

Continuity of care increases physician productivity in primary care

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Continuity of care, defined as an ongoing therapeutic relationship between a patient and a physician, is a defining characteristic of primary care. However, arranging a consultation with one's regular doctor is increasingly difficult as practices face physician shortages. We study the effect of declining care continuity on the productivity of physicians by analyzing data of over 10 million consultations in 381 English primary care practices over a period of 11 years. Specifically, we examine whether a consultation with the patient's regular doctor is more productive than with another doctor in the practice. Using statistical models that account for confounding and selection bias and restricting the sample to consultations with patients who had at least three consultations over the past two years, we find that the time to a patient's next visit is on average 18.1% (95% CI: [16.9%, 19.2%]) longer when the patient sees the doctor they have seen most frequently over the past two years, while there is no operationally meaningful difference in consultation duration. The data shows that the productivity benefit of care continuity is larger for older patients, patients with multiple chronic conditions, and patients with mental health conditions. We estimate that the total consultation demand in our sample could have fallen by up to 5.2% had all practices offered continuity of care at the level of the top decile of practices while prioritizing patients expected to yield the largest productivity benefits. We discuss operational and strategic implications of these findings for primary care practices and for third-party payers.

Key words: healthcare; continuity of care; productivity; primary care

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1. Introduction

Primary care practices around the world are experiencing rising demand at a time when their most critical resource – primary care physician time – is becoming more scarce and more expensive. In the UK, the number of primary care physicians per 100,000 population decreased from 67 in 2009 to 60 in 2018, despite increasing demand from an aging population (Palmer 2019). The UK's Nuffield Trust estimates a shortfall of 7,000 general practitioners in the UK by 2023-24 (Beech et al. 2020), while the Association of American Medical Colleges estimates a shortfall of between 21,400 and 55,200 primary care physicians in the US by 2033 (Dall et al. 2020). These projections were made before the COVID-19 pandemic, which will likely exacerbate the shortfall. To match labor shortages with demographically driven demand growth, primary care practices need to increase the productivity of their physicians.

Productivity of primary care physicians is a complex multidimensional concept and a function of the quality of care provided to patients and the number of patients served per full-time equivalent physician-year. A physician can be considered more productive if they improve the quality of care provided without reducing the number of patients they serve per year, or if they serve more patients without reducing quality of care. In primary care, where patients often have a preferred doctor, these two dimensions are related. If physicians provide high quality care to their regular patients, they are likely to keep them healthier, which reduces the demand for consultations and increases their capacity to serve more patients.

While a physician's productivity is naturally affected by their capabilities and available tools and technology, operations management processes in their practice can also significantly impact their productivity. Specifically, appointment scheduling practices can have a significant effect on physician productivity. For example, in an attempt to increase daily throughput, practices may reduce the time they allocate for a consultation. However, this can create a speed-quality trade-off and lead to the unintended consequence of reducing the quality of care (Liu et al. 2018). Alternatively, practices may choose to prioritize urgent care service and reserve more consultation slots for on-the-day access or assign patients in a round-robin fashion to the next available physician. This has another unintended but important consequence: It reduces continuity of care as it becomes more difficult for patients to arrange a consultation with their preferred doctor (Kajaria-Montag and Freeman 2020). This effect is evidenced by the UK's annual GP practice survey, where the proportion of respondents who reported being able to see their preferred doctor most of the time has dropped from 77% in 2009 to 45% in 2019 (Institute for Government 2019).

Despite the well-established positive impacts of continuity of care on patient health, healthcare system utilization, and staff satisfaction (Palmer et al. 2018), there remains a notable scarcity of evidence exploring the potential effects of declining care continuity on physicians' productivity. In particular, while existing literature suggests that quality of care is enhanced when patients receive treatment from their regular doctors, the impact of continuity of care on physicians' time commitment per patient-year has not been sufficiently examined. In primary care settings, where patients often require repeated interactions with healthcare providers due to chronic and acute health conditions, continuity of care has the potential to influence this metric through two mechanisms: the time per consultation and the interval between consultations. The latter is critically important because primary care is a repeated interaction service with steadily increasing consultation frequencies, due primarily to aging populations. A recent English study estimated an interquartile range of annual face-to-face consultations with primary care physicians between 10 and 14 consultations, with the top 10% of attenders accounting for 40% of all such consultations (Kontopantelis et al. (2021), Tables 2 and 3 in the supplementary material).

Importantly, if patients receiving care from their regular doctors have longer intervals between consultations without requiring longer consultations, then continuity of care can potentially allow physicians to expand their patient list without increasing their time commitment. Combined with existing evidence on the quality-benefit of relational continuity, this would suggest that continuity of care enhances physicians' productivity. The extent to which this relationship between continuity of care and productivity holds has yet to be established empirically. It is important to fill this gap in the literature because, if continuity of care increases physician productivity, then too much focus on throughput at the expense of continuity of care will be counter-productive and can lead to an overall productivity drop. Furthermore, increasing continuity of care may be an effective response to labor market shortages in primary care. The present study represents the first large-scale empirical investigation into the relationship between continuity of care and physician productivity.

We analyze data from over 10 million face-to-face consultations between over 14,000 primary care physicians and 1.8 million patients in 381 English primary care practices over a period of 11 years. For each consultation, we identify the patient's regular doctor as the doctor who had the most consultations with the patient over the past two years, restricting the sample to patients with at least 3 consultations over that period. We then analyze whether a patient's revisit interval (i.e., the time between the focal consultation and the patient's next visit) differed when the consultation was with his regular doctor or with another doctor in the practice. Using a range of empirical methods to control for potential selection and omitted variable bias, we find robust evidence that the revisit interval is extended by an estimated 18.1% (95% CI: [16.9%, 19.2%]) if the patient sees her regular doctor. At the same time, we find no evidence that the consultations with regular doctors are longer in duration.

Having established the main effect, we then study its heterogeneity. We show that the productivity benefit of care continuity is particularly pronounced for patients with more complex needs, specifically older patients, patients with chronic diseases, and patients with mental health conditions. For the 30.7% consultations with patients over the age of 70, seeing the regular doctor extends the revisit interval by 20.8% (95% CI: [19.8%, 22.0%]) versus 13.5% (95% CI: [12.4%, 14.6%]) for younger patients; for the 80.6% consultations with patients with at least one chronic illness, the revisit interval is extended by 16.9% (95% CI: [15.8%, 18.0%]) versus 10.9% (95% CI: [9.7%, 12.0%]) for patients without chronic illnesses; and for the 27.9% consultations with patients with recorded mental health conditions, the revisit interval is extended by 17.5% (95% CI: [16.4%, 18.6%]) versus 15.2% (95% CI: [14.1%, 16.3%]) for patients without such conditions.

Finally, we demonstrate how the estimation methods deployed in this paper can be used as a scoring tool to enable practice managers to identify patients with the largest productivity benefit of continuity. We apply this scoring method retrospectively to the data to estimate a counterfactual

demand reduction. The model suggests that if all practices in the data had offered well-targeted continuity of care for 75% of their consultations (a level achieved by the top decile of practices in the data) then the total consultation demand in the sample would have dropped by up to 5.2%.

2. Literature Review

This paper contributes to the healthcare operations and medical literature on continuity of care. These literature streams have largely focused on the consequences of care continuity on patient outcomes and secondary care utilization, such as emergency visits or hospital admissions, typically for patients with specific conditions. In contrast, we are concerned with the effect of care continuity on physician productivity in primary care practices themselves.

2.1. Continuity of care in healthcare operations

A study by Liu et al. (2018) examines patient preferences and choice behavior in appointment scheduling, focusing on the trade-off between speed of access (waiting time) and quality (continuity of care). The study findings indicate that females are more averse to not seeing their regular doctor and perceive a higher loss of utility than males when faced with longer wait times. On the other hand, males, who tend to be more risk-seeking, derive higher utility from shorter delays. Ahuja et al. (2020b) investigate the effect of providing continuity to patients with diabetes and find that continuity improves three important system utilization metrics: inpatient admissions, hospital length of stay, and readmission rate. In a follow-up study, Ahuja et al. (2020a) partially explain this relationship between continuity and the system utilization metrics by showing that continuity can lead to higher rates of medication adherence and consequently to lower glycemic variability. Senot (2019) also studies the effect of continuity on secondary care usage. Specifically, the study follows the journey of heart failure patients over a one-year period and finds that the continuity of the individual referring provider (along with continuity of the physical location and the accountable care organization) contributes to a reduced risk of hospital readmission for heart failure patients. Queenan et al. (2019) find that providing technology-enabled continuity coupled with increasing patient engagement in their own health reduces hospital readmissions.

The present study complements this research on system utilization effects by focusing on productivity effects within the primary care setting itself. This is important because the direction of the internal productivity effect tells us whether or not practices need to be externally incentivized to provide the continuity of care that will create the documented system utilization benefits.

While the healthcare operations literature has hitherto not engaged much with primary care productivity, Bavafa et al. (2018) is a notable exception. Their paper focuses on the impact of complementing office visits by e-visits on demand in primary care, and the authors show that the introduction of this new communications channel increases demand for office visits. We also

address how demand for primary care services changes as a function of how the service provided. Our focus, however, is on the potential demand-inducing effect of reduced care continuity.

