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Online versus in-person services: Effects on patients and providers

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Abstract
Online delivery of one-to-one services offers potential cost savings and increased convenience, yet relatively little is known about its impacts on providers and consumers. This paper studies the online delivery of healthcare, focusing on primary care doctor consultations. We use novel data from Sweden and an effectively random assignment of patients to nurses, who differ in their propensity to direct patients to online versus in-person consultations. Our findings reveal that online consultations are delivered sooner, are shorter, and yield similar in-consultation outcomes, including rates of diagnosis, prescriptions, and specialist referrals, as well as patient satisfaction. However, in the short term, online consultations lead to more emergency department (ED) visits and additional in-person primary care visits, though no significant medium-term health effects are observed. We discuss the extent to which follow-ups reduce online's cost savings, as well as online's advantages for different patients and how to improve hybrid organizations' cost effectiveness.

Keywords: telehealth, remote work, online services
JEL: J44; I11; O33

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1 Introduction

In today's hybrid world, many decisions affect which one-to-one (1:1) services are delivered online and which ones in person, and to whom.[1] These decisions are consequential for providers as well as for workers and users. Although the shift to online provision can potentially lower costs and increase convenience, the nature of service meetings may differ significantly when conducted through a screen. As a result, switching services to an online format can affect costs, quality, user experience, and downstream outcomes. Despite the increased prevalence of online provision in recent years, there is limited evidence from direct head-to-head comparisons of in-person and online 1:1 services. To better inform decision-makers, we need a deeper understanding of the trade-offs associated with each mode of service delivery.

Choosing the appropriate delivery mode is particularly important in healthcare. For providers, including both private and public healthcare organizations and insurers, the shift to online services presents opportunities for productivity gains, which are urgently needed due to rising costs in aging societies. For patients, online healthcare services provide convenience, around-the-clock access, time savings, reduced risk of contagion, and the potential to level the playing field between urban and rural areas as well as rich and poor ones (Dahlstrand 2023). Key to healthcare delivery are patient consultations with primary care physicians (PCPs), also known as general practitioners (GPs).

In this paper, we examine the impacts of switching doctor consultations from in person to online on various patient outcomes and provider costs. To do so, we assemble new data on individual consultations from Sweden, where national health insurance covers both public and private providers. The primary contributor of our data is Europe's largest digital healthcare firm, which, since 2019, has provided registered patients with comprehensive primary care, including both in-person and online doctor consultations. The data we analyze encompass both consultation types and are matched with anonymized individual panel data on patient demographics, socioeconomic characteristics, and numerous health outcomes from the rest of the healthcare system.

One challenge in comparing online and in-person consultations is that we rarely observe similar patients in both modes. However, we focus on patients registered with a primary care provider that offer both types of consultations. During times when all doctors are busy, these patients initially meet online with nurses, who then determine whether the

[1] By 1:1 services, we mean meetings between one service provider and one user, such as banking or financial advising, tutoring, mental health therapy, legal advising, and healthcare consultations.

patients should consult (as soon as possible) with a doctor, and whether this consultation should be in person or online. We begin our analysis by estimating ordinary least square (OLS) regressions to compare the outcomes of patients directed to in-person versus online consultations, while controlling for a rich set of potential confounders.

A second challenge arises from the potential sorting of patients across delivery modes on unobserved factors. To address this issue, we use the share of patients directed online by each nurse—as opposed to those directed to in-person doctor consultations—as an instrumental variable (IV) for online consultations. We establish sufficient conditions for the validity of this instrument by building on the work of Frandsen et al. (2023), who propose weaker assumptions for expert propensity instruments than standard IV assumptions. We construct a semi-ordered IV model in which nurses making online assessments decide whether patients should consult a doctor (an ordered decision), and if so, whether this consultation should be online (an unordered decision, since online consultations can be arranged sooner but lack the capability for physical examination). We assume that patients—who vary in their illness severity, interest in consulting a doctor, preference for online services, and other characteristics—are randomly matched to nurses. Nurses aim to ensure that only sufficiently ill patients are directed to doctor consultations. However, nurses' observations of patient illness are subject to noise, which is independent of their propensity to direct to online (versus in-person) consultations. The model establishes sufficient conditions for identification: independence, first stage, average exclusion, and average monotonicity. We provide evidence that all these assumptions are plausibly met in our setting.

Compared to the OLS estimates, the IV estimates generally show lower cost savings from online consultations, suggesting that, on average, sicker patients are directed to in-person consultations and that the IV method addresses this sorting problem. The IV estimates indicate that compared to in-person doctor consultations, online ones not only occur sooner and are shorter overall, but also involve significantly less patient-facing time and more administrative time for the doctor (e.g., to write prescriptions and notes after seeing the patient). Online consultations yield similar within-consultation outcomes to in-person ones, including rates of informative diagnosis, prescriptions (and prescription collection by patients who receive prescriptions), and specialist referrals, as well as patient satisfaction.

We next examine the effect of online consultations on avoidable hospitalizations, overall hospitalizations, emergency department (ED, also known as accident and emergency - A&E) visits, and new visits to the primary care provider within 30 days after the nurse meeting or the doctor consultation.[2] We find no significant effect on avoidable hospitalizations, an imprecisely estimated increase on overall hospitalizations, and significant increases in ED visits and doctor-booked in-person consultations. However, for medium-term outcomes (more than 30 days after the doctor consultation), we find no significant effects on any of these four outcomes.

Taken together, our estimates suggest that online consultations offer some cost savings to providers without significant medium-term adverse health effects on patients. However, the increased short-term follow-ups reduce these cost savings for providers from around 75% to just 20% and effectively eliminate cost savings for patients. While these findings indicate that online consultations are not a cost panacea, they still provide patients valuable advantages, such as the ability to consult doctors sooner, reduced contagion risk, and greater scheduling flexibility, including availability outside regular work hours. We also note that our estimates show relatively high follow-up rates for two reasons. First, we study patients directed to consultations by nurses, and those patients are likely sicker and more prone to follow-ups than patients not directed to consultations. Second, our sample mostly consists of patients from big cities (where in-person clinics were first opened), for whom in-person follow-ups are less time-consuming than patients in remote areas. Thus, directing the average Swedish PCP patient to an online consultation (versus an in-person one) is likely to yield larger social savings than those in our sample.

We also find that patients generally view online consultations as replacements for in-person ones. However, older patients and immigrants are more skeptical of online consultations. Given this finding and our results on sorting into online consultations, we explore the possibility that online consultations may be better suited for less vulnerable patients. Consistent with this hypothesis, we find suggestive evidence that patients with histories of hospitalizations or ED visits are considerably more likely to follow up after online consultations than other patients. We also find that directing vulnerable patients to in-person consultations and less vulnerable ones to online consultations may save costs for both providers and patients.

The main contribution of this paper is our examination of the trade-offs between online and in-person 1:1 service provision. This adds to the literature on hybrid work, which has transformed labor markets in recent years (Barrero et al. 2023; Bloom et al. 2015; Aksoy et al. 2022; Bloom et al. 2022; Goodman et al. 2019; Ertem et al. 2021).[3] Current research

[2] Avoidable hospitalizations are those that could have been avoided by timely and adequate primary care.

[3] Barrero et al. (2023) show that the shift to working from home has continued after the pandemic: as of mid-2023, 28% of paid workdays in the US were conducted from home (4 times the 2019 rate and 10

on remote or hybrid work primarily focuses on settings where the mode (online versus in person) changes only for workers (Bloom et al. 2015; Emanuel and Harrington 2023; Emanuel et al. 2023), without obvious implications for customers or clients. In contrast, our study examines implications for both providers and consumers when both are directly affected by moving online.

Recent work has studied service provision, especially teaching, where both providers (teachers) and consumers (students) switched modes during the COVID-19 pandemic (Jack et al. 2023). However, the pandemic's impacts likely extend beyond merely shifting studies online.[4] In addition to this, settings where collaboration or peer effects are central (Emanuel et al. 2023; Agostinelli et al. 2022) differ from those involving the 1:1 service provision that we study.[5]

A nascent literature in economics studies changes in access to, or the (relative) pricing of, online healthcare (Zeltzer et al. 2023; Ellegård et al. 2021; Rabideau and Eisenberg 2022). Our paper sets itself apart by examining a setting where assignment to online versus in-person care occurs *after* patients have already requested care. This allows us to shed light on the respective effects of online and in-person delivery, free from concerns about the sorting of different patients (or the same patients under different symptoms) into care when based on their expectations of online or in-person consultations. Our approach also addresses provider-driven sorting of patients into modes. The differences between our OLS and IV results indicate that, on average, nurses sort simpler cases to online consultations, thereby underscoring the usefulness of our identification strategy. However, we do not examine how the increased availability of online options affects the usage of (and sorting into) consultations. Instead, we focus on the downstream outcomes for those who have already requested consultations.

Methodologically, we build on the literature using expert propensities as instruments (Kling 2006; Doyle Jr 2007; Anwar et al. 2012; Dahl et al. 2014; Aizer and Doyle Jr 2015; Dobbie et al. 2018; Bhuller et al. 2020; Bakx et al. 2020; Chan et al. 2022; Frandsen et al. 2023). We use this approach to study a different research question, namely assessing the

times the rate in the mid-1990s). They also show that in the in the first half of 2023, workers aged 20–64 in the healthcare and social assistance sectors worked from home 1.58 days per week, based on full-time work schedules.

[4]We study hybrid (online and in-person) healthcare that began before the pandemic and continues after it in the same mixed form. Our sample includes periods before and during the pandemic (including the lull of summer 2020) in a country where in-person visits continued throughout the pandemic. We also control directly for time effects.

[5]Carlana and La Ferrara (2021) study online 1:1 service provision (remedial tutoring) and find that it generates positive effects; however, they do not have an in-person comparison group.

impact of online consultations, and use the weaker identification assumptions of Frandsen et al. (2023). Our work is also related to the literature studying IVs with multi-valued treatments, which are typically either ordered (Angrist and Imbens 1995; Heckman and Urzua 2010) or unordered (Lee and Salanié 2018; Mountjoy 2022), where we differ by focusing on a semi-ordered IV model.

Last, our paper relates to the literature on cities as loci of face-to-face interactions even as communication technology improves (e.g., Gaspar and Glaeser (1998) and Michaels et al. (2019)). In our setting, the central location of most patients makes it easy for them to follow up in person after online consultations.

The rest of the paper is organized as follows. Section 2 presents the background, including the institutional setting. Section 3 discusses the data and dataset construction, and Section 4 presents our econometric model. Section 5 reports tests of instrument validity and our empirical findings on patient outcomes, doctor productivity, costs, generalizability, and heterogeneity. Section 6 concludes.

2 Institutional Background

Assessing the impact of online consultations relative to in-person ones involves overcoming two main challenges. First, in many settings primary care consultations are either only in person, as was common in most countries before the COVID-19 pandemic, or only online, as observed in some countries during the pandemic.[6] To compare both types of consultations, we need to observe patients across both delivery modes. Second, in settings with both online and in-person consultations, patient sorting presents a concern. As the relative price or convenience of online consultations changes, for example, patients may choose different modes for different symptoms, and healthcare providers may also sort patients across delivery modes based on their own criteria.

Our setting is helpful in addressing both issues. To observe patients across both consultation modes, we focus on a large Swedish firm (which we refer to as "the firm" or "the provider") that uses an increasingly common model of hybrid primary care: in-person and online doctor consultations. This firm differs from many others by having started hybrid primary care in 2019, before the onset of the COVID-19 pandemic. Although mostly focusing on online primary care, its hybrid model is available to patients who select this firm

[6] Unlike most high-income countries, Sweden maintained a combination of online and in-person consultations (and many other services) even during the worst phases of the COVID-19 pandemic, never implementing a real lockdown.

as their primary care provider under the national health insurance.[7] We use novel data on online and in-person doctor consultations for patients who were registered at four clinics: one that opened in Lund in southern Sweden in September 2019, and three that opened in the Stockholm area since September 2020. The data we use span 2019–2020, covering the period before the pandemic and the first two pandemic waves, as well as the summer lull between them. Sweden was unique among wealthy countries during COVID-19, allowing both types of consultations to continue throughout the study period.

Our setting allows us to observe both consultation types and crucially also address sorting between them. To see how, consider Figure 1, which illustrates the flow of patients who are registered in hybrid clinics. Each registered patient requests a consultation via a mobile phone application, at which point an algorithm determines whether a doctor consultation is immediately available, accounting for the symptoms the patient entered and the current waiting time for doctors. In most circumstances, the algorithm assigns the patient directly to an online doctor consultation (we call this a "drop-in" consultation). However, during busy periods, some patients are instead directed to the next available online nurse, who (like the online doctors) may be based anywhere in Sweden.

This online nurse then makes two quick sequential decisions. First, they decide whether to resolve the case without a doctor or if a doctor consultation is needed.[8] Second, if the nurse decides that a doctor consultation is needed, they then decide whether to book an in-person or an online consultation. We discuss in Section 4 the factors that go into the nurse's decisions. In that section, we also explain how our setting allows us to overcome sorting by using variation across nurses in the propensity to direct patients across the two consultation delivery modes.

Before we proceed, however, it is useful to note a few more aspects of our setting. First, doctors are paid a rate for each shift they work (effectively an hourly rate), and they work from home when online and from clinics when in person. Second, the service is covered by universal health insurance, with a small co-pay.[9] Third, the mobile application lets the

[7] Primary care provision is publicly funded in Sweden and comprises both public (60%) and private (40%) providers. Patients can choose a clinic, but many default to one that is closest to their home. Once registered at a clinic, their healthcare services are funded through capitation by the national health insurance, with some regions using fee for service.

[8] We define a "case" as an online meeting between a patient and a nurse and its resulting treatment (either an online or in-person doctor consultation or no consultation). The nurse cannot prescribe medicine or refer the patient to an external specialist. If the nurse decides (based on the patient's symptoms) that a consultation is needed, they set it up, a step that we refer to as "directing the patient to a doctor consultation". If a consultation is not necessary, the nurse provides self-care advice and resolves the case.

[9] During the sample period in the two regions we study, patients paid a fee of between SEK 200 (approximately USD 22) and SEK 250 for an in-person doctor consultation, and between SEK 100 and SEK 200 for

doctor and the patient see each other via video, in contrast to a phone conversation, which is common in some countries. Fourth, we study patients with a broad range of demographics and conditions who chose a primary care provider with an online option; we discuss their representativeness of the broader population in Section 5.6.1. Finally, the treatment we study—moving consultations online—is bundled with the identities of individual doctors who work online (versus in person). It is important to note that this bundling would have occurred even if we had randomly assigned patients to online and in-person consultations, provided we did not alter the assignment of doctors' work modes. To partly address this issue of bundling, however, we provide some evidence on doctor sorting into online consultations in Section 5.3. We also note that, as discussed in Section 3, almost all the doctors we study worked at least some of the time online.

3 Data

This section briefly outlines our data sources and the construction of our dataset, leaving the details to the Data Appendix in Appendix Section C.

3.1 Data Sources

Our starting point is a dataset covering all primary care visits to a large healthcare provider in Sweden during the 24 months spanning 2019–2020. These include doctor consultations and nurse meetings, both in person and online. Most of this large sample consists of consultations with patients across Sweden who only used this provider for online consultations and who were registered with other providers for their in-person primary care consultations. But our analysis mostly focuses on patients who registered with the provider.

In what follows, we describe how we restrict the data to patients who have the option of both in-person and online care within the same provider. We begin by matching data from Statistics Sweden and the Swedish National Board of Health and Welfare (Socialstyrelsen) spanning 2013–2020, which encompass three main components. First, the matched data cover healthcare provision outside the primary care provider, including inpatient and outpatient care as well as prescriptions and their collection. Second, they contain demographic information, such as age, gender, education level, and immigration status. Finally, the data

an online consultation, up to a total annual ceiling of around 1,150 SEK (approximately 125 USD in 2020). The co-pay ceiling covers all healthcare visits, meaning a combination of a few PCP consultations and ED visits can take a patient to the ceiling, after which they pay nothing for the rest of a rolling calendar year.

include socioeconomic information, such as earnings and education attainment, as further discussed in Appendix Section C.1.

3.2 Dataset Construction

To construct our dataset, we start with all cases where registered patients meet with online nurses (around 240,000 cases) and then impose sample restrictions, as described in Appendix Table A1. The first three restrictions ensure a strictly positive probability that each case is "at risk" of an in-person consultation. This is achieved by removing cases where patients are not yet registered with an open in-person clinic as well as patients with specific conditions (chlamydia, breastfeeding issues, COVID-19) or demographics (infants). We do this to ensure that the patient flows in our sample follow the pathways illustrated in Figure 1.[10] Further restrictions exclude nurses and centers involved in few cases to ensure statistical power. We refer to the 8,907 resulting cases handled by 62 nurses as the "nurse meeting sample" in Figure 1 (or "nurse sample" in brief).

Finally, in the last row in Appendix Table A1, we restrict the sample to cases that result in either an in-person or an online doctor consultation. This restriction leaves us with 4,664 cases, referred to as the "doctor consultation sample" in Figure 1 (or "doctor sample" in brief). Within this doctor sample, roughly 57% of consultations are in person, and 43% are online. These consultations are conducted by 400 doctors, of which 338 are observed as only having online consultations *within the doctor sample*. Of the remaining 62 doctors, 38 are observed in our data both in person and online, and 24 are observed only in person.[11]

The definitions of our main variables are reported in Appendix Table A2, and variable construction is further described in Appendix Section C.6. Most of the outcomes we measure are indicators, reflecting our focus on the extensive margin of healthcare use. We choose this approach for two reasons. First, once a patient receives downstream treatment, their subsequent outcomes depend in part on that treatment and not only on the initial healthcare interaction. Second, this choice gives more weight to the general primary care patient population rather than focusing disproportionately on individuals who are particularly intensive users of the healthcare system. In Appendix Section C.3, we further explain other

[10] For chlamydia cases, patients were sent a home test, and in breastfeeding-related cases, patients were directed to a breastfeeding consultant rather than a doctor. COVID-19 cases were managed through pathways that changed over time, adapting to shifts in testing availability and changing guidelines during the pandemic. Infants (children strictly younger than two years old) are also treated differently.

