figure shows effects relative to sample mean measured two quarters before closure decomposed into a physician effect (light gray) and a disruption effect(dark grey). Total effect relative to the mean is reported in squares above. Table A8 reports the actual shares. To allow for comparison across outcomes, we report effects relative to outcome means two quarters before the closure. For each outcome, the light grey bar shows the part of the effect that is attributable to the change in physician and the dark grey bar show the effect that is attributable to the disruption. The sum of the two bars equals the total effect of the practice closure on the outcome.

Appendix B: Identification of closing practices and the patient physician spell data:

To conduct the preferred analysis, we have two major obstacles to overcome. The first relates to identifying which practice closes for practice, while the second is how to construct a dataset containing physician-patient spells.

We define a practice closure as an event where a physician decides to stop working in her practice, and her patients are subjected to a new provider. This could be (and often is) due to a decision to retire, but could also be due to any other reason. There are several ways to divest ones practice. If the physician can find another physician willing to replace her, the license with its entire list of patients and physical location can be transferred to the new physician at a price decided between the two physicians. Alternatively, if the closing physician cannot find any replacement, she can simply report to the authorities that the practice is closed with a six months’ notice. The license is then transferred back the authorities. The chosen operationalization thus implies that for some individuals, the closure simply constitutes a new physician in the same exact same clinical setting.

In general our identification of closures resembles that frequently implemented in plant closure. Reimbursement are made to clinics based on their license. We identify closures from the health insurance claims data, by identifying the last period a reimbursement is paid out to a license. This limit our sample to clinics who either close, resell their practice or change organizational structure through a merge. As we want to include all cases where we are sure that a patient experience a change of provider, we remove practices where the physicians merge practice. This happens, when several physicians either share a single or multiple licenses. We identify mergers, by removing closing settings, where any physician from the practice that is closing is present at any destination practice for patients from the closing practice.

Appendix C: Predicting pharmaceutical spending

To predict pharmaceutical spending, we follow the approach outlined in Handel (2013) and applied in Simonsen, Skipper, Skipper and Christensen (2018). We construct a predictive model based on population-wide panel data informative about pharmaceutical spending, diagnoses, and cost information.

We first regress pharmaceutical spending in calendar year t on a dummy for gender in addition to t-1 age, age squared, number of office visits to own physician, sum of fee-for-services paid to the physician, total spending on prescription drugs and total expenditures squared, indicators for type of prescription drugs purchased (ATC code level 3; 88 categories), and hospital diagnosis indicators (ICD-10 code level 2; 215 categories). The resulting models explain between 75–80% of the variation in spending. We then use the estimated model to predict individual-level spending in calendar year t + 1.

Appendix D: Classifying closing physicians as retirees

To detect whether a practice closure is most likely driven by retirement, we exploit the fact that the distribution of age of the closing physicians is distinctly different from that of the destination physicians. Let f_{age} be the distribution of ages of closing physicians. These are plotted in panel A of Figure A4. This figure is not weighted by individuals as Figure 4, and the spike at age 50 is not nearly as pronounced. However, it does seem plausible that f_{age} consists of two distinct Gaussian distributions. It is likely the case that these distributions are those who close due to retirement, and those that do not. We would expect the former to have a high mean and low variance, compared the latter. That is, we will fit two Gaussian distributions, to classify whether a closure stems from a decision to retire, or whether it is due to other reasons. This is known as a finite mixture model. We let f_{age} come from 2 distinct classes f_{age}^{retire} and f_{age}^{Other} with the share $\pi_{Retire} + \pi_{Other} = 1$, such that the density of the 2-component mixture model can be written as

$$f_{age} = \pi_{Retire} f_{age}^{retire} + \pi_{Other} f_{age}^{Other}$$

Using the multinomial logistic distribution to model the probability of the classes, it is straightforward to estimate the parameters, and plot the distributions (Hastie et al, 2001). Based on the posterior probabilities of classification assignment, we can simulate which distribution each closure comes from. This is known as soft bracket classification.[20] The separation between whether a closure is due to retirement or not, can be seen in Figure 2 as the point where the two distributions intersect, at 60.3 years, in effect making it more likely to belong the other group. Ultimately, we classify 397 closures as being due to retirement, (mean age of 64.9 years, std. dev. 3.3 years) and 368 closures as driven by non-retirement (mean age 52.5; std. dev. of 5.66 years).

[20] Using a hard bracket classifier gives us similar results. Results are available upon request.

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