Li et al. (2021) focus on telemedicine adoption in an outpatient context. They show that adoption of telemedicine reduces productivity in the short term, by shortening the interval between patient visits, but that the interval between visits increases in the long run. We follow this study in using the revisit interval as a measure of productivity but our focus lies on continuity in primary care.

2.2. Continuity of care in the medical literature

The medical literature differentiates between different types of care continuity, specifically relational continuity, management continuity, and informational continuity (Haggerty et al. 2003). Within a primary care context, the terms relational continuity and continuity of care are often used synonymously and defined as an ongoing therapeutic relationship between a patient and a physician. In this paper, the focus is on this relational component of continuity, as captured by repeat consultations with the same primary care physician.

It is well documented that continuity of care in primary care is valued by patients and doctors alike and surveys highlight various benefits of providing care continuity (Freeman et al. 2010). Specifically, the medical literature has demonstrated various direct health benefits for patients and improved management of health conditions for those who receive care continuity. For instance, studies have shown improvements in quality of life outcomes (Drury et al. 2020, Chen et al. 2017, Ye et al. 2016), blood pressure for diabetic and hypertensive patients (Leniz and Gulliford 2019), mortality (Gray et al. 2018, Cho et al. 2015), adherence to medication plans (Dossa et al. 2017), and the likelihood of filling risky prescriptions (Hallvik et al. 2018).

In terms of system benefits, a meta-analysis by Huntley et al. (2014), involving participants from OECD countries, found that unscheduled secondary care usage is highly influenced by care continuity in the primary care setting. For example, primary care continuity has been associated with reductions in emergency department visits (Pourat et al. 2015) and unplanned hospitalizations of patients with ambulatory care sensitive conditions (Barker et al. 2017). Such advantages have been consistently demonstrated across different patient populations, including patients with serious mental illness (Ride et al. 2019), dementia (Amjad et al. 2016), COPD (Lin et al. 2015), and diabetes (Worrall and Knight 2011, Dossa et al. 2017), as well as older patients (Tammes et al. 2017, Katz et al. 2015, Bayliss et al. 2015, Nyweide et al. 2013). We contribute to this stream of literature by demonstrating that care continuity also affects the need for primary care visits themselves and that this effect is particularly pronounced in older patients and patients with complex conditions, such as chronic diseases or mental illnesses.

In summary, there is rich evidence to show the benefits of relational continuity for both patients and the wider health system in terms of reduced utilization. It is therefore somewhat surprising

that the effect of continuity of care on physician productivity within primary care practices has not yet been investigated. This study expands existing knowledge of the effects of care continuity by showing that care continuity not only improves outcomes and system utilization but also enhances the productivity of primary care physicians.

3. The Hypotheses

Before we present and discuss the paper’s central hypotheses, we clarify the independent variable of interest – care continuity and physician productivity – and the outcomes of interest. We focus on relational continuity of care, defined as a sustained therapeutic relationship between a patient and a doctor. In primary care, this relationship is epitomized by the notion of a “patient list” or “patient panel” that many primary care physicians hold, either formally or informally (Wilkin and Metcalfe 1984, Tammes et al. 2017). These are the patients for whose primary care service the doctor takes responsibility over a prolonged period of time. While, in reality, patients will have consultations with their continuity doctor as well as with other doctors in the same practice, they can be expected to see their continuity doctor most frequently. This is how we identify the patient’s *regular doctor*. We study productivity-related effects at the level of individual patient consultations and distinguish between consultations with a patient’s regular doctor, who provides continuity of care, and consultations with another doctor in the practice, who provides a more transactional service and who we call a *transactional provider*.

We measure two outcomes related to the productivity of a patient consultation: its duration and its effectiveness, i.e., how well the doctor is able to “get it right the first time”. A short but ineffective patient consultation is likely to create the need for additional consultations in the near future, while a longer, more thorough consultation may alleviate this need. Consequently, we consider two clinical productivity-related metrics: (i) the duration of the consultation, as a measure of throughput, and (ii) the revisit interval, i.e., the time to the next consultation, as a proxy measure for the effectiveness of the service.

3.1. Consultation duration

The relationship between continuity of care and consultation duration is determined by two countervailing factors. On the one hand, a regular doctor has a larger incentive to take more time to treat her regular patients thoroughly than a transactional provider. Getting it right the first time will reduce her future workload by preventing revisits, which would likely be her responsibility, while a transactional provider is less likely to see the patient for her next visit (Jeffers and Baker 2016). On the other hand, the regular doctor is more familiar with the patient than a transactional provider and can therefore be more economical in her collection of information (Hill and Freeman 2011, Rosen et al. 2020). It is difficult to argue a priori which of these two factors will prevail and

there is therefore no justification for a directional hypothesis.¹ This question needs to be left to an empirical study, which we provide in Section 6.5.

3.2. Revisit interval

We focus in this paper on the second aspect of consultation productivity, the revisit interval. The paper sets out to provide evidence in support of the following two hypotheses.

HYPOTHESIS 1. If a patient is seen by her regular doctor, there will be a longer time interval to her next consultation than if she is seen by another doctor in the practice.

HYPOTHESIS 2. The effect posited in Hypothesis 1 will be larger for (a) patients with multiple comorbidities, (b) older patients, and (c) patients with mental health conditions.

Before we present the empirical evidence, we propose a number of a priori arguments in support of these hypotheses. Specifically, we draw on four mechanisms that are frequently discussed in the literature on continuity of care (Freeman et al. 2010) – familiarity, security and trust, “collusion of anonymity”, and one-stop-shop incentives – and relate these mechanisms to the time to the patient’s next consultation.

Familiarity. As the patient’s regular doctor sees the patient repeatedly, she becomes familiar with the patient’s health trajectory as well as with their preferences, behaviors and personal circumstances. This allows the regular doctor to provide more effective customized advice and treatment and thereby reduces the need for revisits (Hjortdahl and Borchgrevink 1991).

Specifically, because a regular doctor forms an impression of the patient’s health trajectory she will be able to respond not only to the patient’s health status at the time of the consultation but also to *changes* in their health (Koopman et al. 2003). This longitudinal, and often unrecorded information that a one-off provider does not have allows the regular doctor to make a more accurate assessment of the patient’s health needs (O’Connor et al. 1998, Ramanayake and Basnayake 2018). Indeed, the primary care physicians we interviewed for this study confirmed that when one of their regular patients enters the consultation room, they often know at a glance whether or not the patient is seriously ill and that they cannot do this for patients they are not familiar with.

We have also interviewed geriatricians, who have confirmed that the knowledge of a patient’s longitudinal health trajectory is particularly relevant for older patients, where first-time impressions of patients can be very misleading. More information is gained from an observed change of the patient’s health. Being able to identify these changes and act appropriately allows the patient’s regular doctor to reduce the need for future visits and this effect will be stronger for older patients.

¹ In fact, because our study uses UK data, we expect, a priori, little difference in the average duration of patient consultations between the regular doctor and a transactional provider in this data. This is because, although not a formally imposed guideline, 10 minute consultations have become the de facto standard for primary care in the UK (Royal College of General Practitioners 2019).

Trust. Repeated patient interactions over time provides the regular doctor not only with a more comprehensive understanding of the patient’s needs and circumstances but also allows her to form a trust-based relationship that may help her communicate more effectively with the patient (Tarrant et al. 2010, Özer et al. 2014, Hill and Freeman 2011). The patient may feel more secure sharing information with her regular doctor and, as a consequence, the doctor will be able to design a more appropriate treatment plan (von Bültzingslöwen et al. 2006). Furthermore, trust will increase adherence to an agreed disease management plan (Ahuja et al. 2020a, Dossa et al. 2017, Brookhart et al. 2007) which is likely to reduce the need for revisits.

Trust goes both ways - the regular doctor also knows and trusts her patients and may therefore be more willing to adopt a wait-and-see approach when this is indicated, to avoid undesirable medicalisation (Hjortdahl and Borchgrevink 1991). They feel both sufficiently familiar with the patient and secure to propose such an approach when appropriate. By contrast a transactional provider is more likely to start the patient on an interventional diagnostic trajectory, to be “on the safe side” and avoid the potential risk of litigation. Unnecessary medicalisation is likely to increase the need for follow-up visits and reduce the time to the next consultation.

We expect the advantage of a trust-based relationship to be particularly important for patients with mental health conditions, such as anxiety, depression and schizophrenia (Biringer et al. 2017). The stigma that is attached to mental health might make patients reluctant to be fully transparent with an unfamiliar physician (Knaak et al. 2017). Moreover, medication compliance is a particular problem for mental health patients, due in part to the negative side effects associated with commonly prescribed medications (e.g. weight gain and fatigue) (Semahegn et al. 2018).