[11] However, since the firm's core business is online provision, almost all the doctors who work for it have some online experience. Therefore, of the 24 doctors, at least 17 had worked online in 2019–2020. These doctors consulted patients online who were either not directed by a nurse or had not registered with this firm as their in-person primary care provider.

samples used throughout the paper. When examining post-consultation outcomes, we usually look within 30 days and (separately) after more than 30 days; however, we also report shorter-term outcomes, by week, for some key outcomes.

Summary statistics for the doctor sample are reported in Table 1, which shows that the sample consists of cases with a broad range of patient demographics and nurse-set ICD-10 codes. We defer the discussion of the representativeness of this sample and the generalizability of our estimates to Section 5.5.

4 Model

This section outlines our econometric model of the assignment of patients to online and in-person doctor consultations. The model illustrates the identification problem—potential patient sorting into consultations and across modes based partly on unobservables, which biases OLS estimates of the effects of online delivery. The model also provides justification for our use of nurses' propensities to direct patients to online consultations (in all but the current meeting) as an instrumental variable, following the literature on expert propensities and especially the recent work by Frandsen et al. (2023), on which we build.[12] We differ from existing work by presenting a semi-ordered IV model, which divides the decision-making process into two parts. The first is an ordered decision: a doctor consultation is more intensive than no consultation. The second is an unordered one: online consultations may be arranged sooner and spare ill patients from having to travel, while in-person consultations allow physical examination.

4.1 Model Setup

As outlined in Section 2 and Figure 1, we focus on registered patients who request primary care consultations using the firm's mobile application and who are "at risk" of both types of consultation (in person and online). These patients' cases begin with an online meeting with a nurse. We assume—and later verify—that their assignment to the next available nurse is effectively (conditionally) random. We focus on patients, indexed by i,[13] who are assigned to nurses, indexed by j. We define j_i as the nurse assigned to patient i; I_j as the set of patients

[12] Frandsen et al. (2023) introduce the weaker assumptions of average monotonicity and average exclusion to replace the standard assumptions of monotonicity and exclusion in settings with expert propensities. Under these weaker assumptions (with independence and a first stage), they derive a causal LATE interpretation for IV, which is similar to the familiar one.

[13] We use the single index i to denote a patient when they met with an online nurse to simplify notation and avoid having to carry a time index.

treated by nurse j, which consists of N_j patients; and I as the set of all patients. Each nurse briefly assesses every patient assigned to them and makes two sequential decisions: first, whether to direct the patient to a doctor consultation, and second, if they do direct the patient to a consultation, whether the consultation should be in person or online.

We assume that each patient has a level of illness, θ_i, which causes them to request a doctor consultation;[14] a vector of observable pre-determined characteristics, $\boldsymbol{\psi}_i$; and interest in consulting with a doctor, ϕ_i. We assume that $\phi_i = \theta_i + g(\boldsymbol{\psi}_i) + \zeta_i$, where ζ_i is mean 0 independent and identically distributed (i.i.d.) noise. We also assume that each patient has a preference $\tau_i > 0$ for an in-person (compared to an online) doctor consultation such that $\tau_i = 1$ denotes indifference between in-person and online. The relationship between τ_i and the other patient parameters, including illness, is flexible, which leads to sorting into online consultations that cannot be controlled for using observable characteristics.[15]

We model the patient's utility as

$$U_i = \begin{cases} \phi_i & D^0_{ij} = 1, D_{ij} = 1 \\ \phi_i \tau_i & D^0_{ij} = 1, D_{ij} = 0 \\ 0 & D^0_{ij} = 0, \end{cases} \tag{1}$$

where D^0_{ij} is an indicator for patient i being directed to any consultation (after meeting nurse j), and D_{ij} is an indicator for patient i being directed to an online consultation, as opposed to an in-person one (after meeting nurse j). $\mathbf{Y}_i(d, j)$ denotes the vector of potential outcomes of patient i meeting nurse j, where d is an indicator for an online (versus in-person) consultation. The vector of outcomes for patient i who met nurse j can be written as $\mathbf{Y}_{ij} = \mathbf{Y}_i(1, j) D_{ij} + \mathbf{Y}_i(0, j)(1 - D_{ij})$.

Turning to nurses, we assume that they decide whether to direct a patient to any consultation (versus no consultation) based on their assessment of patient i's illness, θ_{ij}, where $\theta_{ij} = \theta_i + \eta_{ij}$, and η_{ij} is mean zero i.i.d. noise.

Nurses differ in their assessment of the value of online doctor consultations relative to in-person ones, which they consider when deciding the delivery mode, along with the patient's preference for in-person consultations. Specifically, we define ρ_j as the tendency of nurse j to direct patients online, where $\rho_j > 0$. ρ_j varies across nurses, so that $\rho_j \neq \rho_{j'}$ for some j, j'. We assume that the utility of nurse j, who meets patient i, is

[14] Illness reflects the patient's "objective" need to see a doctor when they use the firm's app, which does not necessarily correlate strongly with underlying medical conditions, such as comorbidity.

[15] Were it not for the sorting of patients by nurses, which discussed below, the mix and sickness of patients receiving consultations would also have depended on whether the patients anticipated online of in-person consultations.

$$\widetilde{U}_j = \begin{cases} 1_{\theta_{ij}>0} & D^0_{ij}=1, D_{ij}=1 \\ \frac{\tau_i}{\rho_j} 1_{\theta_{ij}>0} & D^0_{ij}=1, D_{ij}=0 \\ 1_{\theta_{ij}\leq 0} & D^0_{ij}=0. \end{cases} \tag{2}$$

Since the nurses decide the treatment status of patients, patient i will have an online consultation ($D^0_{ij} = 1, D_{ij} = 1$) when $\theta_{ij} > 0$ and $\tau_i \leq \rho_j$; an in-person consultation ($D^0_{ij} = 1, D_{ij} = 0$) when $\theta_{ij} > 0$ and $\tau_i > \rho_j$; and no consultation ($D^0_{ij} = 0$) when $\theta_{ij} \leq 0$.[16]

4.2 Identification

Panel A of Appendix Figure A1 illustrates the treatment of patient i when nurses perceive illness precisely ($Var(\eta_{ij}) = 0$). In this case, only patients with $\theta_i > 0$ receive a doctor consultation. Among these patients, there may be three types: those with very strong preferences for in-person consultations ($\tau_i > \max(\rho_j)$) always consult in person (they are "never takers"), and those with very strong preferences for online consultations ($\tau_i \leq \min(\rho_j)$) always consult online (they are "always takers"). Patients whose preferences for online versus in-person consultations are intermediate (($\min(\rho_j) < \tau_i \leq \max(\rho_j)$) are compliers—their mode of consultation is determined by the nurse to whom they are (conditionally) randomly assigned. Panel B of Appendix Figure A1 shows that when nurses perceive patient illness imprecisely ($Var(\eta_{ij}) \neq 0$), the situation is similar except that some patients who should have consulted a doctor based on θ_i do not, while others who should not have consulted end up having a consultation.

We define the propensity of nurse j to direct patients online, conditional on directing to any doctor, in the hypothetical scenario where the nurse had encountered the entire population of doctor sample patients as $\pi^{pop}_j \equiv \frac{\sum_{i' \in I} D_{i'j}}{\sum_{i' \in I} D^0_{i'j}}$. We similarly define this propensity among the doctor sample patients whom nurse j actually met as $\pi_j \equiv \frac{\sum_{i' \in I_j} D_{i'j}}{\sum_{i' \in I_j} D^0_{i'j}}$.[17] Finally, we define the instrument as nurse j_i's propensity to direct doctor sample patients online, leaving out patient i's meeting: $\pi_i \equiv \frac{\sum_{i' \in I_j; i' \neq i} D_{i'j}}{\sum_{i' \in I_j; i' \neq i} D^0_{i'j}}$.[18]

To use π_i as an instrument for D_{ij}, we specify conditions under which the (weaker) identification assumptions for an IV, as outlined by Frandsen et al. (2023), are satisfied. First, to satisfy the first stage, we require (sufficient) variation across nurses in ρ_j. To

[16] Without loss of generality, we assume that nurses break ties between online and in-person consultations by assigning patients to online consultations.

[17] "Population" here refers to the actual doctor sample, which is held fixed in this counterfactual.

[18] The instrument is implicitly also defined for patients who are not directed to a doctor, for whom it equals π_{j_i}.

satisfy independence in the doctor sample, we rely on the (conditional) random assignment of patients to nurses and the orthogonality of nurse errors in the first decision (η_{ij}) to nurses' propensities to direct patients online. This allows us to write

Lemma 1. $\pi_i \perp \left\{ \mathbf{Y}_i \left(d, j_i\right), D_{ij_i} | D^0_{ij_i} = 1 \right\}$

Proof. $\rho_{j_i} \perp \theta_i, \eta_{ij_i}, \{\mathbf{Y}_i \left(d, j_i\right), D_{ij_i}\} \Rightarrow \pi_i \perp \theta_i, \eta_{ij_i}, \{\mathbf{Y}_i \left(d, j_i\right), D_{ij_i}\}$
$\Rightarrow \pi_i \perp \{\mathbf{Y}_i \left(d, j_i\right), D_{ij_i} | \theta_i + \eta_{ij_i} > 0\}$. □

Or, in other words, under our model's assumptions, the random assignment of patients to nurses results in a random assignment of patients to the doctor sample.

Third, our assumptions on nurse tendencies and decisions imply (strict) monotonicity within the doctor sample: $\forall j' \neq j$, either $D_{ij} \geqslant D_{ij'}$ for all i or $D_{ij} \leq D_{ij'}$ for all i, which in turn implies average monotonicity. Finally, we assume that the instrument satisfies average exclusion:
$E[\sum_{j=1...J} \lambda_j (\pi_j^{pop} - \pi)\gamma_{ij}] = 0$, where $\lambda_j \equiv Pr(j_i = j)$, $\pi \equiv \sum_{j=1...J} \lambda_j \pi_j^{pop}$, and $\gamma_{ij} \equiv Y_i(d, j) - \overline{Y}_i(d)$, is nurse j's direct contribution to patient i's potential outcome.

The next section begins by providing evidence on the validity of these assumptions and hence on the instrument's validity.

5 Empirical Findings

We begin this section by discussing evidence on the validity of our model. We then discuss our main findings on the similarities and differences between online and in-person consultations. Next, we discuss doctor sorting and productivity differences between both modes, followed by showing evidence on the cost trade-offs for providers and patients. We end the section with discussions of the generalizability of our findings and considerations relating to patient heterogeneity.

5.1 Instrument Validity

Appendix Figure A2 shows the variation in π_i. Most of the 62 nurses in our sample direct patients more frequently to in-person consultations, while some tend to recommend online consultations more often, resulting in a mean in-person consultation rate of around 57% in the doctor sample.

To study the instrument's validity, we begin by estimating first-stage regressions of D_i on π_i in the doctor sample:

$$D_i = \beta_0 + \beta_1 \pi_i + \mathbf{Controls}_i' \beta_2 + \epsilon_{1i}. \tag{3}$$

The vector $\mathbf{Controls}_i$ includes a set of *Fixed Effects* for years $\times$ months (e.g., January 2020), days of the week (Monday, Tuesday, etc.), four-hour time blocks (midnight-4am, 4-8am, etc.) of the nurse meeting, and the primary care clinics at which patients are registered. The other controls that we sequentially add are patient characteristics ($\boldsymbol{\psi}_i$), which consists of patient demographics measured in 2018; an indicator for prior patient comorbidity; and fixed effects for patients' ICD (International Classification of Diseases, version 10) code groups, as determined by the nurses.[19]

We use this variation in the instrument to examine the identification assumptions. As Appendix Table A3 shows, the first-stage estimate remains large and precisely estimated when we include the main set of fixed effects (time of day, day of week, month $\times$ year, and clinic) to address the possibility of nurse and patient sorting across times and locations. Reassuringly, when we add further controls (patient demographics, comorbidity indicator, and fixed effects for the nurse-set diagnosis codes), the first-stage coefficient remains stable and large (0.67). The first stage is similarly precisely estimated when we use robust standard errors (s.e.) in our main specifications (following Abadie et al. 2023) as when we cluster the s.e. by nurse (as many previous papers on expert propensities do). In all these cases, the F-statistic for the first stage exceeds 100, alleviating potential concerns about weak instruments, at least for outcomes available for all or most patients.

To examine independence, we proceed in three steps. First, to test the (conditional) random assignment of patients to nurses, we regress the instrument, π_i, on patient characteristics, $\boldsymbol{\psi}_i$, in the nurse sample and report the p-value from a joint F-test on $\boldsymbol{\psi}_i = 0$. Panel A in Appendix Table A4 shows that the instrument is uncorrelated with patient characteristics in this sample, irrespective of controls. Second, to test the assumption that nurses with different propensities to direct online do not systematically differ in their propensity to direct to any doctor, we regress the nurse-level propensity (not the leave-one-out instrument) π_j on nurse j's propensity to assign to any doctor, $\frac{1}{N_j} \sum_{i' \in I_j} D^0_{i'j}$. The estimates in Panel B of Appendix Table A4 show no significant correlation.[20] Finally, to test whether the

[19] These controls are all fully pre-determined, except the nurse ICD groups, but we use these ICD groups as proxies for the patients' pre-determined conditions. We have another variable reflecting patients' self-declared symptoms, but its classification is coarser and less informative and it is often missing. More details about the controls can be found in Table 1 and the Appendix, particularly Appendix Table A2.

[20] This finding also helps address a potential concern (related to that noted in Chan et al. 2022) that low propensity to direct patients to an online consultation reflects excessive caution on the part of less-skilled nurses, who might also refer more cases to doctors.

instrument is orthogonal to the characteristics of patients in the doctor sample, we regress π_i on $\boldsymbol{\psi}_i$ in the doctor sample and report the p-value on a joint F-test for $\boldsymbol{\psi}_i = 0$. The results in Panel C of Appendix Table A4 show balance in the doctor sample.

We present two pieces of evidence to establish average exclusion. First, as Panel A of Appendix Table A5 shows, institutional rules circumscribe nurses' decisions in our setting. So unlike doctors, nurses cannot prescribe medications, or refer patients to (external) specialists, or give patients sick notes.[21] These rules limit nurses' opportunities to affect patient outcomes through channels other than the doctor consultations they direct them to. Even nurses' role in advising patients is less important once they have decided to direct a patient to a doctor.

Second, in Panel B of Appendix Table A5, we observe that nurses have very little time to interact with patients, with a mean patient-facing time of less than five minutes and a median of four minutes. Such short meetings leave little time to do more than ask about the patient's condition, decide whether the patient should consult a doctor, and if so, whether the consultation should be online; even advising patients seems unlikely if the nurse directs the patient to a doctor. Panel B also shows that nurses' mean patient-facing time is about four times shorter than that of doctors, and their median is about three times shorter.[22]

To establish average monotonicity. Appendix Table A6 follows Frandsen et al. (2023) and Bhuller et al. (2020) in reporting the first stage for different subsamples. The first stage is large and statistically significant when patients are broken down by gender, age, education level, annual income, immigrant status, comorbidity status, whether they specified "general health" in their symptoms form (rather than filling out a specific symptom), and whether they requested the consultation during periods with low (or no) COVID-19 (versus the first or second COVID-19 wave). These estimates suggest that most patient groups are compliers, responding to the nurse's tendency toward online versus in-person consultations. This is important as it indicates that our compliers are broadly representative within the studied patient population. We return to the point of generalizability in Section 5.4 when we discuss the external validity of our estimates with regard to costs.

In addition to these tests of the model assumptions, Appendix Table A7 examines whether the instrument reflects nurse skill by examining rare mistakes that nurses make. Similar to Chan et al. (2022), we measure these mistakes as instances when a patient whom

[21] Our setting differs the US, where registered nurses are allowed to perform many of the doctors' tasks.

[22] To ensure comparability between the duration of the nurse meeting and doctor consultation, Panel B restricts the sample to patients for whom the patient-facing duration is observed for both, although this restriction does not matter much in practice.

a nurse *did not* direct to a doctor consultation is hospitalized or observed in the ED within 10 days of the patient's meeting with the nurse.[23] Even these instances, which are rare (on average, nurses have a mistake share of 6%), do not necessarily imply an error of judgement on the nurse's part, as a health problem may have arisen after the nurse meeting. Nevertheless, our estimates suggest that nurses who direct more patients online do not significantly differ in the frequency of rare mistakes they make.

Further evidence for the validity of our identification strategy is discussed in Section 5.2.6, where we show that key outcomes were uncorrelated with the instrument during the weeks leading up to the nurse meeting

5.2 Effects of Online versus In-Person Doctor Consultations

Having provided evidence on the instrument's validity, we proceed to use the doctor sample to estimate our main specification:

$$Y_i = \beta_3 + \beta_4 D_{ij} + \mathbf{Controls}_i^{'}\beta_5 + \epsilon_{2i}, \tag{4}$$

where Y_i are individual outcome components of $\mathbf{Y}_i$. Since D_i is potentially endogenous (e.g., if patients with different health problems or other relevant differences receive online rather than in-person consultations), we also estimate specifications where we instrument for D_i using π_i. The differences between the OLS and IV estimates may inform us whether, on average, sicker patients tend to sort into online or in-person consultations.

5.2.1 Duration and Timing of Consultations

Table 2 reports our first set of results regarding the differences in duration and timing between online and in-person consultations. Panel A of Table 2 shows one clear advantage of online consultations: they take place much sooner after the patient's request, typically on the same day. In contrast, in-person consultations are typically held two to three days after the nurse meeting, reflecting the need to find availability among the smaller set of doctors working in the nearby clinic and the need to schedule for traveling.

Panel B shows that the total consultation duration is much shorter online, which may

[23] Chan et al. (2022) study radiologists' diagnoses of pneumonia, where their decision to diagnose or not is strictly ordered, potentially causing less skilled radiologists to be more cautious and over-diagnose. Our setting is different since we consider the decision to direct patients to online or in-person consultations, which are not necessarily ordered. We separately consider the nurses' decision whether to direct patients to any doctor in our discussion above, and the mistake we measure pertains to that decision rather than to the online versus in-person decision.

be one of the reasons why online consultations themselves are cheaper than in person (we investigate post-consultation costs in Section 5.4). Two patterns in these results are worth mentioning since they recur in many of the other outcomes presented in this section. First, including different sets of controls does not affect the estimates much. Second, the OLS and IV estimates differ, showing a systematic pattern. The OLS estimates suggest that online consultations are about two-thirds shorter, while the IV estimates suggest they are only one-third as short. These findings are consistent with the notion that patients with severe symptoms tend to sort (or be sorted) into online consultations, under the assumption that more complex cases require longer consultations. While our set of controls, although detailed, cannot address this sorting, the IV estimates overcome this sorting and suggest smaller cost savings online than the OLS results would imply—in this case in terms of time saved. As we discuss below, several of our other findings are also consistent with this interpretation.

