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ABSTRACT

Missed clinic appointments present a significant burden to health care through disruption of care, inefficient use of staff time and wasted clinical resources. Short message service (SMS) appointment reminders show promise to improve clinics' management through timely appointment cancellations and efficient re-scheduling, but evidence from large-scale interventions is missing. We study a nationwide SMS appointment reminder program in Chile for chronic disease patients at public primary care clinics. Using longitudinal clinic-level data we find that after two years the program increased clinics' total number of visits per by 5.1% on average. The program did not change the number of visits by chronic patients eligible to receive the reminder, but it instead increased visits by other patients, ineligible to receive reminders in clinics that adopted the program by 7.4% on average. These results suggest that the appointment reminder systems increased clinics' ability to care for more patients through timely cancellations and re-scheduling.

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I. INTRODUCTION

A major obstacle to efficient health care delivery are appointment no-shows; patients who fail to show-up for scheduled appointments without prior cancellation or timely rescheduling. These patients not only fail to receive needed care, but leave appointment slots unused creating operational waste, poor use of staff time, under-utilization of other clinical resources, and longer waiting times (Bech, 2005; Gucciardi, 2008; Gupta & Wang, 2012; Parikh et al., 2010). In the US, no-shows make up between 12% and 50% of scheduled appointments (Dreiher et al., 2008; Geraghty et al., 2008; LaGanga & Lawrence, 2007; Moore et al., 2001; Parikh et al., 2010); resulting in an annual loss of more than $150 billion (Manfredi, 2017). In the UK, 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). In primary care facilities in Chile, no-shows rates are as high as 30% (InterSystems Corporation, n.d.). Appointment no-shows are a major problem not only in the health sector but also in many service sectors such as restaurants and beauty salons.

Reasons for missing appointments typically boil down to different forms of behavioral biases such as inattention and memory (Gabaix, 2019). Specific reasons cited include forgetting or confusing the date, time or the location of the appointment (Barron, 1980; Dantas et al., 2018; Geraghty et al., 2008; González-Arévalo et al., 2009; Husain-Gambles et al., 2004; Lacy et al., 2004; Murdock et al., 2002; Neal et al., 2005; Sawyer et al., 2002; Spikmans et al., 2003). To address these issues, providers have turned to mobile health interventions (Free et al., 2013) such as Short Message Service (SMS) automatic appointment reminders, which is a low-cost scalable management tool that has proven to improve individual visit appointment attendance.[1] Such systems are software driven and integrated into scheduling systems so that they automatically send out reminders with limited human resources and therefore have extremely low marginal costs. SMS appointment reminders can also be used to identify patients who will miss their appointments

[1] For references on the use of SMS reminders in healthcare and their effect on health seeking behavior see for example Altuwaijri et al. (2012), Arora et al. (2015), Baker et al. (2015), Bangure et al. (2015), Berenson et al. (2016), Berg et al. (2005), Bourne et al. (2011), Branson et al. (2013), Chen et al. (2008), Colubi et al. (2012), Hashim et al. (2001), Lee & McCormick (2003), Lieu et al. (1998), Mugavero et al. (2009), Nuti et al. (2012), Reekie & Devlin (1998), Reti (2003), Schectman et al. (2008), and Walburn et al. (2012).

in time to be able to reassign the visit to another patient, thereby reducing clinical dead time and improving efficiency.

All existing evidence, to our knowledge, has focused on the effect of SMS reminders on nudging patients to make their own appointments and not on the effect on repurposing canceled appointments for other patients. Further, while the efficacy of SMS reminders for visit adherence is well established through small pilot programs and short-term studies, these are conducted in randomized controlled settings and none have examined the effectiveness of SMS reminders at scale in a real-world setting (de Jongh 2012; Hamine et al. 2015). In addition to a lack of evidence from scaled-up programs, no peer-reviewed studies to our knowledge have examined how such programs affect medical visits for *all* patients - those who do and do not receive appointment reminders.

This paper examines the effect of a nationwide SMS automatic appointment reminder program (CCAMP) in Chile on primary care visits. The program was phased-in across 267 out of 757 Chilean primary care clinics between January 2015 and December 2016. At clinics that adopted the program, CCAMP sent SMS appointment reminders 24-48 hours prior to the scheduled appointment to patients diagnosed with diabetes, hypertension, and/or dyslipidemia[2] (i.e., also referred to as chronic or eligible patients hereafter) who could then cancel or reschedule their appointment via SMS or over the phone. Patients without these conditions who were seeking acute care did not receive any reminder.