Collusion of anonymity. In the medical literature, collusion of anonymity refers to a situation where a physician has an incentive to do the minimal possible to pass the patient safely on to the next provider (Freeman et al. 2010, Balint 1955). This incentive is larger for a transactional provider, who is less likely to have to take potential follow-up visits. By contrast, the regular doctor has a strong incentive to reduce the likelihood of follow-up consultations, to reduce her future workload. This makes her more likely to diagnose the patient’s problem more carefully in an attempt to “get it right the first time” (Koopman et al. 2003). From a time and productivity perspective, such a more careful root-cause diagnosis may not even cost the doctor much time if she is familiar with the patient.

One-stop-shop incentive. A regular doctor has an incentive to leverage the patient encounter to explore the patient’s health needs beyond the immediate reason for the consultation, as this may prevent an unnecessary visit in the near future (Hill and Freeman 2011). She may check her notes and proactively deal with multiple illnesses or health issues in a single appointment. Transactional

providers lack both the incentive to expand their scope of service beyond the immediate clinical need expressed by the patient and the holistic patient knowledge that facilitates proactive management of the patient’s health (Balint 1955). Opportunities for such proactive interventions, outside the scope of the immediate reason for the visit, are particularly salient when the patient has a chronic disease (Koopman et al. 2003, Goodwin et al. 2010). We therefore expect the productivity benefit of seeing a regular doctor to be larger for patients with multiple chronic conditions.

In summary, these four mechanisms lend a priori support to Hypothesis 1 and 2.

4. Clinical Setting, Data and Variables

In this section, we first provide a brief overview of the specifics of the UK primary care context that are relevant for this study. We then describe the dataset in detail and conclude with the description of the dependent variables, independent variables, and controls to be included in the analysis.

4.1. Primary care context

Although the English National Health Service (NHS) is publicly funded through taxation, primary care practices are privately owned businesses, organized as partnerships of primary care physicians. Unlike hospitals, they operate as independent contractors of the NHS and therefore not under its direct control. Instead, the NHS controls their services through standardized contractual arrangements. A typical practice has 8,000-10,000 registered patients, 4-5 full-time equivalent physicians, and a small number of other healthcare workers and administrative staff. Practice income is largely capitation-based, adjusted for demographic and socioeconomic characteristics of the practice population and geography. In 2021, a typical practice with 9,000 registered patients received an income of £1.44M, approximately £160 per registered patient (NHS Digital 2021).

The contract of a general practice in England defines the geographical catchment area for the practice. Patients who live in this area have the right to register with that practice. Patients may apply for registration with any practice but practices have discretion to accept or deny out-of-area patients. Importantly, patients can only register with a single practice in England and are automatically deregistered when they register with a new practice. Since our data is practice-based, we therefore have full visibility of all primary care appointments of patients for their period of registration in the study practices.

Primary care services in England are free at the point of care. Patients can request to see any doctor at their practice, and practices generally try to accommodate this request if the doctor is available. The NHS contract requires that each patient registered at a practice is assigned to a *named doctor*, who is responsible for ensuring that the patient’s needs are met (Tammes et al. 2017). However, some practices regard this as a purely administrative requirement, so the patient’s

named doctor may not be her regular doctor. This study focuses on the patient’s regular doctor, the physician who has seen the patient most frequently in the past.

Consultations can be face-to-face, over the phone or video link or, in rare cases, at the patient’s home. Appointments are generally booked via the phone with a receptionist. Practices have to accommodate routine and urgent appointments, the latter requiring on-the-day access. Some practices reserve a number of appointment slots for urgent services and, if those slots are booked, refer patients to a hospital emergency department or ask them to call again the next day. Other practices accept all patients who call in before a certain cut-off time or offer unlimited access for acute care throughout the day. These practices have *duty doctors* who are dedicated to serving urgent care patients, typically in a round-robin fashion. The duty doctor role will normally rotate around all doctors in the practice.

A limitation of most primary care medical records, including ours, is that they do not record when an appointment was requested through a receptionist. We can therefore not use the period between appointment request and consultation time to distinguish between urgent and routine appointments. Instead, we use markers, such as antibiotic prescriptions, that are more commonly associated with urgent appointments to help us distinguish the two appointment types.

4.2. Data and sample

In order to understand the effect of a patient seeing her regular doctor in one consultation on the time to her subsequent consultation, we perform a cross-sectional analysis with individual patient consultations as units of observation. We obtained consultation-level data from the UK Clinical Practice Research Datalink (CPRD). This database consists of anonymized electronic medical records covering over 11.3 million patients across 674 practices in the UK; it is representative of the population in terms of age, sex and ethnicity (Herrett et al. 2015). The database encompasses a wealth of information about patients, visits, providers, diagnoses, prescriptions, referrals, treatments, immunization records, and test records. A patient’s primary care data can be linked to several other data sources, including secondary care services, resulting in a fairly complete medical record of the patient’s health resource usage during their registration period with one of the participating practices.

We obtained data for all English practices that had consented to linkage to secondary care usage data. The restriction to English practices improves the homogeneity of the sample as the national health systems operate differently in the four constituent countries of the UK and there are differences in their standard primary care contracts. The starting data set comprised information on 370,890,526 primary care consultations corresponding to 5,475,342 patients. The analysis sample was derived from this data using the inclusion criteria described in Section EC.1 of the e-companion and summarized in Table 1.

Table 1 Data and sample inclusion criteria

Sample inclusion criteria	Patients	Consultations	Sample reduction
Doctor consultations in 407 primary care practices	5,475,342	370,890,526	—
Face-to-face doctor consultations only	5,335,945	200,312,789	46.0%
Consultations after date at which practice data is of research quality	5,037,650	161,556,335	19.3%
Consultations during a patient's continuous registration period	4,921,208	139,455,412	13.7%
Consultations at which the patient was over 18	3,855,445	86,399,813	38.0%
Consultations with ≥ 3 and ≤ 104 consultations in the preceding 2 years	2,952,445	71,797,380	16.9%
Consultations occurring after a patient's first two years following registration	2,537,781	63,087,124	12.1%
Only consultations with a valid revisit interval	2,410,189	60,894,300	3.5%
Only consultations between January 2007 and December 2017	2,322,773	51,711,037	15.1%
Consultations occurring when the patient's regular doctor is available	2,273,571	45,376,070	12.3%
Random sample of consultations from 381 remaining practices	1,883,626	11,344,065	75.0%

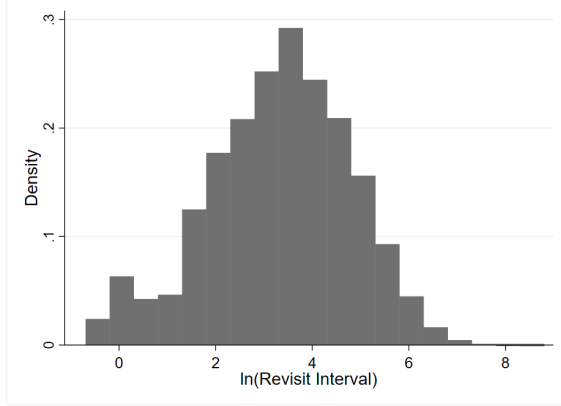
Specifically, the sample for analysis consists of face-to-face clinical consultations between primary care doctors and patients over the age of 18 that took place between 1 January 2007 and 31 December 2017 at times during which (i) a practice's data is confirmed to be of research quality by CPRD, (ii) the patient had sufficient past appointments to identify their regular doctor, and (iii) the patient's regular doctor was available to see them. Data was also filtered to exclude patients visiting more than once per week on average, to only include data from periods in which the patient was continuously registered at a practice, and to exclude any consultations lacking an observable revisit interval. (For more justification, see Section EC.1 of the e-companion.)

The final analysis sample thus consists of 11,344,065 consultations between 1,883,626 patients and 14,123 doctors in 381 practices across 11 years between 2007 and 2017.

4.3. Variable description

4.3.1. Dependent variable. The main dependent variable throughout this study is the patient's revisit interval (RI), which is defined by the time between the focal face-to-face consultation with a doctor and the next face-to-face consultation with a doctor. The RI is measured in days, as the data only records the day of the consultation, not the time of the day. In the infrequent event that a patient has multiple face-to-face consultations with doctors on the same day (occurring for 1% of consultations), we set the revisit interval length to 0.5 days. As is usually the case with durations, the distribution of revisit intervals is right-skewed. We therefore transform the variable by taking its natural logarithm. Figure 1 shows the distribution of the log-transformed revisit interval, and Table 2 contains summary statistics.

4.3.2. Independent variables. The main independent variable is a binary variable which indicates whether or not the focal consultation was with the patient's regular doctor. Since this study spans an 11-year time horizon, the patient's regular doctor may change over time. For example, a doctor may retire or leave the practice, or the patient may switch due to a change in

Figure 1 Distribution of $\ln(\text{Revisit Interval})$

	Revisit Interval	$\ln(\text{Revisit Interval})$
Mean	68.22	3.29
Median	28.00	3.33
Min	0.50	-0.69
Max	4240.00	8.34
Std. Dev.	116.80	1.48

Table 2 Descriptive statistics for the dependent variable

circumstances or a positive experience with another doctor. When we determine a patient’s regular doctor we therefore use a dynamic measure.