Panels C and D of Table 2 break down the total doctor consultation duration into patient-facing and administrative time. Online consultations have significantly shorter patient-facing time but longer administrative time. A possible interpretation of this finding is that with in-person consultations, the doctor writes notes or fills forms while the patient is in the room, whereas online consultations end sooner but the doctor takes notes or fills forms after they end. Another possible interpretation (which is not mutually exclusive) is that doctors need some time to consult notes and/or recuperate after consulting patients. Online, this is recorded separately as administrative time, whereas in person this time may be bundled with patient-facing time.

5.2.2 Within-Consultation Outcomes

Table 3 examines four within-consultation outcomes for the patient (and one that is closely related to them). In Panel A, the OLS estimates suggest that the rate of informative diagnosis is higher online, which would be surprising if it had a causal interpretation, while the IV estimates show more negative but imprecise estimates. In Panel B, the OLS estimates indicate that an online consultation is more likely to yield a prescription (perhaps an easier outcome), while the IV estimates are again insignificant.

Panel C shows that the rates of patient prescription collection are similar for online and in-person consultations. This measure is interesting since it can be seen as an indicator of patient adherence (Neiman et al. 2018).[24] Panel D shows that specialist referrals are either

[24] While our setting is unusual in allowing us to measure it, this outcome comes with two caveats: it

less common online (OLS), again consistent with healthier patients sorting online, or equally common (IV).[25]

Panel E shows estimates of patient satisfaction, an outcome available only for patients who scored the consultation, which is more commonly done online (see Appendix Table A8). The response rate online is most likely higher because patients are more systematically reminded to score consultations online than in person. Consequently, the estimates in Panel E again condition on an outcome (scoring) and should therefore be treated with caution. Nevertheless, the estimates here are also not significantly different for online consultations.

Overall, where within-consultation outcomes differ between the OLS and IV estimates, the OLS estimates tend to paint an overly optimistic picture of online consultations. This is most likely due to the sorting of cases that are easier in some respects that are not observable to us. However, IV corrects this sorting bias, providing more credible estimates.

5.2.3 Post-Consultation Outcomes

In contrast to the similarity of in-consultation outcomes for in-person and online consultations, in Table 4 we observe some differences between both delivery modes in the short-term (within a month) post-consultation outcomes. We find no difference between online and in-person consultations in the rare (and negative) outcome of avoidable hospitalizations. These hospitalizations are for conditions that primary care could plausibly have treated or prevented but either did not do so or did not succeed in doing so (U.S. Agency for Healthcare Research and Quality 2023). Neither the OLS nor the IV estimates in Panel A show any significant difference in this measure between both consultation modes. But avoidable hospitalizations are very rare, and therefore the estimates' confidence intervals are wide compared to the mean of the outcome, suggesting that we may be underpowered to detect significant differences.

Panel B examines overall hospitalizations. While the coefficients suggest that online consultations may result in more hospitalizations, they are marginally imprecise. We revisit this outcome in Section 5.2.6.

Panel C shows significant differences in ED visits after online consultations compared to in-person ones. Online consultations are more likely to be followed by ED visits in both the OLS and IV estimates, and the IV estimates are large. Our interpretation is that an

conditions on an outcome (receiving a prescription), and it has a weaker first stage. We also find no significant differences when examining collection within a week from the consultation.

[25] Due to differences across regions, patients are only observed being referred to specialists in Stockholm and not in Lund, so we estimate this regression for Stockholm patients only.

online consultation is more likely to result in the patient, doctor, or both concluding that the patient should see another doctor in person, at least as a precaution. In some cases, an ED visit could be, at least from the patient's perspective, a way to achieve this quickly.[26]

In Panel D, both the OLS and IV estimates show that following an online consultation, the patient is more likely to have another primary care consultation within 30 days (still within the same provider where patients are registered to receive their primary care). The estimates are all large and statistically significant, and the IV estimates suggest that about 63% of the online consultations (compared to about 37% of the in-person consultations) are followed by another primary care visit within 30 days.

Taken together (and similar to previously discussed outcomes), the differences in post-consultation outcomes between the OLS and IV estimates are consistent with the IV method solving a selection problem and thereby providing a more realistic (and less encouraging) picture of the effects of online consultations.

5.2.4 Robustness of Post-Consultation Outcomes

In Appendix Table A9, we repeat the analysis in Table 4 but this time starting the 30-day count from the nurse meeting. This change avoids a gap in observing patients between the nurse meeting and the doctor consultation, which (as discussed in Section 5.2.3) is larger for in-person consultations. The estimates in Appendix Table A9 are broadly similar to those in Table 4.

5.2.5 Breakdown of Primary Care Follow-Ups

Appendix Table A10 more closely examines the increased rate of primary care follow-ups after online consultations, showing that this is mostly due to more follow-ups booked by doctors and that these additional follow-ups are mostly in person. The table also suggests there may be a slightly higher probability of a patient-initiated primary care follow-up visit, although the estimates are smaller and imprecise. Taken together, the results in this table suggest that doctors working online are often cautious and book an in-person follow-up visit. At the same time, it is possible that some of these follow-up visits reflect patient requests for doctors to follow up or check unrelated health issues. In a longer in-person consultation, there may be time to discuss several health issues, while in a shorter online consultation, there may be time only for one.

[26]Some of the ED visits may result in hospitalizations, possibly explaining the imprecise estimates observed in Panel B.

5.2.6 Patient Outcomes During the Weeks Before and After the Nurse Meeting

In Figure 2, we report IV estimates separately for each week before and after the nurse meeting, where we define as 0 the week starting on the day when the patient had the nurse meeting.[27] The figure reveals two main findings. First, there are no significant differences in health outcomes in the weeks before the nurse meeting between patients assigned to nurses with differing online propensities. Second, the figure provides a detailed view of what happens after the nurse meeting. Panels A and B show that the PCP follow-ups (excluding the doctor consultation to which the nurse directs) are mostly in person and occur within a week of the nurse meeting. Panel C displays that ED visits are less frequent but also typically happen within the same week. Finally, Panel D shows that hospitalizations may slightly increase in the following week, possibly due to follow-ups from the ED visits. However, as discussed above, over the entire 30-day period, this increase is imprecise.

5.2.7 Medium-Term Post-Consultation Outcomes

In Appendix Table A11, we re-estimate the regressions reported in Table 4 except we consider medium-term outcomes—events occurring at least a month after the consultation but before the end of our sample period. This duration of this medium-term varies – some patients (who met a nurse in late 2019) observed for over a year and others (who met a nurse in late 2020) observed for a much shorter duration. Nevertheless, our results suggest no significant differences in these medium-term outcomes between in-person and online consultations.

5.3 Doctor Productivity and the Sorting of Doctors to Online Consultations

So far, we have observed that doctors working online had shorter consultations, even when using IV to control for patient sorting. To further investigate differences in doctor productivity online versus in person (measured here only in terms of consultations per hour), we study doctors' shifts in both delivery modes. We assess these using a much larger sample that includes both registered and non-registered patients, as most online consultations involve non-registered patients.[28] Shifts are defined as starting with the start time of the first consultation and ending with the end time of the last consultation within calendar day. In-person and online shifts are, on average, similarly long (approximately 5 hours).

[27] This is more similar to Appendix Table A9 than to Table 4.

[28] Patients who are registered have one of the company's clinics as their primary care provider, and are "at risk" for both in-person and online consultations with the provider. Those who are not registered have another primary care provider and use the service we study only for online consultations.

Columns (1) and (2) of Table 5 show that when we account for the full shift duration, doctors working online are roughly twice as productive (in terms of patients per hour) as those working in person, although we cannot account for unobserved patient sorting. The shift data, however, do provide sufficient variation to study doctor sorting. As the difference between Columns (2) and (3) shows, more productive doctors do indeed sort online, but only about 13% of the online productivity gains are explained by doctor sorting. Columns (4)–(6) repeat the analysis excluding any breaks between patients, and the results are broadly similar. These results are striking, since doctors are paid per shift and not per patient both online and in person.

5.4 Cost Analysis

We now consider the differences in costs for providers and patients between online and in-person consultations. For provider costs, we focus on entities like insurance companies, health maintenance organizations, or public healthcare providers and insurers that account for all healthcare costs, including ED visits.[29] As Table 6 shows, when we ignore follow-ups, online consultations are four times cheaper than in person.[30] This large cost advantage could reflect the productivity improvements discussed in the previous section as well as reduced overhead costs from operating clinics and other staff costs. However, accounting for the higher incidence of follow-ups in primary care and ED, providers' overall cost of online consultations is only 20% cheaper than in person.

A similar result applies to patient costs. When accounting for patient co-pays, consultation duration, and travel and waiting costs (excluding follow-ups), online consultations are about three times cheaper than in person. However, including costs associated with a higher share of follow-up visits in primary care and ED offsets this advantage, making online consultations about 6% more expensive than in person.

[29]This is also relevant in the setting we study, as the payment model is capitation and in some cases has cost penalties for ED visits. The primary care provider is paid through capitation for the patients studied in this paper in Region Scania, and so it faces a cost from additional primary care follow-ups within the service. In Region Stockholm, primary care providers are paid through a combination of capitation and some fee for service, so the incentives for additional primary care visits are less clear. Additionally, in Region Stockholm, the primary care provider is penalized if a large share of their patients visits the ED, while they get a bonus if there is a low share. This system was not present in Scania during the study period and was implemented starting in 2022.

[30]The costs for both online and in-person consultations are our best estimates of what the public health insurance pays for each and come with some uncertainty. The online cost we use is a cost set by regulation for out-of-region online visits. The in-person cost is an average of what an in-person consultation costs or is reimbursed with. See the notes of Table 6, notes of Appendix Table A12, and Appendix Section C.4 for more details.

While these cost calculations suggest that online consultations are not a cost panacea, they nevertheless offer several advantages over in-person consultations. First, as previously discussed, online patients benefit from seeing doctors sooner. Second, online consultations are more convenient, allowing patients to attend from their preferred location (e.g., home) and avoid travel and waiting in a clinic when they are ill.[31] Third, online consultations offer greater availability outside of regular hours: 51% occur outside regular medical office hours (8am–5pm on weekdays), compared to 28% for in-person consultations. Fourth, online consultations reduce the risk of contagion for patients and others, thus mitigating negative health externalities from in-person care (Neprash et al. 2021). Finally, as we explain in the next section, patients in our sample are more likely to follow up than the average Swedish patient for two reasons: they live in more central locations and are sicker than drop-in patients. Thus, generalizing our cost estimates to the broader Swedish patient population would likely result in higher net social savings online. Furthermore, as we discuss below, the heterogeneity of patients may further improve the cost-effectiveness of online consultations.

5.5 Generalizability of Our Findings

In this section, we examine the generalizability of our findings by comparing the demographics of patients in the doctor sample with the overall Swedish population; the ICD codes in the doctor sample with those among Swedish PCP patients; and the characteristics of compliers with the doctor sample as a whole. We also examine whether—as the model predicts—patients in the doctor sample are likely "sicker" than those who see a doctor without first seeing a nurse.

We begin our discussion of the generalizability of our findings in Appendix Table A13, where we compare the mean demographic characteristics of patients in the doctor sample to those in broader samples. While patients in the doctor sample are a bit younger, better educated, and likelier to have immigrant backgrounds, they are broadly representative of their municipalities. The pattern is similar when compared to the national mean, except in one important respect: patients in the doctor sample are much more likely to reside in big cities. This is due to the fact that the in-person centers were initially established in Stockholm and Lund (near Malmö), meaning that patients' distance to primary care

[31] In our cost calculations, we do not include the waiting time between the nurse meeting and the doctor consultation. Although the wait for in-person consultations is typically two to three days—longer than for online consultations—patients can engage in other activities during this period, making the cost of this waiting time difficult to calculate.

clinics and hospitals with EDs is much shorter than the national average.[32] Patients who live further away from an ED may be less likely to follow up with an ED visit than the patients in our sample, as in Vaz et al. (2014). Thus, expanding the online option to more remote areas may reduce the average cost of follow-ups, reducing the total costs of online consultations.

In Appendix Table A14, we compare the patients in the doctor sample to a more broadly representative sample of PCP patients. Our comparison group consists of approximately 1.6 million PCP consultations, which are the universe of PCP consultations in 2019 in Scania, a region home to 13% of Sweden's population.[33] The results show that despite some differences in the demographic composition, the ICD codes are highly correlated across samples (correlation = 0.84 and rank correlation = 0.68).

We next examine whether compliers are similar to non-compliers in the doctor sample. Some evidence that compliers are similar to others was already shown in Appendix Table A6. In Appendix Table A15 we use a procedure similar to Frandsen et al. (2023) to provide further evidence that compliers are broadly representative of the doctor sample.

Finally, we compare the illness of patients in the doctor sample to those in the nurse sample. Our model predicts that patients in the doctor sample are sicker since they are the ones that nurses directed to doctor consultations. Appendix Table A16 shows that patients in the doctor sample who are directed to an online doctor by nurses are considerably more likely to have a follow-up with a PCP compared to those who consult a doctor online immediately after contacting primary care (without nurse direction). This difference suggests that our cost estimates may be more representative of a pool of patients directed by nurses, as common in some healthcare systems. Since follow-ups are more common after online consultations, our results suggest that among drop-in patients, online consultations may be cheaper.

5.6 Patient Heterogeneity

This section explores heterogeneity in patients' responses to online versus in-person consultations. We first examine how patients' self-reported views on whether online consultations substitute in-person consultations differ by demographics. We then report marginal treat-

[32]In the entire country, the mean distance between a municipality centroid and an ED hospital is 32 kilometers. However, when calculating a weighted mean for the municipalities where the doctor sample patients reside, the distance is only 6.83 kilometers. The most common municipalities of patients in the sample have at least one hospital with an ED. See Appendix Section C.6.2 for more information on distances to EDs.

[33]The Scania data consist overwhelmingly of PCP consultations outside the firm we study.

ment effect (MTE) estimates for outcomes where we can invoke the (stronger) assumptions of monotonicity and exclusion rather than the weaker average versions. Finally, we explore a breakdown of the treatment effect by patients with different degrees of vulnerability.

5.6.1 Heterogeneity in Patients' Views of Online as a Substitute for In-Person

We first examine whether patients with different characteristics perceive online consultations as a substitute for in-person consultations. Table 7 shows results for a sample of non-registered patients, which is much larger than that of registered patients, and allows for heterogeneity analysis. The non-registered patients only used the drop-in service for online consultations. We use results from a specific question asked only of online patients: did they view their online consultation as a replacement for an in-person consultation? An important caveat is that just under half of the patients responded to this question, and those who did respond may have been more favorably inclined toward online consultations. Nevertheless, as the table shows, about 95% of those who answered said that online consultations were a substitute for in person. Those who were less likely to consider them as a replacement were predominantly older, in their 70s or over 80 years old, and to a lesser extent also first-generation immigrants who were neither from Scandinavia nor from Western Europe (i.e., the first 15 countries to join the European Union).

5.6.2 Marginal Treatment Effects

Frandsen et al. (2023) note that identifying MTEs in a setting with expert propensities requires, in addition to the assumptions discussed above, strict monotonicity and exclusion. To test which outcomes satisfy these assumption, we implement their (more powerful) semi-parametric test, giving equal weight to the two components of their test, as we discuss in more detail in Appendix Table A17. Of the seven outcomes we test, strict monotonicity and exclusion are satisfied for three: total consultation duration, hospitalization within 30 days, and new visit to primary care provider within 30 days.

Focusing on these three outcomes, we follow Mogstad et al. (2018) in estimating MTEs for them, using the Stata package by Andresen (2018). Appendix Figure A3 reports the MTE estimates, showing that the treatment effect varies among patients with higher unobserved resistance to participating in an online consultation. While the test rejects significant heterogeneity for all three outcomes, the results plausibly suggest that for patients who are more resistant to online consultations, these may lead to shorter consultation times and more follow-up visits.

5.6.3 Heterogeneous Costs

Since we find that online consultations entail costly follow-ups, it is natural to ask whether cost-effectiveness can be improved by assigning some patients to in-person consultations and others to online consultations. Thus, we explore various aspects of treatment effect heterogeneity, finding mostly insignificant differences. With this caveat in mind, we focus here on one aspect of patient heterogeneity which seems potentially important.

We report key estimates separately for two groups of patients: those who experienced at least one hospitalization or ED visit in the three years (up to 30 days) before meeting the online nurse (Appendix Table A18) and are therefore likely more vulnerable, and those who had no hospitalizations or ED visits during the same period (Appendix Table A19). The IV estimates in the last column of both tables suggest that for more (less) vulnerable patients, online consultations increase their rate of ED visits by 28 percentage points (7 percentage points), new PCP visits by 44 percentage points (18 percentage points), and in-person doctor-booked follow-ups by 46 percentage points (15 percentage points). Given our sample size and power, these heterogeneity estimates should be interpreted with caution. And yet they suggest that in-person consultations may be more cost-effective for more vulnerable patients, while online consultations may work better for less vulnerable ones.

We explore this possibility quantitatively in Appendix Table A20. The table shows that for more vulnerable patients, online consultations increase total provider costs by 22% and patient costs by 64%, while for less vulnerable patients, they reduce total provider costs by 40% and total patient costs by 23%. These figures provide suggestive evidence on the potential for a more effective allocation of patients across consultation modes.

More generally, our findings suggest that effective provision of 1:1 services requires providers to better understand the preferences and behavior of different consumers in response to changing delivery modes, and design their hybrid offering accordingly.

