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How scheduling systems with automated appointment reminders improve health clinic efficiency



^a University of California, Berkeley

^b Escuela de Gobierno and Instituto de Economia, Pontifica Universidad Catolica de Chile

^c University of California, Berkeley, and NBER

^d RAND Corporation

e University of Chicago

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ABSTRACT

Missed clinic appointments or no-shows burden health care systems through inefficient use of staff time and resources. Scheduling software with automatic appointment reminders shows promise to improve clinics' management through timely cancellations and re-scheduling, but at-scale evidence is missing. We study a nationwide text message appointment reminder program in Chile implemented at primary care clinics for patients with chronic disease. Using longitudinal cliniclevel data, we find that the program did not change the number of visits by chronic patients eligible to receive the reminder but visits from other patients ineligible to receive reminders increased by 5.0% in the first year and 7.4% in the second. Clinics treating more chronic patients and those with a relatively younger patient population benefited more from the program. Scheduling systems with automatic appointment reminders were effective in increasing clinics' ability to care for more patients, likely due to timely cancellations and re-scheduling.

1. Introduction

A major obstacle to efficient health care delivery is no-shows; patients who fail to show-up for scheduled appointments without cancelation in time to allow for rescheduling of their appointment slot. These unused appointments create operational waste including poor use of staff time, under-utilization of other clinical resources, and longer waiting times (Bech, 2005; Gucciardi, 2008; Gupta and Wang, 2012; Parikh et al., 2010). In the United States, no-shows make up between 12% and 50% of scheduled appointments (Dreiher et al., 2008; Geraghty et al., 2008; LaGanga and Lawrence, 2007; Moore et al., 2001; Parikh et al., 2010); resulting in an annual loss of more than \$150 billion (Manfredi, 2017). In the United Kingdom, patients missing primary care appointments cost the National Health Service more than £216 million in 2019 alone (Ellis et al., 2017; Iacobucci, 2019; NHS, 2018; Oliver, 2019).

To address these issues, some health care providers have turned to information technology (IT) tools such as appointment scheduling software with automated Short Message Service (SMS) appointment reminders (Abdalkareem et al., 2021; McLean et al., 2016). SMS appointment reminders can be used to reduce the number of missed appointments or no-shows, as well as to identify patients who will miss their appointments in time to reallocate their slot to another patient, thereby reducing clinical dead time. In that sense, SMS interventions can improve clinic efficiency: they can facilitate providers to care for more patients in the same amount of time

* Corresponding author : RAND Corporation, 1776 Main St, Santa Monica, CA 90401.

E-mail addresses: cboone@berkeley.edu (C.E. Boone), gertler@berkeley.edu (P. Gertler), tgracner@rand.org (T. Gracner), jmerodriguez@ uchicago.edu (J. Rodriguez).

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and with the same amount of resources. Additionally, SMS appointment reminders are often software driven and integrated into a wider scheduling system, so they are automatically sent out without need for human assistance at a low marginal cost. Such systems often also allow for patients' appointment confirmation or cancelation via text. Thus, compared to other traditional methods, such as mailed reminders or phone calls, SMS appointment reminders sent automatically are generally less costly, less labor-intensive and can be more easily scaled (Baren et al., 2006; Can et al., 2003; Downer et al., 2006; Haynes and Sweeney, 2006; Macharia et al., 1992; Maxwell et al., 2001; Sawyer et al., 2002; Sharp and Hamilton, 2001).

This paper examines whether appointment scheduling software with automated SMS appointment reminders that allow for patients' response (e.g., to confirm or cancel an appointment via text) can improve a clinic's efficiency, measured by the quantity of primary care visits, without adding more staff or resources. We study at-scale effects of this technology on primary care clinics' efficiency in Chile, which implemented it nationwide across primary care clinics for patients diagnosed with chronic diseases - largely in response to experiencing no-shows rates as high as 17% (InterSystems Corporation. (n.d.) 2022; Salinas et al., 2014). This software, called the Critical Care Appointment Management Program (Mensajería para la Gestión de Citas en Pacientes Crónicos) or CCAMP, was phased-in nationally at primary care clinics between January 2015 and December 2016.

One of CCAMP's key features is sending automatic SMS appointment reminders to patients diagnosed with type 2 diabetes (T2DM), hypertension, and/or dyslipidemia¹ (i.e., also referred to as eligible or chronic patients, hereafter). Specifically, CCAMP sends an SMS reminder with date, location, and time of the appointment 24–48 h prior to it being scheduled. Response to the SMS is not required to keep the appointment, but patients can cancel by simply responding to the SMS. To reschedule, however, patients must still call the clinic. Hence, the scheduling system lowers the cost of cancelling, but does not lower the cost of rescheduling. Reminders are not sent to individuals seeking acute care appointments (i.e., also referred to as ineligible or non-chronic patients, hereafter), as these are usually scheduled in the very short-term and are unlikely to be missed due to the acute nature of illnesses and excess demand for acute care. Thus, if the patients with chronic conditions cancel their appointment in time, it could free up clinics' capacity to see more patients (chronic or non-chronic) in general and thereby reduce number of wasted appointment slots from no-shows. Besides automatic SMS appointment reminders, no other scheduling feature that could be accessed by patients was introduced in CCAMP.

