Time Constraints and the Quality of Physician Care*

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Abstract

This paper studies how easing time constraints improves workers' performance and output quality. I build a unique, high-frequency administrative dataset containing time-use data on all physicians in an outpatient department. I leverage a natural experiment by which physicians, when randomly affected by a cancellation, spend unexpected extra time with their next patient. I find that longer visits lead to improved care, evidenced by more detailed diagnoses, increased testing intensity, and lower drug prescriptions. I also find long-term health effects, measured by fewer hospital readmissions. These findings highlight that relaxing workers' time constraints significantly enhance their productivity and output quality.

Keywords: Administrative Data, Bonus Time, Contracts, Time-use Data, Productivity

JEL Classification: H0; I0; J0

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1 Introduction

Working under time pressure has become a hallmark of today's economy. According to a survey conducted by Eurofound (2017), 36% of the workers in the European Union work under tight deadlines, with 10% indicating a need for additional time to complete their tasks.[1] Time pressure is most critical for the healthcare industry, where precise and timely decision-making is essential to prevent long-term societal costs. Nevertheless, 14% of healthcare workers report not having the minimum time necessary to perform their duties correctly. In this context, it is vital to understand how time constraints influence workers' decisions. However, little is known in that respect.

In this paper, I investigate how the time workers spend in a given task affects their performance and output quality. I study this question within the context of the Spanish healthcare sector, using high-frequency administrative data from an outpatient department, and leveraging on-the-day cancellations as random time shocks. I focus on the provision of a detailed diagnosis as a proxy for a visit's successful completion, given that outpatient physicians' job is to provide clear-cut advice to those patients referred from Primary Care Centers. Additionally, I analyze various healthcare decisions and patient outcomes, including the number and cost of diagnostic tests ordered, the volume of prescribed medications, the frequency of follow-up visits, and the likelihood of medical readmissions.

The main empirical challenge in estimating the causal effect of visit length on physicians' decisions is to obtain a relevant source of time that is also exogenous to the patient's characteristics. I address that challenge by leveraging on-the-day cancellations as random time shocks to physicians' schedules. When a cancellation occurs, physicians typically spend more time with all the visits for the remainder of the shift but also provide the very next scheduled visit with an unexpected extra visit length. I focus on this *bonus* time to draw conclusions about how physicians' diagnostic behavior responds to an unexpected increase in consultation duration. This random time shock is essential as otherwise, physicians, having a complete picture of their shifts, could adjust visit lengths based on their overall workload and the patients' characteristics. On-the-day cancellations account for 15% of all visits.

A second obstacle that might hinder our causal estimation is the physicians' prioritization of patients with specific characteristics once a cancellation occurs. Despite legal obligations to adhere to their daily schedules, physicians could potentially exercise discretion in choosing which patients to see when a slot becomes available. To mitigate this

[1] By comparison, in 1991, only 23% of the European Union workers operated under tight deadlines (Eurofound, 1993).

concern, I focus on first visits to the outpatient department. New patients had no prior contact with their treating physician, thus minimizing the likelihood of selective treatment based on patients' characteristics. Furthermore, the Spanish outpatient system prohibits in-office dropouts and on-the-day appointments, thereby preventing patients from strategically responding to physicians' on-the-day cancellations.

I build a unique dataset containing the universe of visits to a Spanish outpatient department between 2016 and 2018 and complement it with high-frequency information on the physician's schedules and the treatments and diagnoses provided. The main specification uses an IV approach, using the cancellation of the prior scheduled visit as an instrument for the time allocated to examine patients. I include physician fixed effects to account for inherent characteristics of the physicians and, by extension, of their specialties; month-by-year fixed effects to control for seasonality; hour fixed effects to account for variations in patient composition by time of day; and a comprehensive set of controls for patients' characteristics.

I find that longer visits significantly increase the likelihood of providing a diagnosis, which is the main objective of outpatient departments. For every additional minute spent on an examination, the probability of delivering a diagnosis rises by 4%. This effect is particularly pronounced for less common diagnoses, whose early detection is associated with positive long-term health benefits, while no effect is found on the most common diagnoses. This finding suggests that extended consultation times enable physicians to conduct a more thorough examination of patients, thereby delivering a higher-quality service. Consistent with this interpretation, I find that each additional minute spent in a medical consultation leads to a 0.6% reduction in the probability of hospital readmission.

I further show that longer first visits increase the utilization of diagnostic inputs, such as procedures and laboratory tests, and lead to a reduction in drug prescriptions. Specifically, for every extra minute spent examining patients, physicians order 3% more tests, resulting in a 6% increase in overall testing costs, and reduce drug prescriptions by 20%. These results evidence that while longer visits lead to higher number of tests, and by construction, to higher treating costs, drug prescriptions are utilized as a substitute for insufficient examination time. Overall, these findings suggest that physicians leverage the additional consultation time to more thoroughly assess patients' health issues, and in cases of uncertainty, to seek further diagnostic information, ultimately improving the quality of care delivered.

I then examine how physicians' contracts, which are based on seniority, influence diagnostic provision. These contracts often result in senior physicians having less overloaded shifts at the expense of their junior colleagues. I find that longer visits lead to changes in the input composition and the provision of diagnoses only when this extra time is allocated to junior physicians. In contrast, additional time does not impact the practices of senior physicians. Although both junior and senior physicians respond to cancellations by spending more time with subsequent patients, only junior physicians use this additional time to enhance service quality. Based on these findings, I provide a back-of-the-envelope calculation for the direct labor cost of increasing diagnosis rates. Policymakers might consider improving diagnostic rates by extending visit times for all physicians. However, this approach may prove inefficient, as it fails to account for the fact that senior physicians' diagnostic practices are unaffected by further visit length extensions. A tailored approach targeting only junior physicians would help improving healthcare provision while minimizing expenditure.

Understanding the trade-off between time and employee productivity is essential from a policy perspective. On the one hand, allocating additional time to patient visits inherently reduces the number of consultations healthcare providers can manage per shift. This, in turn, creates longer waiting lists, increasing opportunity costs within outpatient departments. On the other hand, longer visits can significantly enhance care quality, leading to improved patient health outcomes and reducing the likelihood of costly readmissions. However, how to quantify the relationship between consultation time and care quality, holding shift duration constant, is empirically and ethically far from trivial.

My contribution to the literature is twofold. First, I construct a novel, high-frequency dataset containing the universe of visits to a Spanish outpatient department between 2016 and 2018, and complement it with detailed information on patient demographics and physician characteristics. This dataset allows me to directly analyze how consultation duration affects both the quality of care provided during each visit and the subsequent long-term health outcomes for patients. Second, I leverage a natural experiment in which physicians, randomly affected by patient cancellations, spend unexpected additional time with their subsequent patient. This bonus time allows me to causally estimate how time influences visit outputs and quality, mitigating confounding factors present in the literature such as physician burnout and shift-end constraints. I find that longer consultations significantly improve visit quality, enhance the provision of diagnostic inputs, and result in better long-term patient outcomes. My results, therefore, can inform policies aimed at enhancing physician productivity and improving the efficiency of healthcare delivery.

This paper builds on two different strands of the literature. First, it complements the growing literature on the determinants of physicians' labor supply. Recent literature has looked at the role of financial incentives (Powell-Jackson et al., 2015; Gupta, 2021), co-working (Chan, 2016), peer pressure (Silver, 2021), and scheduling (Chan, 2018).

More specifically, this paper complements the recent literature studying the workload-quality trade-off in the healthcare sector.[2] Mixed evidence has been found on how workload affects physicians' decisions. Shurtz et al. (2022) evaluates how physicians' decisions depend on their daily workload and finds that physicians provide higher diagnostic inputs and lower drug prescriptions on high-workload days. Neprash (2016) finds that when physicians fall behind schedule, they spend less time on their subsequent visits, order fewer procedures, and provide fewer diagnoses. Freedman et al. (2021) investigates how primary care providers react to time pressure induced by cancellations and add-ins, finding that such pressure pushes physicians to provide fewer diagnostic inputs, more follow-up care, and lower referral rates. All these papers can only explore an average intention-to-treat effect of perturbations to a physician's schedule, disregarding whether the estimated effect is driven by a longer examination, reduced workload pressures, or actual discretionary time. Moreover, existing studies are based on general practitioner systems, in which patients may endogenously opt out of consultations based on perceived physician workload. The main contribution of this paper is to causally examine the direct impact of longer consultation times, rather than indirect measures of workload or time pressure, on healthcare quality and medical treatment decisions analyzing both immediate and longer-term implications within a double-blind experimental design, ensuring that neither patients nor physicians can influence treatment selection endogenously. Additionally, I show that actual consultation length, rather than indirect workload intensity or discretionary free time, is the principal factor driving increased physician effort under relaxed time constraints.

Second, this work contributes to the literature on the impact of time pressure on output quality, which harks back to Tversky and Kahneman (1974). Recent experimental studies provide compelling evidence that greater time pressure increases risk-taking behaviors (Kirchler et al., 2017; Essl and Jaussi, 2017; El Haji et al., 2019), and leads to more misjudgements (Suri and Monroe, 2003; Cao et al., 2022), particularly among female participants (De Paola and Gioia, 2016). Frakes and Wasserman (2017, 2023) estimate the causal relationship between the time allocated to reviewing patents and the examiners' effort, showing that less examination time results in reduced scrutiny and the granting of patents of lower quality than average. This paper contributes to this literature by causally estimating the relationship between consultation time and physicians' performance in a setting where workers operate as single units in a single-stage process. Furthermore, this paper looks at the incentives at play, emphasizing that seniority-based contracts may lead to inefficient time-to-input utilization.

[2] This issue has also been studied in other industries, such as the service industry (Tan and Netessine, 2014; Bruggen, 2015), banking (Xu et al., 2022), and the justice system (Coviello et al., 2015), among others.

The remainder of the paper is organized as follows: Section 2 explains the institutional setting. In Section 3, I present and describe the data used. Section 4 exposes the empirical strategy followed. Section 5 presents the main results, and Section 6 provides a quantification exercise. Finally, Section 7 concludes.

2 Institutional Setting

2.1 Spanish Healthcare System

In Spain, healthcare is universal and free of charge. Its provision is structured around two main actors, Primary Care Centers and Specialized Care Centers, which together form Basic Health Zones (hereafter, BHZ). A BHZ is an administrative unit containing several Primary Care Centers mapped into a Specialized Care Center. Individuals are sorted into different BHZs based on their place of residence. Specialized Care Centers cover multiple services, such as the intensive care unit, the emergency room, and the outpatient department, which are usually located in hospitals.

This study focuses on the outpatient department. Initial access to this department is solely decided by the patients' treating primary care center, which allocates them to outpatient physicians based on their availability upon analyzing the patients' health conditions. The referral notification from the primary care center to the outpatient department is provided to patients some days after a patient visits her general practitioner, including information on the appointment time and date and the physician's name. This implies that the individuals' place of residence fully determines their outpatient department of reference, disallowing walk-in visits and blocking patients from choosing among clinics. Moreover, the region in which the department of my sample operates, Catalonia, does not allow patients to choose their outpatient physician, minimizing any possible relationship between physicians and their patients before a first visit.

2.2 Hospital Management Flow

The hospital manages patients following a production-line approach. Upon arrival, patients register at the main counter, where the administration secretary provides them with directions to their designated waiting room and electronically notifies the treating physician of their arrival. In the waiting room, the physician calls patients following the appointment schedule, keeping track of who is in the waiting room. After the visit is completed, if a follow-up visit is prescribed, patients return to the main counter, selecting the date and time slot of the follow-up visit within the physician's recommendations. Throughout this process, physicians have full access to real-time information on all patients' availability status and health conditions.

Figure 1 presents the type of agenda displayed to physicians. At any given time, physicians have precise information on those patients who have not arrived, those who have canceled their appointments, and those currently in the waiting room. Physicians are also presented with patient characteristics, such as the patient's name and residence. For instance, in the example, a physician is looking at her schedule at 10:00 a.m. The physician has already examined six patients, while one missed her 9:00 a.m. appointment. She has four more visits until the end of the shift, one of which has already been canceled. Notably, the physician is ahead of schedule, having already concluded the appointment originally set for 10:00 a.m. Due to such a comprehensive information system, physicians have a complete picture of their shift, allowing them to react on the spot to changes such as cancellations.

Throughout a shift, physicians are required to examine every patient with an appointment and update their patients' medical records. When a cancellation occurs or a visit concludes more quickly than anticipated, physicians utilize this extra time to catch up on their schedule and complete their record-keeping duties. Additionally, physicians are allotted non-scheduled time for coffee and lunch breaks. Following the pre-booked appointment order, physicians must ensure that all visits are completed on the scheduled date. This structured system ensures that patient care is timely and that all administrative duties are managed efficiently within the shift.

3 Data

3.1 Hospital Data

I use data from one Spanish medium-sized, contracted hospital covering a wide range of specialties in the metropolitan area of Barcelona. My dataset contains all the 67,530 first visits to outpatient physicians from January 1, 2016, through June 30, 2018, assigned to 86 physicians across 18 different specialties. These physicians always operate within their specialty, providing clear-cut advice to patients referred from Primary Care Centers.

All physicians are employed under fixed-wage contracts, with their compensation being mostly determined by their tenure, plus a variable component based on other responsibilities performed within the hospital. Notably, physicians do not receive individual performance-based incentives or remuneration linked to resource utilization. Their schedules are typically fully booked, requiring them to complete all assigned consultations within standard working hours. Furthermore, physicians undertake additional responsibilities outside the scope of this study, including night shifts, surgical procedures, and rehabilitative care.