6 Conclusion

Online delivery is now possible for many 1:1 services, such as banking/financial advice, tutoring/teaching, therapy, and healthcare. Online platforms offer potential savings and convenience, yet the trade-offs for providers and consumers when transitioning these services online are not well-understood. To the best of our knowledge, this paper is the first to study the effects of online versus in-person 1:1 services in a setting where consumers have already opted for the service and where sorting between the two delivery modes is addressed. Our focus is on healthcare, specifically primary care consultations, where cost pressures are rising and ensuring quality is essential.

Our findings suggest that sorting across delivery modes is considerable, with sicker patients typically directed to in-person care, a selection issue that our IV strategy addresses. We observe that online consultations are more readily available and scheduled sooner, and generally shorter, with a much shorter doctor-patient time but longer administrative time. Additionally, the increased speed at which doctors work online appears largely robust to the sorting of individual doctors into online consultations.

We also observe that despite the differences in speed and timing, the within-consultation rates of diagnosis, prescription, specialist referral, and patient satisfaction in online consultations are similar to those in in-person consultations. However, patients are more likely to follow up with ED visits and PCP consultations (especially in person) shortly after online consultations. These follow-ups could suggest concerns from doctors, patients, or both that some aspects of care was overlooked online compared to in person. Nevertheless, medium-term outcomes are similar, indicating that the initial increase in follow-ups does not adversely affect the overall effectiveness of care.

While the cost of the online consultations themselves is about a quarter of the cost of in-person consultations, the increased frequency of short-term follow-ups after online consultations diminishes much of the potential savings for both providers and consumers. However, online consultations do offer patients advantages, such as quicker access to doctors, reduced contagion risk, and greater scheduling flexibility, including availability outside of regular work hours. We also find evidence that a more widely representative pool of patients, which is less urban and healthier than those in our sample (rather than sorted by nurses, as in our setting), is likely to follow up at lower rates, potentially increasing the savings from online consultations.

Our findings also suggest that while most patients view online consultations as a suitable replacement for in-person visits, older patients and, to some extent, those from immigrant backgrounds, are more skeptical of online care. Further, our results suggest that directing more vulnerable patients (who are less likely to follow up) to in-person consultations and less vulnerable ones to online settings could further improve cost savings.

Taken together, our findings inform decisions whether to provide 1:1 services online or in person, and to whom. Finding the right mix of online and in person is an important challenge for hybrid organizations, which encompass a large and growing number of providers worldwide.

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Table 1. Summary Statistics for Key Variables in the Doctor Sample

	Mean	SD	Min	Max	Observations
Key model variables					
Doctor consultation was online	0.43	0.49	0	1	4,664
Nurse propensity to online π_i (Instrument)	0.43	0.12	0.24	1	4,664
Proxies for fixed effect controls					
Nurse meeting was on a weekend	0.17	0.38	0	1	4,664
Nurse meeting was from 8am-8pm	0.87	0.33	0	1	4,664
Patient registered at clinic in Stockholm	0.52	0.50	0	1	4,664
Demographic controls (measured in 2018)					
Patient female	0.49	0.50	0	1	4,664
Patient age	33.0	13.7	0	85	4,664
Born outside Sweden	0.30	0.46	0	1	4,663
Second-generation immigrant	0.089	0.29	0	1	4,663
Born outside EU15 and Scandinavia	0.24	0.43	0	1	4,663
Patient married	0.27	0.45	0	1	4,532
Patient divorced	0.10	0.31	0	1	4,532
Patient not eligible to marry (age<18)	0.090	0.29	0	1	4,664
Patient working ($16 \leq$age≤ 74)	0.72	0.45	0	1	4,529
Patient not of working age	0.058	0.23	0	1	4,664
Patient comorbidity control					
Any comorbidity (from 2013-2018)	0.18	0.39	0	1	4,664
Nurse-set ICD group controls					
Infectious	0.023	0.15	0	1	4,651
Endocrine, nutritional, metabolic	0.0084	0.091	0	1	4,651
Mental and behavioural	0.021	0.14	0	1	4,651
Nervous system	0.0080	0.089	0	1	4,651
Eye and adnexa	0.0090	0.095	0	1	4,651
Ear and mastoid process	0.072	0.26	0	1	4,651
Circulatory system	0.025	0.16	0	1	4,651
Respiratory system	0.029	0.17	0	1	4,651
Digestive system	0.025	0.15	0	1	4,651
Skin and subcutaneous tissue	0.035	0.18	0	1	4,651
Musculoskeletal, connective	0.19	0.39	0	1	4,651
Genitourinary system	0.049	0.22	0	1	4,651
Symptoms (cough, rash, etc.)	0.37	0.48	0	1	4,651
Injury or poisoning	0.042	0.20	0	1	4,651
Health status factors	0.091	0.29	0	1	4,651
Other	0.0069	0.083	0	1	4,651
Outcomes (for cases observable at least 30 days)					
Any avoidable hospitalization within 30 days	0.0012	0.035	0	1	4,004
Any hospitalization within 30 days	0.0092	0.096	0	1	4,004
Any emergency department visit within 30 days	0.047	0.21	0	1	4,004
New visit to primary care provider within 30 days	0.41	0.49	0	1	4,004
Other variables					
Nurse propensity to direct to any doctor	0.54	0.092	0.28	0.85	4,664
Nurse "mistake" share	0.063	0.035	0	0.17	4,664
Other physical health issue	0.30	0.46	0	1	4,664
University educated (age>22)	0.58	0.49	0	1	3,396
Annual income (in thsnd. SEK, age>20)	328.4	299.2	0	5301	3,759
Low COVID-19 spread	0.49	0.50	0	1	4,664

Notes: This table presents summary statistics of key variables in the doctor sample (N=4,664). The variables refer mostly to the controls used in the main regressions (see Appendix Table A2 for descriptions). The demographics are based on 2018 or 2017 if the value is missing in 2018.

Table 2. Online's Effect on Timing and Duration of Doctor Consultations

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Days between nurse meeting and doctor consultation								
Consultation was online	-2.30	-2.28	-2.30	-2.35	-3.15	-2.75	-2.74	-2.79
	(0.065)	(0.066)	(0.067)	(0.069)	(0.34)	(0.40)	(0.42)	(0.43)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,664	4,664	4,528	4,515	4,664	4,664	4,528	4,515
First-stage K-P F-statistic					198	145	138	133
Baseline mean	2.4	2.4	2.5	2.5	2.4	2.4	2.5	2.5
B: Total consultation duration (in minutes)								
Consultation was online	-25.8	-25.7	-25.6	-26.0	-12.6	-14.0	-15.0	-15.0
	(0.62)	(0.62)	(0.64)	(0.66)	(3.52)	(4.01)	(3.99)	(4.14)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,512	4,512	4,382	4,369	4,512	4,512	4,382	4,369
First-stage K-P F-statistic					194	141	134	130
Baseline mean	39.8	39.8	39.7	39.7	39.8	39.8	39.7	39.7
C: Patient-facing part of the consultation (in minutes)								
Consultation was online	-26.8	-26.7	-26.8	-27.0	-22.6	-23.2	-23.0	-22.8
	(0.44)	(0.44)	(0.46)	(0.48)	(2.17)	(2.42)	(2.48)	(2.57)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,343	4,343	4,220	4,208	4,343	4,343	4,220	4,208
First-stage K-P F-statistic					200	147	137	134
Baseline mean	32.3	32.3	32.2	32.2	32.3	32.3	32.2	32.2
D: Administrative part of the consultation (in minutes)								
Consultation was online	1.32	1.38	1.43	1.30	6.32	6.49	6.47	6.34
	(0.34)	(0.34)	(0.34)	(0.35)	(1.94)	(2.21)	(2.27)	(2.33)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,332	4,332	4,211	4,199	4,332	4,332	4,211	4,199
First-stage K-P F-statistic					198	145	136	133
Baseline mean	7.2	7.2	7.2	7.2	7.2	7.2	7.2	7.2

Notes: This table reports regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the control variables, please see the main text and appendix (in particular Appendix Table A2). Fixed effects include year×month, 4-hour blocks, day of the week, and where the patient was registered. The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table 3. Online's Effect on Within-Consultation Outcomes

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Doctor set an informative diagnosis								
Consultation was online	0.035	0.037	0.039	0.029	-0.12	-0.14	-0.15	-0.12
	(0.013)	(0.014)	(0.014)	(0.014)	(0.075)	(0.087)	(0.090)	(0.087)
Observations	4,664	4,664	4,528	4,515	4,664	4,664	4,528	4,515
First-stage K-P F-statistic					198	145	138	133
Baseline mean	0.68	0.68	0.68	0.68	0.68	0.68	0.68	0.68
B: Patient received a prescription								
Consultation was online	0.15	0.15	0.15	0.15	-0.011	0.017	0.025	0.060
	(0.013)	(0.013)	(0.014)	(0.014)	(0.070)	(0.079)	(0.082)	(0.083)
Observations	4,664	4,664	4,528	4,515	4,664	4,664	4,528	4,515
First-stage K-P F-statistic					198	145	138	133
Baseline mean	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
C: Patient collected prescription within 30 days (conditional on getting a prescription)								
Consultation was online	-0.0017	-0.0020	0.0019	0.0038	-0.027	-0.0074	0.024	0.035
	(0.017)	(0.020)	(0.020)	(0.022)	(0.13)	(0.19)	(0.18)	(0.19)
Observations	1,073	1,073	1,042	1,039	1,073	1,073	1,042	1,039
First-stage K-P F-statistic					27	16	17	17
Baseline mean	0.92	0.92	0.91	0.91	0.92	0.92	0.91	0.91
D: Doctor gave a specialist referral (Stockholm only)								
Consultation was online	-0.092	-0.093	-0.094	-0.096	-0.035	-0.016	-0.0022	-0.016
	(0.010)	(0.010)	(0.011)	(0.011)	(0.057)	(0.068)	(0.070)	(0.069)
Observations	2,419	2,419	2,333	2,324	2,419	2,419	2,333	2,324
First-stage K-P F-statistic					82	60	58	63
Baseline mean	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
E: Patient satisfaction score (5 is best)								
Consultation was online	-0.012	-0.022	-0.024	-0.039	-0.074	-0.21	-0.21	-0.23
	(0.042)	(0.044)	(0.046)	(0.049)	(0.26)	(0.32)	(0.34)	(0.33)
Observations	1,466	1,466	1,429	1,423	1,466	1,466	1,429	1,423
First-stage K-P F-statistic					53	34	28	30
Baseline mean	4.7	4.7	4.7	4.7	4.7	4.7	4.7	4.7

Notes: This table reports coefficients from regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table 4. Online's Effect on Patient Outcomes Within 30 Days After the Doctor Consultation

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Any avoidable hospitalization within 30 days								
Consultation was online	-0.00011	-0.00016	-0.00017	-0.00027	0.0021	0.0020	0.0016	0.0022
	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0035)	(0.0054)	(0.0058)	(0.0054)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
B: Any hospitalization within 30 days								
Consultation was online	0.0024	0.0024	0.0026	0.0025	0.035	0.040	0.043	0.046
	(0.0031)	(0.0030)	(0.0032)	(0.0033)	(0.018)	(0.021)	(0.023)	(0.024)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
C: Any emergency department visit within 30 days								
Consultation was online	0.017	0.014	0.014	0.016	0.12	0.11	0.13	0.13
	(0.0070)	(0.0070)	(0.0073)	(0.0078)	(0.044)	(0.054)	(0.057)	(0.059)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.040	0.040	0.041	0.041	0.040	0.040	0.041	0.041
D: New visit to primary care provider within 30 days								
Consultation was online	0.081	0.085	0.090	0.096	0.13	0.21	0.25	0.26
	(0.016)	(0.016)	(0.016)	(0.017)	(0.089)	(0.11)	(0.11)	(0.11)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37

Notes: This table reports coefficients from regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table 5. Doctor Consultations per Hour in Online and In-Person Doctor Shifts

	Shift incl. all breaks			Shift excl. all breaks		
	(1)	(2)	(3)	(4)	(5)	(6)
Shift was online	1.88	1.94	1.68	2.34	2.47	2.00
	(0.078)	(0.078)	(0.12)	(0.084)	(0.084)	(0.15)
Time fixed effects		✓	✓		✓	✓
Doctor fixed effects			✓			✓
Observations	78,413	78,413	78,413	78,413	78,413	78,413
Baseline mean	1.81	1.81	1.81	2.88	2.88	2.88

Notes: This table reports regressions using the doctor shift sample, which consists of consultations with both registered and non-registered patients collapsed to the doctor×day level. A shift starts with the start of the first consultation and ends with the end of the last consultation within a calendar day. Breaks are times in between the consultations. For the construction of the doctor shift sample and the shift variables, please see Appendix Section C.3.2. Time fixed effects include year×month and day of the week fixed effects. The baseline mean is the mean of the dependent variable for in-person doctor shifts, and robust standard errors are in parentheses.

Table 6. Costs of Online and In-Person Consultations for Providers and Patients

	(1) **In-person**	(2) **Online**	(3) **Table**
A. Provider cost (in SEK)			
Cost of doctor consultation without in-person follow-up	2,002	500	
Expected follow-up cost of in-person revisit in primary care	140	661	Table A10, Panel B
Expected follow-up cost of in-person ED	164	683	Table 4, Panel C
Total provider cost including follow-up cost times fraction of follow-ups	2,306	1,844	
B. Patient cost (in SEK)			
Co-pay or patient fee in primary care (average)	159	106	
Expected patient-facing consultation time	96	28	Table 2, Panel C
Expected waiting time for the doctor	89	45	
Expected round trip commuting costs to the GP	176	0	
Expected parking fee (primary care, during the day)	5	0	Table 2, Panel C
Expected public transport fee (single ticket, one-way)	9	0	
Patient cost without any follow-up	534	179	
Expected follow-up cost of in-person revisit in primary care	48	228	Table A10, Panel B
Expected follow-up cost of in-person ED	68	284	Table 4, Panel C
Total patient cost including follow-up cost times fraction of follow-ups	650	691	

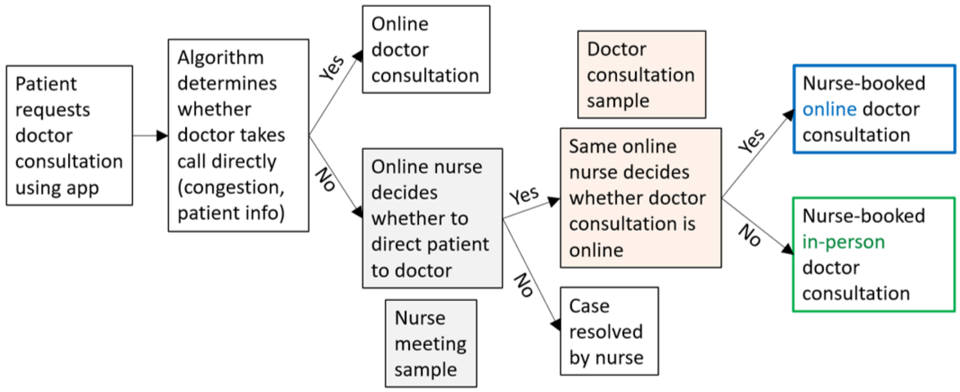
Notes: This table reports cost estimates of doctor consultations in SEK (= 0.11 USD, average for 2020). Column (3) of this table indicates that the cost calculation uses estimates from Column (8) of the specified table. Follow-ups are either in-person revisits to PCP or ED visits, both within 30 days. The provider costs for follow-ups are weighted by the probability that the treatment happens (sources for these costs are listed in Appendix Table A12). For more information on the cost table, see Appendix Section C.4. Patient time cost estimates are based on consultation time multiplied by the mean hourly wage of private sector workers in Sweden (178.5 SEK/hour in January 2020). The fee for paying patients in 2023 is, on average, 225 SEK for in person and 150 SEK for online, which is multiplied by the fraction of paying patients (70.58% of our sample). Mean consultation times are 32.2 minutes for in person and 9.5 minutes for online, while waiting times are 30 minutes for in person (Ekman 2018) and 15.31 minutes online (based on our data). Commuting costs include travel time weighted by travel and parking time round trip, multiplied by the average hourly wage. Transport includes commuting by car (including fuel costs), public transport (including tickets), biking, and walking, which is multiplied by the probability of commuting type (Rosberg & Enström 2019). The average time to a PCP is 23.42 minutes round trip after including frequencies of commuting. We assume that patients spend 5 minutes parking/walking to the doctor's office before and after the consultation. For follow-ups, we multiply the costs by the probability that the follow-up occurs. ED fees in Stockholm and Scania are 400 SEK, multiplied by the fraction of paying patients. We assume patients drive to an ED, and the commuting costs to an ED equal the average travel time to an ED, multiplied by the average hourly wage (including parking time and fuel costs). The mean drive time to an ED is 31 minutes round trip, and the median stay of a patient in an ED is 3.18 hours. The round trip commuting costs are 423 SEK, and the ED time costs are 957 SEK.