In theory, CCAMP could increase, decrease, or have no effect on the number of chronic disease patients visits to clinics. Chronic patients have regular clinic preventive visits every 3 to 6 months scheduled far in advance. CCAMP appointment reminders could increase their visits by nudging them to keep and not skip their regularly scheduled appointments. However, CCAMP could have no effect on the number of chronic disease visits if the reminders have little effect on patients keeping their appointments and patients simply reschedule canceled appointments. CCAMP could also decrease chronic disease visits by increasing cancelations that are not rescheduled. This may happen when a (asymptomatic) chronic patient simply cancels the appointment without rescheduling and waits for the next regularly scheduled appointment instead. In fact, CCAMP makes cancelling appointments easier as patients can simply reply to the SMS reminder, but it does not make rescheduling easier as the patient must still call the clinic to reschedule. These possible outcomes are all consistent with the literature on the effect of SMS reminders on visits with some studies finding positive effects (Arora et al., 2015; Bourne et al., 2011; Branson et al., 2013; C.-L. Lin et al., 2016; H. Lin and Wu, 2014), some finding negative effects (Chung et al., 2020; Hashim et al., 2001; Macharia et al., 1992; Oppenheim et al., 1979), and others finding null effects (Bellucci et al., 2017a; Bos et al., 2005; Clough and Casey, 2014).

In fact, the literature argues that the primary goal of reminding patients of their appointment is not necessarily to increase patient arrival rates and decrease cancelations, but rather to identify appointment cancelations in time so that the appointment slots can be rescheduled. The use of SMS appointment reminders has been previously shown to actually increase cancelation rates prior to the scheduled appointment in time for the clinic to fill that slot with another patient (Hashim et al., 2001; Ross et al., 1993).

There are reasons why one might expect that at least some of the canceled appointments will go to non-chronic care patients. Other work evaluating similar scheduling systems to CCAMP has found that freed slots were least likely to be accepted by patients with a higher number of comorbidities or by those with already scheduled visits for chronic conditions, and most likely by people with acute conditions who need and can take the slot (Chung et al., 2020). This is especially likely in Chile, where non-chronic patients often experience significant wait times and are seen on a first-come first-served basis (MINSAL, 2018a; Vargas and Poblete, 2008).² CCAMP explicitly accommodates more of non-chronic patients by allocating canceled appointments slots visits via timely cancellations or rescheduling using a well-defined protocols of the management of canceled appointments (MINSAL 2015). Thus, freed slots due timely cancellations or rescheduling in Chile were in many cases allocated to acute (non-chronic) patients given the short timeline of cancelation, long waiting wait times for these types of patients and the fact that chronic patients were largely previously scheduled (Chung et al., 2020).

We study the effects of CCAMP on clinics' total number of visits, and the number of visits by SMS-eligible (chronic) and SMSineligible (acute care or non-chronic) patients using clinic-level administrative longitudinal data. We first use an event-study approach to test for the effect of CCAMP on clinical visits over time. The flexibility in the functional form allows for observation of whether clinics and patients learn how to best use the technology over time. Informed by the observed patterns in the event-history study, we then use a difference-in-difference (DiD) approach to examine the impact of CCAMP on visits during in the short-run learning phase

¹ Dyslipidemia is an elevated amount of lipids (e.g. triglycerides, cholesterol and/or fat phospholipids) in the blood or a low level of high-density lipoprotein (HDL) cholesterol.

² In 2005, Chile guaranteed access to care with limited waiting time for a specific set of health problems including patients with chronic conditions, but not patients with non-chronic conditions under the Health Explicit Guarantees (GES) Act (Vargas, V., and Poblete, S., 2008). Chronic conditions therefore consume most of the clinics' capacity resulting in prolonged waiting times for the remaining "non-prioritized" health problems. While chronic disease patients wait on average 45 days, non-chronic care patients more than triple that (MINSAL, 2017).

(first year of adoption) and the subsequent medium term (second year) after the impact stabilized. We account for potential biases in staggered DiD designs using methods proposed in de Chaisemartin & d'Haultfoeuille (2020). Finally, we explore several dimensions of heterogeneity by testing for different effects by clinic types (e.g., clinic size and types of patients they treat).

Our results show that the program increased clinics' total number of visits by 3.3% on average: 3.1% in the year of program adoption and rising to 5.1% after the first year. The effects are mostly driven by visits from patients needing acute (and not chronic) care, who were ineligible to receive the reminders. Their visits increased by 4.6% on average, and by 7.4% in year two. We observe no such effects for eligible patients.

We find that the clinics with the largest share of visits by eligible patients at baseline benefited the most from the CCAMP program. These clinics experienced a 11.6% increase in visits from ineligible patients on average (vs 2.8% increase in clinics with a smaller share of eligible patients' visits). We also find that the clinics treating a relatively higher share of young patients with chronic conditions (e.g., aged below 65 years) experienced an 8.5% increase in ineligible patient visits (vs 3.4% in clinics treating older patients). For ineligible patients, the program benefited large and small clinics equally. No increase in visits was observed for visits by eligible patients along any dimension of heterogeneity tested.