This dataset consists of high-frequency visit times and medical treatment information. It includes information on the patient's time of arrival in the hospital, the visit appointment time, the referral date, and the visit starting and ending times. Visit length is measured based on the duration the patient's profile remains open on the physician's terminal. These times are automatically recorded by the terminals rather than being self-reported by physicians. Therefore, visit length includes both face-to-face interactions with patients and the time spent recording their medical diagnosis.[3] Referral and appointment dates are also crucial for reconstructing the entire outpatient process, from the initial first visit to all subsequent follow-ups, which is essential to examine whether and how longer first visits impact the overall outpatient process. The dataset also includes details on treatments provided during each visit, such as imaging and laboratory tests, drugs prescribed, and the associated testing costs.[4]

Table 1 provides descriptive statistics for the variables used in the analysis. For instance, the average patient is a middle-aged Spanish woman living in an area adjacent to the hospital and covered by public health insurance. The average first visit takes 12 minutes, with an average waiting period of 30 days and an 8% likelihood of receiving a diagnosis.[5]

3.2 Shift Distortions - Cancellations

A standard work shift runs from 9 a.m. to 1.30 p.m., with its structure and composition determined annually and tailored to each physician's specialty. Shifts are characterized by being fully booked (the average waiting time for a first visit is 30 days) and compulsory for the physician (i.e., the physician cannot prioritize or decline visits). The complete dataset

[3] In instances where physicians leave the terminal open after a patient exits and the subsequent patient enters the office, the conclusion of the former visit is recorded as the starting time for the latter. In the rare event where a physician keeps multiple terminal tabs open until the end of the shift or since the beginning of it, the entire working day is excluded from the analysis.

[4] We cannot retrieve the drug costs as prescriptions are issued based on the drugs' active components. See Law 29/2006.

[5] The hospital managing our outpatient department is regarded as a high-performing center within the Catalan health system. As of 2017: i) the reported patient satisfaction was 8.2 out of 10, compared to 7.5 in the region; ii) the probability of readmission within 30 days was 9.22%, compared to 9.81% in the region; and iii) the average waiting time for a first visit was 41 days, compared to 121 days in the region. Therefore, the results presented in this study can be considered a lower bound relative to other outpatient departments.

encompasses 347,277 scheduled visits, categorized into first visits (24.4%), follow-up visits (50.1%), and external consultations (23.1%). Figure 2a illustrates the distribution of these encounters throughout the shift by visit type. The period from 9 a.m. to 1.30 p.m. is the busiest, with 86.5% of the visits occurring during this time frame. While the outpatient department uses the hospital facilities in the morning, the same spaces are repurposed for rehabilitations and surgeries later in the day, however they are not included in this study. First visits are distributed evenly throughout the shift.

Cancellations represent the main perturbations on the physicians' schedules. This analysis includes only those cancellations that occur on the appointment date, as cancellations made prior are typically re-booked. The entire dataset contains 54,057 on-the-day cancellations, which consist of visits withdrawn before their scheduled slot (18%) and no-shows (82%). No patient walk-outs are found in the data. Figure 2b presents the distribution of cancellations over the course of the shift, using 30-minute bins based on all visits' appointment times. Visually, the data shows is no clear pattern of clustered cancellation periods.

I focus on how prior cancellations affect subsequent first visits during a shift. Using the benchmark sample as in Table 1, Figure 2c illustrates that the number of cancellations before a given visit accumulates over the schedule, showing higher variation in the evening shift due to the overlap of newly arrived physicians with those continuing from the preceding morning shift. Figure 2d shows the evolution of the probability of having the previous visit canceled, highlighting a higher incidence at the beginning of the morning and evening shifts. Hour fixed effects are used in the study to account for this variation in the likelihood of receiving a cancellation and the different compositions of patients across hours.

Figure 3 exposes the distribution of first visits in relation to prior cancellations. Subfigure 3a presents the fraction of visits with no prior cancellation and those with a prior cancellation at higher horizons. Overall, 62% of all the first visits had at least one preceding visit canceled, with 16% experiencing the immediately preceding visit being dropped. Subfigure 3b presents the evolution of real and expected visit lengths with respect to the distance from a prior cancellation.[6] We can appreciate that i) the hospital structurally assigns more time-consuming visits to earlier slots, where there is a lower probability of having any prior cancellation; ii) when faced with a cancellation, physicians spend more time on their subsequent visit; and iii) for all distances, expected visit length generally exceeds the actual visit length, indicating that the outpatient department allocates insufficient time to compensate

[6] The expected visit length is a metric provided by the outpatient department which estimates the "desired" duration of a visit, taking into account the type of visit, the medical specialty, and associated administrative tasks. Although expected and scheduled visit lengths should theoretically coincide, this is not the case in our sample, as 21% of the visits are overbooked.

for overbooking and administrative duties.

Lastly, Figure 4 makes transparent the heterogeneity of performance, in terms of visit length, observed for physicians working in diverse specialties. We observe that physicians' visit length widely varies between 7 and 26 minutes per visit, and by construction, it negatively correlates with the number of cancellations per day. However, the average time spent by physicians examining patients does not predict whether their visits will be affected by prior cancellations nor whether physicians will have higher probabilities of testing, prescribing, and diagnosing. Figure 5 presents an analogous analysis at the specialty level, showing that although medical specialties tend to have longer consultations, all specialties exhibit a similar likelihood of being impacted by prior cancellations. Likewise, there is important variation in the diagnostic probability during a first visit, with some specialties not providing one until later stages in the outpatient process. To account for this heterogeneity, physician fixed effects, and by construction, specialty-level fixed effects, are utilized in the study.

4 Empirical Strategy

In the first empirical exercise, I examine the extent to which medical treatments are influenced by the time spent on a visit using the following model:

$$Y_{i,j,s} = \beta_0 + \beta_1 Length_{i,j,s} + \theta T_s + \delta_j + \Psi X_{i,s} + \varepsilon_{i,j,s} \tag{1}$$

where Y identifies a given visit outcome, as described in Section 4.1, for a patient i, a physician j, and a slot s. The key independent variable, *Length*, identifies how many minutes a physician j spends with patient i in a visit slot s. I control for patient characteristics, $X_{i,s}$, such as gender, age, nationality, insurance coverage, and district distance to the hospital. All regressions include i) physician fixed effects, δ_j, which allows us to account for time-invariant variation across physicians, and by construction, across specialties; ii) month-year fixed effects, T_s, which mitigate the fact that results are confounded by seasonality (e.g., periods in which patients are more prone to suffer from diseases, such as with the seasonal flu, may also lead them to miss their hospital visits more frequently); and iii) hour fixed effects, T_s, which accounts for different hour-patient compositions.

Estimating Equation 1 using OLS may result in biased estimates for several reasons. First, there could be omitted variables not captured by the rich set of controls and fixed effects. These confounding variables may correlate with our measure of visit length and with some unobserved components in the error term. For example, physicians' good/bad moods or health conditions may affect both visit lengths and medical treatments. Second, given that physicians have complete information on all their on-the-day visits, they may allocate visit lengths based on their current and future patients' characteristics. This anticipation may create a situation of simultaneous causation between the time spent with patients and the treatment provided. On the one hand, physicians may decide to spend more time with those patients found to be more challenging, allowing them to assess better if further treatment is required. On the other hand, physicians may decide to provide patients with treatments as a substitute for the time spent. That substitution decision is plausible as examining and testing physicians may differ. To address these concerns, I focus solely on first visits. Patients attending these initial visits lack prior knowledge of the physician's schedule, and the physicians are unfamiliar with these patients, eliminating the potential for strategic scheduling based on patient familiarity.

I use prior cancellations to capture exogenous variations in physicians' available time. Those cancellations comprise all the on-the-day visit withdrawals, such as those that occur before their appointment and the no-shows. I define a first visit to be affected by a cancellation if the visit preceding it was canceled using its real cancellation time. Specifically, *PriorCancel* is a dummy variable that takes value 1 if the previously scheduled visit was a no-show,[7] or if another visit appointed later in the same day is canceled during the current visit. Using the exact cancellation time is crucial because physicians can adjust to cancellations for which they have been notified in advance. This method represents a lower bound of the impact a cancellation has on subsequent visits, taking as not treated any other first visit that does not immediately follow a cancellation. Figure 6a shows the impact of cancellations on the length of subsequent visits. Physicians spend significantly more time on visits following a cancellation compared to those before. Additionally, the time spent on first visits immediately after a cancellation is significantly longer than on any other first visit. Figure 6b shows that physicians cannot predict cancellations and adjust their face-to-face time with patients accordingly. For those reasons, the present analysis defines a treated visit as a first visit immediately after a cancellation, while all other first visits are considered untreated.[8]

The validity of the instrument hinges on several considerations. The first issue relates to the random assignment of cancellations. Those patients dropping a visit do so without

[7] A no-show is a visit for which its patient never showed up. In other words, I do not leverage on the *extra* visiting time provided by those *pending* patients who did not show up on time to their visits but did it later in the shift.

[8] Table A1 shows that prior cancellations lead to extra visiting time for all patients examined during the physician's shift. Prior cancellations do not lead to longer checkups when physicians work overtime.

knowing the physician's schedule. However, visits could still be more frequently canceled when certain patient characteristics, such as older patients or those with more chronic problems, are present. Moreover, physicians could exercise discretion in choosing which patients to see after a visit gets canceled. Table 2 displays the covariate test on patient characteristics and shared physician-patient characteristics. Prior cancellation does not predict any patient characteristics used in the study, which are visible to physicians. More importantly, physicians do not select patients based on their shared characteristics, namely sex and age. This evidence supports the claim that first visits are randomly affected by prior cancellations.[9]

A second issue pertains to any other utilization of the physician's extra disposable time created by a prior cancellation. Prior to the treated visit, physicians decide how quickly to take the new patient, which might reduce their working delay. In turn, the estimates presented would be biased if such a less-rushed environment directly affects medical treatment, not only via visit length, thus violating the exclusion restriction. This indirect path is mostly attenuated by the use of fixed effects at the hour and the physician level, as the visits with a prior cancellation are compared to adjacent visits with similar levels of time pressure. Nevertheless, it could still be the case that the allocation of such extra time affects the first visit after a cancellation significantly differently to those at different horizons. To test whether a less-rushed environment directly affects the outcomes of interest, I extend Equation 1 to include the variable *Delay*, which represents the difference between the visit start time and the visit appointment time. The average *Delay* in the sample is 16.2 minutes. Following Neprash (2016), I instrument the variable *Delay* using a dummy variable which indicates whether the preceding realized visit arrived late to her appointment time, *PriorLate*. The variable takes value 1 if the patient appointed before a given visit arrived at the outpatient department after her scheduled appointment. When patients arrive late to the outpatient department, physicians await them for some courtesy time, which might lead to higher delays suffered by the following patients. Table A5 evidences no clear link of *Delay* directly affecting visit outcomes. Moreover, when comparing the variable *Length* in Table A5 to the main result provided in Table 3, we can see how including *Delay* does not affect the predictability of our variable of interest.[10] For those reasons, I dismiss the premise that, in the context

[9] As an exception, some specialties in the outpatient department allow their first-visit patients to choose their preferred slot at their corresponding Primary Care Centers. Using only those patients, Table A2 shows that having a prior cancellation is not predictive of either those patients' characteristics or the shared physician-patient characteristics. Similarly, Table A3 uses scheduled appointment times, rather than actual visit times, showing similar effects to those of the benchmark estimation. Thus, supporting the claim that physicians do not prioritize patients based on unobserved characteristics.

[10] Table A4 tests whether the instruments *PriorCancel* and *PriorLate* predict observable patient characteristics, finding no systematic evidence.

of this study, changes in time pressure, originated from sudden schedule changes, affect the outcomes of interest other than through the visit duration.

4.1 Outcomes of Interest

I use the previously detailed instrumental variable framework to study how physicians respond to extra time, examining a broad set of outcomes that can be classified into diagnosis provision and treatment choice.

Regarding diagnosis provision, I investigate whether longer visits are beneficial in assessing patients' diagnoses. Given that the outpatient department's main objective is to provide a correct assessment of the patient's issues, leveraging their clear-cut medical knowledge, I use the provision of a diagnosis, *Diagnosis*, as an indicator of a visit's successful completion. According to Aranaz et al. (2005), the probability of a diagnostic error in the Spanish healthcare system is 0.13%. It is crucial to note that diagnosis provision is intertwined with other inputs, such as diagnostic testing, as physicians utilize tests to evaluate and confirm their diagnoses. Furthermore, physicians typically commence a first visit with a preliminary diagnosis provided by the referring general practitioner. Thus, the establishment of a diagnosis at the specialist level represents an enhancement of initial recommendations. This is particularly pertinent when the specialist's diagnosis is uncommon, as such diagnoses are associated with reduced hospital readmission rates. Specifically, uncommon diagnoses reduce readmissions within the treating specialty by 3.3%, or 27% when compared to the average specialty readmission rate, whereas common diagnoses do not exhibit a comparable long-term impact. I classify diagnoses as common if they are among the three the most repeated within their specialty, and uncommon otherwise. In the absence of a diagnosis at the conclusion of the outpatient process, which typically encompasses an initial visit and multiple follow-up appointments, the patient will continue to receive treatment from their referring general practitioner. This treatment will be based on the initial preliminary diagnosis, which has now undergone additional verifications.[11] Following this logic, I include as outcomes a variable identifying whether the patient had to return in the future to the treating specialty, after the outpatient process was already finalized, *Future Readmission*. It is important to highlight that, due to the embedded structure of General Practitioners within specialized care units, readmissions rarely occur in a unit different from the one that previously provided treatment. Similarly, I include a variable identifying whether the current first

[11] I am unable to access the precise preliminary diagnoses provided by the referring general practitioner to the outpatient department, as this information belongs to a different unit within the Spanish healthcare system.

visit resulted in a physician-scheduled follow-up appointment at the same hospital, denoted as *Follow-up*.