Specifically, we consider a rolling two-year time window over which we calculate the patient’s regular doctor. For consultation i , we define a patient’s regular doctor as the doctor with whom the patient had the most face-to-face consultations over the preceding two year. To break ties (occurring in 11% of cases), we choose established over unestablished doctors² and, if the tie persists, we choose the doctor who the patient saw most recently. The independent variable RD_i is thus a binary variable that is equal to 1 for consultation i if the consultation is with the patient’s regular doctor at the time of the consultation, and 0 otherwise. Overall, 50% of consultations in our analysis sample occur between a patient and their regular doctor. We provide additional information on the independent variable and the patient-level factors that affect it in Section EC.3.

4.3.3. Control variables. The relationship between continuity of care and a patient’s revisit interval is likely to be confounded by demographic factors, the patient’s consultation and revisit interval history, attributes of the regular doctor, temporal factors, and practice-level factors. To account for these potential confounders, we define a range of control variables for inclusion in the empirical analysis. A summary of the controls is provided in Table 3 and an explanation for each of the controls is given in Section EC.5.

5. Econometric Specifications

The idealized randomized experiment to test Hypothesis 1 is a random assignment of each patient consultation to either the patient’s regular doctor or a randomly chosen other doctor from the

² The data allow us to distinguish between two types of physicians: *established* physicians, who have a contract with the practice, and *unestablished* physicians, who are not permanent employees of the practice but may be self-employed or employed with an agency. The latter work on an ad-hoc basis, often in multiple practices, and are paid on an hourly basis.

Table 3 Table of controls

Variable	Type	Description	Time-Invariant
Patient demographics			
Age	Categorical (14)	Age of the patient at the time of consultation, split into age bands (18-25, 26-30, 31-35, . . . , 81-85, 86+)	No
Number of comorbidities	Categorical (6)	Number of comorbidities at the time of consultation, calculated using the Cambridge Comorbidity Index (CCI), split into bands (0, 1, . . . , 4, 5+)	No
Individual comorbidities	Binary (26)	For each of the 26 comorbidities as defined by the CCI, a variable to indicate whether the patient suffers from that comorbidity at the time of the consultation	No
Mental health	Binary	A variable to indicate whether the patient suffers from a mental health condition as defined by the CCI	No
Gender	Binary	Equal to 0 if the patient is female and 1 if the patient is male	Yes
Deprivation Index	Categorical (5)	Index of multiple deprivation assigned to the patient	Yes
Prescriptions	Categorical (10)	The number of repeat prescriptions the patient is prescribed within the 6 months preceding the focal consultation, split into bands (0, 1, 2, 3, 4-5, 6-7, 8-9, 10-12, 13-15, 16+)	No
Tests	Binary	A variable to indicate whether a test was ordered within the 6 months preceding the focal consultation	
Referrals	Binary	A variable to indicate whether there was an outpatient referral within the 6 months preceding the focal consultation	
Patient's past history			
# of past consultations	Categorical (20)	The total number of consultations in the 2 years preceding the patient's focal consultation, split into 20 bands: 3-10 consultations (8 categories of size 1), 11-20 consultations (5 categories of size 2), 21-26 consultations (2 categories of size 3), 27-30 consultations (1 category of size 4), 31-35 consultations (1 category of size 5), 36-55 consultations (2 categories of size 10), 56+ consultations (1 category).	No
Past revisit interval	Continuous	The average revisit interval of the patient calculated over the past 2 years, as described in Section EC.7.4 of the e-companion.	No
Attributes of the regular doctor			
Established doctor	Binary	A variable to indicate if the patient's assigned regular doctor for the focal consultation is an established or unestablished doctor (see Footnote 2)	No
Temporal factors			
Year	Categorical (11)	Year during which the consultation took place (2007-2017)	No
Month of Year	Categorical (12)	Month of the year in which the consultation falls (Jan-Dec)	No
Day of Week	Categorical (7)	Day of the week in which the consultation took place (Mon-Sun)	No
Practice-level factors			
Practice-level demand	Continuous	Total practice demand during the focal week of each consultation, standardized by a weekly average in a 52-week period around the focal week	No
Practice	Categorical (381)	The practice at which the consultation took place	Yes

Notes: If a variable is categorical, the number in (·) in the "Type" column indicates the number of levels.

same practice. We would then measure the time to the next consultation (and the duration of the visit) and report statistical differences. This section describes empirical strategies to identify these statistical differences using observational instead of experimental data.

5.1. Ordinary least squares estimator

We first perform a consultation-level least squares estimation, using the logged revisit interval after consultation i , $\ln(RI_i)$, as the dependent variable and the indicator for the regular doctor, RD_i , as the main explanatory variable, where the index i refers to a consultation. Specifically,

$$\ln(RI_i) = \beta_0 + \beta_1 RD_i + \mathbf{X}_i \boldsymbol{\beta} + \epsilon_i, \quad (1)$$

where \mathbf{X}_i specifies the $1 \times n$ vector of controls corresponding to consultation i (as defined in Table 3) and $\epsilon_i \sim \mathcal{N}(0, \sigma^2)$ is the error term. We do not assume independence of the observations and cluster standard errors at the patient level. The effect of interest is captured by the coefficient β_1 , where Hypothesis 1 posits that $\beta_1 > 0$.

The OLS estimate of β_1 provides an unbiased estimate of the average treatment effect (ATE) when the conditional independence assumption (CIA) holds, i.e., when there is independence between assignment to the treatment (here, seeing the regular doctor or not) and the outcome (here, the revisit interval), conditional on observed variables (here, \mathbf{X}). When one is confronted with selection on unobserved variables, the CIA fails to hold and the ATE is biased. The remainder of Section 5 is dedicated to econometric approaches for addressing violations of the CIA.

5.2. Confounding

There are two major confounding sources which can bias the coefficient β_1 in equation (1): Patient acuity and patient selection. They bias the coefficient in different directions.

Patients who present with high acuity needs may be unable to wait for an appointment with their regular doctor and are therefore more likely to see a transactional provider. At the same time, because of the acute nature of their condition, these patients may also require near-term follow-up appointments, leading to a shorter revisit interval. This biases the estimated β_1 in the OLS model (1) upwards. In the extreme case when all acute consultations are with transactional providers and all non-acute consultations with regular doctors, the variable RD_i picks up non-acuity, not continuity of care, and a positive β_i tells us that non-acute patients have longer re-visit intervals, as expected because they require fewer near-term follow-ups.

The second major confounding source is patient selection during the appointments process and is a reflection of patient preferences. Doctors and their patients are more likely to acknowledge the benefits of a continuity of care relationship when the patient has more severe medical needs. It is therefore reasonable to assume that they will make more of an effort to ensure a consultation takes place with the regular doctor. Table 4 provides some descriptive evidence that this is the case. These sicker patients are likely to visit the practice more frequently and will therefore, on average, have shorter revisit intervals. They may also have waited longer for the appointment with

Table 4 Consultation level summary statistics for transactional providers ($RD_i = 0$) and regular doctors ($RD_i = 1$)

	$RD_i = 0$	$RD_i = 1$
Average revisit interval (days)	71.11	68.35
Average revisit interval (log)	3.28	3.36
Average age	55.88	60.68
Average number of comorbidities	2.06	2.37
Average number of prescriptions	3.93	4.70
Average mental health prevalence	0.26	0.30

their doctor and their health may deteriorate in the meantime. Again, this should lead to shorter revisit intervals. This selection effect may not be fully captured by the available control variables and may therefore work in the opposite direction and attenuate the coefficient β_1 in Equation (1).

5.3. Higher acuity subsamples

As we cannot directly measure patient acuity, nor do we observe when the appointment was booked, adding control variables to account for heterogeneity in acuity is not feasible with our data.

To explore the potential for acuity-related confounding to be biasing the results, we first perform exploratory analyses using subsamples of consultations that are associated with patients who are likely to be higher in their level of acuity: (i) the subsample of consultations where the patient was prescribed an antibiotic, and (ii) the subsample of consultations with patients who visited an emergency department (ED) in the seven-day window prior to the focal consultation. If acuity confounds the effect, then we would expect a substantially smaller and perhaps insignificant coefficient β_1 in (1) when estimated on these subsamples. (Analyses conducted on additional acuity subsamples are documented in EC.8 of the e-companion.)

5.4. Instrumental variable estimators

The acuity subsample analyses provide useful prima facie evidence but they do not account for all confounding, and specifically not for the patient selection effect described in Section 5.2. To address confounding more generally, we use two instrumental variable estimation techniques, control functions and two-stage least squares.

5.4.1. Control functions. The control function (CF) approach is based on estimating the following selection and outcome equations

$$RD_i^* = \alpha_0 + \mathbf{X}_i \boldsymbol{\alpha} + \alpha_{n+1} IV_i + \delta_i, \quad RD_i = \mathbb{1}[RD_i^* > 0], \quad (2)$$

$$\ln(RI_i) = \beta_0^{CF} + \beta_1^{CF} RD_i + \mathbf{X}_i \boldsymbol{\beta}^{CF} + \gamma_1^{CF} \widehat{RD}_i + \epsilon_i^{CF}, \quad (3)$$

where RD_i^* is a latent variable, $\mathbb{1}[\cdot]$ is the indicator function, \mathbf{X}_i is the $1 \times n$ vector of controls, IV_i is an instrumental variable (to be described shortly), \widehat{RD}_i is the generalized probit residual of

observation i , and $\delta_i \sim \mathcal{N}(0, 1)$, $\epsilon_i^{CF} \sim \mathcal{N}(0, \sigma^2)$. We do not assume independence of the observations and cluster standard errors at the patient level.