This study is related to the literature on the effects of mHealth tools for disease management (Roberto and Kawachi, 2015). Existing studies mostly focus on how SMS appointment reminders affect patients' treatment adherence but typically fail to incorporate the analyses of clinic efficiency gains of such technological tools. A considerable variation in significance and magnitude of the associations between SMS reminders and clinic attendance is observed in the literature (Berrouiguet et al., 2016; Gurol-Urganci et al., 2013; Kannisto et al., 2014; Schwebel and Larimer, 2018); ranging from null (Bellucci et al., 2017b; Bos et al., 2005; Clough and Casey, 2014) to significant and large positive ones (Altuwaijri et al., 2012; Arora et al., 2015b; Baker et al., 2015; Bangure et al., 2015; Berenson et al., 2016; Bourne et al., 2011; Branson et al., 2013; Chen et al., 2008). Among the potential explanations put forth for inconclusive results is variation in characteristics of patients and clinics, type, or frequency of appointments, and in treatment duration across varied (mostly small scale) service settings for which interventions are studied. Our study also contributes to the literature on health care efficiency (Shipman and Sinsky, 2013), and provides new evidence that a low-cost IT technology can significantly improve clinics' efficiency by reducing no shows among high-use patients. There are many other interventions and policies that improve efficiency such as telemedicine (Kruse et al., 2017), supply-side incentives for value-based care (Gertler et al., 2014; Miller and Babiarz, 2013), and decision support tools (Ali et al., 2011; Scheitel et al., 2017). In contrast to the intervention studied here, most of these are costly to implement, especially at-scale.

In Section 2, we briefly discuss the Chilean health care system and CCAMP. In Section 3, we describe the data. In Section 4, we describe the selection into the CCAMP. Section 5 describes our empirical approach, and Section 6 presents the results and robustness. We conclude in Section 7.

2. Institutional context and the automated appointment reminder program

Chilean healthcare is a two-tier system with nearly 80% of the population enrolled in public insurance (called Fondo Nacional de Salud or FONASA) with the rest enrolled through private insurers (FONASA, 2018; Goic, 2015). FONASA's public healthcare system is organized in a gatekeeping model where patients are required to visit a general practitioner, usually located in public primary care clinics, before being referred to a specialist or to more advanced care units. Patients covered by FONASA are administratively assigned exclusively to use on one clinic based on their place of residence and allowed to obtain primary care at any other public clinic. Therefore, while the public healthcare system is characterized by excess demand, seeking better access to care by trying another clinic is unlikely (MINSAL, 2021). Similarly, it is unlikely that patients will seek care at private clinics because they are very expensive and FONASA, public insurance, is unlikely to cover care at private facilities.

In Chile, approximately 11 million people (57% of the population) have at least one chronic disease condition, yet, they receive care from a primary care public system that is built to accommodate about 4 million people (Margozzini and Passi, 2018). These patients consume 84% of total primary care health resources (MINSAL, 2008), placing a significant burden on the public health care system. Part of this burden is attributable to missed appointments. Unlike patients with acute, non-chronic illnesses who are largely seen on a first-come first-served basis, visits for patients with chronic illness are scheduled well in advance and are often missed (Goic 2015). In 2019, 16.7%³ of scheduled appointments were missed, resulting in poor use of staff time and under-utilization of clinical resources, contributing to longer wait-times for all - but especially for patients with acute non-chronic conditions. On average, wait-times for patients with acute conditions, the wait-times in Chile are among the longest in OECD countries (Bedregal et al., 2017). This is partly due to a large health reform in 2005 that prioritized care for patients with chronic conditions over patients with acute non-chronic conditions who are not covered by the guarantees in the reform (MINSAL, 2017a, 2018; FONASA, 2018; Martínez et al., 2019). Since 2005, the public system guarantees access to care with limited waiting time for a specific set of health problems under the Health Explicit Guarantees (GES) Act (also previously known as Plan AUGE), which include patients with chronic conditions, but not patients with non-chronic conditions (Vargas and Poblete, 2008). Therefore, chronic conditions consume most of the clinics' capacity resulting in prolonged waiting times for the remaining "non-prioritized" health problems.

To increase clinics' ability to care for more patients by addressing high no-show rates and long waiting times, the Chilean Ministry of Health rolled out the Critical Care Appointment Management Program (Mensajería para la Gestión de Citas en Pacientes Crónicos)

³ Own calculations from the online repository maintained by the Ministry of Health (see http://www.deis.cl/rem-2017-2018/).



Fig. 1. Program Implementation Across Primary Care Clinics 2013–2016. Authors' calculations based on data obtained from the Ministry of Health, Chile.

or CCAMP across public primary care clinics in Chile. In January 2015, all primary care clinics in Chile were offered the option to opt-into the CCAMP, provided they were using electronic systems for registering patients. This applied to approximately 90% of all clinics (MINSAL, 2014). Fig. 1 describes program implementation across primary care clinics over time. In total 267 out of 757 clinics opted into CCAMP by the end of 2016 with the vast majority enrolling in early 2015.

A critical feature of CCAMP's scheduling tool is sending automated SMS appointment reminders to patients with a diagnosed chronic condition (i.e., T2DM, hypertension or dyslipidemia) 24–48 h prior to the scheduled appointment with information on its date, location and time. The content of the message was as follows:

"Dear [Patient Name], this is a reminder that you have a medical appointment on the day [Date of appointment] at [Time] hours at [Clinic Name] with the doctor [Name of the doctor]. Do you confirm your time? Yes/No"

Patients could cancel or reschedule their appointment by replying to the SMS at no cost to them or could reschedule their appointment via phone; patient's response to the SMS was optional and not required to keep their scheduled appointment. If the patient canceled their appointment, the time slot was re-assigned to any other patient seeking to schedule an appointment with the clinic regardless of diagnosis. Many of these were likely allocated to acute (non-chronic) patients given the short timeline of cancelation, long wait times for these types of patients and the fact that chronic patients were largely previously scheduled (Chung et al., 2020). If the patient did not respond, the appointment was kept as scheduled. Patients without chronic conditions did not receive any reminder, as they are mostly seen on a first-come-first-serve basis without a scheduled appointment long in advance. To the best of our knowledge, CCAMP introduced no other scheduling feature that interfaced with patients (e.g., such as scheduling via online portal), except the automatic SMS appointment reminders sent to patients with chronic conditions.