Referring to the treatment choice, I investigate whether visit length is used as a substitute or complement to the provision of tests and drugs during the visit. On the one hand, physicians with extra visiting time may examine patients more thoroughly, inspecting their symptoms more carefully, reducing the need for intensive testing. In such a case, testing would be a substitute for visit length. On the other hand, visit length could complement intensive care as physicians with such extra visiting time could further deepen their knowledge of the clinical case and consequently order more tests. Moreover, extra visit length would give physicians a clearer idea of the patient's needs, thus modifying their drug prescription to more accurate doses.

The variables used to explore how visit length relates to treatment choices are i) *Tests*, which is a dummy variable measuring whether medical tests, e.g., imaging and laboratory tests, have been ordered, ii) *Num. Tests*, which is a variable identifying the absolute number of tests ordered in a given visit, iii) *Test Cost*, which measures the total cost of the tests ordered, iv) *Drugs*, which is a dummy variable measuring whether drugs have been prescribed, and v) *Num. Drugs*, which measures the total number of drug doses ordered in a given visit. I compute the testing cost using internal cost information provided by the outpatient department in the sample. As for the number of drugs prescribed, I follow the aggregation method based on the Defined Daily Doses prescribed as proposed by the WHO. A Defined Daily Dose is a measure of drug utilization that stands for the assumed average maintenance dose per day for a drug used for its main indication in adults. I use this measure instead of the number of drugs provided, as it aggregates different drug groups weighted by their relative intensity, avoiding issues related to the drugs' package size and strength.

5 Results

Table 3 reports the estimation results using the 2SLS model previously outlined.[12] Column 1 introduces our first stage estimates using *Prior Cancel* as the source of exogenous variation, and controlling by a comprehensive set of fixed effects. Our first coefficient of interest,

[12] For completeness, I include in the Appendix the benchmark specification without controls (Table A6), and the OLS estimation (Table A7). They are quantitative and qualitatively similar to the benchmark estimation. Table A8 presents the total effect of a prior cancellation on the main outcomes of interest, which is also comparable to the benchmark analysis. Similarly, Table A9 replicates the benchmark specification using the number of prior cancellations as instrument. Finally, Table A10 shows the log-linear version of the benchmark specification.

Prior Cancel, tells us that when shocked by a cancellation, physicians spend an average of 1.62 minutes more with the subsequent patient compared to those with no immediately prior cancellation. This significant effect represents a 12.8% increase over the average visit duration. It corresponds to the lower bound effect of a cancellation's impact on visit duration, as visits at higher distances from a cancellation, used in this study as controls, may also be affected.

In Column 2, I evaluate whether extended visit duration assist physicians in assessing patients' diagnoses. We can observe that longer visits have a positive impact on the likelihood of providing a diagnosis. Specifically, for each additional minute spent examining a patient, the probability of delivering a diagnosis increases linearly by 0.36 percentage points. This translates into a 4.4% higher chance of providing a diagnosis for every extra minute spent with a patient, relative to the average diagnostic probability. This observed positive relationship between visit length and diagnosis provision could be attributed to two factors: a more thorough examination process facilitated by longer consultations, and the availability of sufficient time for physicians to record the diagnosis. To test that hypothesis, I analyze the most frequently repeated diagnoses for each specialty. If the additional time primarily allows physicians to record diagnoses or to acquiesce to patients' diagnostic demands, we would expect to see an increase in both common and uncommon diagnoses as visit length increases. Conversely, if the extra time enables a more comprehensive examination, we should observe a significant increase only in uncommon diagnoses, as physicians can conduct more thorough screenings and provide more precise diagnoses. Table 4 shows that longer examinations help physicians identifying more uncommon diagnoses, while no effect is found on the provision of the most frequently repeated diagnoses. Those uncommon diagnoses require an average of 13.3 minutes and are associated with a 3% lower probability of hospital readmission within the same specialty. In contrast, common diagnoses take 12.5 minutes and do not correlate with long-term health benefits. Overall, these findings suggest that additional consultation time is utilized for more in-depth examinations, leading to more accurate and uncommon diagnoses rather than merely increasing the rate at which common diagnoses are recorded.

Back to Table 3, I examine how visit length affects input choices. In Column 3, I explore how consultation time causally relates to the probability of ordering tests during a given visit. The variable *Length* shows that for every extra minute spent examining patients, there is an increase in the probability of ordering a test by 0.65 percentage points. Compared to the average visit ordering pattern, an increase of one minute in visit length due to a prior cancellation corresponds to a 3.6% higher likelihood of ordering tests. Column 4 expands the outcome definition by checking whether visit duration affects the number of tests ordered. The results parallel those in Column 3 show that increased visit duration lead to more tests being ordered. Although the estimated effect is small in magnitude, with an increase of 0.0096 tests per additional minute of consultation, this translates into a 3.4% increase in the number of tests ordered, when compared to the average number of tests. These findings suggest that physicians utilize the additional time resulting from cancellations to order more tests, indicating that test ordering complements visit duration. Given the right-skewed distribution of test ordering, as shown in Table 1, the main driver of this relationship is the extensive margin. Column 5 further investigates whether increases in visit duration affect testing costs. The results show that an additional minute of consultation time leads to an increase of *Test Cost* by €0.8. This effect represents a 6.4% increase in the average testing cost, implying that visit duration and total testing cost are complementary inputs. These findings are in line with existing studies using intention-to-treat estimates of workload, further suggesting that consultation length, rather than indirect workload intensity or discretionary free time, is the principal factor driving increased physician effort under relaxed time constraints.

In Columns 6 and 7, I focus on drug prescription. Column 6 shows that visit duration does not significantly impact the probability of prescribing drugs. However, Column 7 reveals that increased visit duration does influence the dosage prescribed. Specifically, each additional minute spent in consultation results in a reduction of prescription doses by 0.4 units, representing a substantial 20.1% decrease from the average dose. These results evidence that when physicians have more time time for consultations, they prescribe lower doses of medication. This reduction in dosage can be interpreted as a shift towards better prescribing practices, as physicians can utilize that extra time to better understand the patient's condition, leading to more accurate drug prescriptions.[13] In line with that interpretation, Table 5 shows that providing physicians with extra time is specially effective in reducing more demand-driven prescriptions, such as painkillers and antibiotics, probably having a long-run impact on the individual's pharmacological resistance (Neu, 1992).

Lastly, Column 8 analyzes whether the duration of a visit influences the probability of scheduling a follow-up visit. On the one hand, physicians might schedule follow-up visits at the hospital to monitor further tests prompted by the extended initial visit. On the other hand, a longer visit could enable a more thorough assessment, potentially allowing the physician

[13] The medical literature supports this interpretation, indicating a negative correlation between consultation length and medical over-prescription. Longer visits provide physicians with more time to educate patients and offer psychological support, which can reduce the need for higher doses of medication (Dugdale et al., 1999; Ventelou et al., 2010; Allen et al., 2022; Neprash et al., 2023).

to redirect the patient back to the primary health care center instead of scheduling a follow-up within the outpatient system. The results indicate that a one-minute increase in visit length raises the probability of a follow-up visit by 0.92 percentage points, translating into a 3.3% increase over the mean probability. Table A11 shows that a one-minute increase in the duration of a first visit increases the total duration of the outpatient process in 1.16 days. This result is driven entirely by the higher probability of a having a follow-up visit following an extended first visit.

These results suggest that visit length is a key factor in understanding input utilization. However, they could hide an intertemporal input substitution decision, motivated by the extra time available during their first visits. If this were the case, one would expect physicians who were *shocked* during a given first visit to inversely adjust their input utilization during the corresponding follow-up visit.[14] Table 6 tests that hypothesis using a similar strategy to that employed in Table 3, focusing on a subsample of first visits with a follow-up visit within the outpatient department. The results show that increases in visit length during the first visit do not significantly impact the input utilization during the follow-up visit. This finding reinforces the idea that physicians do not use extra visit length to transfer treatments intertemporally; instead, they provide patients with extra care they would not have otherwise received in their medical process. Interestingly, Column 7 highlights that extra visiting length during a first visit increases the likelihood of having the same treating physician during the follow-up visit. Specifically, for every extra minute spent on a first visit, the likelihood that a patient will continue with the same physician increases by 1.05 percentage points. This finding can be interpreted in two ways. First, it might suggest that physicians, having gained a more comprehensive understanding of the patient's case during the extended first visit, choose to retain their patients for follow-up visits. Alternatively, it might indicate that patients, experiencing higher satisfaction from longer initial consultations, are less likely to cancel their follow-up visits with the same physician. Table 7 sheds light on this dynamic, evidencing that it is primarily the physicians who are driving this continuity of care, rather than the patients. Physicians achieve this by actively securing that ordered diagnostic procedures are ready when a follow-up visit occurs, thus keeping the same patients over time. In practice, for every extra minute spent in a first visit, the probability that physicians cancel the follow-up visit decreases by 12.9%. Conversely, no significant effect is found on cancellations initiated by the patients. In line with previous research (Finan et

[14] I test whether having a prior cancellation predicts any patient characteristic in the sample of follow-up visits. Table A12 in the Appendix shows no systematic sample selection based on observable patient characteristics.

al., 2017), these findings provide suggestive evidence supporting the hypothesis that the additional care provided by physicians is driven by their intrinsic motivation rather than being solely attributed to altruistic motives.

Lastly, I investigate whether the unanticipated additional consultation time, resulting from a prior cancellation, impacts the patient's long-term health. To address this question, I focus on patient readmissions at the specialty level. Specialty readmissions serve as a proxy for visiting quality, as they indicate whether previous consultations with specialists were successful in accurately diagnosing the patient's health conditions, thereby reducing the need for further referrals for additional consultations. Table 8 illustrates how extra visiting time impacts the patient's long-run health condition, measured by a patient's readmission to the same treating specialty. We can observe that each additional minute spent during the initial visit reduces the probability of hospital readmission at the treating specialty level in 0.6 percentage points. This result suggests that additional care provided during the initial visit is beneficial for the patients' long-term health. Moreover, I find no association between extended visiting time and hospital readmissions in other specialties, which suggest that more thorough examinations in one specialty do not influence health conditions that pertinent to other specialties.

These results evidence that physicians use the extra time to assess the patient diagnosis better, to recommend further intensive care treatments, and to correct drug prescription excess. Nevertheless, how intensely physicians use such time might depend on multiple factors. In the following subsections, I explore whether patients' characteristics are key in understanding time utilization and shed light on the relevance physicians' contracts have on such a relationship.

5.1 Which Patients' Characteristics are Driving These Effects?

In this section, I explore the influence of patient and shared patient-physician characteristics have on how physicians utilize extra visiting time.

I begin by examining whether the gender of patients influences physicians' use of extra visiting time. While patients may require different treatments along their gender, the exogenous exposure to cancellations allows us to study whether physicians treat them differently. Table 9 shows that visit length affects male and female patients differently. We can observe how, following a cancellation, physicians spend more time similarly with both male and female patients. However, physicians seem to use this extra time only more intensively with their female patients, with increased tests ordered and lower prescription doses. This input use is not explained by a systematic difference in their unconditional means (i.e., 12.4 minutes for men, and 12.7 for women), hinting towards some limited preferential treatment towards women. Next, I inspect whether physicians treat patients differently based on shared gender. On the one hand, we could expect that physicians use time more intensively on those patients sharing their gender, due to a higher sense of proximity. On the other hand, they might screen patients of the same gender more quickly, using extra time more efficiently on patients of a different gender. Table 10 shows that physicians use extra visiting time only more intensively on patients of a different gender. Overall, these results suggest that physicians provide more intensive care to female patients and those of a different gender.

I then look at whether physicians treat patients differently based on their nationality. Table 11 shows that both national and non-national patients get more consultation time after a cancellation. However, physicians seem to provide diagnostic inputs and more tests only to national patients. In particular, this differential usage is not explained by differences in their unconditional means (i.e., 12.6 minutes for national patients, and 12.5 for non-nationals). This relation is in line with the policy of the outpatient department, which considers non-national patients as more demanding, as indicated by their longer expected visit lengths (15.17 minutes, compared to 14.8 minutes for national patients). Despite this, physicians provide more valuable service only to national patients when given extra visit time.

Next, I focus on the treatment provided to patients depending on the waiting time to access the outpatient department. As explained in Section 2.1, patients scheduled their first visit at the outpatient department at their corresponding primary care center. At that level, primary care physicians can speed up patients with worse health conditions, flagged as urgent to the outpatient physician. Conversely, patients who wait longer for their appointments are presumed to have less urgent health issues, as they always have the alternative option of accessing emergency room services if necessary. Table 12 provides evidence that physicians use extra visiting time differently depending on the patient's waiting time. Physicians use longer visits to order more tests, decrease the drug dose prescribed, and provide a diagnosis, but only for those patients whose waiting time was below the average time for their specialty. These results suggest that physicians prioritize more urgent patients, providing them with more valuable services.

Finally, I investigate whether all specialties within the hospital allocate extra face-to-face time in a similar manner. To address that issue, I classify the specialties into two broad groups: internal medicine and surgical specialties. Surgical specialties rely on pre-established treatment protocols and surgical procedures to diagnose and resolve patients' health issues. In contrast, internal medicine specialties are characterized by a more intensive use of visiting time and drug prescriptions, as seen in Table 5. Table 13 illustrates how physicians respond to additional visiting time along these two broad categories. On average, visits to internal medicine specialties involve more visiting time and drug prescription, compared to surgical specialties which emphasize on test provision. When a cancellation occurs, physicians respond by increasing their visiting time, regardless of their specialty. On the one hand, internal medicine physicians utilize this additional time to conduct more tests and provide diagnoses; for each extra minute, there is a 7.4% increase in the probability of providing a diagnosis, compared to their average diagnostic probability. Conversely, surgical specialists use the additional time to perform more tests and reduce drug dosages, without impacting the diagnosis rate.[15]

Overall, these results highlight that the utilization of extra consultation time depends significantly on the patient's inherent characteristics and the physicians' specialty. Physicians' responses to relaxed time constraints are not uniform across subgroups, showing a tendency to favor female, Spanish-born, and more urgent patients.