Table 7. Patient Views on Whether Online Consultation Was a Replacement to In Person

	Patient answered that online consultation is a replacement for an in-person one					
	(1)	(2)	(3)	(4)	(5)	(6)
Any comorbidity	-0.003					-0.003
	(0.0008)					(0.0008)
In employment (ages 16-74)		0.01				
		(0.001)				
Patient female			0.01			0.01
			(0.0007)			(0.0007)
Patient age 10-19			-0.006			-0.0008
			(0.0010)			(0.001)
Patient age 20-29			-0.006			0.003
			(0.0009)			(0.002)
Patient age 30-39			-0.003			0.010
			(0.0010)			(0.002)
Patient age 40-49			-0.004			0.007
			(0.001)			(0.002)
Patient age 50-59			-0.01			-0.0001
			(0.002)			(0.002)
Patient age 60-69			-0.02			-0.01
			(0.003)			(0.003)
Patient age 70-79			-0.04			-0.03
			(0.006)			(0.006)
Patient age 80 and over			-0.08			-0.07
			(0.02)			(0.02)
In education				-0.0002		0.003
				(0.0008)		(0.002)
Primary school education				-0.01		-0.007
				(0.001)		(0.001)
Short high-school				-0.02		-0.01
				(0.002)		(0.002)
University (less than 3 years)				-0.004		-0.004
				(0.001)		(0.001)
University (3 years or more)				-0.005		-0.006
				(0.001)		(0.001)
Second-generation immigrant					-0.01	-0.01
					(0.001)	(0.001)
Immigrant (born within EU15 or Scandinavia)					-0.01	-0.009
					(0.002)	(0.002)
Immigrant (born outside EU15 and Scandinavia)					-0.03	-0.03
					(0.001)	(0.001)
Observations	456,498	283,410	437,297	434,144	437,023	433,878
Dependent variable mean	0.95	0.95	0.95	0.95	0.95	0.95

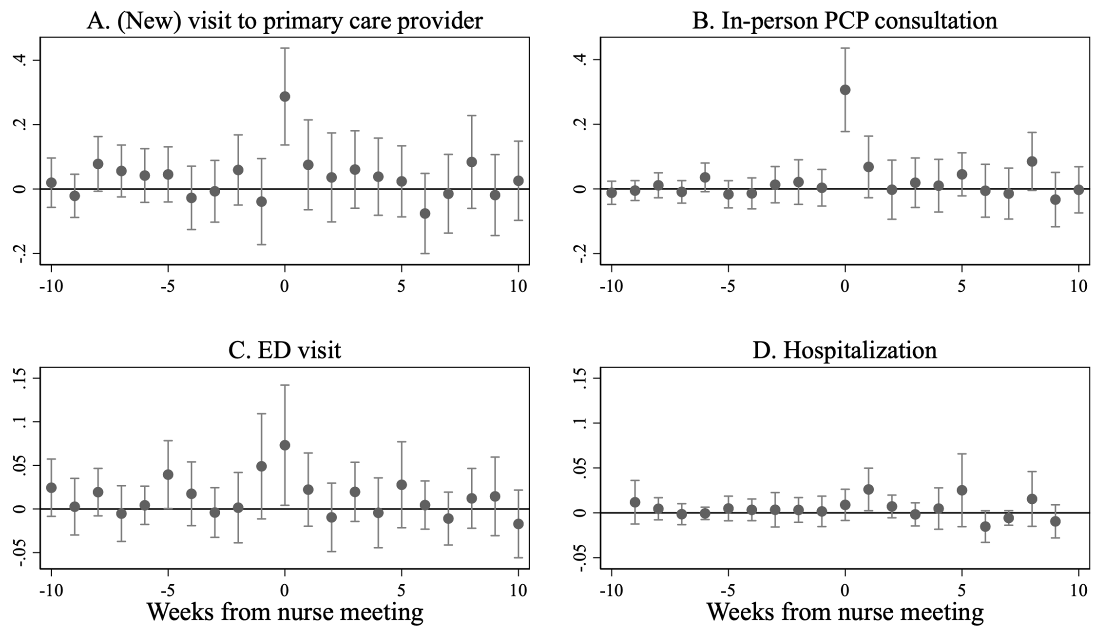
Notes: This table reports the correlation of patient characteristics to survey responses on whether their online consultation replaced an in-person one. This analysis is based on a larger sample of online doctor consultations with patients not registered at one of the firm's in-person clinics and who were directed to an online doctor (not a nurse) when requesting an appointment. We use this sample because the survey question was only asked in online consultations. Positive answers to the survey are coded as 1, "Don't know" responses as 0.5, and negative responses as 0. Consultations related to chlamydia or COVID-19 are dropped. The baseline for the age bins is children aged 0–9, and for the education variables, the baseline is high school education. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). Robust standard errors are in parentheses.

Figure 1. Assignment of Registered Patients to Online versus In-Person Consultations



Notes: This figure shows the flows of patients registered with the healthcare company. Cases in the box with a gray background are defined as the "nurse meeting sample" (or "nurse sample" for short), and cases in the box with an orange background are defined as the "doctor consultation sample" (or "doctor sample" for short). We define a case as an online meeting between a patient and nurse and its resulting treatment (either an online or in-person doctor consultation or no consultation).

Figure 2. Patient Outcomes During the Weeks Before and After the Nurse Meeting



Notes: This figure shows estimated effects of an online doctor consultation 10 weeks before and after the nurse meeting. Each of the 21 estimates is based on a separate regression using our main IV specification in the doctor sample with full controls (fixed effects, demographics, a comorbidity indicator, and indicators of nurse-set ICD group). "Week 0" shows the effect for the week starting with the patient's nurse meeting, "week 1" for the following week, and "week –1" for the preceding week. In Panels A and B, the (new) visit to the primary care provider and in-person PCP consultation are indicators for any visit or consultation that the patient had in the respective time period, excluding the consultation that the patient was directed to. For variable descriptions, see the main text and appendix (in particular Appendix Table A2). Additionally, the confidence intervals are at the 95% level and constructed using robust standard errors.

Online Appendix

Online versus In-Person Services: Effects on Patients and Providers

A Appendix Tables

Table A1. Sample Restrictions

	Directed in-person	Directed online	Not directed	Total
Cases (each is an episode where a patient is handled by an online nurse)	4,460	50,987	185,674	241,121
	(1.8)	(21.1)	(77.0)	(100.0)
+ Keep only cases with registered patients whose clinics are open	2,993	2,592	8,535	14,120
	(21.2)	(18.4)	(60.4)	(100.0)
+ Remove cases related to chlamydia, breastfeeding, or COVID-19	2,945	2,375	5,112	10,432
	(28.2)	(22.8)	(49.0)	(100.0)
+ Remove cases with infants (children strictly younger than two years old)	2,931	2,327	4,957	10,215
	(28.7)	(22.8)	(48.5)	(100.0)
+ Remove cases associated with clinics that have very few observations	2,924	2,246	4,773	9,943
	(29.4)	(22.6)	(48.0)	(100.0)
+ Remove cases where nurses directed less than 20 patients to a doctor				
→ **Nurse sample**	2,670	1,994	4,243	8,907
	(30.0)	(22.4)	(47.6)	(100.0)
+ Cases directed to a doctor				
→ **Doctor sample**	2,670	1,994		4,664
	(57.2)	(42.8)		(100.0)

Notes: This table shows the number of cases (which are observations in the doctor sample) as we apply sample restrictions for our analysis. The columns show the different case pathways: the nurse can direct the patient to either an in-person or online consultation. In parentheses, we show the percentage split between the pathways. Additionally, each row in the table adds another restriction, with the first row showing the total number of cases, defined as a care episode where an online nurse starts seeing a patient. We first restrict the same to cases with patients registered at one of the primary care provider's in-person care clinics, where the clinic was open for consultation. This requirement ensures that patients have a greater than zero probability of being directed by the nurse to both an online or in-person doctor consultation. A clinic is open for consultations when the first nurse directs a patient there for an in-person visit. We then remove cases where the patient's symptom is related to chlamydia, breastfeeding, or COVID-19 as patients with these symptoms follow special care paths. For the same reason, we remove cases with children strictly younger than two years old (see Appendix Section C.3). We also remove cases associated with clinics that have very few observations, leaving us with cases linked to four clinics in Stockholm and Lund. Last, we only consider cases where the nurse had at least 20 cases after imposing the previous restrictions. With this restriction, we define what we refer to as the "nurse sample". If we further only focus on cases where the nurse directed a patient to a doctor, we are left with 4,664 cases (observations), which we refer to as the "doctor sample".

Table A2. Variable Descriptions

Outcome variables	Description
Days between nurse meeting and doctor consultation	This variable denotes the number of calendar days between the nurse meeting and doctor consultation.
Total consultation duration	This variable denotes the total consultation duration in minutes.
Patient-facing part of the consultation	This variable denotes the patient-facing consultation duration in minutes.
Administrative part of the consultation	This variable is made up of the total consultation time minus the patient-facing consultation time in minutes.
Doctor set an informative diagnosis	An indicator that the ICD-10 code is neither in "R" (symptoms such as cough or rash) nor in "Z" (health status factors) categories.
Patient received a prescription	An indicator for patients that received a prescription.
Patient collected prescription within 30 days	An indicator that the patient in the prescription data picked up a prescription we tied to the primary care consultation.
Doctor gave a specialist referral	An indicator that the doctor consultation resulted in a specialist referral. Due to differences across regions, this outcome is defined only for patients in Stockholm.
Patient satisfaction score	This variable denotes the patient's score of the consultation on a 1-5 scale based on a voluntary post-consultation patient survey. The best score is 5.
Any avoidable hospitalization within 30 days	An indicator that the patient had an inpatient hospitalization within 30 days of the doctor's consultation (possibly on the same day as the consultation) where the hospital-set ICD-10 code is from a list of ICD-10 codes known to have been preventable in primary care (see Appendix Section C.6.3).
Any hospitalization within 30 days	An indicator that the patient had an inpatient hospitalization within 30 days of the doctor's consultation (possibly the same day as the consultation.
Any emergency department visit within 30 days	An indicator that the patient had an outpatient acute care visit within 30 days of the doctor's consultation (possibly on the same day as the consultation). Our ED definition includes hospital associated EDs, specialty emergency clinics (e.g., psychiatric clinics), as well as minor injury emergency clinics. About 70% of the EDs in our sample are hospital associated.
New visit to primary care provider within 30 days	An indicator that the patient had a second visit to the primary care provider within 30 days of the doctor's consultation. A new visit is a new meeting or consultation with a nurse or doctor. We have excluded visits with psychologists and visits in which the patient and clinician may have not interacted, e.g., visits labelled "tests ordered" and "prescription renewals".

Table A2. Variable Descriptions (Continued)

Outcome Variables	Description
Patient answered that online consultation is a replacement for an in-person one	This variable denotes the patient's response to a post-online consultation survey asking the patients whether the online consultation replaced an in-person consultation (see e.g., Table 7). Positive responses are coded as 1,"Don't know" responses as 0.5, and negative responses as 0.
Patient answered satisfaction score	An indicator that the patient gave a response to a post-online consultation survey asking the patients whether the online consultation replaced an in-person consultation. See e.g., Appendix Table A8 for the probability that patients answered the satisfaction survey.
Doctor booked a revisit within 30 days	An indicator for a (matched) primary care follow-up consultation with the provider booked by the clinician within 30 days. Revisits can be limited to only in-person or only online revisits. See Appendix Section C.2 for details on the matching.
Patient initiated follow-up visit which took place within 30 days	An indicator that the patient, rather than a clinician, initiated the primary care follow-up visit with the provider.
Shift (including all breaks)	This variable denotes doctor online or in-person shifts in hours. Start of a shift is the start of the first consultation and end of shift is the end time of the last consultation. All breaks are included. Consultations that extended beyond than midnight are removed. See Appendix Section C.3.2 for details on the definitions of shifts.
Shift (excluding all breaks)	This variable denotes doctor online or in-person shifts in hours. Start of a shift is the start of the first consultation and end of shift is the end time of the last consultation. All breaks are removed. Consultations that extended beyond than midnight are removed. See Appendix Section C.3.2 for details on the definitions of shifts.

Table A2. Variable Descriptions (Continued)

Control variables	Description
Fixed effects	
Time of day indicators, 4h blocks	Indicators for four-hour time windows: 12am-4am; 4-8am; 8am-12pm; 12pm-4pm; 4pm-8pm; 8pm-12am during which the nurse meeting was held.
Day of the week indicators	Indicators for the days of the week (e.g., Monday, Tuesday) during which the nurse meeting was held.
Provider center indicators	Indicators for each of the four provider centers and non-registered patients.
Year×month indicators	Indicators for particular months, e.g., September 2019 during which the nurse meeting was held.
Demographics	
Patient female indicator	An indicator for the gender of the patient. Female patients are denoted by 1, male patients by 0.
Patient age	This variable denotes the age of the patient in 2018. An interaction of age is additionally included in the controls.
Born outside Sweden indicator	An indicator for whether the patient is a first-generation immigrant, that is, the patient was born outside of Sweden.
Second-generation immigrant indicator	An indicator for whether the patient is a second-generation immigrant born in Sweden, whose both parents were born outside Sweden.
Born outside EU15 and Scandinavia indicator	An indicator for whether the patient was born outside the EU15 countries and Scandinavia. EU15 refers to the time when the EU had only 15 members. See also Appendix Section C.1.2.
Patient married and patient divorced indicators	Indicators for civil status of the patient in 2018 and if the patient is eligible to marry or divorce in 2018. Married or divorced is denoted by 1, not married or divorced by 0. Patients strictly below 18 are not eligible to be married or divorced. See also Appendix Section C.1.2.
Work status indicators	Indicators for active work status in 2018 and if the patient is of working age. Patients strictly younger than 16 and strictly older than 74 are not considered of working age. See also Appendix Section C.1.2.
Patient comorbidity control	
Any comorbidity indicator	An indicator for whether the patient had any comorbidity from 2013-2018 in our specialist (inpatient and outpatient) data, based on the Elixhauser comorbidity index (see Appendix Section C.6.1).
Nurse-set ICD group control	
Nurse-set ICD group	This categorical variable uses the letter level disease group category of the ICD-10 code set by the nurse who redirected the patient to the doctor consultation in the doctor sample. ICD-10 code letters that occurred less than 30 times are included in category "Other."

Table A2. Variable Descriptions (Continued)

Variables	Description
Annual income	This variable denotes the total individual annual income in 2018 for patients age 21 and above. See also Appendix Section C.1.2.
Education	This variable is based on the education the patient had in 2018. It is presented in two formats, either as an indicator or as a factor variable. The indicator "University educated" is defined only for patients age 23 and above to ensure they have had the time to complete their education (e.g., in Appendix Table A6). The factor variable includes "In education" defined for individuals strictly below age 16, and other education categories for individuals age 16 and above (e.g., in Table 7). See also Appendix Section C.1.2.
Nurse "mistake" share	This variable focuses on the patients that the nurse did not direct to a doctor consultation. The mistake share is the fraction of those non-directed patients who visited an ED or were hospitalized within 10 days of the nurse meeting.
Other physical health issue indicator	An indicator for whether the provider's algorithm has labeled the patient as needing in-person care. The algorithm based this label on the patient's self-reported symptom, which the patient should provide as a first step when seeking care via the provider's mobile app.
Low COVID-19 spread indicator	An indicator for low COVID-19 spread, which is the case for consultations before March 11, 2020 and between July 6, 2020 until October 24, 2020.

Table A3. First Stage

	Consultation was online			
	(1)	(2)	(3)	(4)
Nurse propensity to online π_i	0.78	0.70	0.69	0.66
	(0.055)	(0.058)	(0.059)	(0.058)
	[0.053]	[0.057]	[0.056]	[0.055]
Fixed effects		✓	✓	✓
Demographics			✓	✓
Any comorbidity			✓	✓
Nurse-set ICD group				✓
Observations	4,664	4,664	4,528	4,515
K-P F-statistic	198	145	138	133
Clustered K-P F-statistic	214	153	150	147
Baseline mean	0.43	0.43	0.43	0.43

Notes: This table reports coefficients from regressions using the doctor sample. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). The F-statistic refers to the Kleibergen-Paap F-statistic. The baseline mean is the mean of the dependent variable for in-person doctor consultations. Robust standard errors are in parentheses, and standard errors clustered by nurse are in brackets.

Table A4. Instrument Independence

A: Balance of instrument, π_i, on patient characteristics (nurse sample)

Joint test on:						
Demographics	✓	✓	✓	✓	✓	✓
Any comorbidity			✓	✓	✓	✓
Nurse-set ICD group					✓	✓
Conditional on fixed effects		Yes		Yes		Yes
Joint test p-value	0.52	0.88	0.54	0.88	0.40	0.92
Observations	8,634	8,634	8,634	8,634	8,604	8,604

B: Balance of propensity to direct online, π_j, on nurse propensity to direct to any doctor

Propensity to direct to doctor	0.18	0.080
	(0.22)	(0.18)
Weighted by num. meetings:	Directed	Total
Observations	62	62
Baseline mean	0.43	0.43

C: Balance of instrument, π_i, on patient characteristics (doctor sample)

Joint test on:						
Demographics	✓	✓	✓	✓	✓	✓
Any comorbidity			✓	✓	✓	✓
Nurse-set ICD group					✓	✓
Conditional on fixed effects		Yes		Yes		Yes
Joint test p-value	0.39	0.51	0.46	0.56	0.16	0.36
Observations	4,528	4,528	4,528	4,528	4,515	4,515

Notes: Panels A and C show instrument balance tests using the nurse sample and the doctor sample. Joint tests and their p-values are reported in both panels and always exclude fixed effects. In Panel B, we collapse the nurse sample to the nurse level. The estimates in the panel show the correlation between the nurse propensity to direct patients to online doctor consultations, π_j, with the propensity to direct to any doctor (in-person or online). We present two different weighting schemes in Panel B given our sample restrictions: (1) the total number of patients a nurse has directed to a doctor (Directed), and (2) the total number of meetings held by a nurse (Total). The baseline mean is the mean of the dependent variable for in-person doctor consultations. Robust standard errors are in parentheses.

Table A5. Average Exclusion

A: Tasks that doctors and nurses are allowed to perform

	Doctors	Nurses
Prescribe medications	✓	
Refer to (external) specialist	✓	
Write sick notes for patients	✓	
Advise patients on self-care	✓	✓

B: Nurse meetings are short (and shorter than doctor consultations)

	Mean	Quartiles Q_{25}	Q_{50}	Q_{75}	Count
Nurse patient-facing time	4.7	2.5	4	6.1	4,267
Doctor patient-facing time	20.0	4.2	12.6	30.1	4,267

Notes: In Panel A we outline tasks that doctors and nurses are allowed to perform when seeing patients. In Panel B we show the difference in the meeting duration between doctor consultations and nurse meetings (in minutes) in the doctor sample.