Using, clinic-level panel data from administrative records held by the Ministry of Health in Chile, we implement an event-study approach to test for changes over time and difference-in-difference (DiD) estimators to examine how CCAMP affected clinics' total number of patients' visits, visits by chronic patients eligible to receive the reminder, as well as the indirect program effects on those that were not eligible, that is, the number of acute care visits.

Our results show that the program increased clinics' total number of visits by 3.3% on average. The increase was observed the first semester after the CCAMP implementation and increased over time through the first year of its implementation. By the second year of the data treated clinics' total visits increased by 5.1%. The effects are mostly driven by visits from acute care patients who were ineligible to receive the reminders, a 4.6% increase on average, and a 7.4% increase in the

[2] Dyslipidemia is an elevated amount of lipids (e.g. triglycerides, cholesterol and/or fat phospholipids) in the blood.

program's second year, while we estimate positive but not statistically significant effects on visits from chronic disease patients, who were eligible to receive the reminder.

These results are similar whether we use a standard two-way fixed effects estimator, a DiD estimator that is identified off only cells where treatment changes, and are robust to new methods that account for potential biases in staggered DiD designs as discussed recently in de Chaisemartin & d'Haultfoeuille, (2020). Our results are also robust to different placebo CCAMP start dates and we also show evidence of no differential trends in outcomes across clinics before the program was implemented.

Finally, our heterogeneity results show that the clinics that had a larger burden of chronic patients before the intervention benefited the most from the program as they experience a 9.8% increase in visits from ineligible for SMS patients. We also show that clinics with a younger population experienced a 7.2% increase in the number of visits for chronic patients, suggesting that IT technologies work better for managing health of relatively younger adults.

There are a large number of interventions and policies to improve efficiency, for example telemedicine (Kruse et al., 2017), supply-side incentives for value-based care (Gentry & Badrinath, 2017; Tompkins et al., 2009), and decision support tools (Ali et al., 2011; Scheitel et al. 2017), but many are costly to implement in practice. Our paper contributes to the literature on health care efficiency (Shipman & Sinsky, 2013), and provides evidence that a low-cost technology can improve management practices and reduce missed visits among high-use patients resulting in an improvement in overall clinic efficiency.

Our paper also contributes to the literature on the effects of 'nudges' for health seeking behavior (Roberto & Kawachi, 2015), particularly using mHealth tools as nudges for disease management. Existing studies mostly focus on how SMS appointment reminders affect patients' treatment adherence directly but fail to incorporate the analyses of overall clinic efficiency gains. A considerable variation in significance and magnitude of the associations between SMS reminders and clinic attendance is observed in the literature so far (Berrouiguet et al., 2016; Gurol-Urganci et al., 2013; Kannisto et al., 2014; Schwebel & Larimer, 2018); ranging from null (Bellucci et al., 2017; Bos et al., 2005; Clough & Casey, 2014) to significant and large positive ones (Altuwaijri et al., 2012; Arora et al., 2015; 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 is unique in its size, duration, setting and inclusion of outcomes for patients, ineligible to receive treatments, and in using a quasi-experimental design for causal inference.

In the next section, we briefly discuss the Chilean health care system and the CCAMP - the SMS appointment reminder implemented across primary care clinics in Chile that we evaluate. Section 3 describes the data and the empirical strategy used to evaluate its impact on primary care visits. Section 4 discusses results and discusses robustness, and Section 5 concludes.

II. The SMS Appointment Reminder Program

In Chile, there are 11 million people (57% of the population) estimated to have one chronic condition that utilize health services from a primary care system that is able to accommodate only 4 million (Margozzini & Passi, 2018).[3] 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 waste from missed appointments. According to data from the Ministry of Health, in 2019 nearly 16.7% of appointments to a specialist physician were missed.[4] Consequently, patients in several primary care clinics cannot schedule appointments more than a month in advance, and many fail to schedule any (Alvarez et al., 2018). Although waiting times have decreased in the last years, they still remain at high levels compared to OECD standards (Bedregal et al., 2017); with the longest waiting lists being that of appointments for non-chronic conditions that are not covered by the health guarantees implemented since 2005 (FONASA, 2018; Martínez et al., 2019).

To reduce delays and increase efficiency in delivery of care, beginning in January 2015, the Chilean Ministry of Health offered the option to opt-into the Critical Care Appointment Management Program (Mensajería para la Gestión de Citas en Pacientes Crónicos or CCAMP) to

[3] The Chilean healthcare system is a two-tier system with nearly 80% of the population enrolled in public insurance (FONASA, 2018; Goic, 2015). In the public sector, primary care clinics are fundamental in providing a wide range of preventative care services as well as for ongoing treatment of patients with chronic diseases, such as hypertension and Type 2 diabetes mellitus (T2DM).