3. Data

We obtained publicly available longitudinal clinic-level data for the period 2013 through 2016 aggregated to the semester level from the Chilean Department of Statistics (DEIS). To obtain our analysis sample, we began with all public health care clinics (N = 877) and excluded clinics located in extreme regions (N = 71 clinics) due to the low number of medical appointments, and clinics without any patients diagnosed with a chronic condition (N = 49 clinics). Our final sample consisted of 757 primary care clinics in total (N = 267 serve as treated, and N = 490 as a control group), located across 303 municipalities. Fig. 2 visualizes our sample selection steps.



Fig. 2. CCAMP eligibility and inclusion in the final sample for the analysis. CCAMP is the Critical Care Appointment Management Program (Mensajería para la Gestión de Citas en Pacientes Crónicos). HTN refers to hypertension, and DM to T2DM. Extreme regions are De Arica Parinacota, Aisén del General Carlos Ibáñez del Campo, the Chilean Antarctic, and Easter Island.

These data are administrative records on the number of visits and the number of patients assigned to the clinic by FONASA. The primary outcomes of interest are the total number of visits, overall and by patient type: eligible and ineligible patients to receive the reminder. The data also provides information on CCAMP start date for each clinic that implemented the program.

We merged the clinic data with socioeconomic controls, such as mean age, sex, income per capita, share of rural population, and share of population below the poverty line at municipality-level from the National Socioeconomic Survey (MDS, 2013).

3.1. Descriptive statistics

A total of 757 clinics were analyzed; 267 of them implemented the program between 2015 and 2016 (Table 1). In 2014, clinics that implemented the program had 17,416 patients on average: 2595 patients with (eligible) and 14,669 without (ineligible) chronic conditions. Fifteen percent of clinics were rural primary care clinics, 10% were low-complexity hospitals, but the majority were urban primary care clinics (75%). We observe that the urban primary care clinics were more likely to implement CCAMP compared to low-complexity hospitals. Related to this, the mean monthly income per capita was higher among municipalities with treated clinics.

4. Selection into the CCAMP program

As we discuss in the next section, we use event study and difference-in-differences models to estimate the causal impact of CCAMP program on medical visits over time. Both approaches depend on the assumption that take-up is driven by clinic characteristics that are fixed over time. In this section we investigate the drivers of CCAMP adoption by estimating discrete time hazard models. Specifically, we estimate the probability that a clinic in each semester adopted the program as a function of time-invariant and time-variant municipality and clinic-level characteristics using the discrete-time hazard estimator with logistic regression. We use this approach to test for idiosyncratic time varying shocks that could influence take-up, in addition to time-invariant clinic and municipality characteristics, and time trends that we control for via clinic or time fixed effects in our impact estimation strategies. The results are presented in Appendix Table A1.

The results show that a clinic's decision to implement the SMS program is not related to municipality or clinic characteristics, except for urbanicity status of primary care clinic (p<0.05) and baseline share of chronic patients (p<0.01), which are both controlled

Table 1

Descriptive statistics. *** p<0.01, ** p<0.05, * p<0.1. Treated clinics include any clinic that ever-implemented CCAMP. Column 3 shows treated mean minus control mean. Municipality level characteristics from the 2013 CASEN national socioeconomic survey that is representative at the municipality level. Clinic-level characteristics are from the analysis dataset and are measured at baseline (semester 2 of 2014). Mean income per capita 2015 CLP is converted to 2020 USD. Low-complexity hospitals are often present in rural areas and provide primary care in addition to emergency and inpatient services.

	Treated Clinics		Control Clinics Mean (SD)		Mean difference (p-val from t-test)
Municipality-level characteristics					
Proportion male	0.48	(0.00)	0.48	(0.00)	0.00
Age (years)	36.90	(0.17)	36.92	(0.11)	-0.02
Monthly household income p.c. (log USD)	5.95	(0.02)	5.90	(0.01)	0.05**
Proportion population below poverty line	0.15	(0.01)	0.15	(0.00)	0.00
Educational attainment: primary school	0.44	(0.01)	0.45	(0.00)	-0.01
Educational attainment: secondary school	0.44	(0.00)	0.44	(0.00)	0.00
Educational attainment: tertiary school	0.12	(0.01)	0.11	(0.00)	0.01**
Proportion rural	0.21	(0.01)	0.23	(0.01)	-0.02
Clinic-level characteristics					
Total clinic population (1000s)	18.04	(0.85)	17.08	(0.63)	0.96
Ineligible clinic population (1000s)	15.22	(0.75)	14.37	(0.54)	0.85
Eligible clinic population (1000s)	2.89	(0.14)	2.74	(0.11)	0.15
Share of eligible patients over 65 years	0.25	(0.01)	0.26	(0.01)	-0.01
Clinic type: rural primary care clinic	0.11	(0.02)	0.17	(0.02)	-0.07***
Clinic type: urban primary care clinic	0.80	(0.02)	0.72	(0.02)	0.08**
Clinic type: low-complexity hospital	0.09	(0.02)	0.11	(0.01)	-0.01
Number of clinics	267		490		