Table A6. Average Monotonicity

	Patient female	Patient male	Patient age > median	Patient age ≤ median
Propensity for online	0.73	0.67	0.67	0.72
	(0.085)	(0.081)	(0.083)	(0.082)
Fixed effects	✓	✓	✓	✓
Observations	2,299	2,365	2,246	2,418
First-stage K-P F-statistic	74	68	67	77
Baseline mean	0.45	0.40	0.42	0.43
	University educated	Not university educated	Annual income > median	Annual income ≤ median
Propensity for online	0.72	0.66	0.80	0.58
	(0.090)	(0.11)	(0.089)	(0.094)
Fixed effects	✓	✓	✓	✓
Observations	1,975	1,421	1,879	1,880
First-stage K-P F-statistic	63	39	82	37
Baseline mean	0.39	0.45	0.40	0.43
	Born outside EU15 and Scandinavia	All other	Any comorbidity	No comorbidities
Propensity for online	0.76	0.69	0.85	0.67
	(0.12)	(0.068)	(0.14)	(0.064)
Fixed effects	✓	✓	✓	✓
Observations	1,140	3,523	850	3,814
First-stage K-P F-statistic	43	103	37	109
Baseline mean	0.41	0.43	0.46	0.42
	Other physical health issue	No other physical health issue	Low COVID-19 spread	All other
Propensity for online	0.80	0.65	0.67	0.72
	(0.10)	(0.070)	(0.10)	(0.071)
Fixed effects	✓	✓	✓	✓
Observations	1,408	3,256	2,298	2,366
First-stage K-P F-statistic	61	85	43	103
Baseline mean	0.42	0.43	0.41	0.45

Notes: This table reports the first stage of the IV in different sub-samples of the doctor sample. The median age in the sample is 33, while the median annual income is 309,800 SEK restricted to patients strictly above age 20. We restrict university education to patients above or equal to 23 years old. For a description of all variables, please see the main text and appendix (in particular Appendix Table A2). The baseline mean is the mean of the dependent variable for in-person doctor consultations. The First-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table A7. Nurse Mistake Share Uncorrelated With Instrument

Nurse "mistake" share	-0.27	-0.31
	(0.58)	(0.49)
Weighted by num. meetings:	Directed	Total
Observations	62	62
Baseline mean	0.43	0.43

Notes: In this table we have collapsed the nurse sample to the nurse level. We show the correlations between the nurse propensity to direct patients to online doctor consultations, π_j, with the nurse "mistake" shares using two different weighting schemes. The nurse "mistake" share focuses on the patients that the nurse did not direct to a doctor consultation. The "mistake" share is the fraction of those non-directed patients who visited an ED or were hospitalised within 10 days of the nurse meeting. The two different weighting schemes are: (1) the total number of patients a nurse has directed to a doctor (Directed), and (2) the total number of meetings held by the nurse (Total). The baseline mean is the mean of the dependent variable, π_j. Robust standard errors are in parentheses.

Table A8. Probability of Patient Answering the Satisfaction Survey

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Consultation was online	0.21	0.21	0.22	0.21	0.16	0.20	0.23	0.23
	(0.014)	(0.014)	(0.014)	(0.015)	(0.073)	(0.084)	(0.086)	(0.089)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,664	4,664	4,528	4,515	4,664	4,664	4,528	4,515
First-stage K-P F-statistic					198	145	138	133
Baseline mean	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2

Notes: This table presents the estimated probability that the patient answers the satisfaction survey in the doctor sample. The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table A9. Online's Effect on Patient Outcomes Within 30 Days After the Nurse Meeting

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Any avoidable hospitalization within 30 days (after the nurse meeting)								
Consultation was online	-0.000091	-0.00014	-0.00016	-0.00027	0.0021	0.0019	0.0016	0.0020
	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.0035)	(0.0052)	(0.0056)	(0.0052)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,050	4,050	3,939	3,926	4,050	4,050	3,939	3,926
First-stage K-P F-statistic					147	104	97	91
Baseline mean	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
B: Any hospitalization within 30 days (after the nurse meeting)								
Consultation was online	0.0026	0.0024	0.0026	0.0023	0.032	0.034	0.037	0.039
	(0.0031)	(0.0030)	(0.0032)	(0.0033)	(0.018)	(0.021)	(0.022)	(0.023)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,050	4,050	3,939	3,926	4,050	4,050	3,939	3,926
First-stage K-P F-statistic					147	104	97	91
Baseline mean	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
C: Any emergency department visit within 30 days (after the nurse meeting)								
Consultation was online	0.013	0.0095	0.011	0.013	0.12	0.11	0.12	0.13
	(0.0070)	(0.0071)	(0.0073)	(0.0078)	(0.044)	(0.053)	(0.056)	(0.058)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,050	4,050	3,939	3,926	4,050	4,050	3,939	3,926
First-stage K-P F-statistic					147	104	97	91
Baseline mean	0.044	0.044	0.044	0.044	0.044	0.044	0.044	0.044
D: New visit to primary care provider within 30 days (after the nurse meeting)								
Consultation was online	0.096	0.10	0.10	0.11	0.17	0.25	0.29	0.31
	(0.016)	(0.016)	(0.016)	(0.017)	(0.090)	(0.11)	(0.11)	(0.11)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,050	4,050	3,939	3,926	4,050	4,050	3,939	3,926
First-stage K-P F-statistic					147	104	97	91
Baseline mean	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36

Notes: This table reports coefficients from regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table A10. Online's Effect on Primary Care Use Within 30 Days of the Doctor Consultation

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Doctor booked a revisit within 30 days								
Consultation was online	0.10	0.10	0.10	0.11	0.17	0.22	0.23	0.24
	(0.012)	(0.012)	(0.013)	(0.013)	(0.069)	(0.082)	(0.084)	(0.088)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11
B: Doctor booked an in-person revisit within 30 days								
Consultation was online	0.098	0.099	0.10	0.11	0.20	0.25	0.25	0.26
	(0.010)	(0.011)	(0.011)	(0.012)	(0.063)	(0.075)	(0.076)	(0.079)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
C: Doctor booked an online revisit within 30 days								
Consultation was online	0.0040	0.0025	0.00097	-0.0013	-0.031	-0.023	-0.016	-0.016
	(0.0065)	(0.0066)	(0.0068)	(0.0069)	(0.034)	(0.041)	(0.043)	(0.045)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
D: Patient initiated follow-up visit which took place within 30 days								
Consultation was online	0.024	0.031	0.033	0.038	0.030	0.079	0.11	0.12
	(0.014)	(0.015)	(0.015)	(0.016)	(0.079)	(0.094)	(0.098)	(0.10)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27

Notes: This table reports coefficients from regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). Panels A, B, and C show estimates on whether the doctor booked a second consultation for the patient within 30 days, which we determine by matching the doctor consultation with the revisit. Panel D shows estimates on whether the patient contacted the primary care provider to book another meeting within 30 days. The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table A11. Online's Effect on Medium-Term Outcomes

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Any avoidable hospitalization more than 30 days after the doctor consultation								
Consultation was online	-0.00027	-0.00030	-0.00019	-0.00015	-0.0026	-0.0021	-0.0026	-0.0019
	(0.00085)	(0.00087)	(0.00089)	(0.0010)	(0.0041)	(0.0053)	(0.0057)	(0.0056)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Mean days observed	111	111	111	111	111	111	111	111
B: Any hospitalization more than 30 days after the doctor consultation								
Consultation was online	0.0022	-0.00030	-0.00053	-0.0025	0.029	-0.0055	-0.0032	-0.0068
	(0.0041)	(0.0042)	(0.0044)	(0.0044)	(0.028)	(0.035)	(0.036)	(0.038)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
Mean days observed	111	111	111	111	111	111	111	111
C: Any emergency department visit more than 30 days after the doctor consultation								
Consultation was online	0.013	0.0067	0.010	0.0087	0.13	0.055	0.085	0.088
	(0.0073)	(0.0074)	(0.0076)	(0.0079)	(0.046)	(0.053)	(0.055)	(0.058)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.048	0.048	0.046	0.046	0.048	0.048	0.046	0.046
Mean days observed	111	111	111	111	111	111	111	111
D: New visit to primary care provider more than 30 days after the doctor consultation								
Consultation was online	-0.020	-0.035	-0.033	-0.030	0.23	0.010	0.054	0.058
	(0.016)	(0.015)	(0.015)	(0.016)	(0.091)	(0.096)	(0.098)	(0.10)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	4,004	4,004	3,893	3,880	4,004	4,004	3,893	3,880
First-stage K-P F-statistic					148	102	95	89
Baseline mean	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Mean days observed	111	111	111	111	111	111	111	111

Notes: This table reports coefficients from regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). Note that the outcomes in all panels indicate events events occurring at least a month after the consultation (see Table 3). The longest duration patients can be observed after 30 days from the doctor consultation is about one year and one month. The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table A12. Sources for Provider Cost

	Provider cost estimates	How cost is calculated	Year	Source
PCP online	500 SEK	Out-of-region compensation for digital care services	2019/2020	Vård- och omsorgsanalys (2022)
PCP in person	(1,838+2,166)*0.5 = 2,002 SEK	Average cost of 2019/2020 (National estimates)	2019/2020	Vård- och omsorgsanalys (2022)
ED visit	(3,963+4,020)*0.5 = 3,991.5 SEK	Average cost of 2019/2020 (Southern Sweden)	2019/2020	Södra Regionsvårdsnämnden (2020)

Notes: This table reports provider costs for 2019 and 2020 and adds background information to the cost table (Table 6). The PCP online provider costs were extracted from reports for 2019 by Vård- och omsorgsanalys (2022, p. 127) and for 2020 by Södra Regionsvårdsnämnden (2020, p. 91). The PCP in-person provider costs can be found in the same report for 2019 (Vård- och omsorgsanalys 2022, p. 201) and for 2020 (Vård- och omsorgsanalys 2022, p. 202), which together make up the average PCP in-person cost. The in-person PCP provider costs must be estimated as there are no fixed total fees and reimbursement is based on a mix of capitation and some service fee. The ED provider costs are based on southern Sweden for 2019 (Södra Regionsvårdsnämnden 2019, p. 47) and for 2020 (Södra Regionsvårdsnämnden 2020, p. 47), which also together make up the average ED cost. See Appendix Section C.4 for more information and sources regarding the cost table.

Table A13. Patient Representativeness of the Swedish Population

	(1) Doctor sample mean	(2) Municipality mean	(3) National mean
Female	0.49	0.50	0.50
Age	35.0	39.3	41.3
University educated	0.58	0.49	0.39
Married	0.30	0.40	0.42
First- or second-generation immigrant	0.39	0.35	0.26
Big city municipality	0.85	0.85	0.32
Annual income (in thsnd. SEK)	340.2	353.7	328.9

Notes: This table compares patients in the doctor sample (N=4,664) to the Swedish population. Column (1) reports unweighted means of our sample in 2019. The means in Column (2) take municipality-level means in 2019 and average them using the share of each of the 96 municipalities in the Doctor sample as weights. The means in Column (3) are the means for Sweden in 2019. "University educated" is reported for people aged 23 and above, "Married" is reported for people aged 18 and above, and "First- or second-generation immigrant" is an indicator for individuals who were either born outside Sweden or whose parents were both born outside Sweden. "Big city municipality" is an indicator for municipalities with big cities, including Stockholm and Lund. "Annual income" includes annual earnings from wages and self-employment in thousands of SEK and is reported for individuals strictly over age 20. More information can be found in Section C.5.

Table A14. Comparison of Doctor Sample Patients to Those in a Wider Sample of PCP Consultations

	(1) Doctor sample	(2) Scania sample
Demographics		
Patient female	0.49	0.59
Patient age	33.0	49.2
ICD codes		
Infectious	0.023	0.035
Endocrine, nutritional, metabolic	0.0084	0.050
Mental and behavioural	0.021	0.083
Nervous system	0.0080	0.020
Eye and adnexa	0.0090	0.016
Ear and mastoid process	0.072	0.050
Circulatory system	0.025	0.082
Respiratory system	0.029	0.10
Digestive system	0.025	0.037
Skin and subcutaneous tissue	0.035	0.056
Musculoskeletal, connective	0.19	0.11
Genitourinary system	0.049	0.057
Symptoms (cough, rash, etc.)	0.37	0.18
Injury or poisoning	0.042	0.047
Health status factors	0.091	0.054
Other	0.0069	0.028
Observations	4,664	1,603,592

Notes: This table presents summary statistics for doctor consultations from the Scania sample in 2019 and the doctor sample. The Scania sample consists of all PCP visits in Scania, a region in southern Sweden where 13% of the Swedish population lives. The ICD codes are based on letter-level codes and we use the same letter groupings from the nurse-set ICD group controls for the doctor sample. For the Scania sample, we also use the same letter groupings, but base it on the doctor consultation as opposed to the nurse meeting. The variables report patient age based on 2018 for the doctor sample and 2019 for the Scania sample. More information on the Scania sample can be found in Appendix Section C.3.

Table A15. IV Complier Characteristics

	(1) Sample mean	(2) Complier mean
Demographics		
Patient female	0.49	0.47
Patient age	33.0	30.9
Born outside EU15 and Scandi.	0.24	0.26
Patient married	0.27	0.14
Patient divorced	0.10	0.085
Patient ineligible to marry	0.090	0.12
Patient working	0.72	0.70
Patient not of working age	0.058	0.045
Comorbidity control		
Any comorbidity	0.18	0.19
Nurse-set ICD group		
Infectious	0.023	0.0069
Endocrine, nutrit., metabolic	0.0084	-0.000092
Mental and behavioural	0.021	0.028
Nervous system	0.0080	0.017
Eye and adnexa	0.0090	0.0086
Ear and mastoid process	0.072	0.023
Circulatory system	0.025	0.011
Respiratory system	0.029	-0.0065
Digestive system	0.025	0.025
Skin and subcutaneous tissue	0.035	0.057
Musculoskeletal, connective	0.19	0.071
Genitourinary system	0.049	0.030
Symptoms (cough, rash, etc.)	0.37	0.50
Injury or poisoning	0.042	0.037
Health status factors	0.091	0.18
Other	0.0069	0.0074
Other variables		
Other physical health issue	0.30	0.37
University educated	0.58	0.67
Annual income (in thsnd. SEK)	328.4	404.0

Notes: This table characterizes the complier population in the doctor sample (N=4,664). We follow the procedure described in Frandsen et al. (2023) and present in Column (2)—for some pre-determined characteristic X_i—the estimate of $\frac{E[\omega_i X_i]}{E[\omega_i]}$, where ω_i is the weight given to case i by the IV. Column (1) shows the mean of X_i in our sample for comparison. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2).

Table A16. Comparison of Patients Directed to Online Consultations (in Doctor Sample) to Sample of Registered Patients Who Consulted Online Doctors Without First Meeting Nurses

	OLS				
	(1)	(2)	(3)	(4)	(5)
A: Doctor booked an in-person revisit within 30 days					
Consultation is in online doctor sample	0.083	0.16	0.15	0.19	0.14
	(0.0093)	(0.016)	(0.015)	(0.033)	(0.019)
Fixed effects		✓	✓	✓	✓
Demographics			✓	✓	✓
Any comorbidity			✓	✓	✓
ICD code				✓	
Symptom ID					✓
Observations	22,096	22,096	21,538	21,458	21,289
Dependent variable mean	0.089	0.089	0.088	0.088	0.088
B: Any emergency department visit within 30 days					
Consultation is in online doctor sample	0.0069	0.026	0.026	0.039	0.019
	(0.0058)	(0.016)	(0.016)	(0.024)	(0.018)
Fixed effects		✓	✓	✓	✓
Demographics			✓	✓	✓
Any comorbidity			✓	✓	✓
ICD code				✓	
Symptom ID					✓
Observations	22,100	22,100	21,542	21,462	21,293
Dependent variable mean	0.050	0.050	0.051	0.051	0.051
C: Any hospitalization within 30 days					
Consultation is in online doctor sample	-0.000051	-0.0042	-0.0046	-0.0074	-0.0071
	(0.0026)	(0.0093)	(0.0095)	(0.012)	(0.010)
Fixed effects		✓	✓	✓	✓
Demographics			✓	✓	✓
Any comorbidity			✓	✓	✓
ICD code				✓	
Symptom ID					✓
Observations	22,100	22,100	21,542	21,462	21,293
Dependent variable mean	0.011	0.011	0.011	0.011	0.011

Notes: This table shows descriptive OLS regressions based on the doctor sample (limited to online consultations) merged with drop-in consultations limited to the same restrictions as described for the doctor sample. We compare the nurse-directed online doctor patients to patients who went straight to online doctors. The controls for the online doctor sample are based on the nurse meeting and on the doctor consultation for the drop-in patients. Fixed effects include year×month, four-hour blocks, day of the week, and the clinic where the patient was registered. Demographics include age, immigrant background, civil status, and work status. The ICD-10 code for the online drop-in sample is based on the nurse meeting, while the ICD-10 code for the drop-in consultations builds on the doctor consultation. Robust standard errors are in parentheses.

Table A17. Test of Strict Monotonicity and Strict Exclusion for Different Outcomes

Outcomes	From	Strict monotonicity/exclusion conditional on: (1) Fixed effects	(2) Full set of controls	Only average monotonicity/exclusion
Total consultation duration	Table 2, B	✓	✓	
Doctor set an informative diagnosis	Table 3, A			✓
Patient received a prescription	Table 3, B			✓
Any hospitalization within 30 days	Table 4, B	✓	✓	
Any Emergency Department visit within 30 days	Table 4, C			✓
New visit to primary care provider within 30 days	Table 4, D	✓	✓	
Doctor books an in-person revisit within 30 days	Table A10, B			✓

Notes: This table shows results from the semi-parametric test for strict monotonicity and exclusion proposed by Frandsen et al. (2023). Our main analysis is based on the assumptions of average monotonicity and exclusion, which we have separately argued for. These results complement that analysis by for which outcomes stronger assumptions than what we require may apply. Because the test is defined in relation to an outcome, we present the results in relation to some of our primary outcomes. Column (1) shows whether the test fails to reject strict monotonicity/exclusion at the 95% level, conditional on our fixed effects. Column (2) shows whether the test fails to reject strict monotonicity/exclusion at the 95% level, conditional on our complete set of controls, which includes our standard set of fixed effects, demographic controls, a comorbidity indicator, and nurse-set ICD groups. Column (3) indicates whether average monotonicity and exclusion are the only valid assumptions. The test consists of two components: (1) whether the nurse assignment has significant explanatory power and (2) whether the implied treatment outcomes are unreasonably large. The test is implemented through the Stata package *testjfe*. In our implementation, we choose the parametric form through cross-validation (implemented in the package) and specify that the test's two components are given equal weight. Note that the instrument tested through this test differs slightly from the one we use in our analysis. We use an unconditional leave-one-out nurse propensity estimate, whereas the package estimates the propensity without leave-one-out and conditional on the specified controls. Finally, according to testing by Frandsen et al. (2023), our sample size—and in particular the number of observed cases per nurse—is on the lower limit for the test to perform accurately.