5.2 Role of Physicians' Contracts

In this section, I study the role of physicians' contracts in shaping how extra visiting time is used.

According to the general Spanish healthcare legislation, physician's contracts are composed of two main components: a fixed wage, common to all physicians; and a flexible component, primarily determined by the physician's tenure.[16] These contracts are updated annually on a per-physician basis, including adapting visit workloads according to the physicians' responsibilities and tenure, which might ultimately lead to a differential use of the extra time provided by cancellations.[17]

I use physicians' age as a proxy of their tenure, given that i) physicians enter the medical

[15] For a comprehensive analysis, I include Table A13, which shows no differential time use along the patients' age profile; and Table A14, which indicates that the nature of the shock –whether the prior visit was a no-show or a notification – does not differentially influence the utilization of extra time. In contrast, Table A15 shows that physicians respond significantly more to additional visiting time on particularly busy days, when time is most constrained.

[16] The fixed component is similar across physicians as it is based on educational attainment, which is, by law, required to be a bachelor's degree in medicine and to have passed a national exam (See Art. 4 in the Royal Decree 127/1984).

[17] For further knowledge on the collective bargaining agreement, please refer to the Resolution EMO/1742/2015 present in the Catalan Regional Bulletin n. 6923.

market right after finishing their studies,[18] and ii) the physicians' market has low unemployment.[19] I define physicians to be senior if their age is higher than the median age ($\approx$ 50 years old); otherwise, I define them as junior. As indicated previously, the older physicians are, the more seniority they are likely to have, thus the higher their salary. While the hospital has the incentive to retain these experienced physicians, it cannot freely raise the physicians' salaries, as they are publicly regulated. As a response, senior physicians are compensated with more advantageous shifts instead. Table 14 shows that senior physicians' schedules include fewer patients per hour and fewer overbooked visits, while the expected visit duration is similar to that of junior physicians. Furthermore, Table 15 shows that patients visiting senior outpatient physicians do not differ systematically from those visiting their junior colleagues. These tests show that while seniority affects the physician's workload through more relaxed schedules, it does not imply a change in patient composition.[20]

Back to our benchmark specification, Table 16 shows that extra visit duration affects the input utilization differently, depending on whether that bonus time is provided to senior or to junior physicians. The first insight we obtain from Columns 1 and 2 is that both senior and junior physicians similarly react to cancellations by increasing the duration of the consultations with their subsequent patients. Despite such similar increase in visit length after a cancellation, the unconditional visit length for junior physicians is 11.7 minutes, while for their senior colleagues, 14 minutes. This shows that even if junior physicians were to utilize more time, it would not be enough to compensate for the difference across these two groups. The way contracts are formulated, being physician-specific, facilitates less rushed environments for older professionals at the expense of their younger colleagues.

This formulation fully determines how extra visit length is used. In Column 3, we observe that junior physicians use extra visiting time more effectively by providing more diagnoses. Specifically, each additional minute a junior physician spends examining a patient increases their probability of providing a diagnosis by 0.73 percentage points, which corresponds to a 9.6% increase relative to the average probability. Conversely, senior physicians, despite having more time with patients following a prior cancellation, do not utilize this extra time to enhance their diagnosis provision. These findings suggest that extending visit length is not output-efficient for physicians who already have more relaxed schedules. Table

[18] According to the Spanish Health Ministry, the average age of those physicians entering practice in one of the specialties covered in the sample is 26 years, which corresponds to the age at which students finish their studies (Spanish Health Ministry, 2015).

[19] According to the Spanish Health Ministry, physician's unemployment in 2017 was 2.3% (Spanish Health Ministry, 2019). The unemployment rate in Spain in 2017 was 17.2%.

[20] A total of 13.7% of the visits correspond to 16 physicians who did not want their data to be made public. This section does not consider them.

17 further substantiates this by showing that junior physicians use the extra visiting time to provide more in-depth diagnoses, as evidenced by an increase in uncommon diagnoses. This indicates that junior physicians effectively leverage the additional time to deliver a higher quality of care.

Back to Table 16, Columns 4 to 8 illustrate how consultation time influences input choices. Junior physicians, when exposed to additional time, tend to provide patients with more tests both intensively and extensively, which leads to higher costs. Quantitatively, for every extra minute a junior physician spends with a patient, the probability of ordering a test increases by 0.68 percentage points (representing a 4% increase over the average ordering probability), the number of tests ordered is increased by 0.013 units (representing a 4.9% increase over their average ordering rate), and total testing cost increases by 10.8%. Conversely, the effect of longer visits on drug prescriptions operates through the intensive margin. Each additional minute a junior physician spends with a patient results in a decrease in the average dose prescribed by 0.68 daily defined doses, which corresponds to a 28.8% reduction relative to their average prescribed dose. Senior physicians also reduce prescription doses, though to a lesser extent, with a reduction of 0.19 doses per additional minute spent, reflecting an average decrease of 8.2% in prescribed doses.[21]

These results highlight that correcting insufficient time per visit might have welfare-improving effects, as in the case of junior physicians. For senior physicians, longer visits do not entail further care expansions, suggesting they are already at their optimal level of time-to-input utilization. These results suggest that defining schedules based on seniority might hinder high costs related to suboptimal utilization of visiting time. In Section 6, I provide a quantification analysis stressing these inefficiencies and show that time expansions to less experienced physicians might be cost-effective.

6 Quantifying the Cost of a Diagnosis

In this section, I quantify the direct cost of increasing visit lengths.[22] In particular, I evaluate the impact of extending the duration of first visit through increased budget expenditures,

[21] In the same spirit, Table A16 shows that extra visiting time helps least productive physicians catching up in the care provided, while no effects are found on high-performing doctors. Table A17 compares only physicians in the 1st and 4th quantile of the physician's age distribution, finding comparable results to the benchmark specification.

[22] Throughout this exercise, I assume that the outpatient department's fixed capacities are non-binding along small visit length expansions. Additionally, I do not internalize the positive crowding-out effect more prolonged first visits may have on other services, such as the emergency room, or on the probability of a specialty readmission as indicated in Table 8.

rather than by postponing patient consultations over time, to avoid the higher health costs associated with delayed checkups (Ziedan et al., 2022).

Suppose we want to increase the probability of providing a diagnosis by one percentage point ($\approx$ 12% at the sample average). We can achieve this in two ways: i) by increasing all physicians' visiting times; or ii) by favoring only those physicians with less experience.

6.1 Broad Increase

Let us say we opt to increase the length of all first visits to achieve a one-percentage-point increase in the diagnosis rate. That can be achieved with an increase in the average visit length of 2.77 minutes, using the IV-fixed-effects estimates in Column 3 of Table 3.

We calculate the direct costs associated with increasing visit length such that it increases the diagnosis rate by one percentage point, assuming that physicians will optimally utilize their *bonus* visiting time. In our case, using a linear approximation, we have the following:

$$\hat{\Delta}_{minutes} = 2.77 \times 6.55 \times 102.44 \ = 1,858.62 \text{ minutes per year and physician}$$

where 6.55 refers to the average number of first-visit patients per day and physician, and 102.4 is the average number of days worked per physician. $\hat{\Delta}_{minutes}$ amounts to about 31 hours extra per year and physician, representing a 1.8% increase in the physician's yearly working hours. We now extrapolate our physician-specific estimates to the general Spanish economy, such that:

$$\hat{\Delta}_{cost} = \hat{\Delta}_{minutes} \times (0.5876 \times (1 + 0.0092 \times 10.55) + 0.8045) \times 76,562 \ \approx €206m$$

where 0.5876 represents the average physician wage per minute,[23] 0.0092 represents the increased probability of scheduling a follow-up visit due to a one-minute increase in the first visit duration, and 10.55 the average follow-up visit length. 0.8045 represents the average treatment cost ordered for every extra minute spent with a patient,[24], and 76,562 refers to the total number of outpatient physicians in Spain in 2018 (Spanish Health Ministry, 2019). Thus, increasing the diagnosis rate in first visits by one percentage point would have an

[23] The average working hours of a physician in the Spanish health system is 1,645 hours, regulated by Decree 2/2012 and Royal Decree 20/2012. The average outpatient physician salary in 2018 is €58,000 (Medscape, 2019).

[24] The average treatment cost is calculated using internal information of the sample outpatient department. Both in this and the following calculations, it is assumed to be representative of the health system as a whole.

estimated labor cost of €206m for the general Spanish economy.

6.2 Tailored Increase

Suppose we now opt to provide more time per visit only to those physicians who will use it more efficiently. Following the previous procedure, I study how many more minutes junior physicians should have to increase their diagnosis rate by one percentage point. That increment can be achieved by increasing the visit length of junior physicians by 1.37 minutes, using the IV-fixed-effects estimates in Column 3 of Table 16. This change at the visiting intensive margin helps junior physicians assess their patients adequately while leaving senior physicians' schedules unchanged. Following the same structure as before, we have:

$$\hat{\Delta}_{minutes,junior} = 1.37 \times 6.82 \times 95.45 \; = 891.82 \text{ minutes per year and junior physician}$$

Now we extrapolate these changes to the overall economy, such that:

$$\hat{\Delta}_{cost} = \hat{\Delta}_{minutes,junior} \times (0.575 \times (1 + 0.0116 \times 10.09) + 1.294) \times 42,863 \; \approx €74m$$

where 0.575 represents the per-minute wage,[25] 0.0116 represents the increased probability of scheduling a follow-up visit due to a one-minute increase in the first visit duration, and 10.09 is the average follow-up visit length. 1.294 represents the average treatment cost ordered for every extra minute spent with a patient, and 42,863 represents the estimated number of junior physicians.[26]

In summary, comparing the targeted increase in consultation time for junior physicians to the previous broad increase across all physicians, it emerges the targeted approach as more cost-effective in achieving the same outcome: a one-percentage-point increase in diagnostic provision. With all due caveats, this exercise underscores the potential efficiency gains from aligning contracting incentives based on seniority, allowing for more effective diagnostic delivery at a lower cost.

[25] The salary for junior physicians corresponds to a physician with a fixed position, around 40 years old, and 15 years of experience. The annual salary of such a physician is €56,755. For further reference, see OMC (2019).

[26] I use information from the OECD database - Healthcare Utilization. Given that the number of outpatient physicians is not tabulated by age, I assume that the distribution of physicians by age is the same for the overall population of physicians and that of outpatient physicians.

7 Conclusion

This paper investigates how relaxing time constraints influences worker performance and output quality using a unique, high-frequency administrative dataset containing time-use data on all physician in a Spanish outpatient department. I exploit a natural experiment by which physicians, when randomly affected by a cancellation, allocate unexpected additional time with their subsequent patient. Conceptually, I compare those visits characterized by unexpectedly longer consultation times due to a preceding cancellation, to all other visits, holding any other parameters in the environment constant.

I find that longer first visits lead to a higher likelihood of providing a diagnosis. For every additional minute spent on an examination, the probability of delivering a diagnosis rises by 4%. This effect is driven by uncommon diagnoses, whose provision requires a more in-depth analysis. Similarly, extended consultation times also have long-term health benefits, as highlighted by the lower hospital readmission probability. In particular, each additional minute spent in a medical consultation leads to a 0.6% reduction in the probability of hospital readmission. This suggests that the additional time spent initially helps in accurately diagnosing and managing patients' health conditions, thereby reducing the need for subsequent hospital visits. Longer first visits increase diagnostic input utilization while decreasing drug dose prescriptions. This dual effect suggest that physicians use the extra visiting time to assess the patient's health problems in more detail and, in the event of indecision, to request further diagnostic inputs, ultimately improving the service provided. Importantly, I find no evidence of an input substitution effect between first and follow-up visits, suggesting that the benefits derived from longer first visits persist throughout the clinical process, rather than being offset or substituted during subsequent visits.

This avenue of research is extremely important for policymaking. This paper leverages the Spanish system to causally identify how insufficient examining time affects workers' decisions and output quality. However, its conclusions are more general, as they relate to all those time-constrained situations in which workers must decide between speeding up their processes and exerting higher effort per task. This study highlights that minimal time expansion may have large welfare implications when targeted at those workers most in need.

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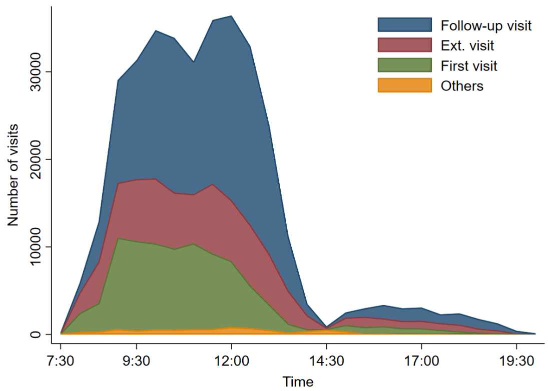
Figures and Tables

Figure 1: Daily Physician's Schedule Viewed at 10:00 am.