Following the probit estimation of equation (2) as a first stage, \widehat{RD}_i is calculated as

$$\widehat{RD}_i = \frac{\phi(\mathbf{X}'_i \boldsymbol{\alpha}') [RD_i - \Phi(\mathbf{X}'_i \boldsymbol{\alpha}')] }{\Phi(\mathbf{X}'_i \boldsymbol{\alpha}') [1 - \Phi(\mathbf{X}'_i \boldsymbol{\alpha}')] },$$

where $\mathbf{X}'_i \boldsymbol{\alpha}' = \hat{\alpha}_0 + \mathbf{X}_i \hat{\boldsymbol{\alpha}} + \hat{\alpha}_{n+1} IV_i$, and $\phi(\cdot)$ and $\Phi(\cdot)$ denote the density and cumulative distribution functions of the standard normal distribution, respectively. The estimation is then completed by estimating the second stage equation (3).

The CF approach is similar to the more common two-stage least square (2SLS) method. However, in contrast to 2SLS, the CF approach estimates a probit model (i.e., equation (2)) in the first stage and then uses the generalized probit residual \widehat{RD}_i as an additional control in the outcome equation (i.e., equation (3)). The addition of the generalized probit residual then adjusts the coefficient β_1^{CF} for unobserved confounders that affect both the endogenous regressor RD_i and the dependent variable $\ln(RI_i)$ (Wooldridge 2015a).³ The t -statistic of the coefficient γ^{CF} can be used in a straightforward manner to test for endogeneity in the CF model (Wooldridge 2002).⁴

Consistency of the CF approach requires the probit model to be a correct specification for the likelihood of seeing the regular doctor, i.e., $P(RD_i = 1 | \mathbf{X}_i, IV_i) = \Phi(\mathbf{X}'_i \boldsymbol{\alpha}')$. In contrast, the 2SLS estimator does not impose strict distributional assumptions on $P(RD_i = 1 | \mathbf{X}_i, IV_i)$. However, using the standard 2SLS estimator with a nonlinear model in the first stage renders the estimates inconsistent (Wooldridge (2002) refers to this as the “forbidden regression”). An alternative is a 2SLS approach with a linear probability specification in the first stage, i.e., replacing the probit first stage with an OLS estimate. We use this method as a second IV approach.

5.4.2. The instrumental variable. Both the CF and 2SLS approaches rely on the availability of an instrumental variable (IV) (Wooldridge 2002). The IV must be relevant, i.e., a significant predictor in the first stage equation, and it must be valid, i.e., affect the dependent variable $\ln(RI_i)$ in the second stage equation only through its correlation with the independent variable RD_i . In this study, we use an IV that captures whether the focal patient’s regular doctor is relatively more accessible for her regular patients during the week of the focal consultation, compared to her long-run average accessibility. This measure is calculated using the set of patients who share the same regular doctor as the focal patient at the time of the consultation, but it excludes any visits by the focal patient herself. The formal description of the IV calculation is given in Section EC.7.

³ \widehat{RD}_i is the generalized residual after accounting for observed confounders in the first-stage selection equation, and serves as a proxy for unobserved confounders in the outcome equation. It is used as a control in the outcome equation and if appropriately controlled for, then conditional on observed covariates, RD_i will be exogenous.

⁴ We estimate the CF model using Stata’s `etregress` command with the two-step option and bootstrapped standard errors. We refer to Wooldridge (2002, 2015a) for a technically detailed explanation of the CF approach.

We believe this is a relevant IV in our study context. A doctor who is more (or less) accessible than usual to her other regular patients is also likely to be more (or less) accessible to the focal patient (who is also one of her regular patients). Consistent with this intuition, we find a positive correlation between the IV and the patient’s propensity to see her regular doctor ($\rho = 0.16$, $p < 0.001$). Formal hypothesis testing for under- and weak identification, reported in Section EC.7.1 of the e-companion, provide strong evidence that the instrument is relevant and the endogenous regressor is not weakly identified.

Turning to the validity condition, it is possible that there are unobserved factors that correlate with both the relative accessibility of the regular doctor for other patients and the focal patient’s revisit interval (e.g., a flu outbreak that reduces the expected revisit interval of the focal patient and also makes it harder than normal for patients to access their regular doctors). Importantly, however, such factors should affect the revisit interval not only of the focal patient but also of the doctor’s other patients. Therefore, it is possible to account for these unobservable factors by adding as a control variable the average of $\ln(RI)$ of other patients who (i) share the same regular doctor as the focal patient and (ii) visit a doctor in the same week as the focal patient. When the average revisit interval of other patients changes (e.g., due to a flu outbreak), then this control variable also adjusts the expected revisit interval of the focal patient in the same direction. This control variable accounts for unobserved factors correlated with both the IV and the outcome, thus strengthening the validity of the IV. A similar approach is used in Freeman et al. (2020) and Bobroske et al. (2021). The full description of this control variable is provided in Section EC.7.4 of the e-companion.

Another concern would be if patients with certain conditions were scheduled to arrive on specific weeks of the year, were more likely to see their regular doctors for these conditions, and also return for follow-up appointments at intervals that differ in average length from those of other patients. If this were the case, the instrument might be correlated with the outcome. While the IV control variable should partially address this concern, the context of this study is also such that patients, diseases, and appointment types are, for the most part, randomly distributed across different weeks of the year, meaning that there should be no systematic bias. Additionally, follow-up appointments are usually initiated by patients, not doctors, and are typically managed by nurses or other clinical staff. As a result, it is unlikely that regularly spaced follow-up appointments with a regular doctor will occur in this study. We have confirmed this by investigating the revisit intervals of patients with each of the 26 comorbidities that we use as controls, and find no visual or statistical evidence of any pattern in their revisit schedules. Finally, since the validity of the instrumental variable cannot be formally tested, we add two propensity score-based estimators to further stress-test the robustness of the results (see EC.9 of the e-companion for more details).

Table 5 Sensitivity of OLS coefficient estimates to the inclusion of different control structures

OLS: Dependent variable = Natural logarithm of the revisit interval						
$RD_i = 1$	0.074*** [0.072,0.076]	0.060*** [0.058,0.062]	0.127*** [0.125,0.129]	0.158*** [0.156,0.160]	0.158*** [0.156,0.159]	0.157*** [0.155,0.159]
Practice fixed effects	No	Yes	Yes	Yes	Yes	Yes
Temporal factors	No	Yes	Yes	Yes	Yes	Yes
Patient demographics	No	No	Yes	Yes	Yes	Yes
Patient's past history	No	No	No	Yes	Yes	Yes
Attributes of regular doctor	No	No	No	No	Yes	Yes
Practice-level demand	No	No	No	No	No	Yes
Adjusted R^2	0.000	0.044	0.103	0.159	0.159	0.159
Number of observations	11,344,065	11,344,065	11,344,065	11,344,065	11,344,065	11,344,065

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; 95% confidence intervals in square brackets, with standard errors clustered at the patient level; Variables included within the categories of controls are specified in Table 3.

6. Results

6.1. OLS findings

Table 5 shows the OLS estimates, based on equation (1), for various control structures. Standard errors are clustered at the patient level to account for correlations of error terms when consultations are associated with the same patient. Controls are added step-wise into the model to help us understand how the inclusion of different control categories alters the main effect estimate. The step-wise introduction of factors that are correlated with poorer health, such as consultation frequency, past average revisit interval, comorbidity controls and age and socioeconomic factors, increase the effect of seeing the regular doctor. This is suggestive of heterogeneity, which we will address directly in Section 6.4.

Examining the results, we find evidence that patients' consultations with their regular doctor are robustly associated with a longer revisit interval ($\beta_1 = 0.157$, 95% CI: [0.155, 0.159], p -value < 0.001 in the fully controlled model). Since the dependent variable has a log-scale, the fully controlled OLS model suggests that the revisit interval increases by 17.0% [16.8%, 17.2%], on average, when a patient is seen by their regular doctor.⁵

6.2. Acuity subsamples

Estimating the fully controlled OLS model on the subsample of consultations with antibiotic prescriptions provided a smaller coefficient $\beta_1 = 0.117$ (95% CI: [0.112, 0.122]), suggesting that the continuity of care effect may be less pronounced for acute conditions. This is expected, as after an acute visit, a regular doctor is more likely to see the patient again for a follow-up and may have

⁵ Note that since we estimate a log-linear model with a binary independent variable, the reported effect size (17.0%) differs from the β_1 coefficient in Table 5 (15.7%) and is calculated as $(Y(1) - Y(0))/Y(0) = e^{\beta_1} - 1$. All effect sizes and confidence intervals reported in the body of the paper are similarly calculated (Wooldridge 2015b).