Table A18. Outcomes for More Vulnerable Patients (With at Least One ED or Hospital Visit from Three Years to 30 Days Prior to Nurse Visit)

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Patient-facing part of the consultation (in minutes)								
Consultation was online	-27.4	-26.9	-27.0	-27.3	-21.8	-21.2	-21.6	-21.6
	(0.70)	(0.71)	(0.73)	(0.76)	(3.70)	(4.26)	(4.34)	(4.69)
Observations	1,844	1,844	1,826	1,820	1,844	1,844	1,826	1,820
First-stage K-P F-statistic					70	47	45	40
Baseline mean	19.65	19.65	19.70	19.74	19.65	19.65	19.70	19.74
B: Any emergency department visit within 30 days								
Consultation was online	0.026	0.025	0.025	0.031	0.23	0.22	0.25	0.28
	(0.012)	(0.013)	(0.013)	(0.014)	(0.092)	(0.11)	(0.12)	(0.13)
Observations	1,671	1,671	1,659	1,653	1,671	1,671	1,659	1,653
First-stage K-P F-statistic					47	32	32	25
Baseline mean	0.063	0.063	0.064	0.064	0.063	0.063	0.064	0.064
C: New visit to primary care provider within 30 days								
Consultation was online	0.027	0.037	0.045	0.047	0.26	0.40	0.41	0.44
	(0.024)	(0.025)	(0.025)	(0.026)	(0.17)	(0.20)	(0.20)	(0.22)
Observations	1,671	1,671	1,659	1,653	1,671	1,671	1,659	1,653
First-stage K-P F-statistic					47	32	32	25
Baseline mean	0.44	0.44	0.45	0.44	0.44	0.44	0.45	0.44
D: Doctor booked an in-person revisit within 30 days								
Consultation was online	0.080	0.083	0.093	0.10	0.33	0.41	0.41	0.46
	(0.016)	(0.017)	(0.017)	(0.018)	(0.11)	(0.14)	(0.14)	(0.15)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	1,671	1,671	1,659	1,653	1,671	1,671	1,659	1,653
First-stage K-P F-statistic					47	32	32	25
Baseline mean	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11

Notes: This table reports coefficients from regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). The sample is restricted to patients who had any ED or hospital visit three years before the nurse meeting, excluding 30 days prior (43% of doctor sample). The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table A19. Outcomes for Less Vulnerable Patients (With no ED and no Hospital Visit from Three Years to 30 Days Prior to Nurse Visit)

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A: Patient-facing part of the consultation (in minutes)								
Consultation was online	-26.4	-26.5	-26.6	-26.8	-23.1	-24.6	-24.1	-24.2
	(0.57)	(0.57)	(0.59)	(0.62)	(2.66)	(2.96)	(3.02)	(3.05)
Observations	2,499	2,499	2,394	2,388	2,499	2,499	2,394	2,388
First-stage K-P F-statistic					132	100	94	98
Baseline mean	20.41	20.41	20.24	20.26	20.41	20.41	20.24	20.26
B: Any emergency department visit within 30 days								
Consultation was online	0.0077	0.0045	0.0065	0.0044	0.058	0.062	0.065	0.066
	(0.0080)	(0.0081)	(0.0085)	(0.0090)	(0.047)	(0.056)	(0.060)	(0.059)
Observations	2,333	2,333	2,234	2,227	2,333	2,333	2,234	2,227
First-stage K-P F-statistic					103	70	65	66
Baseline mean	0.036	0.036	0.036	0.036	0.036	0.036	0.036	0.036
C: New visit to primary care provider within 30 days								
Consultation was online	0.12	0.12	0.13	0.14	0.063	0.12	0.16	0.18
	(0.021)	(0.021)	(0.021)	(0.023)	(0.11)	(0.12)	(0.13)	(0.13)
Observations	2,333	2,333	2,234	2,227	2,333	2,333	2,234	2,227
First-stage K-P F-statistic					103	70	65	66
Baseline mean	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
D: Doctor booked an in-person revisit within 30 days								
Consultation was online	0.11	0.11	0.11	0.12	0.13	0.17	0.15	0.15
	(0.014)	(0.014)	(0.015)	(0.017)	(0.078)	(0.091)	(0.094)	(0.095)
Fixed effects		✓	✓	✓		✓	✓	✓
Demographics			✓	✓			✓	✓
Any comorbidity			✓	✓			✓	✓
Nurse-set ICD group				✓				✓
Observations	2,333	2,333	2,234	2,227	2,333	2,333	2,234	2,227
First-stage K-P F-statistic					103	70	65	66
Baseline mean	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11

Notes: This table reports coefficients from regressions using the doctor sample (see the main text for a discussion). The instrument in the IV specifications is the leave-one-out propensity to direct patients to online consultations, π_i. For a description of the variables, please see the main text and appendix (in particular Appendix Table A2). The sample is restricted to patients who had no ED or hospital visit three years before the nurse meeting, excluding 30 days prior (57% of doctor sample). The baseline mean is the mean of the dependent variable for in-person doctor consultations. The first-stage K-P F-statistic refers to the Kleibergen-Paap F-statistic, and robust standard errors are in parentheses.

Table A20. Breakdown of Costs for Providers and Patients by Patient Vulnerability

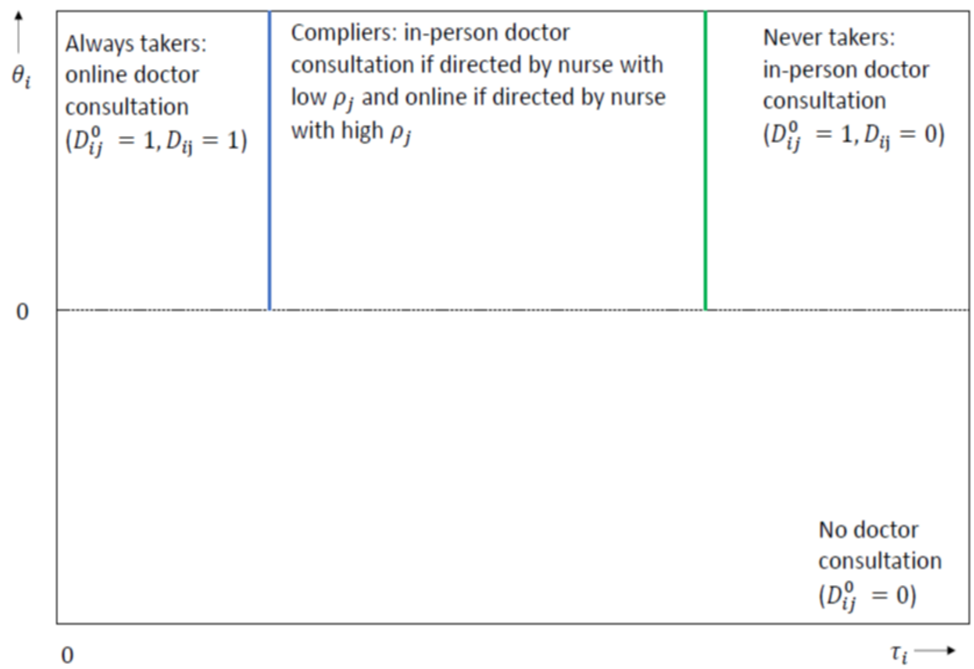
	Costs (SEK)					
	Full sample costs		More vulnerable patient costs		Less vulnerable patient costs	
A. Provider cost	In-person	Online	In-person	Online	In-person	Online
Cost of doctor consultation without in-person follow-up	2,002	500	2,002	500	2,002	500
Expected follow-up cost of in-person primary care	140	661	220	1,141	220	521
Expected follow-up cost of in-person ED	164	683	255	1,373	144	407
Total provider cost including follow-ups	**2,306**	**1,844**	**2,477**	**3,014**	**2,366**	**1,428**
Cost savings from online relative to in person		20%		-22%		40%
	Costs (SEK)					
	Full sample costs		More vulnerable patient costs		Less vulnerable patient costs	
B. Patient cost	In-person	Online	In-person	Online	In-person	Online
Patient cost without in-person follow-up	**534**	**179**	**495**	**146**	**497**	**140**
Total patient cost including follow-ups	**650**	**691**	**678**	**1,112**	**633**	**489**
Cost savings from online relative to in person		-6.3%		-64%		23%

Notes: This table reports heterogeneous cost estimates in SEK (= 0.11 USD, average for 2020). The full sample costs are taken from Table 6. More vulnerable patients are defined as those who had an ED or hospitalization visit three years before the nurse meeting, excluding 30 days prior. Less vulnerable patients did not have any such ED or hospitalization visit prior to the nurse meeting. The cost estimates for more and less vulnerable patients are calculated the same way as for Table 6 but instead using probabilities from Appendix Table A18 for more vulnerable patients and from Appendix Table A19 for less vulnerable patients. More details on the cost calculations can be found in Appendix Section C.4.

B Appendix Figures

Figure A1. Patient Sorting in the Model

A. When the nurses perceive illness precisely ($Var\,(\eta_{ij}) = 0$)



B. When the nurses perceive illness imprecisely ($Var\,(\eta_{ij}) \neq 0$)

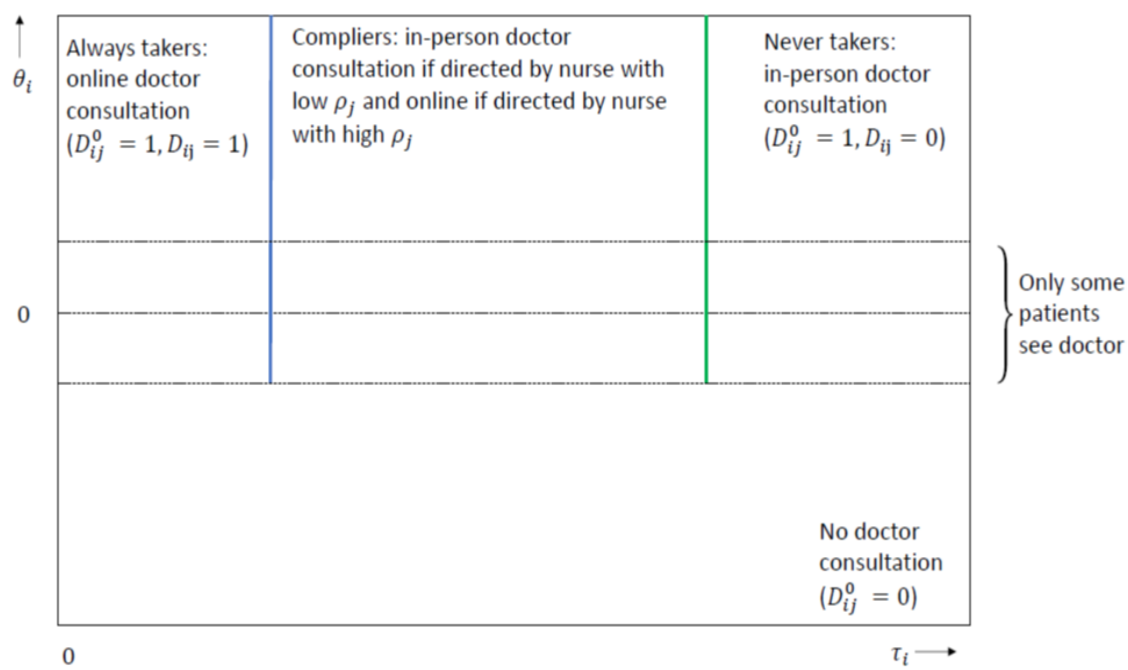
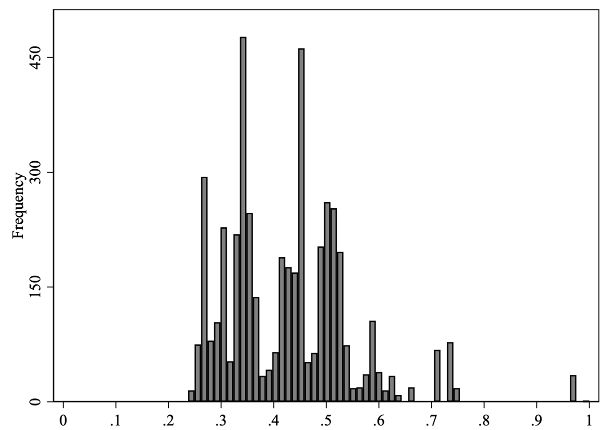
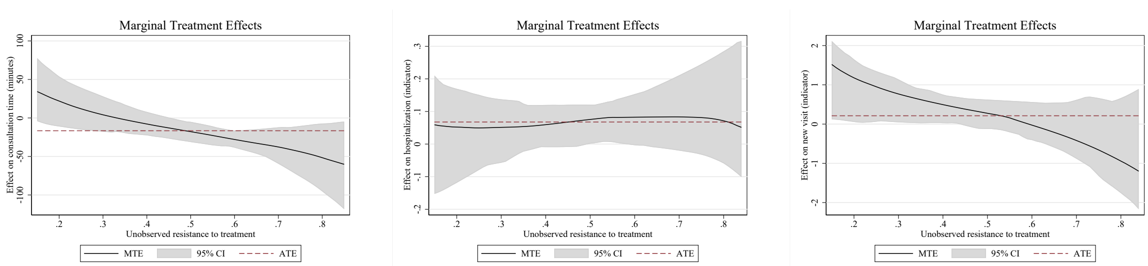


Figure A2. Distribution of the Instrument



Notes: This figure shows the distribution of the instrument π_i—the nurse's leave-one-out propensity to direct patients to online consultations—in the doctor sample.

Figure A3. Marginal Treatment Effects (MTEs)



A. MTE for total consultation duration

B. MTE for any hospitalization within 30 days

C. MTE for new visit to primary care provider within 30 days

Notes: These three figures present the MTE estimates for selected outcomes, which are chosen because the prerequisite assumptions cannot be rejected for them (see Appendix Table A17). The figures show the estimated MTEs along the interval defined by the range of the propensity score functions (one for the treated and one for the untreated subsample). For each outcome, joint tests reject the presence of significant heterogeneity in the MTE. The figures are produced through the *mtefe* Stata package. In our implementation, we have trimmed 0.5% of the treated and untreated subsamples with the sparsest support. In practice, this means removing some propensity scores close to 0 or 1 with limited common support. The standard errors are bootstrapped with 100 iterations.

C Data Appendix

C.1 Data Sources

Our analysis is primarily based on consultation-level data from the start of 2019 to the end of 2020 from a Swedish private primary healthcare provider to which we refer as "the firm" or "the provider". The firm offers in-person and online medical consultations to patients at the primary care level. For all patients, we obtain matched administrative individual-level panel data from Statistics Sweden's Integrated Database for Labour Market Research (LISA) from 2013 to 2020. Visit-level healthcare panel data for all specialist care between 2013 and 2020 come from Socialstyrelsen, and they include all inpatient and outpatient care (e.g., a hospital stay or a specialist visit but not primary care). Finally, prescription collection data from 2013 to 2020 are obtained from Socialstyrelsen as well. These data include picked-up prescriptions from all types of healthcare (i.e., inpatient, outpatient, and primary care).

All datasets are proprietary and confidential and were accessed after obtaining approval from the Stockholm Regional Ethics Council (2018, number 2108/2318-31) and the Swedish Ethics Authority (2019, number 2019-06062). Additionally, Statistics Sweden and Socialstyrelsen carried out their own confidentiality assessments before approving the sharing of data. Statistics Sweden matched all datasets, anonymized the personal identifiers, and then only shared an anonymized version of the data.

C.1.1 Primary Care Provider Data

The firm's above-mentioned data on individual consultations form the backbone of our analysis. The firm began operating in 2016 as an online healthcare provider, but since 2019, it has extended its offering to include in-person doctor consultations. These consultations were rolled out at different times for different locations, with services first offered in Lund (a city in the Scania region) and then expanded to different areas in and around Stockholm. In our analysis, we rely on the observed opening date, which is the date of the first logged in-person doctor consultation at the clinic. This allows us to focus on patients who are "at risk" of being directed to either in-person or online consultations.

For each patient meeting, we have data on the exact timing (up to the minute), the type of meeting (e.g., a nurse meeting or a doctor consultation), whether it was in person or online, and the patient fee. While any patient in the country can use the firm's online care, Swedish residents must register with a primary care provider to receive in-person primary care, which they can change at will without incurring a fee. These providers can be either public or private; private providers contract with the public health insurance, so patients pay the same for a given service irrespective of whether they use a public or private provider. We know which clinic each patient was registered with when they entered the database. Therefore, for patients registered with the firm, we have data on the location of their in-person consultations.

The database also includes information on the duration of each meeting, detailing both the patient-facing time spent by the clinician (whether a nurse or doctor) and the total duration of the consultation, where the latter also encompasses administrative work related to the consultation. We also have data on the provider's internal code for the symptom that the patient provides when initially seeking care through the provider's mobile app. This app is the primary channel for seeking care and the only one relevant to our study.

Finally, we also know the consultation "type"; this is an internal categorization of consultations depending on whom the patient met (e.g., "nurse meeting" or "psychology meeting"), whether it was booked ahead of time (e.g., "drop-in" or "doctor booked revisit"), or the purpose (e.g., "prescription renewal" or "test ordered"). We are primarily concerned with a sequence of consultations starting with a "nurse meeting" and resulting in a "doctor booked revisit" (booked by the nurse; see Appendix Section C.2 for more details).

For the consultation outcomes, we have data on the clinician's diagnosis and whether the patient received any prescription. The patient diagnosis is in the form of an ICD-10-SE code with four to five characters. Because we do not have data from the provider on what was prescribed, we use the prescription registry data from Socialstyrelsen. For the Stockholm-based clinics, we also have data on whether the doctor referred the patient to a specialist.

C.1.2 Demographic and Socioeconomic Data

To complement the primary care data, we use demographic and socioeconomic micro-data on patients from Statistics Sweden, drawn from the Integrated Database for Labour Market Research (LISA). This panel dataset provides information on individual annual income, educational attainment, municipality, immigration background, working status (working, some work, not working), and civil status (married, unmarried, divorced, widowed). The variables are provided at the patient-year level. Income is annual, education attainment is measured at the end of the year's spring semester, and immigration background is constant across years. The remaining data are measured at the end of the represented year (i.e., December 31st or January 1st the year after).