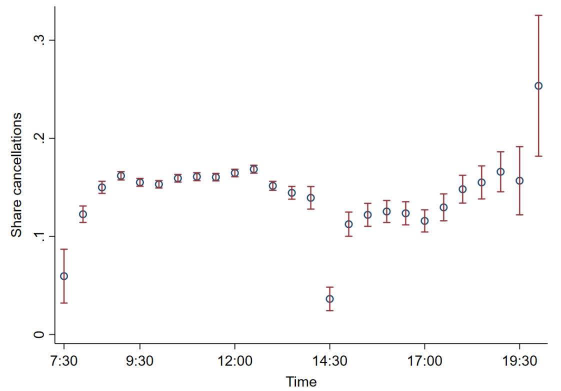
Appointment Time	Patient ID	Patient	Basic Health Zone	Status	Arrival time	Visit type
8:30	1	Antonio García Gracia	Barcelona 2-B	Completed	8:25	Follow-up
9:00	2	Jordi Bosch Fernández	Barcelona 3-A	Not present	-	Follow-up
9:10	3	Montserrat Muñoz Sánchez	Barcelona 4-D	Completed	9:05	First Visit
9:15	4	María del Carmen González Serra	Barcelona 5-D	Completed	9:00	First Visit
9:30	5	Anna Solé Pérez	Barcelona 1-C	Completed	9:10	Follow-up
9:40	6	José Giménez Sánchez	Barcelona 2-E	Completed	9:00	Long Cure
10:00	7	Wei Wang	Barcelona 8-B	Completed	9:40	Injection
10:15	8	María José Pérez Iglesias	Barcelona 4-C	Pending	9:45	First Visit
10:25	9	Montserrat Batlle Figueres	Barcelona 5-C	Pending	-	Follow-up
10:43	10	María del Mar Cardel Pérez	Barcelona 3-E	Canceled	-	First Visit
11:00	11	Mohammed Alaoui	Barcelona 5-A	Pending	-	Follow-up

Notes: The figure shows how the schedules used in the outpatient department look like, using fictitious information. *Appointment Time* refers to the time at which a patient is appointed to start her visit. *Status* refers to the visiting status, which can be "Completed" if the visit finished already, "Not Present" if the visit was supposed to happen but the patient was not present, "Pending" if the visit will happen later, and "Canceled" if the visit was appointed for a later time but canceled earlier on the day. *Arrival time* refers to their arrival time to the outpatient department. If *arrival time* is not displayed (e.g. −), it means the patient has not registered yet at the outpatient department. *Visit type* highlights broadly the type of visit, which can be "First Visit", "Follow-up", "Long Cure", or "Injection".

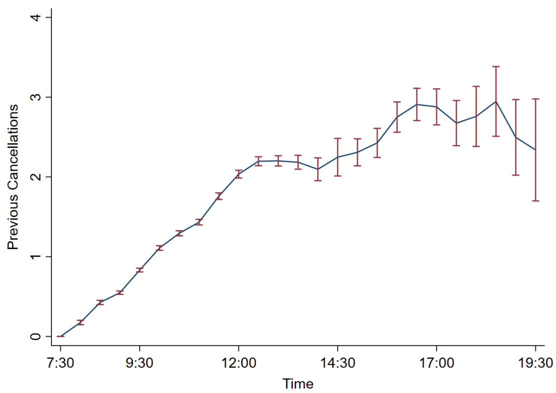
Figure 2: Distribution of Visits Over the Day



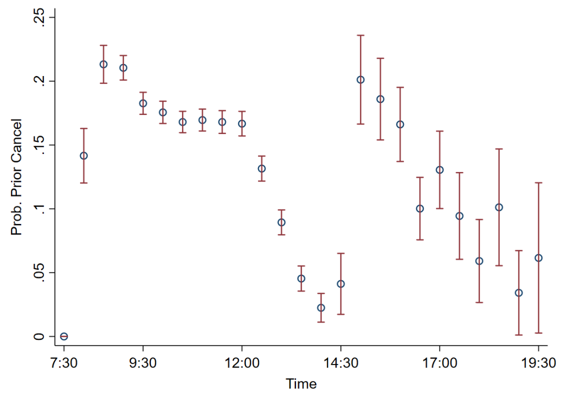
(a) Distribution by visit type



(b) Share of cancellations (Appointment)



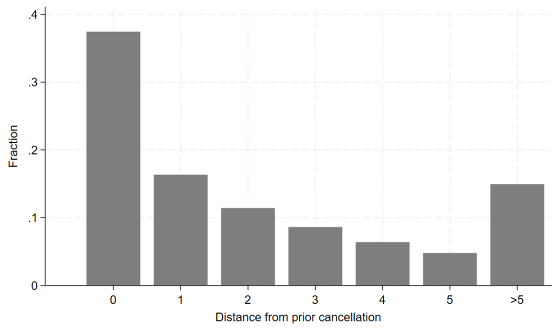
(c) Previous cancellations (First visits)



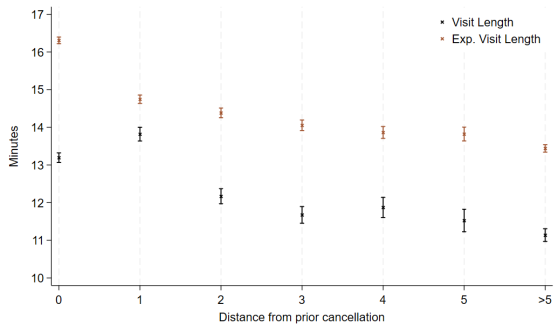
(d) Prob. Prior cancel (First visits)

Notes: The figure reports how visits and cancellations span over the schedule. Subfigures 2a and 2b use the sample including all the visits, namely first, external, and follow-up visits, canceled or not, while subfigures 2c and 2d only use our final sample of first visits. Subfigure 2b displays the share of cancellations as to when those visits were appointed. Subfigures 2c and 2d use the real notification time of those cancellations as in our main analysis. Prior cancel identifies those visits that had their prior visit slot canceled using their real cancellation time. 95% confidence intervals are included. All subfigures use 30-minutes bin sizes.

Figure 3: Distances to Prior Cancellation



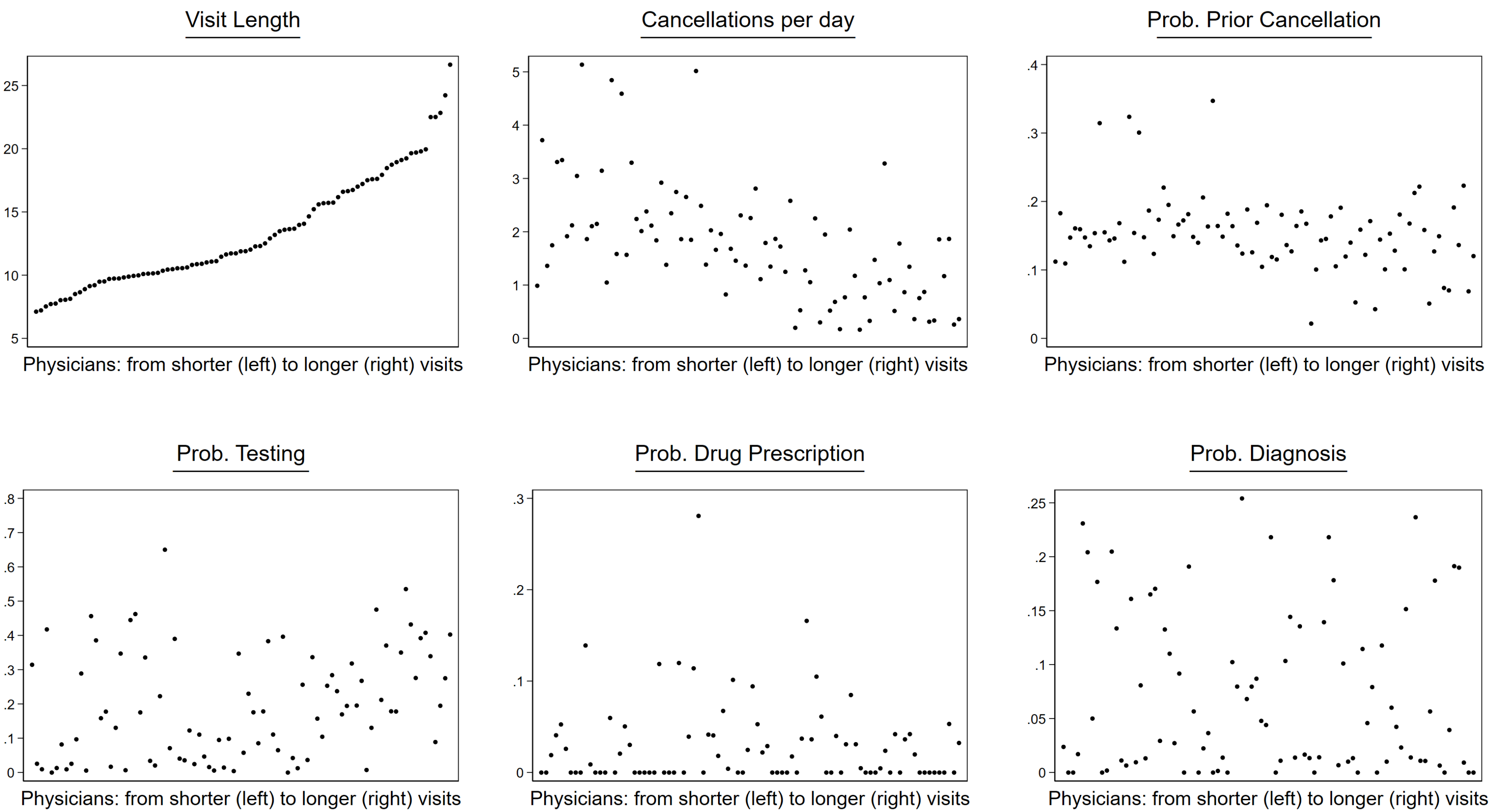
(a) Distribution



(b) Unconditional means

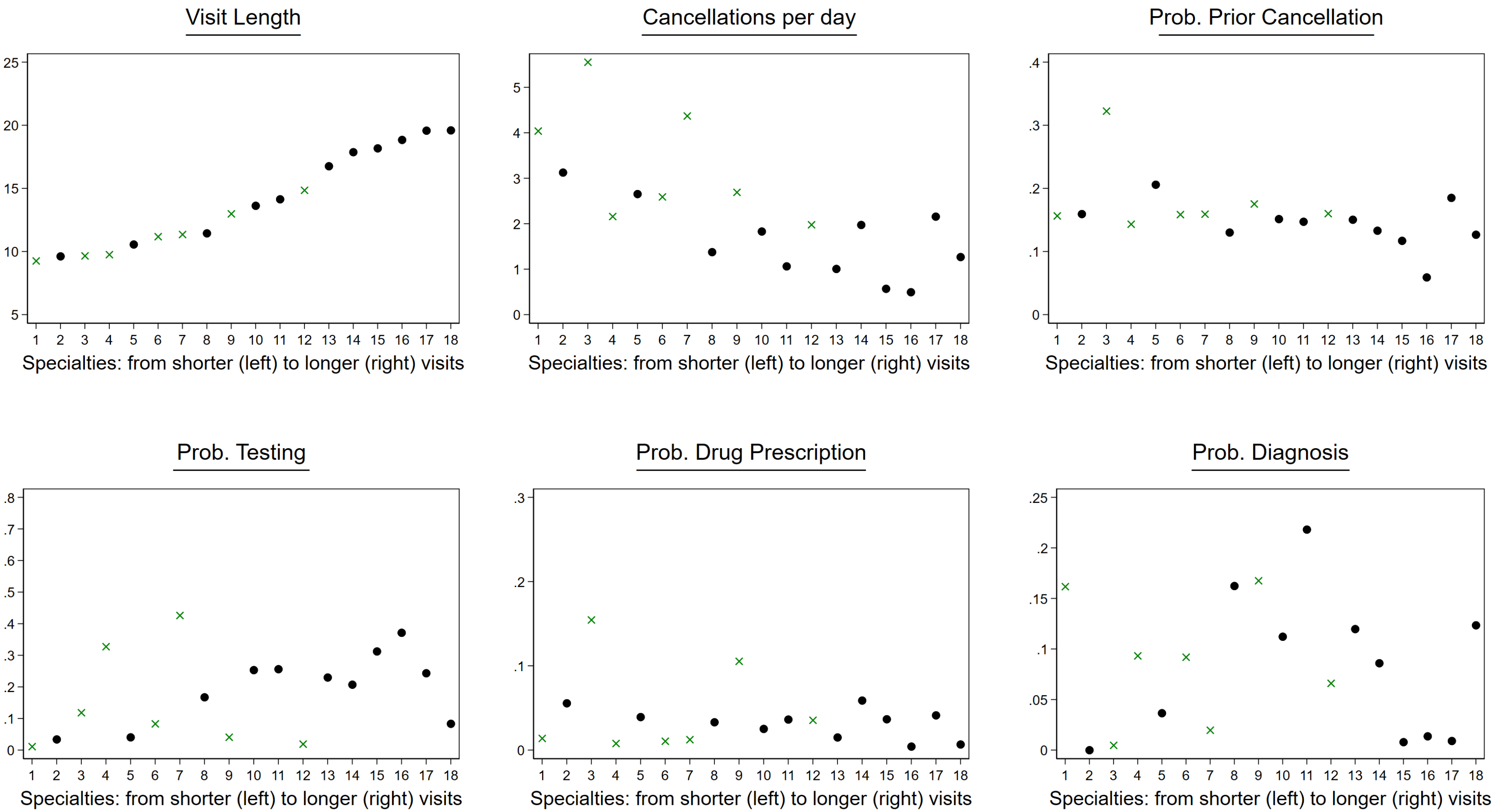
Notes: The figure reports the proportion of visits by distance to a cancellation and their visit lengths. The sample use corresponds to the final sample as exposed in Table 1. Subfigure 3a shows the proportion of visits which had no previous cancellation (distance 0), a cancellation in the previous visit (distance 1), and so forth. Subfigure 3b displays the unconditional mean of both visit length and expected visit length by the distance to a preceding cancellation.