for with clinic fixed effects in all of our later regressions on program impact. Shocks to utilization are uncorrelated with program take-up. Program take-up is significantly predicted by time showing that the probability of take-up is decreasing over time. This is consistent with the fact that take-up is very large in the earlier periods as shown in Appendix Figure A1, where we observe a large spike in program adoption immediately after the program was offered. These results suggest our event study and difference-in-differences approaches are likely robust to potential confounders after adjusting for time and clinic fixed effects. The variation in start dates over time also validates our use of the de Chaisemartin & d'Haultfoeuille (2020) estimator, which we describe below.

5. Empirical strategy

We start by estimating a non-parametric event-study design to study the link between CCAMP program adoption and change in clinic-level outcomes over time by estimating the following regression model:

$$Y_{it} = \sum_{\tau=-5}^{3} \beta_{\tau} Q_{\tau} + X_{it}' \delta + \lambda_{t} + \gamma_{i} + \epsilon_{it}$$
(1)

 β_{τ} are coefficients on semester indicators (Q_{τ}) for time relative to the CCAMP program adoption (at $\tau = 0$) at a clinic *i*. The key coefficients of interest are the β_{τ} 's that estimate the difference in outcomes at a clinic *i* at a given τ relative to the omitted category, Q_0 . Each model is adjusted for seasonality and common temporary shocks with semester indicators (λ_i) and controlled for time-invariant attributes that may determine clinic's outcomes of interest irrespective of CCAMP by including clinic-level indicators or fixed effects (γ_i). We also incorporate a vector of additional controls, such as average municipality age, sex ratio, and income per capita, and trends specific to clinics with more than the top quartile share of patients eligible to receive the reminder at baseline (X_{ii}). ϵ_{ii} is an error term correlated within clinics across time. We calculate robust standard errors, clustered at the level of the intervention, that is, at the clinic level (Abadie et al., 2020).

We then use a parametric, two-way fixed effect DiD approach to obtain average and heterogenous CCAMP effects during our study period. We estimate the following regression model:

$$Y_{it} = \alpha + \beta CCAMP_{it} + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{it}$$
⁽²⁾

 Y_{ii} is the log of number of visits for clinic *i* at semester *t*, *CCAM* P_{ii} is an indicator variable that takes value one for all semesters *t* in each clinic *i* after the CCAMP was implemented. For clinics that did not implement the CCAMP by the end of the last semester of 2016, this variable is always zero (N = 490). The main coefficient of interest is β ; a DiD estimate which measures the impact of the CCAMP program on the outcome of interest and corresponds to the Average Treatment on the Treated (ATT) parameter. As above, each model was adjusted for seasonality, clinic-type specific linear trend, common temporary shocks with semester indicators (λ_t), and clinic-level indicators or fixed effects (γ_i). We again calculated robust standard errors, clustered at the clinic level.

Estimates obtained using our main DiD approach – a two-way fixed DiD - could be biased as adoption of the CCAMP was staggered over time across primary care clinics and if the treatment effect of CCAMP varied across clinics (treatment effect heterogeneity).⁴ de Chaisemartin & d'Haultfoeuille (2020) (C&H) provide tests and adjustments to account for potential biases stemming from treatment effects heterogeneity. We use C&H to re-estimate average treatment effects as a robustness check: without weighting, and then with weighting by the number of clinics that took up the program in each period (weights are included in appendix table A4).

Finally, we examine whether clinics benefited differently from the program. To observe heterogeneity in the program response, we extend equation (4) by including the interaction between the CCMAP indicator variable with a binary variable that (i) equals one if the clinic had more than the top quartile share of visits by eligible patients at baseline; defined as the semesterly number of eligible visits divided by the semesterly total number of visits, averaged over four semesters of 2014. Other heterogeneity analyses were applied by interacting the CCMAP indicator variable with an indicator variable for whether a clinic is in the (ii) bottom quartile share of visits by eligible patients that were aged 65 years and over, and (iii) top quartile of total number of visits by eligible patients at baseline in 2014. We estimate the following regression model three times:

$$Y_{it} = \alpha + \beta CCAM P_{it} + \xi CCAM P_{it} * Type_i + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{it}$$
(3)

Where T_{ype_i} is an indicator variable that equals 1 for each clinic type (i, ii or iii). Other components are the same to those described in Eq. (3).

6. Results

6.1. Event study

The results from the event study analysis are presented in Fig. 3 (see table A3 for corresponding regression analyses). The key identifying assumption that allows us to interpret coefficients on indicators for time after the program adoption as causal is that, conditional on its adoption and included controls, potential outcomes are uncorrelated with *the timing* of the program adoption. Although this is not testable, Fig. 3 shows that there are no trends in outcomes in periods leading to the program adoption, yet the differences in outcome patterns change sharply after the event. Specifically, Fig. 3, panel A, illustrates an increase in total number of visits soon after the program implementation, and that number increases slightly over time. This increase in total visits, however, is driven largely by visits from patients who were ineligible to receive appointment reminders, that is, acute care patients (Fig. 3, panel B). Their total number of visits increased by about 5.6% in the first semester, and by 7.5% in the third semester after the CCAMP implementation (table A3, column 3). No similar increase is observed for patients with chronic conditions, that is for those who were eligible to receive the reminders (Fig. 3, panel C).