Table 6 Coefficients of RD_i (seeing the regular doctor) on $\ln(RI_i)$ (log revisit interval) for different model specifications

Dependent variable = Natural logarithm of the revisit interval									
Method	Coefficient (β_1)	Std. Error	t -statistic	$P > t $	95% CI		Effect Size($e^{\beta_1} - 1$)	95% CI (Effect size)	
OLS	15.7%	0.1%	177.33	0.00	15.5%	15.9%	17.0%	16.8%	17.2%
CF	16.6%	0.5%	30.57	0.00	15.6%	17.6%	18.1%	16.9%	19.2%
2SLS	16.2%	0.6%	28.01	0.00	15.1%	17.3%	17.6%	16.3%	18.9%

Notes: This table reports the estimated coefficients (β_1) of seeing the regular doctor on the natural logarithm of the revisit interval for the models specified in Section 5. Standard errors are clustered at the patient level. The final three columns report the effect sizes associated to the coefficients. Since we estimate a log-linear model with a binary independent variable, the reported effect sizes differ from the β_1 coefficient and is calculated as $(Y(1) - Y(0))/Y(0) = e^{\beta_1} - 1$.

less leeway to extend the revisit interval length. However, the coefficient still remains significantly positive and the effect remains large. This observation is corroborated by the second subsample analysis, consisting of consultations with patients who had visited an Emergency Department (ED) in the seven-day window prior to the focal consultation. Again, the coefficient is lower than in the full sample ($\beta_1 = 0.120$, 95% CI: [0.104, 0.135]) but the effect remains statistically highly significant and the average extension of the revisit interval remains practically significant as well.

In summary, the subsample analyses suggest that confounding by acuity, if it occurs, is relatively small and does not explain the main effect. The analyses are fully documented in Section EC.8 of the e-companion, alongside analyses corresponding to additional acuity subsamples.

6.3. IV-based model specifications

Table 6 summarizes the results from the IV-based models introduced in Section 5. The first row reports the estimated coefficient associated with seeing the regular doctor on the natural logarithm of the revisit interval using OLS, the second row reports the coefficient using the CF model, and the third row uses the 2SLS model.

We find that the results are consistent across all modeling techniques employed and confirm the beneficial effect of continuity of care posited in Hypothesis 1. The coefficient of the bias correction term in the CF model is statistically insignificant at the 5% significance level ($\hat{\gamma}^{CF} = -0.006$, 95% CI: [-0.012, 0.001]), hence we find that there is little evidence of major confounding. Since the dependent variable has a log-scale, the CF model suggests that the revisit interval increases by 18.1% [16.9%, 19.2%], on average, when a patient is seen by their regular doctor. This is consistent with an unobserved selection of less healthy patients for continuity of care (see Section 5.2).⁶ As the CF approach is indicated for use in contexts with a binary first stage selection equation (see Section 5.4.1), we select this approach as the main model specification going forward.

⁶ We also confirmed these results using a non-IV-based approach to account for potential endogeneity bias that is based on propensity-based matching methods, known as the minimum biased estimator (MBE). The MBE results (reported in EC.9) are similar in terms of both implications and magnitude to those reported here.

6.4. Moderating effects

In this section, we test the moderating effects of comorbidity, age and mental health as posited in Hypothesis 2. To this end, we re-estimate the CF model (equations (2) and (3)) but now also include interaction terms between the three patient-level moderation variables and the main independent variable RD_i . We also include interactions of the three patient-level moderation variables with the instrumental variable to create three new instruments (Wooldridge 2011). As the moderators are naturally correlated (in particular age and comorbidity), we have included all interaction terms in a single model to estimate their moderation effect net of the correlated effects of the other moderators.

Estimates of the average marginal effects based on the moderation results are reported in Table 7 and a graphical representation of the results is given in Figure EC.10 in the e-companion. Table 7 reports the estimated revisit interval (in natural logarithm) for an average individual (within the segment specified by the first column of the row) assuming they either saw a transactional provider ($RD_i = 0$ columns) or their regular doctor ($RD_i = 1$ columns). For example, an average 18-25 year old who saw a transactional doctor is estimated to have a (natural logarithm of the) revisit interval of 3.31, as compared to 3.35 if they had instead seen their regular doctor. The average marginal effect, or difference between these two values, is equal to 6.8% (95% CI: [5.5%, 8.1%]) for an average 18-25 year old patient. (The coefficients corresponding to the moderating effect estimates are reported in Table EC.22 in the e-companion.)

6.4.1. Comorbidity. The comorbidity panel in Table 7 confirms that patients who see their regular doctor ($RD_i = 1$ columns) have, on average, longer revisit intervals than those who see a transactional provider ($RD_i = 0$ columns), and this effect is independent of the number of comorbidities. The effect size columns confirms Hypothesis 2(a) by showing that the extension of the revisit interval that the regular doctor achieves is higher for patients with comorbidities. The difference between zero and one comorbidities is statistically significant. Additional differential effects beyond two comorbidities are insignificant.

6.4.2. Age. The age band panel in Table 7 shows the effect of patient age. As in the case of comorbidity interactions, the table confirms that patients who see their regular doctor ($RD_i = 1$ columns) have longer revisit intervals than those who see a transactional provider ($RD_i = 0$ columns). The marginal effect columns shows the difference and confirms Hypothesis 2(b): seeing a regular doctor is particularly productive for older patients. The extension of the revisit interval length increases from 6.8% (95% CI: [5.5%, 8.1%]) for 18-25 year-old patients to 22.7% (95% CI: [21.4%, 23.9%]) for patients over 86.

Table 7 Average marginal effects associated with seeing the regular doctor when using age, comorbidity and mental health as moderators, calculated using the control function model

	$RD_i = 0$		$RD_i = 1$		Marginal Effect	
	$\ln(RI)$	95% CI	$\ln(RI)$	95% CI	M.E.	95% CI
Comorbidity						
0 comorbidities	3.38	[3.38,3.39]	3.51	[3.51,3.52]	12.8%	[11.7%,13.9%]
1 comorbidity	3.29	[3.28,3.29]	3.44	[3.44,3.45]	15.9%	[14.8%,17.0%]
2 comorbidities	3.23	[3.21,3.23]	3.39	[3.38,3.39]	16.7%	[15.6%,17.8%]
3 comorbidities	3.18	[3.17,3.18]	3.35	[3.34,3.36]	17.2%	[16.1%,18.4%]
4 comorbidities	3.16	[3.15,3.16]	3.33	[3.32,3.33]	17.1%	[15.9%,18.3%]
≥ 5 comorbidities	3.15	[3.13,3.15]	3.30	[3.29,3.31]	16.0%	[14.9%,17.2%]
Age band						
18-25yrs	3.33	[3.32,3.33]	3.39	[3.38,3.40]	6.8%	[5.5%,8.1%]
26-30yrs	3.31	[3.30,3.32]	3.40	[3.39,3.41]	8.8%	[7.4%,10.1%]
31-35yrs	3.30	[3.30,3.31]	3.40	[3.39,3.41]	9.9%	[8.6%,11.2%]
36-40yrs	3.32	[3.31,3.33]	3.42	[3.41,3.43]	10.1%	[8.8%,11.3%]
41-45yrs	3.31	[3.31,3.32]	3.43	[3.43,3.44]	12.0%	[10.8%,13.2%]
46-50yrs	3.31	[3.30,3.31]	3.44	[3.43,3.45]	13.3%	[12.1%,14.5%]
51-55yrs	3.30	[3.29,3.30]	3.44	[3.44,3.45]	14.6%	[13.4%,15.8%]
56-60yrs	3.28	[3.28,3.29]	3.44	[3.44,3.45]	16.0%	[14.8%,17.2%]
61-65yrs	3.27	[3.26,3.27]	3.44	[3.43,3.44]	17.2%	[16.0%,18.4%]
66-70yrs	3.24	[3.23,3.25]	3.42	[3.41,3.43]	17.9%	[16.7%,19.1%]
71-75yrs	3.20	[3.20,3.21]	3.40	[3.39,3.40]	19.4%	[18.2%,20.6%]
76-80yrs	3.15	[3.15,3.16]	3.37	[3.36,3.37]	21.1%	[19.9%,22.3%]
81-85yrs	3.10	[3.09,3.11]	3.32	[3.31,3.33]	22.1%	[20.9%,23.3%]
86+yrs	2.99	[2.98,3.00]	3.21	[3.21,3.22]	22.7%	[21.4%,23.9%]
Mental Health						
No	3.24	[3.24,3.25]	3.39	[3.39,3.40]	15.2%	[14.1%,16.3%]
Yes	3.23	[3.23,3.24]	3.41	[3.40,3.41]	17.5%	[16.4%,18.6%]

Notes: ' $RD_i = 0$ ' (resp., ' $RD_i = 1$ ') columns specify the estimated natural logarithm of the revisit interval ($\ln(RI)$) together with 95% confidence intervals (CIs) for a patient who saw a transactional (resp., regular) provider; 'Marginal Effect' columns give the average marginal effect (M.E.), with 95% CIs, associated with a patient seeing a regular doctor versus a transactional provider, implemented using Stata's margins command.