Figure 4: Differences of performance between physicians



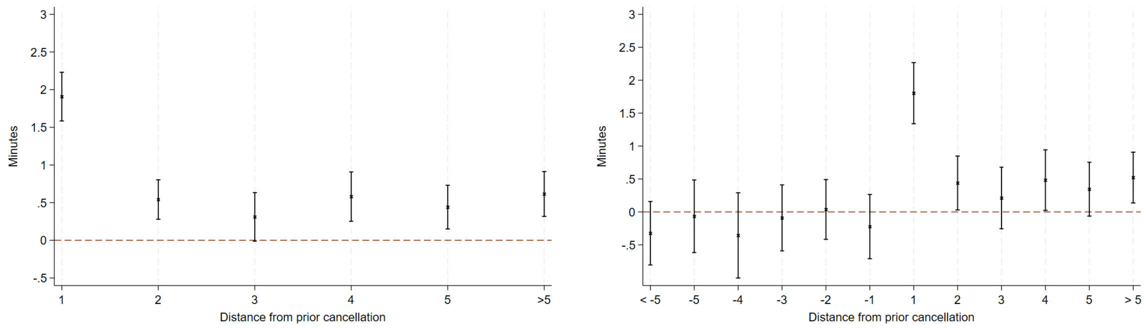
Notes: The figure displays the average of different performance indicators for each physician. *Visit Length* corresponds to every physician's average time examining patients. *Cancellations per day* measures every physician's average number of cancellations per working day. *Prob. Prior Cancellation* measures the probability that a given visit had its preceding scheduled visit canceled. *Prob. Testing* identifies every physician's testing probability. *Prob. Drug Prescription* identifies every physician's drug prescription probability. *Prob. Diagnosis* identifies every physician's diagnostic provision rate.

Figure 5: Differences of performance across specialties



Notes: The figure displays the average of different performance indicators for each specialty. *Visit Length* corresponds to every specialty's average time examining patients. *Cancellations per day* measures every specialty's average number of cancellations per working day. *Prob. Prior Cancellation* measures the probability that a given visit had its preceding scheduled visit canceled. *Prob. Testing* identifies every specialty's testing probability. *Prob. Drug Prescription* identifies every specialty's drug prescription probability. *Prob. Diagnosis* identifies every specialty's diagnostic provision rate. The specialties represented are: 1) Ophthalmology, 2) Dermatology, 3) Maxillofacial surgery, 4) Urology, 5) Allergology, 6) General surgery, 7) Orthopaedic surgery, 8) Neurology, 9) Otolaryngology 10) Palliative care, 11) Endocrinology, 12) Cardiovascular surgery, 13) Pulmonology, 14) Rheumatology, 15) Internal medicine, 16) Oncology, 17) Pain pathologies, and 18) Cardiology. Surgical specialties are represented with a green cross, and internal medicine specialties with a black dot.

Figure 6: First Stage at Multiple Distances



(a) All shifts

(b) Shifts with one or no cancellation

Notes: The figure reports how cancellations impact surrounding visits. Subfigure 6a uses the final sample as exposed in Table 1, and shows graphically the first stage results using dummy variables identifying those visits at 1, 2, 3, 4, 5, or more than 5 visits from a cancellation. Subfigure 6b uses only those shifts with one or no cancellations, and shows graphically the first stage results using dummy variables identifying those visits at 1, 2, 3, 4, 5, or more than 5 visits from a cancellation, both prior and posterior to a cancellation. The results presented in both figures include all the fixed effects and controls as in our benchmark specification (see Table 3). Confidence intervals at the 95%.

Table 1: Summary Statistics

	Mean	SD	Min	Max	N
Patient characteristics					
Male	0.45	0.50	0	1	67530
Age	58.85	19.55	0	106	67530
Reference BHZ	0.60	0.49	0	1	67530
Distance from hospital (km)	4.37	12.87	0	1979	67530
Born in Spain	0.68	0.47	0	1	67530
Public coverage	0.98	0.12	0	1	67530
Chronic condition	0.06	0.23	0	1	67530
Physician characteristics					
Physician: Male	0.59	0.49	0	1	66350
Physician: Age	49.78	9.32	32	65	58301
Visit characteristics					
Visit length (mins)	12.58	9.59	1	120	67530
Follow-up visit	0.28	0.45	0	1	67530
Out of agenda	0.15	0.35	0	1	67530
Internal referral	0.11	0.32	0	1	67530
Waiting list (days)	29.73	52.02	0	770	67530
Waiting room (mins)	27.22	32.62	0	545	67530
Tests	0.29	0.75	0	15	67530
Test cost	12.67	50.58	0	2019	67530
Drugs	2.04	27.34	0	2600	67530
Diagnosis	0.08	0.27	0	1	67530

Notes: The table provides a summary statistics for our sample of interest. Reference BHZ is an indicator variable that identifies whether the patient comes from a Basic Health Zone covered by the outpatient department. Distance from hospital is a variable that measures how many kilometers apart is the patient's Basic Health Zone centroid from the hospital using a linear distance algorithm. Public coverage is an indicator variable that identifies whether the treated patient is covered by the general public health insurance. Chronic condition is an indicator variable that identifies if the patient previously was been diagnosed any chronic condition. Visit length identifies how long a visit is using the patient's profile opening and closure in the physician's terminal. Out of agenda identifies whether the visit was placed in a slot not covered by the physician's agenda (visit schedule). Internal referral identifies if the visit was appointed by another hospital physician as opposed to a general practitioner. Waiting room is a variable that measures how many minutes has the patient been waiting prior to the visit start. Test cost indicates the testing cost per visit in euros. The variable Drugs captures the number of drugs prescribed measured using the Defined Daily Dose (DDD) definition. Diagnosis is an indicator variable identifying if a visit led to the definition of a precise diagnosis. Physician related variables such as age or sex have missing observations as some physicians preferred not disclosing such information. All other variables are self-explanatory.

Table 2: Covariate Test

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list	(9) Same sex	(10) Same age
Prior Cancel	-0.0039	0.2213	0.0057	-0.0434	0.0032	0.0003	-0.0052	1.0568	-0.0030	0.0046
	(0.0045)	(0.1812)	(0.0056)	(0.1492)	(0.0023)	(0.0012)	(0.0047)	(0.7029)	(0.0046)	(0.0043)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530	66350	58301
Dep. Var. Mean	0.447	58.85	0.598	4.365	0.0582	0.984	0.677	29.73	0.517	0.152

Notes: The table tests whether having a prior cancellation predicts the patient and the shared physician-patient characteristics. Ref. BHZ is an indicator variable that identifies if the patient comes from a Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of Visit Length on Visit Outcomes - Main Analysis

	(1) Length	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Testing cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Length		0.0036**	0.0065***	0.0096**	0.8045**	-0.0010	-0.4106*	0.0092***
		(0.0018)	(0.0023)	(0.0042)	(0.3470)	(0.0011)	(0.2166)	(0.0032)
Prior Cancel	1.6222***							
	(0.1598)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat	–	104.3	104.3	104.3	104.3	104.3	104.3	104.3
FDR p-values	–	0.066	0.02	0.042	0.042	0.341	.068	0.02

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). FDR p-values are False Discovery Rates adjusted p-values, following the procedure in Anderson (2008). *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effect of Visit Length on Diagnosis Provision

	(1) Diagnosis	(2) Common	(3) Uncommon
Length	0.0036**	0.0001	0.0034**
	(0.0018)	(0.0008)	(0.0014)
Month-Year FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	67530	67530	67530
Dep. Var. Mean	0.0819	0.0123	0.0695
F - Stat	104.3	104.3	104.3

Notes: The reported regressions correspond to the 2nd Stage with the following outcomes: i) the probability of a diagnosis (Col. 1), ii) the probability of a common diagnosis (Col. 2), and iii) the probability of an uncommon diagnosis (Col. 3). Diagnoses are classified as common identify those diagnoses most repeated in a given specialization, while uncommon represent any other non modal diagnosis. See Table 3 for further reference on the controls used. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Effect of Visit Length on Drug Prescriptions

	(1) Length	(2) Drugs	(3) Antibiotics	(4) Painkillers	(5) Antidepressants	(6) Other Drugs
Length		-0.4106*	-0.1616*	-0.0282**	-0.0019	-0.2190
		(0.2166)	(0.0895)	(0.0121)	(0.0013)	(0.1369)
Prior Cancel	1.6222***					
	(0.1598)					
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	6530
Dep. Var. Mean	12.58	2.043	0.436	0.179	0.00322	1.425
F - Stat		104.3	104.3	104.3	104.3	104.3

Notes: The reported regressions correspond to the 2nd Stage with the following outcomes: i) the amount of drugs prescribed (Col. 2), ii) the amount of antibiotics prescribed (Col. 3), iii) the amount of painkillers prescribed (Col. 4), iv) the amount of antidepressants prescribed (Col. 5), and v) the amount of other drugs prescribed (Col. 6). All drug-related outcomes are measured in Daily Defined Doses (DDD). See Table 3 for further reference on the controls used. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Effect of Current Visit Length on the Next Visit Outcomes

	(1) Length	(2) F. Length	(3) F. Tests	(4) F. Num. Tests	(5) F. Drugs	(6) F. Num. Drugs	(7) Same Physician
Length		0.0953	0.0008	-0.0013	0.0008	0.5331	0.0105***
		(0.1848)	(0.0034)	(0.0055)	(0.0008)	(0.4414)	(0.0037)
Prior Cancel	1.8596***						
	(0.2439)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14350	14350	14350	14350	14350	14350	14350
Dep. Var. Mean	14.39	11.19	0.143	0.195	0.00613	0.552	0.656
F - Stat	–	58.82	58.82	58.82	58.82	58.82	58.82

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-7). The sample used refers to all those visits that had a follow-up visit appointed on that same first visit. The outcomes used refer to the follow-up visit. For information on the outcome variables, please refer to Section 4.1. *Same Physician* is a dummy variable that takes value one if the visit was conducted by the same physician that conducted the first one, and zero otherwise. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. All the controls used are measured as in the first visit. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effect of Current Visit Length on the Next Visit Cancellation

	Length	Next visit cancelled		
	Length	All	By patient	By physician
	(1)	(2)	(3)	(4)
Length		-0.0001	0.0036	-0.0037**
		(0.0048)	(0.0043)	(0.0018)
Prior Cancel	1.8328***			
	(0.1947)			
Month-Year FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	14.34	0.240	0.211	0.0287
F - Stat	–	89.65	89.65	89.65

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-7). The sample used refers to all those visit that had a follow-up visit appointed on that same visit. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. All the controls used are measured as they were during the first visit. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Effect of Visit Length on Hospital Readmissions

		Future Readmission	
	Length	Same Specialty	Other Specialty
	(1)	(2)	(3)
Length		-0.0063*	0.0029
		(0.0038)	(0.0044)
Prior Cancel	1.6700***		
	(0.1913)		
Month-Year FE	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	31266	31266	31266
Dep. Var. Mean	12.46	0.123	0.394
F - Stat		77.11	77.11

Notes: The regressions presented are as follows: Column 1 presents the 1st Stage estimate of the effect of having a prior cancellation on the duration of the initial visit to the specialist, Column 2 provides the 2nd stage estimates of the impact of that extra visiting length have on the likelihood of readmission to the same specialty, while Column 3 examines the likelihood of readmission to a different specialty. The sample includes all patients residing in the hospital's reference area who had their first visit within the initial two years of the main data sample. See Table 3 for further reference on the controls used. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Effect of Visit Length on Visit Outcomes - By Patient sex

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Length	Length Male	Diagnosis	Test	Num. Tests	Test Cost	Drug	Num. Drugs
Length			0.0033	0.0081**	0.0107	1.4358***	-0.0019	-0.5883**
			(0.0022)	(0.0034)	(0.0067)	(0.4917)	(0.0019)	(0.2329)
Length × Male			0.0005	-0.0033	-0.0024	-1.3088*	0.0020	0.3682
			(0.0028)	(0.0044)	(0.0088)	(0.7509)	(0.0025)	(0.2928)
Male	-0.0163	12.3993***	-0.0052	0.0315	0.0138	16.6131*	-0.0232	-4.0772
	(0.1029)	(0.5845)	(0.0352)	(0.0565)	(0.1139)	(9.6802)	(0.0313)	(3.6727)
Prior Cancel	1.5313***	0.0901						
	(0.1754)	(0.0844)						
Prior Cancel × Male	0.2067	1.5743***						
	(0.1656)	(0.2835)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.0949	0.106	0.120	0.810	0.995	0.446
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	19.15	19.15	19.15	19.15	19.15	19.15

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and the patient's sex (*Male*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Male*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Effect of Visit Length on Visit Outcomes - By Patient-Physician sex

	(1) Length	(2) Length Male	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0046**	0.0103***	0.0220***	1.4593***	0.0008	-0.3642
			(0.0021)	(0.0036)	(0.0064)	(0.4992)	(0.0016)	(0.2773)
Length × Same sex			-0.0021	-0.0073*	-0.0242***	-1.2207*	-0.0036	-0.0894
			(0.0027)	(0.0044)	(0.0091)	(0.7327)	(0.0026)	(0.2728)
Same sex	-0.0772	12.3465***	0.0292	0.0940*	0.3127***	16.4118*	0.0428	0.6551
	(0.1067)	(0.5926)	(0.0332)	(0.0561)	(0.1161)	(9.2885)	(0.0319)	(3.4255)
Prior Cancel	1.6723***	0.0824						
	(0.1621)	(0.1057)						
Prior Cancel × Same sex	-0.0264	1.4853***						
	(0.1727)	(0.2761)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66350	66350	66350	66350	66350	66350	66350	66350
Joint Length p-value	–	–	0.261	0.288	0.718	0.639	0.116	0.0506
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	17.44	17.44	17.44	17.44	17.44	17.44