6.2. Difference-in-differences

Table 2 describes the average effect of the CCAMP on medical visits using the DiD approach. Using the two-way fixed effects DiD estimator we find that on average, adopting the SMS program increases clinics' total number of semesterly visits by 3.3% (see Table 2, panel A, column 1). Consistent with our event study results, this observed increase is largely due to a higher number of visits from acute care patients who were ineligible to receive the reminders – their visits increased by 4.6% (see Table 2, panel A, column 3) – and not by visits from eligible patients for whom no change in the number of visits was observed (see Table 2, panel A, column 2). Due to the program, clinics had on average 1031 more visits from acute care patients without chronic conditions in the post-treatment period (on average we observe clinics for 3 semesters after implementing CCAMP).⁵

Because we observe an increase in the treatment effect for visits overall and by ineligible patients over time (Fig. 3, panels A and C respectively), we re-estimate the equation (4) using the weighted and unweighted C&H estimator.⁶ Our conclusions remain nearly unchanged regardless of the estimator used. On average, adopting the CCAMP increases clinics' total number of semesterly visits by 4.0% (unweighted) or 4.1% (weighted) (see Table 2, panel B, column 1 and Table 2, panel C, column 1). Again, this increase in visit is largely driven by visits from patients who were ineligible to receive the reminders – their visits increased by 5.9% (unweighted) or 5.7% (weighted) (see Table 2, panel B, column 3 and Table 2, panel C, column 3).

In the event history analysis, we observe that, compared to the first year, the treatment effects appear higher in the second year of exposure. This could be because clinics and patients are learning how best to use the new scheduling system. Based on the event history results we re-estimate the DiD specification allowing for the treatment effect to vary by year in the post-treatment period (Table 3). In the first year of program adoption, total visits increased by 3.1% on average, and visits by ineligible patients needing acute care increased by 5.0% (Table 3 columns 1 and 3 respectively). After one year the effect increased to 5.1% and 7.4% for

⁴ See Abraham & Sun (2018), Athey & Imbens (2018), Borusyak & Jaravel (2017), Callaway & Sant'Anna (2019), de Chaisemartin & d'Haultfoeuille (2020), and Goodman-Bacon (2018).

 $^{^{5}}$ To estimate additional visits by ineligible patients at treated clinics attributable to CCAMP we multiplied treatment effect on visits by ineligible patients, 4.6% by each clinic's pre-treatment average non-chronic visits per semester and summed across the post-treatment period.

⁶ C&H demonstrate that β from two-way fixed effect estimators can be expressed a weighted average of the treatment effects in each group, time cell. Another diagnostic to understand if β is biased is to regress these weights on a variable that is associated with the treatment effect. We find a small but statistically significant correlation between the weights and semesters (-0.09, *p*<0.05, see appendix table A4), providing more support for our use of the C&H estimator.



Fig. 3. Changes in Total Number of Visits per Clinic per Semester Over Time. Figures show regression estimates based on Eq. (2) in log points. Vertical bars denote 95% confidence intervals. The x-axis is number of semesters until or since the clinic implemented the program.

visits by all and ineligible patients respectively (Table 3 columns 1 and 3). No increase in visits is observed for patients with chronic conditions, eligible to receive the reminder.

Though we observe no significant increase in visits by eligible patients, we do observe that two semesters after program adoption, visits by eligible patients actually fell by 4.4% (Table 3, column 2, p-value <0.1). There are several possible explanations for a negative effect. One is that the CCAMP makes cancelling (but not rescheduling) of appointments easier via SMS (Hashim et al., 2001). Alternatively, patients are attending their care more regularly due to CCAMP (and not necessarily more often) and need fewer unscheduled visits due to improved disease management.

However, we are cautious in interpreting this result. In contrast to all other results, this drop in visits for eligible patients is only significant at p<0.1, it could simply be significant due to a sampling variation and is not robust to alternative specifications. For instance, we observe no significant change in visits for eligible patients after re-estimating this model using the C&H estimator adjustments; while results for other outcomes remain nearly unchanged.

Table 2

Clinic-level results for the impact of CCAMP on visits by patient type.^{***} p<0.01, ^{**} p<0.05, ^{*} p<0.1. Robust standard errors in parentheses clustered at clinic level. Each model includes municipality level controls: share of municipality that is male, mean age, share of municipality that is rural, share of municipality's population below Chile's poverty line. Each model also includes a control for the number of chronic patients at baseline, and controls for differential trend by clinic type. Treated is an indicator equal to 1 in the semesters on and after a clinic adopted CCAMP, 0 otherwise. Models in panel A estimated using the two-way fixed effect difference-in-differences estimator. Models in panels B and C were estimated using de Chaisemartin and D'Haultfoeille weighted difference in differences estimator, which is a weighted combination of 2 × 2 comparisons. A switcher is a clinic that took up the program in a given semester. 100 bootstrap replications used.