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

all primary care clinics, provided they were using electronic systems for registering patients, which applied to approximately 90% of all clinics (Ministerio de Salud de Chile, 2014).[5]

CCAMP's objective was to reduce no-shows among chronic patients at public primary care clinics with the goal of improving clinics' efficiency in care, time and resources. If enrolled in the CCAMP program, clinics sent automatic SMS appointment reminders to patients with T2DM and/or hypertension 48 hours prior to the scheduled appointment with information on date, location and time of the appointment. Patients could cancel or reschedule their appointment by replying to the SMS at no cost to them or could reschedule their appointment via phone. 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. If the patient did not respond, the appointment was kept. 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"

By December 2015, 210 primary care clinics adopted CCAMP, with an additional 57 clinics adopting by the end of 2016;[6] in total 267, covering 303 municipalities (out of 345) in Chile. Figure 1 describes program implementation across primary care clinics over time.

III. Data

We obtain semesterly, balanced longitudinal clinic-level data from all Chilean public primary care clinics eligible for CCAMP between 2013 and 2016 from the Chilean Ministry of Health's Primary Care Division (N = 877). A clinic was eligible if it has an electronic health records system. These data are administrative records detailing the number of visits by patient type, and the number of patients enrolled at each clinic, and are publicly available from the Chilean

[5] The second requirement was that primary care clinics also participate in the Pharmacy Fund Program – a program aimed at ensuring of pharmacological treatments of the population that is attended in the Primary Health Care system with a priority on patients with chronic conditions. It is determined at the municipality level for all of its primary care clinics. By 2015, 99% municipalities participated in this program.

[6] The list of health clinics with their date of implementation was obtained from a request of public information to the Ministry of Health on Dec 26th of year 2016.

Department of Statistics (DEIS). Each clinic tracks the number of patients enrolled at their clinic who have been diagnosed with one or more conditions of hypertension, T2DM, or dyslipidemia.

We dropped clinics located in extreme regions (N=71 clinics) due to the low number of medical appointments, and those 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). Figure 2 visualizes our sample selection steps.

Each clinic in our data has a unique clinic-level identifier. The data provided information on the number of patients and their medical visits per clinic over time – in total and by patient type. In particular, we observed two types of patients in these data: 1) those with dyslipidemia, hypertension and/or T2DM and thus eligible to receive SMS reminders for each scheduled appointment, and 2) those who are ineligible to receive SMS reminders, that is, were diagnosed with neither dyslipidemia, hypertension or T2DM. These data also included information on CCAMP start date for each clinic that implemented the program.

The primary outcomes in these data are changes in number of medical visits per clinic per semester, overall and by patient type: eligible and ineligible to receive the reminder. Visits by chronic patients included all routine and non-routine visits made by a patient who was eligible to be enrolled in the SMS reminder program. Each outcome was a continuous measure, and log-transformed for the analyses. To observe heterogeneity in the program response, we identified clinics in the bottom quartile of the distribution of share of visits in 2014 by patients older than 65[7] (younger clinics), clinics in the top quartile of the distribution number of eligible chronic patients needing ongoing care (specialized clinics), and clinics in the top quartile of total number of visits in 2014 (large clinics).

To obtain municipality-level controls, such as mean age, sex, income per capita, share of rural population, and share of population below the poverty line, we matched the administrative clinic data with the National Socioeconomic Survey (Casen 2013) at the municipality level (303 municipalities) (MDS, 2013).

Descriptive Statistics

A total of 757 clinics were analyzed; 267 of them implemented the program between 2015 and 2016 (see table 1). In 2014, clinics that implemented the program had 17,416 patients on

[7] The administrative data on visits does not contain patient age, but does contain counts of patients under 65 and a count of patients over 65.

average: 2,595 chronic (eligible) and 14,669 non-chronic (ineligible) patients. 15% 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

IV. Empirical Strategy

Our strategy to identify the causal impact of CCAMP program on medical visits employs event study and difference-in-difference (DiD) models. We first use a discrete time hazard model to show how program take-up correlates with fixed and time variant clinics characteristics and then test for whether pre-intervention trends in outcomes differ between treated and untreated clinics. For our analysis, we use clinic-level longitudinal data at the semesterly (6 month) level between the first semester of 2013, and the last semester of 2016.