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the patient and physician have the sex (*Same sex*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length × Same sex*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Effect of Visit Length on Visit Outcomes - By Nationality

	(1) Length	(2) Length Spanish	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0044**	0.0054*	0.0095*	0.9784**	-0.0000	-0.5015
			(0.0021)	(0.0030)	(0.0057)	(0.4856)	(0.0014)	(0.3364)
Length × Non-Spanish			-0.0024	0.0031	0.0001	-0.5006	-0.0028	0.2617
			(0.0035)	(0.0059)	(0.0096)	(0.8946)	(0.0042)	(0.4364)
Non-Spanish	0.1674	12.2274***	0.0243	-0.0395	-0.0079	5.6797	0.0300	-3.5730
	(0.1450)	(0.5984)	(0.0465)	(0.0754)	(0.1228)	(11.1152)	(0.0487)	(5.5017)
Prior Cancel	1.6390***	0.0538						
	(0.1748)	(0.0677)						
Prior Cancel × Non-Spanish	-0.0507	1.5372***						
	(0.2392)	(0.2804)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.501	0.0629	0.178	0.468	0.392	0.269
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	20.59	20.59	20.59	20.59	20.59	20.59

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). The table presents the interaction of *Length* and whether the patient was born in Spain (*Spanish*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value refers to the joint significance of *Length* and *Length* × *Spanish*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Effect of Visit Length on Visit Outcomes - By Waiting List

	(1) Length	(2) Length WaitLong	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0061**	0.0109***	0.0153***	0.7824*	-0.0023	-0.4661**
			(0.0025)	(0.0033)	(0.0058)	(0.4064)	(0.0016)	(0.2311)
Length × WaitLong			-0.0091**	-0.0149**	-0.0191**	0.0976	0.0042	0.1840
			(0.0037)	(0.0061)	(0.0097)	(0.5968)	(0.0035)	(0.2255)
WaitLong	-0.7258**	11.6228***	0.1012**	0.1604**	0.1836	-4.6967	-0.0540	-2.7691
	(0.3084)	(0.5002)	(0.0494)	(0.0768)	(0.1196)	(7.3844)	(0.0408)	(2.8035)
Prior Cancel	1.6671***	0.0187						
	(0.1834)	(0.0498)						
Prior Cancel × WaitLong	-0.1346	1.3745***						
	(0.2117)	(0.2154)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.221	0.370	0.593	0.0860	0.432	0.274
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	25.17	25.17	25.17	25.17	25.17	25.17

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-9). The table presents the interaction of *Length* and whether the patient had to wait more than the average service waiting list (*WaitLong*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. Joint Length p-value refers to the joint p-value of *Length* and *Length* × *WaitLong*. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Effect of Visit Length on Visit Outcomes - By Specialty Type

	(1) Length	(2) Diagnosis	(3) Tests	(4) Num. Tests	(5) Test Cost	(6) Drugs	(7) Num. Drugs	(8) Follow-up
Panel A: Internal medicine specialties								
Length		0.0055***	0.0060	0.0110**	1.1976**	0.0003	-0.6096	0.0136***
		(0.0015)	(0.0039)	(0.0055)	(0.5922)	(0.0011)	(0.5049)	(0.0034)
Prior Cancel	2.2361***							
	(0.3030)							
Observations	23339	23339	23339	23339	23339	23339	23339	23339
Dep. Var. Mean	15.65	0.0747	0.197	0.278	14.07	0.0295	2.840	0.343
F - Stat	–	55.86	55.86	55.86	55.86	55.86	55.86	55.86
Panel B: Surgical specialties								
Length		0.0022	0.0063**	0.0087	0.4616	-0.0020	-0.2617**	0.0065
		(0.0028)	(0.0028)	(0.0061)	(0.3715)	(0.0016)	(0.1070)	(0.0048)
Prior Cancel	1.3514***							
	(0.1691)							
Observations	44141	44141	44141	44141	44141	44141	44141	44141
Dep. Var. Mean	10.95	0.0857	0.172	0.291	11.94	0.0353	1.624	0.248
F - Stat	–	65.23	65.23	65.23	65.23	65.23	65.23	65.23
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). Panel A includes all observations covering visits that happened in an internal medicine specialties, while Panel B includes those that happened at a surgical specialties. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. The specialties classified as internal medicine are: Allergology, Cardiology, Dermatology, Endocrinology, Internal Medicine, Neurology, Oncology, Pain pathologies, Pulmonology, and Rheumatology; while those specialties classified as surgical are: Cardiovascular surgery, General surgery, Maxillofacial surgery, Ophthalmology, Orthopedics, Otolaryngology, and Urology. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Visit characteristics by Senior Physicians

	(1) Exp. Visit Length	(2) Overbook	(3) Visits/hour	(4) Overloaded day
Senior Physician	-0.2446	-0.0367***	-0.2967***	-0.0829***
	(0.1983)	(0.0115)	(0.0955)	(0.0268)
Month-Year FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301
Dep. Var. Mean	14.93	0.212	4.255	0.240

Notes: The table tests whether senior physicians, measured as those above the median age in the outpatient department, have different type of visits. Exp. Visit Length is a hospital-provided variable that measures how long a given visit should be. Overbook is an indicator variable that identifies those visits that were appointed on the time slot of a prior visit. Overloaded day is an indicator variable that identifies those days in which the total expected visiting time a physician has, exceeds the time he/she is at the outpatient department. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Patient characteristics by Senior Physicians

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list
Senior Physician	-0.0115	0.5690	0.0243	-0.0957	-0.0007	-0.0237	0.0099	-3.8768*
	(0.0093)	(0.3451)	(0.0306)	(0.5525)	(0.0027)	(0.0157)	(0.0168)	(2.0910)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specialty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301	58301	58301	58301
Dep. Var. Mean	0.447	58.85	0.598	4.365	0.0582	0.984	0.677	29.73

Notes: The table tests whether senior physicians, measured as those above the median age in the outpatient department, have different type of patients compared to their junior colleagues. Ref. BHZ is an indicator variable that identifies if the patient comes from a Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Effect of Visit Length on Visit Outcomes - By Seniority

	(1) Length	(2) Length Senior	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs	(9) Follow-up
Length			0.0073**	0.0068*	0.0130***	1.2940**	-0.0017	-0.6812*	0.0116***
			(0.0030)	(0.0036)	(0.0049)	(0.5066)	(0.0016)	(0.4093)	(0.0044)
Length × Senior			-0.0075*	-0.0029	-0.0071	-1.1112*	0.0009	0.4865	-0.0064
			(0.0042)	(0.0046)	(0.0091)	(0.6618)	(0.0021)	(0.3965)	(0.0060)
Senior	-0.7348***	11.1466***	0.0473	0.0473	0.1047	17.6521**	-0.0135	-6.2473	0.1078
	(0.2682)	(1.0392)	(0.0523)	(0.0558)	(0.1189)	(7.9696)	(0.0239)	(4.9516)	(0.0729)
Prior Cancel	1.7592***	-0.0574**							
	(0.2560)	(0.0274)							
Prior Cancel × Senior	-0.1712	1.7390***							
	(0.3677)	(0.2621)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301	58301	58301	58301	58301
Joint Length p-value			0.949	0.223	0.443	0.680	0.598	0.0720	0.245
Dep. Var. Mean			0.0763	0.169	0.266	11.97	0.0384	2.363	0.283
F - Stat			22.05	22.05	22.05	22.05	22.05	22.05	22.05

Notes: The reported regressions correspond to the 1st Stages (Col. 1-2), and to the 2nd Stage with multiple outcome variables (Col. 3-8) and visit length interacted by the physician's seniority. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length × Senior*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Effect of Visit Length on Diagnosis Provision - By Seniority

	(1) Length	(2) Length Senior	(3) Diagnosis	(4) Common	(5) Uncommon
Length			0.0073**	0.0009	0.0064***
			(0.0030)	(0.0014)	(0.0021)
Length × Senior			-0.0075*	-0.0010	-0.0065**
			(0.0042)	(0.0016)	(0.0033)
Senior	-0.7348***	11.1466***	0.0473	-0.0004	0.0476
	(0.2682)	(1.0392)	(0.0523)	(0.0199)	(0.0415)
Prior Cancel	1.7592***	-0.0574**			
	(0.2560)	(0.0274)			
Prior Cancel × Senior	-0.1712	1.7390***			
	(0.3677)	(0.2621)			
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301
Joint Length p-value	–	–	0.949	0.945	0.959
Dep. Var. Mean	–	–	0.0763	0.0110	0.0653
F - Stat	–	–	22.05	22.05	22.05

Notes: The reported regressions correspond to the 1st Stages (Col. 1-2), and to the 2nd Stage with the following outcomes: i) the probability of a diagnosis (Col. 3), ii) the probability of a common diagnosis (Col. 4), and iii) the probability of an uncommon diagnosis (Col. 5). Diagnoses are classified as common identify those diagnoses most repeated in a given specialization, while uncommon represent any other non modal diagnosis. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Senior*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A Tables

Table A1: Effect of a Prior Cancellation on Visit Length - Time to End Shift

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	6 Hours	5 Hours	4 Hours	3 Hours	2 Hours	Last Hour	Overtime
	Length	Length	Length	Length	Length	Length	Length
Prior Cancel	2.5271***	1.9414***	1.6238***	1.6337***	1.7079***	0.6215**	-0.3333
	(0.6106)	(0.2728)	(0.2345)	(0.2409)	(0.2304)	(0.2858)	(1.1706)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2014	6558	12031	14323	14687	11964	3862
Dep. Var. Mean	13.44	13.29	12.64	12.64	12.18	12.42	10.92

Notes: The reported regressions correspond to the first stage estimation using *Prior Cancel* as the main regressor. The ending time in a given shift is calculated using appointment times. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Covariate Test - Patient Choice Specializations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Male	Age	Ref. BHZ	Dist. BHZ	Chronic	Pub. Cov	Spanish	Waiting list	Same sex	Same age
Prior Cancel	-0.0037	0.2639	0.0108	-0.2057	0.0038	-0.0003	-0.0051	1.2624	0.0010	0.0088*
	(0.0054)	(0.2226)	(0.0066)	(0.1277)	(0.0032)	(0.0010)	(0.0055)	(0.9336)	(0.0056)	(0.0052)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47832	47832	47832	47832	47832	47832	47832	47832	46652	40682
Dep. Var. Mean	0.465	60.28	0.645	3.812	0.0610	0.991	0.703	31.63	0.526	0.143

Notes: The table tests whether having a prior cancellation predicts the patient and shared physician-patient characteristics, on those specializations in which patients can choose their preferred slot. Ref. BHZ is an indicator variable that identifies if the patient comes from Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Effect of Visit Length on Visit Outcomes using Appointment Time

	(1) Length	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Testing cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Length		0.0041**	0.0074***	0.0103**	0.6199*	-0.0009	-0.3594*	0.0068**
		(0.0018)	(0.0025)	(0.0043)	(0.3466)	(0.0010)	(0.1963)	(0.0031)
Prior Cancel (Appointment)	1.6638***							
	(0.1475)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour Appointment FE	Yes							
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat		128.7	128.7	128.7	128.7	128.7	128.7	128.7

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. See Table 3 for further reference on the controls used. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Covariate Test - Late Prior Patient

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list	(9) Same sex	(10) Same age
Prior Cancel	-0.0039	0.2141	0.0060	-0.0497	0.0032	0.0002	-0.0052	1.0555	-0.0032	0.0046
	(0.0045)	(0.1806)	(0.0056)	(0.1495)	(0.0023)	(0.0012)	(0.0047)	(0.7017)	(0.0046)	(0.0042)
Prior Late	0.0009	-0.3156	0.0112	-0.2361***	0.0003	-0.0046**	-0.0016	-0.2962	-0.0096	-0.0011
	(0.0062)	(0.2046)	(0.0068)	(0.0824)	(0.0024)	(0.0020)	(0.0042)	(0.8013)	(0.0059)	(0.0031)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530	66350	58301
Dep. Var. Mean	0.447	58.85	0.598	4.365	0.0582	0.984	0.677	29.73	0.517	0.152

Notes: The table tests whether a late arrival of the previous patient predicts the current patient and shared physician-patient characteristics. Ref. BHZ is an indicator variable that identifies if the patient comes from Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Effect of Visit Length and Delay on Visit Outcomes

	(1) Length	(2) Delay	(3) Diagnosis	(4) Tests	(5) Num. Tests	(6) Test Cost	(7) Drugs	(8) Num. Drugs	(9) Follow-up
Length			0.0036**	0.0062***	0.0095**	0.7484**	-0.0005	-0.3482**	0.0105***
			(0.0017)	(0.0024)	(0.0045)	(0.3344)	(0.0009)	(0.1726)	(0.0032)
Delay			-0.0000	-0.0003	-0.0001	-0.0686	0.0006*	0.0764	0.0016*
			(0.0006)	(0.0006)	(0.0010)	(0.0802)	(0.0003)	(0.0686)	(0.0008)
Prior Cancel	1.6256***	-1.1688**							
	(0.1595)	(0.4783)							
Prior Late	0.1356	6.1898***							
	(0.1120)	(0.6744)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	16.20	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat	–	–	42.39	42.39	42.39	42.39	42.39	42.39	42.39

Notes: The reported regressions correspond to the two 1st Stages (Col. 1-2), and the 2nd Stage with multiple outcome variables (Col. 3-9). Prior Late is an indicator variable that identifies whether the previous patient arrived to the hospital after her scheduled visit time. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table A4 for the corresponding instrument covariate test. F-Stat corresponds to the first-stage joint F-statistics measure proposed by Kleibergen and Paap (2006). Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Effect of Visit Length on Visit Outcomes - No Controls