To ensure that all control variables are predetermined, we use the values representing 2018 for the demographic and socioeconomic controls employed throughout the paper. However, for individuals missing values for 2018, we use their values for 2017 instead (for education, we also infer from 2016). Additionally, when we compare the doctor sample in Appendix Table A13, we use the 2019 values for both our sample and the municipality and nationwide public data, which ensures that the values are comparable and reflect the time when the patients sought care (in 2019 or 2020).

Demographic controls in the main regressions include patient gender, patient age, indicators for migrant background, married and divorced dummies, working dummy, and indicators for being ineligible to be either married/divorced (below age 18) or working (below age 16 and above age 74). Table 1 provides summary statistics of these controls.

C.1.3 Specialist Care Data

Non-primary care data are obtained from Socialstyrelsen. Covering 2013–2020, these data are divided into inpatient and outpatient care. Inpatient care means that the patient is admitted to the hospital, i.e., hospitalized. Outpatient care includes ED visits and other non-primary care visits to clinics, e.g., planned specialist consultations.

The inpatient and outpatient datasets contain up to 30 ICD-10 diagnostic codes with a precision of three characters. They also include external cause codes for applicable cases, classifying events such as falls and bites. Both datasets provide the visit date and for inpatient visits also the discharge date. The outpatient data also include the exact admission, assessment, and discharge times for emergency visits.

C.1.4 Prescription Data

The prescription data, spanning 2013–2020, are obtained from Socialstyrelsen and include all prescriptions that patients collected during this period. Each collected prescription is recorded on a separate observation line, meaning that multiple observations may reflect a single pharmacy visit. Additionally, the dataset provides anonymized information about the prescribers. This includes codes for the prescribing clinic, the type of care from which the prescription was issued (e.g., psychiatric, primary care, or pediatric), and the specialization of the prescribing clinician.

C.2 Matching Nurse Meetings to Doctor Consultations

We do not have any variable from the firm to track directions to subsequent doctor visits. However, by using institutional knowledge, we can match meetings or consultations with follow-ups that are scheduled by the clinician (nurse or doctor).

We start by considering doctor consultations that were booked by a clinician, following a direction made during an initial (originating) meeting with a clinician at the firm (online or in person). This originating meeting can be of any type, e.g., nurse meeting, drop-in, or psychologist visit. When attempting to match to an originating meeting, we consider only meetings in the 30 days before the doctor consultation.

We use two strategies to find this initial meeting, where the first takes precedence over the second. In the first strategy, we match the doctor consultation with a preceding meeting that has the same "symptom" label specified by the patient when seeking care. This label usually follows the patient automatically in a care episode with multiple visits. The doctor handles the rebooking process, so the initial symptom that the patient originally specified usually remains the same. However, sometimes the symptom is relabeled in clinician-booked follow-ups as a "revisit" or "phone triage." In these cases, we use our second strategy where we allow the clinician-booked follow-up visit to match the closest preceding meeting with the firm in the preceding 30 days.

Our matching strategy allows for multiple potential matches. As mentioned, matches using the first strategy are always prioritized over those found using the second. But two other conflicts may arise. First, a doctor consultation may match with more than one potential originating meeting in the first strategy. To resolve this issue, we prioritize matches in which the window between the clinician-booked follow-up visit and the originating meeting is as short as possible. Second, two different doctor consultations may match with the same preceding meeting. In such cases, conflicts are resolved by prioritizing earlier clinician-booked follow-ups over later ones, which ensures that the matched meetings and consultations are arranged in a chronological sequence.

C.3 Defining Samples

C.3.1 The Doctor Sample and the Nurse Sample

Appendix Table A1 shows how our two primary samples are created. Our analysis focuses on patient cases from 2019-2020, starting with an online nurse meeting. As the first row of the table shows, there are 241,121 total cases. We define a "case" as an online meeting between patient i and nurse j and its resulting "treatment" (either an online or in-person doctor consultation or no consultation).

We exclude visits with the provider that do not fit the case definition described above, which primarily involve excluding drop-ins where patients are directly matched to doctors when seeking care. Visits are also excluded if the healthcare firm has categorized them as pertaining to a different care path. Specifically, these are visits to a psychologist; prescription renewal visits; visits where the patient was given an automatic recommendation by the system for a pediatrician or a doctor speaking some language, or for a revisit; consultations where the patient booked an appointment with a specific doctor of their choice; consultations where patients chose a specific appointment time instead of the next available; and visits for ordered tests.

The table also shows how we sequentially construct our main samples. We impose five conditions on the cases. The first three ensure the patient is always "at risk" of being directed to an in-person consultation. The first removes patients not registered with this firm as their primary care provider, since patients registered with other providers cannot access in-person care at the firm's clinics. We also remove cases with patients who are registered at a firm clinic when that clinic does not yet have any in-person consultations. The next two conditions exclude patients with a few specific symptoms (chlamydia, breastfeeding issues, and COVID-19) as well as infants (children strictly younger than two at the time of meeting the nurse). These patients follow care pathways that differ from those outlined in Figure 1. For chlamydia cases, patients were sent a home test, and in breastfeeding-related cases, patients were directed to a breastfeeding consultant rather than a doctor. COVID-19 cases were managed through pathways that changed over time, adapting to shifts in testing availability and changing guidelines during the pandemic. The final two conditions are imposed to limit our sample to cases where we have sufficient statistical power. We refer to the 8,907 resulting cases handled by 62 nurses as the "nurse meeting sample" in Figure 1 (or "nurse sample" in brief).

In the last row in Appendix Table A1, we impose a restriction that the case results in either an in-person or online doctor consultation to obtain our primary analysis sample. This leaves us with 4,664 cases, referred to as the "doctor consultation sample" in Figure 1 (or "doctor sample" in brief).

C.3.2 Doctor Shift Sample

To study doctors' productivity in consultations as we do in Table 5, we define a larger sample of doctor consultations for both unregistered and registered patients, either in person or online. Our motivation for creating this larger sample is that during a given shift, doctors work both with the patients in our smaller analysis sample and also (mostly) with patients outside of that sample. To study the doctors' productivity, we must consider all the patients they see. We exclude prescription renewals, which are almost all (over 99.9%) online. We also exclude the ordering of tests, since we have no record of their start or end time.

We also remove consultations without any duration time, consultations that end after midnight (since we use calendar days to define shift limits), and all consultations on the same day a doctor had both in-person and online consultations. In total, 13,909 consultations (1.1%) are removed. To avoid unrealistically short (or negative) durations, we winsorize the duration at the lower level based on the first percentile of the duration time (2.58 minutes). Ultimately, the "doctor shift sample" consists of 1,269,163 individual doctor consultations, which are then collapsed to the shift level per doctor and calendar day. There are 2,046 in-person doctor shifts and 76,367 online doctor shifts in our doctor shift sample based on 731 doctors.

The definition of a shift starts with the time of the first consultation and ends with the time of the last consultation within a calendar day. The times in between patient consultations are defined as breaks and are cleaned of noise to entail only positive values. Breaks longer than one hour make up 1.63% of the sample. It is unclear whether these intervals represent actual breaks, waiting times, or periods when the doctor is not working. The first consultation of the day lacks breaks since there is no preceding consultation. Given this limitation, we define two different shift variables that either include all inter-consultation times or excludes them. The shifts can be either fully online or fully in person.

The outcome variables in Table 5 are created at the shift level, meaning they are estimated per doctor and calendar day. After collapsing from the consultation to the shift level, the outcome variables have no missing values. In total, there are 2,046 in-person doctor shifts and 76,367 online doctor shifts in our doctor shift sample, of which 127 in-person shifts and 306 online shifts consist of only one consultation.

C.3.3 Scania Sample

We also have data on all PCP visits (not only within the firm but also for all primary care providers) in Scania, a region in southern Sweden where 13% of the country's population resides. These data cover the period from 2013-2019 and can be linked to the other data sources described in Appendix Section C.1. The demographic data (including age and civil status) from Appendix Section C.1.2 can only be obtained up until 2017. To restrict the analysis to PCP consultations, we drop meetings that are not with a doctor, are not in person (e.g., telephone calls), or are marked as acute.[34] To get as close as possible to the doctor sample restrictions (see Appendix Table A1), we also limit patients to be at least one year old or older. The resulting "Scania sample" is used in Appendix Table A14 to compare the representativeness of the doctor sample to a wider sample of PCP consultations with doctors. The ICD-10 codes in this sample are based on the PCP consultations with doctors, while the ICD-10 codes in the doctor sample are based on the initial nurse meetings.

C.4 Cost Calculations

There are two important costs to consider when looking at online healthcare—the cost to the health provider and the cost to the patient. Provider costs consist of costs to the insurer, in our case the public health insurance, as well as expenses that account for full healthcare costs, like a health maintenance organization or a provider paid by capitation (our provider is paid by capitation for registered patients). In Table 6, we attempt to approximate the costs of these actors to compare online and in-person doctor services. The cost estimates

[34] Only around 1% of the consultations in the Scania data are marked as acute.

are in Swedish krona (SEK); the average exchange rate in 2020 for SEK to USD is 1 SEK = 0.11 USD (Riksbank 2024).

The provider costs are based on the sources listed in Appendix Table A12. For the costs of online consultations, we use the public payers' recommended reimbursement for online doctor consultations in cases where the consultation was not under capitation. This was 500 SEK in 2019 (Vård- och omsorgsanalys 2022, p. 127) as well as in 2020 (Södra sjukvårdsregionen 2020, p. 91). The in-person provider costs must be estimated as there are no fixed total fees and reimbursement is through a mix of capitation and a service fee in some regions. The estimates for in-person provider costs for 2019 and for 2020 (Vård- och omsorgsanalys 2022, p. 201-202) are the basis for the simple average for in-person doctor consultations, which is 2,002 SEK. For provider costs that occurred when patients visited an ED, we take the cost estimates for ED visits from the regions in southern Sweden for 2019 and 2020 to again obtain the average of both years. Based on report estimates (Södra sjukvårdsregionen 2019, 2020, p. 47), the average cost of an ED visit for providers is 3,991.5 SEK.

We estimate patient costs in a more detailed way, which consist of several components. The average fee for a primary care visit with a doctor is taken from Region Stockholm and Scania because the majority of our sample patients are located in these regions. Patients between the ages of 18 and 85 (73.49% of our sample) have to pay a co-pay/visit fee in Stockholm Region, while patients between the ages of 20 and 85 (67.67% of our sample) have to pay a fee in Scania.[35] The average percentage of paying patients over these two regions is 70.58%. The fee for paying patients was 225 SEK in person (the mean of 250 SEK for Stockholm and 200 SEK for Scania) and 150 SEK online (the mean of 100 SEK for Stockholm and 200 SEK for Scania) in 2023.

The patient time cost estimates are the product of patient time spent in (or getting to and from) a consultation, multiplied by the mean hourly wage of private sector workers in Sweden: 178.5 SEK/hour in January 2020 (SCB 2024). The waiting time in the doctor's office for in-person consultations is 30 minutes, based on Ekman (2018), and 15.3 minutes for online, based on our full data with registered and unregistered patients. The online waiting time is restricted to online doctor consultations without missing values, negative values, or waiting time values above 60 minutes.

Transport costs include commuting by car, public transport, biking, and walking, along with the respective probabilities of each mode being chosen (Rosberg and Enström 2019). We use the average time and frequency of commuting to work to estimate the likelihood of a patient using a particular mode of transport to the doctor's office. The commuting costs

[35] Patients who have reached the deductible ceiling do not have to pay until the next year, but we do not consider this.

by car for primary care are based on fuel costs, transport fees, the commuting time, and parking fees. The average time to primary care is 11.71 minutes one way and 23.42 minutes round trip after including frequencies of commuting types. We assume a mean tempo of 60km/h for the fuel cost and a fuel use of 0.5 liter/km. The fuel price of 16.03 SEK/liter is taken from January 1, 2020 (Circle K 2024), and the fuel cost is calculated for a 20-minute drive to the doctor and back. We calculate the fuel costs and multiply it by the probability of 57% that patients use their car to get to work. Parking fees close to the city center in Stockholm during the day were 15 SEK/hour in 2020 (Stockholms stad 2020). We weight these fees by the patient-facing consultation time and multiply them by the probability that patients would go by car.

We assume it takes 5 minutes for patients to find a parking spot before the doctor's appointment and 5 minutes after (including the walking distance to the doctor's office). The transport fee for Stockholm in 2020 is a single ticket for 37 SEK, valid for 75 minutes (Trafikförvaltningen 2020), which we multiply by the probability that the patient takes public transport to the appointment (24%). We also assume that patients do not buy two tickets due to time constraints for their appointment.

The average travel time to an ED is 15.5 minutes one way and 31 minutes round trip, estimated by calculations based on the transport probabilities by Rosberg and Enström (2019) and travel times to EDs by Vård- och omsorgsanalys (2018). We assume that commuting to an ED is only done by car and therefore include fuel costs as well. We also assume that there are no parking fees for an ED visit because we suspect that most ED visits occur during the night when no parking fees may apply, or free parking spots may be available for acute visits. The median stay time of a patient in an ED is 3.18 hours over all regions in Sweden (Socialstyrelsen 2017).

We also calculate heterogeneous costs for more or less vulnerable patients in Appendix Table A20. The cost estimates for these patients are calculated in the same way as those in Table 6 but instead using probabilities from Appendix Table A18 for more vulnerable patients and from Appendix Table A19 for less vulnerable patients.

C.5 Sample Patient Representativeness

Appendix Table A13 compares patients in the doctor sample with broader populations of Swedish municipalities and the nation as a whole. Since there are no nationwide data on Swedish primary care patients, this comparison uses inhabitants at the national level rather than patients. The public data for the municipality and national mean mainly come from the Swedish government agency Statistics Sweden, also called SCB (2023). The table consists of three columns that include the means of three different samples in 2019. Column (1) is based on the 4,664 patients in the doctor sample, focusing on the year 2019.

Column (2) takes doctor sample patients but links them to municipality-level public data from 2019. As only 96 of the 290 municipalities in Sweden are represented in the doctor sample, we weight the mean by the municipality frequency of sample patients, who primarily come from municipalities located in the regions of Stockholm and Scania (most notably Malmö and Lund). If not specified otherwise, the number of observations in a category is divided by the total municipality population to obtain the municipality mean. The "University educated," variable is made up of three education categories that indicate post-secondary education: less or more than 3 years of post-secondary education, and post-graduate. Similar to the doctor sample, we limit to age 23 or older and divide by the municipality population aged 23 or older. The variable "Married" in Column (2) is based on data that have four categories: unmarried, married, divorced, and widowed. We show the mean only for those in the married category divided by the municipality population above 18 years old, as it is only legal to marry in Sweden after turning 18. An immigrant in variable "First- or second-generation immigrant" is defined as an individual who was born outside of Sweden or whose both parents were born outside of Sweden. The mean for "Annual income" is based on all individuals 20 years of age or older, which includes salary and pension income from other Nordic countries.

The variable "Big city municipality" is based on data obtained from Tillväxtverket (2021), another Swedish government agency. This variable categorizes municipalities into three categories: rural, mixed, and big city. A municipality is a big city municipality if at least 80% of its inhabitants live in densely populated areas and if it also shares a combined area with other municipalities with at least 500,000 inhabitants.

Column (3) is independent of Columns (1) and (2) and takes the mean over all of Sweden in 2019, using the same variable definitions as for Column (2). If not age restricted, the number of people is divided by Sweden's total population to obtain the national mean, which was 10.32 million in 2019. The indicator "Big city municipality" on the national level is created by matching municipality population sizes to each municipality and then collapsing the indicator to its mean with weights on the municipality population.

C.6 Construction of Variables

C.6.1 Patient Comorbidity

Throughout the paper, we often control for whether the patient has any comorbidity. This is indicated by them having at least one of several diagnoses from prior healthcare in the national registries (except primary care, which does not exist in national registries). The diagnoses defined as comorbidities are taken from the Elixhauser comorbidity index, which defines approximately 30 diagnoses in the patient's medical histories that the medical literature has found to be important comorbidities. We study the patient's medical history during 2013–2018 in specialist care (inpatient and outpatient care) medical records from Socialstyrelsen. Specifically, we use the Stata command "Elixhauser" by Vicki Stagg, Dr. Robert Hilsden, and Dr. Hude Quan from the University of Calgary, Canada.

The complete list of comorbidities is the following: cardiac arrhythmias; valvular disease; pulmonary circulation disorders; peripheral vascular disorders; hypertension, uncomplicated; paralysis; other neurological disorders; chronic pulmonary disease; diabetes, uncomplicated; diabetes, complicated; hypothyroidism; renal failure; liver disease; peptic ulcer disease excluding bleeding; AIDS/HIV; lymphoma; metastatic cancer; solid tumor without metastasis; rheumatoid arthritis/collagen vascular; coagulopathy; obesity; weight loss; fluid and electrolyte disorders; blood loss anemia; deficiency anemia; alcohol abuse; drug abuse; psychoses; depression; and hypertension, complicated.

C.6.2 ED Distances to Municipality Centroids

To assess the distance from patient locations to their nearest EDs, we use municipality centroids, since we do not have more precise information on patient locations than their municipalities. There are in total 71 EDs in Sweden (Swedish Healthcare Information 1177 2023), excluding specialty clinics that have an acute intake. Sweden has 290 municipalities within 21 regions, and therefore not every municipality has an ED.

We use an address list of Swedish EDs (Swedish Healthcare Information 1177 2023) to obtain geolocations (latitude and longitude), and then calculate the shortest (linear) distance of each ED to all of the 290 municipality centroids using Vincenty's formula. The shortest distance to an ED is 1.09 km for Jönköping, while the largest is 208.74 km for Arjeplog. On average, the distance from an ED to a municipality centroid is 31.94 km. When weighted by the number of EDs each municipality has, the average distance is 34.33km.

C.6.3 Avoidable Hospitalizations

The avoidable hospitalization variable we use in Table 4 is an indicator for whether the patient was hospitalized and given an ICD-10 code indicating that the hospitalization might have been preventable in primary care under the right circumstances. Avoidable hospitalizations as a concept, sometimes also called ambulatory care sensitive conditions, is defined in the medical literature as a hospital admission that could have been avoided with sufficient and timely primary care (the definition of conditions that count as avoidable is listed by medical research independently from this study). We follow the definition by Page et al. (2007); see Table A1 in Page et al. (2007) for a complete list of the ICD-10 codes used.

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