Selection into the CCAMP Program

We start by testing for systematic differences in the timing of CCAMP adoption by primary care clinics. Our identification strategy controls for time invariant characteristics of clinics with clinic fixed effects, and for time trends with semester fixed effects. To test for idiosyncratic time varying shocks that could influence take-up, which are not controlled for in our two-way fixed effects approach, we estimate discrete time hazard models.

Specifically, we estimate the probability that a clinic in a given 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 test characteristics including average age of patients at the clinic, share of patients enrolled in each level of FONASA, as well as data on municipality-level characteristics, such as but not limited to median income, from the CASEN 2013 Socioeconomic survey of Chile.

We estimate two discrete time hazard models where the outcome is the probability of SMS program take-up in each semester from semester 1 2015 onward. First, we include time invariant municipality characteristics to understand whether program take-up is related to a municipality's socioeconomic status, which we operationalize as mean income per capita, and education. We also include time invariant clinic characteristics such as clinic type and share of visits at the clinic by chronic patients to understand whether particular characteristics of clinics predict program take-up. Lastly, we include time fixed effects. We then extend the model by adding time-varying clinic characteristics: both characteristics of patients at the facility, and clinic staff characteristics.

Event-study

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

$$Y_{it} = \sum_{\tau=-5}^{3} \beta_\tau Q_\tau + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{it} \qquad (3)$$

Where 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_t) 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 median share of patients eligible to receive the reminder at baseline (X_{it}). ϵ_{it} is an error term correlated within clinics across time.

Difference-in-differences

In our second step, we use a more parametric, two-way fixed effect DiD approach, which we first estimate as described in equation (4) below:

$$Y_{it} = \alpha + \beta CCAMP_{it} + X_{it}'\delta + \lambda_t + \gamma_i + \epsilon_{it} \qquad (4)$$

Where Y_{it} is the log of number of visits for clinic i at semester t, $CCAMP_{it}$ 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 (490 clinics). 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 and 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.

Recent studies have shown that the OLS estimate of β in (4) may be biased if the treatment effect of a policy or program varies across units of analysis (treatment effect heterogeneity).[8] de Chaisemartin & d'Haultfoeuille (2020) (C&H) show this for the general case where different units are used as a treatment group and control group at different points in time. As the adoption of the policy we study was staggered over time across health facilities, estimation of (4) through OLS could be biased under treatment effect heterogeneity. C&H provide tests and adjustments to account for potential biases from treatment effects heterogeneity and we estimate a version of (4) using their approach as a robustness check.

Last, we implement different heterogeneity analyses to understand which clinics and patients where most benefited from the program. To observe this heterogeneity in the program response, we extend the standard, two-way fixed effects DiD model interacting the CCMAP indicator variable with a binary variable that (i) equal to one if the clinic had above median share of visits by chronic patients before the program started at baseline; defined as the semesterly number of chronic visits divided by the semesterly total number of visits, averaged over all four semesters of 2014. Other heterogeneity analyses were done by using indicator variables for whether a clinic is in the (ii) bottom quartile share of 2014 visits by patients that were aged 65 and over, and (iii) top quartile of total number of medical visits. We run the following regression:

$$Y_{it} = \alpha + \beta CCAMP_{it} + \xi CCAMP_{it} * Type_i + X_{it}'\delta + \lambda_t + \gamma_i + \epsilon_{it} \quad (5)$$

Where $Type_i$ is an indicator variable that equals 1 for each clinic type (i, ii or iii). Other components are the same to those described in equation (3).

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

V. Results

Take-up analyses

Across both models, the results in table 2 show that a clinic's decision to implement the SMS program is not related to municipality or clinic characteristics, with the exception of urbanicity status of primary care clinic ($p<0.05$) and baseline share of chronic patients ($p<0.01$), which are both controlled for with clinic fixed effects. Program take-up is significantly predicted by time showing that the probability of take-up is decreasing over the time period in our analysis. This is consistent with the fact that tale-up is very large in the first periods we analyze, as shown in Figure 3, 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 including time and clinic fixed effects. The variation in start dates over time also validates our use of the C&H estimator.

Event study

The results from the event study analysis are presented in figure 4 (see table A2 in Online Appendix). 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, Figure 4 shows that pre-trends in outcomes are very similar across treated and untreated clinics which supports the parallel trend assumption needed for identification. In particular, differences in outcomes change sharply around the event.

Figure 4 illustrates an increase in visits in the first semester after the program implementation, and that the effect slightly rises after the start of the program (figure 4, panel A). The figure also shows that the effect of reminders on the production of medical visits is driven by visits from patients ineligible to receive appointment reminders (figure 4, panel B), but no such change is observed for chronic patients, eligible to receive the reminders (figure 4, panel C).