	Log visits by patient type				
	Total (1)	Chronic (2)	Non-chronic (3)		
Panel A: Two-way fixed	effects DiD				
Treated (β)	0.033**	-0.014	0.046***		
	(0.014)	(0.020)	(0.017)		
Panel B: C&H Estimator Unweighted					
Treated (β)	0.041***	-0.023	0.059***		
	(0.015)	(0.021)	(0.019)		
Panel C: C&H Estimator Weighted by N Switchers					
Treated (β)	0.040***	-0.023	0.057***		
	(0.015)	(0.021)	(0.018)		
Observations	5986	5986	5986		
Control group mean	5214	957	4071		
visits					
Number of clinics	757	757	757		
Clinic fixed effects	Y	Y	Y		
Semester fixed	Y	Y	Y		
effects					

Table 3

Clinic-level results for the impact of CCAMP on visits by patient type by semester. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses clustered at clinic level. Each model includes municipality level controls: share of municipality that is male, mean age, share of municipality that is rural, share of municipality's population below Chile's poverty line. Each model also includes a control for the number of chronic patients at baseline, and controls for differential trend by clinic type. Treated is an indicator equal to 1 in the semesters on and after a clinic adopted CCAMP, 0 otherwise.

	Log visits by patient type		
	Total (1)	Chronic (2)	Non-chronic (3)
Treated (β) 0–1 semesters after treatment	0.031** (0.015)	-0.03 (0.020)	0.050*** (0.018)
Treated (β) 2+ semesters after treatment	0.051** (0.021)	-0.044* (0.024)	0.074*** (0.025)
Observations	5986	5986	5986
Control group mean visits	5214	957	4071
Number of clinics	757	757	757
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

6.3. Robustness

To examine whether our results are driven by a change in the number of patients assigned to each clinic and not an efficient reallocation of time between existing patients as we interpret above, we estimate equation (4) with the log-transformed total number of patients assigned to each clinic as the dependent variable. We find that the effects are largely small and insignificant (table A7). To address the concern that there is another event prior to the CCAMP implementation affecting our results, we move the onset of

Table 4

Heterogeneity in clinic-level results for the impact of CCAMP on visits by patient type. *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors in parentheses clustered at clinic level. Each column in each panel is shows coefficients from a separately estimated two-way fixed effects difference-in-differences model. Each model includes municipality level controls: share of municipality that is male, mean age, share of municipality that is rural, share of municipality's population below Chile's poverty line. Each model also includes a control for the number of chronic patients at baseline, and controls for differential trend by clinic type (specialized, young, and large). Treated is an indicator equal to 1 in the semesters on and after a clinic adopted CCAMP, 0 otherwise. $\beta + \xi$ is the coefficient on a test that the treated + interaction term coefficients are equal to zero. Specialized is an indicator for if the clinic's share of chronic patients that are over 65 years old is in the bottom quartile. Large clinic is an indicator for if the clinic's semesterly number of total visits was in the top quartile. Each heterogeneity variable was measured in 2014 (before CCAMP was implemented).

		Log visits by patient type			
	Total (1)	Chronic (2)	Non-chronic (3)		
Panel A: Heterogeneity by share of ch	ronic patients				
Treated (β)	0.020	-0.016	0.028*		
	(0.014)	(0.018)	(0.016)		
Treated x Specialized Clinic (ξ 1)	0.063*	0.002	0.088*		
	(0.036)	(0.039)	(0.048)		
$\beta + \xi 1$	0.083**	-0.014	0.116***		
	(0.033)	(0.035)	(0.045)		
Panel B: Heterogeneity by relative sha	are of chronic patients <65	years			
Treated (β)	0.021	-0.020	0.034*		
	(0.014)	(0.017)	(0.017)		
Treated x Young Population (ξ 2)	0.051**	0.020	0.050**		
	(0.022)	(0.038)	(0.025)		
$\beta + \xi 2$	0.071***	-0.001	0.085***		
	(0.021)	(0.036)	(0.023)		
Panel C: Heterogeneity by clinic size:	large				
Treated (β)	0.032**	-0.010	0.045**		
	(0.016)	(0.019)	(0.020)		
Treated x Large Clinic (53)	0.004	-0.020	0.007		
	(0.025)	(0.030)	(0.030)		
$\beta + \xi 3$	0.036*	-0.030	0.052**		
	(0.020)	(0.024)	(0.023)		
Observations	5233	5233	5233		
Control group mean visits	5253	958	4109		
Number of clinics	756	756	756		
Clinic fixed effects	Y	Y	Y		
Semester fixed effects	Y	Y	Y		

the program earlier by two semesters, and find no such evidence (table A8). Our event study results show no pre-treatment trend in our outcomes of interest. Here, we also provide evidence on parallel trends in treated and control clinics by presenting clinic-specific mean number of visits per semester by clinic type in the period before any clinic implemented the CCAMP program (Figure A1). Though the likelihood of patients moving between treated and control clinics due to CCAMP is small because patients are assigned to a specific clinic based on their residence, we show that empirically as well. We compare the number of visits in never treated clinics before and after a nearby clinic (within 5 km or within 20 km) implemented the CCAMP. We found no empirical evidence of spillover effects (Table A10). Finally, we clustered our standard errors at the municipality level and our findings remain unchanged (Table A11).