6.4.3. Relationship between age and comorbidity Figure 2 combines the effect of providing care continuity to patients in different age groups who have either 0, 1 or 2 or more comorbidities. This is estimated by including the interaction between age, comorbidities and RD_i . The largest productivity-enhancing effect comes from providing care continuity to patients 86+ years of age with one comorbidity (27.6%; 95% CI: [24.9%, 30.3%]). The productivity gain from providing care continuity to younger patients with no comorbidities compared to younger patients with two comorbidities is much higher than for older patients; for older patients, in terms of productivity gains from providing care continuity, it does not make a significant difference whether the patient has 0, 1 or 2 or more comorbidities.

6.4.4. Mental health. Mental health patients are more frequent users of primary care, with a shorter revisit interval, on average, than patients without mental health conditions. Our data supports Hypothesis 2(c) that continuity is more effective for such patients. Specifically,

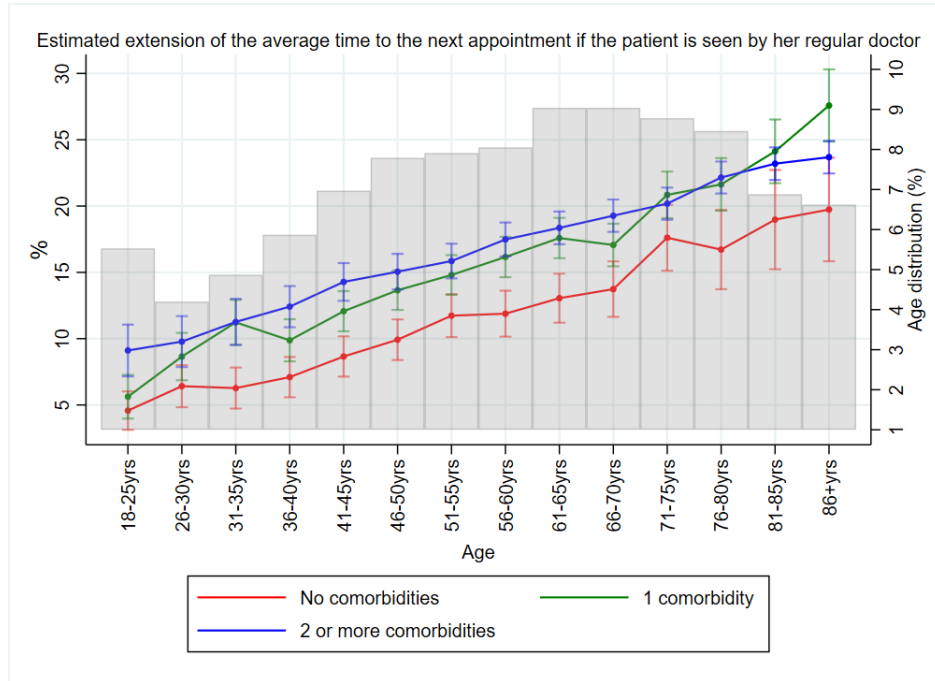


Figure 2 Differential effect of providing care continuity on the revisit interval for patients across different age groups with 0, 1 or 2 or more comorbidities

we find that providing continuity extends the revisit intervals of these patients by 17.5% (95% CI: [16.4%, 18.6%]), compared to a 15.2% (95% CI: [14.1%, 16.3%]) improvement for patients without such conditions. This differential effect, albeit significant, is relatively small compared to the effect of comorbidity and age.

6.5. Duration of consultations

As mentioned in Section 3, in addition to the length of the revisit interval, which is the focus of our analysis, consultation length is a second important productivity measure. On the one hand, consultations between a patient and her regular doctor may take longer as the doctor may take more time to avoid a potential revisit that she will have to serve. On the other hand, the regular doctor knows the patient better and may therefore be able to save the time that a transactional provider would need to spend to elicit the necessary information to obtain the same result.

We explore the duration effect empirically, using the same methods we used for revisit intervals, and report the results in Section EC.13 of the e-companion. Regular doctors spend, on average, less consultation time with their patients than transactional providers. However, the effect size is not large enough to allow a physician to accommodate an additional patient in a typical four-hour clinical session. Nevertheless, these estimations provide strong evidence that the patients' regular doctors do not achieve the extension of the revisit interval at the cost of increasing their consultation time with these patients.

6.6. Quality-related outcomes

The medical literature provides ample evidence of the health benefits of continuity of care in primary care (see Section 2.2). In order to validate these findings and ensure that seeing a regular doctor had health benefits for the patients in our data, we estimated the effect of a consultation with the patient's regular doctor on their propensity to require an ED visit within 1, 3 or 7 days of the focal consultation. Increased ED visit rates would be an indication that regular doctors are, on average, not as thorough in their consultations as transactional providers. We have also estimated whether regular doctors are more reluctant to prescribe medicines, which could also be causing poorer health outcomes. Using the control function model, we find the opposite: ED presentation rates are lower and prescription rates are higher after consultations with regular doctors (see e-companion EC.15 for more details).

We also investigated whether the potential productivity gain resulting from the longer revisit intervals after a visit to the regular doctor has negative long-term health implications for patients. To assess this, we first identify aggregate measures that can serve as a proxy for long-term health outcomes. These include the annual number of ED visits, emergency hospital admissions, and elective hospital admissions by a patient. Using panel data methods at the patient-year level, we then estimated the impact of the extension to revisit intervals due to continuity of care provision in year t and the proportion of patient i 's consultations conducted by their preferred doctor in year t on each of the three outcomes in year $t + 1$. We have used patient fixed effects to account, in aggregate, for all patient-level characteristics, and have included practice-year fixed effects to account for any changes within the patient's practice over time. For each of the three outcomes, we find that all the coefficients related to the extension in revisit intervals are negative and practically insignificant (the magnitude of the effect size is less than 1%). Furthermore, we find that higher levels of continuity of care in the past are associated with improved long-term health outcomes. Combined with the evidence presented in the previous paragraph, our findings indicate that the increased clinical productivity resulting from continuity does not negatively affect either short-term or long-term health outcomes for patients.

6.7. Further analyses and robustness checks.

To further confirm the robustness of the results outlined in the previous sections, we estimate a number of additional model specifications that: (i) use other continuity measures, drawn from the academic literature; (ii) measure the independent and the instrumental variable over different time frames; (iii) account for doctor-level and patient-level heterogeneity through fixed and random effect models, respectively; (iv) account for potential inaccuracies in the identification of the regular doctor when a patient's regular doctor leaves the practice; (v) apply different inclusion criteria; (vi)

use a more granular mapping of mental health conditions; and (vii) add additional time/seasonality controls. The findings, documented in the e-companion, are consistent with those reported here.

Finally, it is conceivable that a regular doctor achieves the extension of the revisit interval after a face-to-face consultation through more frequent use of follow-up phone consultations, which would add additional work for the regular doctor that we had not accounted for. In our data, 5.51% of face-to-face consultations are followed by a phone consultation before the patient’s next face-to-face consultation. Using the main control function model but with a follow-up phone consultation as a binary dependent variable, we find that the probability of a phone consultation following a face-to-face visit is 5.50% (95% CI [5.47%,5.52%]) when a patient sees a transactional provider, compared to 5.52% (95% CI [5.51%,5.55%]) when a patient sees her regular doctor. This effect difference is too small to have provide an alternative explanation for the main effect. Adding this binary phone consultation variable as a control to the main model, to assess its mediating effect, shows that it has no impact (see e-companion EC.18.7 for more details).

7. Counterfactual Analysis: Targeting Continuity of Care

Our results suggest that practices could improve productivity by increasing continuity of care and that they could unlock further productivity gains by reallocating continuity to patients who benefit from it the most. In this section, we conduct two analyses to explore retrospectively what the effect would have been on the consultation demand in our data if practices had followed this recommendation in the past.

Using the insights from Hypothesis 2, we propose a scoring system that can be used by practice managers to prioritize care continuity, targeting those patients for whom it will have the greatest productivity-enhancing effect. The scoring system ranks consultations by the estimated number of days gained if the consultation is offered by the regular doctor rather than a transactional provider. The estimate is obtained as the difference between the predicted return intervals with and without continuity of care. The prediction is based on equation (1), which we augment by including interactions between the regular doctor variable RD_i and every other covariate in the model. Section EC.15 of the e-companion provides more details on this estimation approach.