	(1) Length	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Test Cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Length		0.0021	0.0066***	0.0098**	0.7940**	-0.0012	-0.4193*	0.0093***
		(0.0022)	(0.0023)	(0.0043)	(0.3484)	(0.0011)	(0.2182)	(0.0032)
Prior Cancel	1.6205***							
	(0.1585)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No	No
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat	–	105.8	105.8	105.8	105.8	105.8	105.8	105.8

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Effect of Visit Length on Visit Outcomes - OLS

	(1) Diagnosis	(2) Test	(3) Num. Tests	(4) Test cost	(5) Drug	(6) Num. Drugs	(7) Follow-up
Length	0.0011***	0.0012**	0.0029***	0.2017***	0.0003***	0.0210**	0.0034***
	(0.0002)	(0.0005)	(0.0011)	(0.0569)	(0.0001)	(0.0100)	(0.0006)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280

Notes: The reported regressions correspond to the OLS estimation using *Length* as the main regressor. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Effect of a Prior Cancellation on Visit Outcomes - ITT

	(1) Diagnosis	(2) Test	(3) Num. Tests	(4) Test Cost	(5) Drug	(6) Num. Drugs	(7) Follow-up
Prior Cancel	0.0058*	0.0105**	0.0155**	1.3050**	-0.0016	-0.6661*	0.0149***
	(0.0029)	(0.0041)	(0.0072)	(0.5999)	(0.0017)	(0.3433)	(0.0052)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280

Notes: The reported regressions correspond to the ITT estimation using *Prior Cancel* as the main regressor. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Effect of Visit Length on Visit Outcomes
Instrumenting with the Number of Previous Cancellations

	(1) Length	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Test Cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Length		-0.0017	0.0131***	0.0175**	0.6108*	-0.0023	-0.0514	0.0091*
		(0.0052)	(0.0038)	(0.0068)	(0.3578)	(0.0018)	(0.2078)	(0.0052)
# Previous Cancellations	0.3343***							
	(0.0415)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No	No	No
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	12.58	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat		65.56	65.56	65.56	65.56	65.56	65.56	65.56

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Effect of Log Visit Length on Visit Outcomes

	(1) Ln(Visit Length)	(2) Diagnosis	(3) Test	(4) Num. Tests	(5) Testing cost	(6) Drug	(7) Num. Drugs	(8) Follow-up
Ln(Visit Length)		0.0445**	0.0806***	0.1191**	10.0245**	-0.0125	-5.1171*	0.1144***
		(0.0217)	(0.0286)	(0.0536)	(4.3448)	(0.0132)	(2.7239)	(0.0390)
Prior Cancel	0.1066***							
	(0.0136)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Dep. Var. Mean	2.222	0.0819	0.181	0.286	12.67	0.0333	2.043	0.280
F - Stat		88.46	88.46	88.46	88.46	88.46	88.46	88.46

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Effect of Visit Length on Clinical Process Duration

	(1) Length	(2) Case duration	(3) Length	(4) Case duration
Length		1.1678**		0.6699
		(0.5564)		(0.9142)
Prior Cancel	1.6222***		1.8414***	
	(0.1598)		(0.1961)	
Month-Year FE	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	67530	67530	18846	18846
Dep. Var. Mean	12.58	30.13	14.36	108
F - Stat	–	104.3	–	89.24

Notes: The reported regressions correspond to the 1st Stage (Col. 1 & 3), and the 2nd Stage (Col. 2 & 4). The variable Case duration measures the number of days, after a first visit, that has taken a clinical process to end. Columns 1 and 2 use the whole sample and provide a value 0 to those first visits that had no follow-up, and Columns 3 and 4 use only those first visits that scheduled a follow-up visit. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Covariate Test - Follow-up Visits

	(1) Male	(2) Age	(3) Ref. BHZ	(4) Dist. BHZ	(5) Chronic	(6) Pub. Cov	(7) Spanish	(8) Waiting list	(9) Same sex	(10) Same age
Prior Cancel	-0.0071	0.2368	0.0158	0.2433	0.0045	0.0031	-0.0226**	1.9820	0.0043	0.0072
	(0.0096)	(0.4141)	(0.0113)	(0.3040)	(0.0051)	(0.0023)	(0.0108)	(1.2038)	(0.0095)	(0.0087)
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14350	14350	14350	14350	14350	14350	14350	14350	14266	12530
Dep. Var. Mean	0.432	62.16	0.663	4.078	0.0702	0.977	0.696	27.09	0.523	0.134

Notes: The table tests whether having a prior cancellation predicts the patient and the shared physician-patient characteristics in a sample of visits with a follow-up appointments. Ref. BHZ is an indicator variable that identifies if the patient comes from a Basic Health Zone covered by the hospital. Dist. BHZ measures how many kilometers apart is the patient's Basic Health zone from the hospital using a linear distance algorithm. Chronic is an indicator variable that identifies if the patient previously had any chronic condition. Pub. Cov. identifies if a visit was covered by the public insurance scheme. Spanish identifies those patients born in Spain. Waiting list measures the days that patients wait to access a first visit from their corresponding Primary Care center. Same sex identifies if both physician and patient share the same sex. Same age identifies if both physician and patient have a similar age, measured using a 10 years window. All other variables are self-explanatory. Standard errors are clustered at the physician level. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Effect of Visit Length on Visit Outcomes - By Retired Patients

	(1) Length	(2) Length Retired	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0035	0.0043	0.0107	0.7382	-0.0010	-0.4595*
			(0.0029)	(0.0031)	(0.0066)	(0.4982)	(0.0013)	(0.2470)
Length × Retired			0.0000	0.0051	-0.0019	0.1852	-0.0001	0.1144
			(0.0043)	(0.0053)	(0.0095)	(0.7283)	(0.0016)	(0.2279)
Retired	0.2615	12.6102***	-0.0057	-0.0886	-0.0202	-5.4413	0.0006	-1.4926
	(0.1708)	(0.5866)	(0.0569)	(0.0661)	(0.1227)	(9.4129)	(0.0207)	(3.0157)
Prior Cancel	1.5211***	-0.0264						
	(0.1618)	(0.0627)						
Prior Cancel × Retired	0.2585	1.7836***						
	(0.1876)	(0.2516)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.177	0.0180	0.144	0.0683	0.413	0.142
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	27.58	27.58	27.58	27.58	27.58	27.58

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the patient's age is over 65 (*Retired*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Retired*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Effect of Visit Length on Visit Outcomes - By Shock Type

	(1) Length	(2) Diagnosis	(3) Tests	(4) Num. Tests	(5) Test Cost	(6) Drugs	(7) Num. Drugs	(8) Follow-up
Panel A: No-Show								
Length		0.0036**	0.0078***	0.0111**	0.7637*	-0.0010	-0.3939*	0.0084***
		(0.0018)	(0.0027)	(0.0047)	(0.3910)	(0.0010)	(0.2106)	(0.0032)
Prior No-Show	1.6082***							
	(0.1594)							
Observations	66320	66320	66320	66320	66320	66320	66320	66320
Dep. Var. Mean	12.53	0.0817	0.181	0.286	12.63	0.0332	2.055	0.280
F - Stat	–	103	103	103	103	103	103	103
Panel B: Notification								
Length		0.0037	-0.0036	-0.0022	1.1875	-0.0011	-0.5477	0.0149
		(0.0046)	(0.0058)	(0.0097)	(0.8695)	(0.0027)	(0.3340)	(0.0091)
Prior Notification	1.7260***							
	(0.2885)							
Observations	57702	57702	57702	57702	57702	57702	57702	57702
Dep. Var. Mean	12.39	0.0816	0.180	0.286	12.59	0.0319	2.055	0.279
F - Stat	–	36.20	36.20	36.20	36.20	36.20	36.20	36.20
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The reported regressions correspond to the 1st Stage (Col. 1), and the 2nd Stage with multiple outcome variables (Col. 2-8). Panel A includes all observations, but those with a prior withdrawal, while Panel B includes all observations, but those with a prior no show up. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Montiel Olea and Pflueger (2013). *** p<0.01, ** p<0.05, * p<0.1.

Table A15: Effect of Visit Length on Visit Outcomes - By Overloaded Days

	(1) Length	(2) Length Non Overload	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0043	0.0099*	0.0132*	0.9296	-0.0015	-0.5138*
			(0.0027)	(0.0054)	(0.0079)	(0.5892)	(0.0030)	(0.2643)
Length × Non Overload			-0.0011	-0.0052	-0.0054	-0.1730	0.0007	0.1523
			(0.0037)	(0.0059)	(0.0099)	(0.7140)	(0.0033)	(0.2747)
Non Overload	0.6932***	12.0272***	0.0042	0.0458	0.0549	2.9035	-0.0115	-1.6484
	(0.1776)	(0.5285)	(0.0461)	(0.0715)	(0.1144)	(8.5425)	(0.0393)	(3.3703)
Prior Cancel	1.9344***	0.0763						
	(0.2555)	(0.0887)						
Prior Cancel × Non Overload	-0.4097	1.4005***						
	(0.2570)	(0.2099)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.184	0.0406	0.140	0.0699	0.434	0.136
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	27.58	27.58	27.58	27.58	27.58	27.58

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the physician had a non-pressing day (*Non Overload*). The variable *Non Overload* identifies those days in which the total expected visit length exceeds the physician's daily schedule. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length × Retired*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table A16: Effect of Visit Length on Visit Outcomes - By High-Performing Physicians

	(1) Length	(2) Length High-Performing	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs
Length			0.0023	0.0056**	0.0116**	0.7769**	-0.0003	-0.3945
			(0.0016)	(0.0025)	(0.0053)	(0.3669)	(0.0008)	(0.2833)
Length × High-Performing			0.0041	0.0026	-0.0064	0.0846	-0.0021	-0.0510
			(0.0048)	(0.0052)	(0.0084)	(0.7778)	(0.0026)	(0.3128)
High-Performing	-1.2899	9.3470***	-0.1316**	-0.1999**	-0.2265	-15.6842	0.0448	1.6781
	(1.6542)	(1.8655)	(0.0540)	(0.0800)	(0.1508)	(9.5695)	(0.0435)	(4.8503)
Prior Cancel	1.8436***	-0.0519***						
	(0.2197)	(0.0195)						
Prior Cancel × High-Performing	-0.5610*	1.4276***						
	(0.3258)	(0.2391)						
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67530	67530	67530	67530	67530	67530	67530	67530
Joint Length p-value	–	–	0.156	0.0810	0.434	0.225	0.350	0.0280
Dep. Var. Mean	–	–	0.0819	0.181	0.286	12.67	0.0333	2.043
F - Stat	–	–	18.13	18.13	18.13	18.13	18.13	18.13

Notes: The reported regressions correspond to the 1st Stage regression (Col. 1-2) and the 2nd Stage with multiple outcome variables (Col. 3-8). The table presents the interaction of *Length* and whether the physician's average time used to provide a diagnosis is lower than the average time used in her specialization (*High-Performing*). For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Retired*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table A17: Effect of Visit Length on Visit Outcomes - By Seniority (1st vs. 4th. Quantile)

	(1) Length	(2) Length Senior	(3) Diagnosis	(4) Test	(5) Num. Tests	(6) Test Cost	(7) Drug	(8) Num. Drugs	(9) Follow-up
Length			0.0058**	0.0053	0.0101	0.8234	-0.0045*	-0.3879	0.0216**
			(0.0030)	(0.0043)	(0.0075)	(0.7038)	(0.0025)	(0.3418)	(0.0091)
Length × Senior			-0.0083*	-0.0041	-0.0039	-0.3824	0.0034	0.3072	-0.0173*
			(0.0046)	(0.0050)	(0.0121)	(1.0123)	(0.0033)	(0.3806)	(0.0103)
Senior	0.8705	13.8849***	0.0868	0.0322	0.0323	4.1249	-0.0563	-5.0421	0.1903
	(0.9317)	(0.9744)	(0.0629)	(0.0768)	(0.1706)	(14.9792)	(0.0444)	(5.2682)	(0.1397)
Prior Cancel	1.3518***	-0.0629							
	(0.3211)	(0.0901)							
Prior Cancel × Senior	0.9470*	2.3268***							
	(0.5381)	(0.4270)							
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58301	58301	58301	58301	58301	58301	58301	58301	58301
Joint Length p-value	–	–	0.449	0.607	0.498	0.518	0.646	0.542	0.374
Dep. Var. Mean	–	–	0.0780	0.161	0.250	10.85	0.0424	2.166	0.288
F - Stat	–	–	9.475	9.475	9.475	9.475	9.475	9.475	9.475

Notes: The reported regressions correspond to the 1st Stages (Col. 1-2), and to the 2nd Stage with multiple outcome variables (Col. 3-8) and visit length interacted by the physician's seniority. The sample used corresponds to those physicians in the 1st and 4th quantile of their age distribution. For information on the outcome variables, please refer to Section 4.1. All regressions include the following controls: Patient sex, age, square age, whether the patient is from the reference BHZ, the distance from the patient BHZ to the hospital, whether the patient is a chronic, whether the patient was born in Spain, whether the patient is covered by the public insurance, the days and squared days passed since the first visit referral, whether the visit was forced into the agenda, and whether the visit was referred by a colleague. See Table 2 for further reference. Joint Length p-value is the joint p-value of both *Length* and *Length* × *Senior*. Standard errors are clustered at the physician level. F-Stat corresponds to the first-stage F-statistics measure proposed by Kleibergen and Paap (2006). *** p<0.01, ** p<0.05, * p<0.1.