6.4. Heterogeneity by population and clinic characteristics

We test for heterogenous responses in visits to CCAMP by clinic types. First, we study whether the impact of CCAMP varied by clinics with a relatively large number of visits by eligible patients in the pre-intervention period, a proxy for the intensity of exposure to the CCAMP at the clinic level. We observe a larger, 8.3% increase in total number of visits at clinics in the top quartile of share of visits by eligible chronic patients needing ongoing care in 2014 (Table 4, panel A, column 1). Again, this effect was largely due to a 11.6% increase in visits by ineligible patients in those clinics (Table 4, panel A, column 3). This is expected, as clinics with more visits scheduled for high-use, chronic patients will, if CCAMP improves efficiency, experience a larger decrease in no-shows and thus a higher benefit from the program.

Next, we compute the share of chronic patients who are 65 years old⁷ or younger and construct an indicator variable that equals one if a clinic's share of chronic patients over 65 years old is at the bottom quartile of the distribution of patients over 65 years old in 2014 (see table 4, panel B). We label this indicator "Young Population". We find that the CCAMP increased total visits more in clinics treating relatively younger patients. On average, clinics classified as having a "Young population" increased the total number of visits by 5.1% more than clinics treating relatively older patients. The results in column 3 show that the effect is again largely driven by visits of ineligible patients, while visits of eligible patients remain unchanged. Compared to older adults, younger adults miss more scheduled appointments, so clinics treating more of them may benefit more from a scheduling software such as the CCAPM (Parikh et al., 2010; Neal et al., 2001). Possible explanations may be that, compared to a younger population, older adults have more severe conditions that necessitate attending an appointment, or may be more cognizant of their healthcare. The benefit from the CCAMP may also be higher among younger patients because on average they are more technologically literate and more likely to use mobile phones (Neal et al., 2001; Parikh et al., 2010; Zhang et al., 2015).

Finally, we explore whether the effect of the program varies by clinic size, proxied by an indicator variable that equals one if a clinic's total number of visits was at the top quartile in 2014 (see table 4, panel C). We label this indicator as "Large Clinic". The results in Table 4, panel C, column 3, show that there are no significant differences in total visits between clinics that are large vs small.

Table A9 shows these findings hold when we estimate one regression model, in which we include all interactions at once.

7. Conclusions

In this paper, we examine whether new IT scheduling tools sending automated SMS appointment reminders (with the option to confirm or cancel the appointment via SMS) in primary care clinics can improve their ability to care for more patients without adding more staff or resources. We study this in the context of Chile, which implemented this technology nationwide across primary care clinics for patients diagnosed with chronic diseases. We find that though the CCAMP did not change the number of visits by chronic patients eligible to receive the reminder, they instead increased the number of clinical visits by acute care patients, ineligible to receive the reminder, by 5.0% in the first year and 7.4% after that. This resulted in on average 1031 additional visits per clinic over a period of 3 semesters after implementing the CCAMP.

The fact that we observe no significant increase in the number of visits by eligible chronic disease patients, but an increase in visits by ineligible patients seeking acute care, is not surprising. The literature on the effect of SMS reminders is mixed with several studies presenting null results (Bellucci et al., 2017b; Bos et al., 2005; Clough and Casey, 2014). There is also some evidence that show that the primary benefit from telephoning patients to remind them of their appointments is not increased arrival rates, but rather identifying appointment cancellations (Hashim et al., 2001; Ross et al., 1993). In Chile, eligible patients schedule their next chronic condition management visit 3, 6 or 12 months in advance, depending on their disease severity (MINSAL, 2017b). Thus, automatically sent SMS appointment reminders may have influenced patients' behavior by reminding them to cancel and reschedule (and not simply miss) their appointment in the case of scheduling conflicts, thereby keeping their total number of visits lower or unchanged (Hashim et al., 2001). This may have then freed up slots for patients seeking acute care who get their appointments on an as-needed basis and are seen based on clinic's availability - resulting in a significant increase of their visits. Other work evaluating similar rescheduling systems have found that freed slots were most likely accepted by people with acute conditions, and least likely by patients with a higher number of comorbidities or those with already scheduled visits for chronic conditions (Chung et al., 2020).

The major result of these analyses is that the CCAMP system increased visits by non-chronic patients. One question not answered by our analyses is what these patients were doing before CCAMP. They could have been waiting for appointments at public clinics, seeking care at private facilities, or using emergency rooms at hospitals. It is possible, therefore, that CCAMP could have reduced the use of private clinics and emergency rooms. There is evidence that improvements in ambulatory care can significantly reduce emergency department visits, particularly for low-income beneficiaries that are not able to afford private care (Alvial et al., 2021; Dolton and Pathania, 2016; Kangovi et al., 2013; Pinchbeck, 2019; Santelices and Santelices, 2017). As such, while these data were not available to us, the program could be reducing emergency department visits by non-chronic patients that would have otherwise occurred in the absence of the program.

Maximizing the use of clinic and staff time is an important part of the work in delivering healthcare given increasing demands and fewer resources. This study suggests that a scheduling tool sending automated SMS appointment reminders may be a practical, cost-effective, and easily scalable strategy to increase clinic's ability to care for more patients without appreciably expanding staff or resources. Software that sends automated SMS appointment reminders decrease administrative scheduling burden on staff and reduce no-shows via timely rescheduling or cancellations. Future work needs to examine individual-level data to investigate whether appointment reminders improve health outcomes at the individual, local or population level.

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 $^{^{7}}$ We choose age 65 because our administrative data tracks the number of visits at each clinic only by eligible vs. ineligible for the CCAMP, and above or below age 65.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jhealeco.2022.102598.

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