Our first analysis does not assume that practices changed their proportion of continuity consultations. Instead, we only explore the demand reduction they would have achieved had they *optimized* these consultations by shifting them to the most productivity-enhancing patients, using the above scoring system. Figure 3a shows that such targeting of continuity of care has the potential of unlocking productivity gains, even without changing the overall proportion of continuity consultations. If all practices had retained continuity at the same level but better targeted continuity at the most productivity enhancing patients, then the total consultation demand in the sample

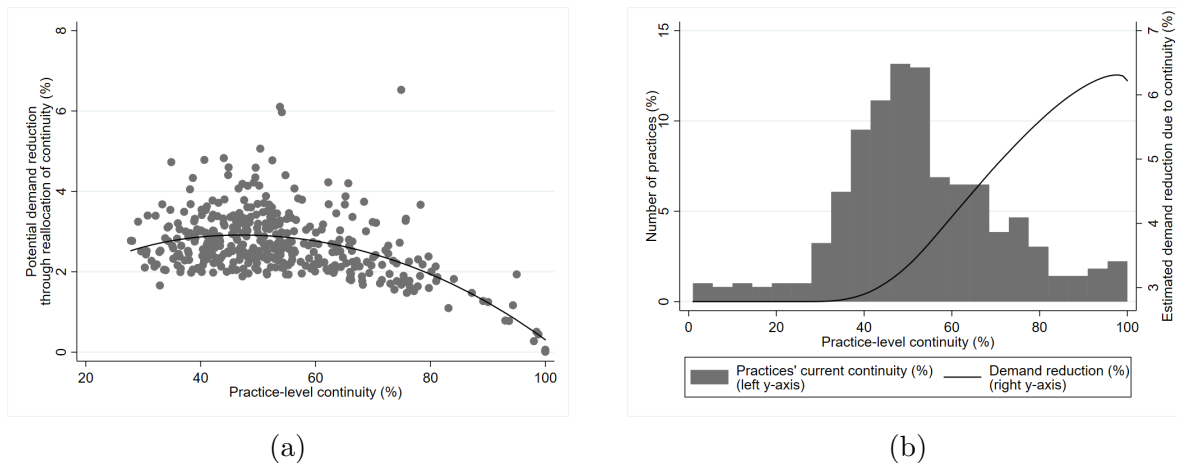


Figure 3 (a) Practice-level gains from reallocating consultations with the regular doctor to the most productivity enhancing patients, while keeping the % of the practice's consultations with regular doctors unchanged. (b) System-level reduction in demand if all practices offer a minimum continuity level (specified on the x-axis) to their most productivity-enhancing patients. The underlying histogram shows the current distribution of the continuity levels across practices. If all practices offered continuity at the across-practice 90th percentile (74.1%), the total system-level demand could have reduced by up to 5.2%

would have reduced by 2.7%. In fact, as Figure 3a shows, some practices would have reduced their demand significantly more.

In our second analysis, we consider what would have happened in our sample if practices not only better targeted care continuity but also increased the level of continuity of care provided.⁷ To explore this, we first select a target proportion $0\% \leq x \leq 100\%$ of continuity consultations. We then identify all practices that offered less than $x\%$ continuity, and consider the impact on productivity if these practices had offered continuity to $x\%$ of their patients instead. (For those practices offering more than $x\%$ continuity, we leave their proportion of continuity consultations unchanged.) We then re-allocate, as above, the available proportion of continuity consultations in each practice to the most productivity-enhancing patients. This allows us to estimate the counterfactual demand reduction as continuity of care is increased (i.e., by increasing x) and optimally allocated.

The results are summarized in Figure 3b. If continuity of care levels were increased for those practices with levels below the across-practice median ($x = 51.3\%$ continuity), 75th percentile ($x = 62.3\%$ continuity) and 90th percentile ($x = 74.1\%$ continuity), then total system demand could have reduced by up to 3.4%, 4.3% and 5.2%, respectively. These estimates show that there are

⁷ In this counterfactual analysis, we extrapolate from the individual physician level (the locus of our productivity study) to the practice level. The difference is subtle but important. In particular, we assume that continuity levels can be adjusted within a practice without any negative spillovers onto other drivers of practice productivity. In reality, there may be trade-offs at the practice-level, and thus the findings reported here should be seen as an upper bound on the potential gains that can be achieved from adjusting continuity levels within a practice.

significant productivity gains to be realized by increasing the proportion of patients seeing their regular doctors and by better targeting continuity of care at patients who benefit from it most.

8. Managerial and Policy Implications

It is well known that continuity of care in primary care is beneficial for patient health and reduces downstream system utilization. But is it also operationally beneficial for the primary care practice itself? Or do patient health and system benefits accrue at the cost of more up-stream primary care, as primary care physicians spend more time with their continuity of care patients to keep them healthy and out of hospital? If the latter is the case, primary care practices will need to be incentivized to provide continuity of care. Our findings suggest that continuity of care can in fact save primary care resources by making primary care physicians more productive.

We study the physician productivity effect of care continuity by focusing on short-term consultation level duration effects, not on long-term population health effects, of which there is ample evidence in the literature. In other words, the idealized randomized experiment for this study is a coin-flip at the individual consultation level, with a patient assigned to their regular doctor vs another doctor in the practice for that consultation, not a patient level analysis, with a patient provided with a high or low dose of continuity of care over a prolonged period of time.

The study data on over 11M consultations in 381 English practices over a period of 11 years provides evidence that consultations between a patient and a primary care physicians are more productive if the physician is familiar with the patient. Specifically, we find that, after controlling for confounding and patient selection, when patients have a consultation with the doctor they have seen most frequently over the past two years, they have a significantly extended time to their next consultation – by an estimated 18.1% (95% CI: [16.9%, 19.2%]) – while their consultation duration is, on average, marginally but statistically significantly shorter. We also find that targeting the right patients for continuity of care is important, as the productivity benefit is more pronounced for patients with comorbidities, for older patients, and for patients with mental health conditions.

These findings are of direct relevance to appointments scheduling processes in primary care practices and we have demonstrated how our estimation models can be applied as scoring tools to identify patients for whom continuity of care provides high productivity benefits. In addition, our findings have important strategic implications for practice managers, regulators and payers.

First, as indicated in the introduction, practice managers face a chronic shortage of primary care physicians. The existing workforce has to cope with growing demand and is increasingly stressed, leading to early retirements and part-time working, which further exacerbates the problem. There are two fundamental operational mindsets to address this challenge. The first mindset is to industrialize primary care, to scale it up from a fragmented cottage industry of small shops and

organize it so that the number of consultations per physician day is maximized. Fast and convenient access to a primary care consultation, no matter with whom, becomes the operational goal and a physician hour becomes the main operational currency. The second mindset is to recognize the value of continuity of care and double down on relationships between doctors and physicians, to organize the practice so that access to “your primary care physician” is the main goal and the maintenance of the patient-physician relationship becomes the operational currency.

Our findings suggest that practice managers who emphasize daily throughput and fast access should pause and reflect whether this strategy harms continuity and is counter-productive, as it harms the physicians’ productivity and generates avoidable demand for future consultations. In fact, doubling down on continuity can be an effective strategy to improve productivity, with positive financial implications, in particular if a practice operates in a capitation-based funding environment. This strategy is also likely to be more sustainable as populations age and more patients become more complex. In addition, where continuity of care is difficult to achieve across the board, practice managers can substantially improve productivity by targeting specific patient groups for care continuity, as demonstrated in our counterfactual analysis.

Second, our findings are of importance for regulators and third-party payers in relation to the demand for faster and more convenient primary care access, which has led to the emergence of at-scale online providers and has accelerated during the COVID-19 pandemic. Online primary care providers offer a transactional platform for online appointments, matching on-the-spot demand and supply. Much of the advantage comes from technology and scale that allows for effective pooling of clinical time. The service is a single consultation between a doctor and a patient, not a long-term relationship. Our findings have several implications for this business model, for regulators and payers who wish to create a sustainable primary care environment, and for primary care practices that need to respond strategically to the emergence of this new online service model.

Our findings are consistent with the view that the online business model of primary care is particularly profitable in a fee-for-service environment, where patients or third parties pay for any additional consultations generated by transactional services. By contrast, the model is less compelling in a capitation-based funding environment, where providers are paid a fixed fee per patient per month or year and the risk of excess demand is born by the practice. Our analysis of moderators – chronic disease, age, and mental health – shows that in a capitation context, online primary care providers will have a significant incentive to design their services to make them less attractive for more demanding or more vulnerable patients. This will minimize the negative productivity effect of the transactional primary care model at the core of their business. Over time, this dynamic may manifest itself in a segmentation of primary care services, with low-risk

patients being served quickly and conveniently by transaction-focused online providers, while high-risk patients are served by local practices that offer the relational continuity of care required for an effective and efficient service for these patients. Most patients will reach times in their lives when they wish to move from one segment to the other.

While such a service segmentation may well be beneficial in steady state, regulators must anticipate the destabilizing effect that this transformation will have on traditional practices during a transition period. Specifically, regulators and payers will need to respond with adequate risk-adjusted funding models. The scoring method used in our counterfactual analysis offers a suggestion for how such models could be developed.

The differentiation between relational and transactional primary care services also poses a strategic challenge for local practice managers: Should they provide services for both segments in-house, managing the tensions between the transactional and relational service model, or should they out-source transactional primary care and “double down” on relational services for patients who benefit most from continuity of care and from the close integration of their primary care practice in a local provider network that at-scale online providers will find difficult to replicate? More research is required to advise practices on this decision.

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Hospital Episode Statistics (HES) Data: Copyright ©2018, re-used with the permission of The Health & Social Care Information Centre. All rights reserved.

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