Difference-in-differences

Table 3 describes the effect of the CCAMP on medical visits using three DiD approaches. Using the standard, two-way fixed effects estimator we find that on average, adopting the SMS program increases clinics' total number of semesterly visits by 3.3% (see table 3, panel A, column

1). However, this increase in visits is largely driven by visits from patients who were ineligible to receive the reminders – their visits increased by 4.6% (see table 3, panel A, column 3) – and not by visits from eligible patients for whom no change in the number of visits was observed (see table 3, panel A, column 2). Due to the program, clinics had on average 1,031 more visits from non-chronic patients in the post-treatment period (on average we observe clinics for 3 semesters after implementing CCAMP).[9]

We also estimate average treatment effects using the estimator proposed by de Chaisemartin & d'Haultfoeuille (2020), first without weighting (table 3, panel B), and then weighted by the number of switchers in each period (table 3, panel C; weights are included in Online appendix table A3). This estimator also relies on the common trends assumption, but does not allow any weights to be negative, which can be an issue with the two-way fixed effect estimator when heterogenous treatment effects are present and treatment is phased in over time. In the event studies we observe an increase in the treatment effect on visits by total and non-chronic patients over time (figure 4, panels A and C respectively), justifying our use of the C&H estimator[10].

We find very similar results using both the unweighted, and weighted estimators: on average, adopting the SMS program increases clinics' total number of semesterly visits by 4.0% (unweighted) or 4.1% (weighted) (see table 3, panel B, column 1 and table 3, 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 3, panel B, column 3 and table 3, panel C, column 3). We proceed with standard, two-way fixed effects estimator DiD as our preferred specification because the results from the three DiD specifications in table 3 are economically similar.

We next present results using this DiD estimator where we allow the ATE to vary by year in the post-treatment period (table 4). In the semester of program adoption, total visits increased by 3.5% and visits by non-chronic patients increased by 5.6% (table 4 columns 1 and 3 respectively). The effect of the program is lower in the semester after adoption and increases to 5.1% and 7.4% for visits by all and non-chronic patients respectively (table 4 columns 1 and 3).

[9] To estimate additional non-chronic visits at treated clinics attributable to CCAMP we multiplied treatment effect on non-chronic visits, 4.6% by each clinic's pre-treatment average non-chronic visits per semester and summed across the post-treatment period.

[10] 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 online appendix table A4), providing more support for our use of the C&H estimator.

There is no effect for chronic patients, who do receive the reminder, until two semesters after program adoption, when visits by chronic patients fall by 4.4% (table 4, column 2).

To reassure our interpretation that the results in tables 3 and 4 show reallocation of time to existing patients rather than a change in patient inflow we change our dependant variable to total number of patients in equation (4). Results in table A6 in the online appendix show that the effects on the number of patients are small and insignificant, hence our main results are not driven by a change in the flow of patients. In addition to the analysis of selection, we further assess the validity of our results by implementing a placebo test where we lag the onset of the program in time by four semesters (see Online Appendix table A7). The results in table A6 show that there is a small and insignificant association between patients visits and treatment status in the preprogram period. This suggests that pre trends are unrelated to treatment onset.

Heterogeneity by population and clinic's characteristics

We implement different heterogeneity analyses to understand which clinics and patients benefited most from the program, using two-way fixed effect DiD estimators. First, we study whether the impact of CCAMP varied by clinics with a relatively large number of visits by eligible patients at baseline (i.e., in the pre-intervention period). We observe a larger, 7.1% increase in total number of visits in clinics with above the median share of visits by eligible chronic patients needing ongoing care (table 5A, Column 1). Again, this increase was largely due to a 9.8% increase in visits for ineligible patients in those clinics (table 5A, column 2).

Next, we compute the share of chronic patients who are 65 years old or younger and construct an indicator variable that equals to 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. We label this indicator "Young Population". The results in table 5B show that the effect of the program on chronic patients' visits is positive for clinics whose population of chronic patients is younger. The results show that on average clinics classified as having a "Young population" increased the number of visits by chronic patients by 5.5%. The results in column 3 show that the effect on non-chronic visits is entirely driven by clinics where the population of patients is older, which suggests that the efficiency gains in these clinics are more in terms of rescheduling rather than improved visit adherence of chronic patients.

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. We label this indicator as "Large". The results in table 4, column 3, show that there are no differences in total visits between clinics of large/small size. However, when we separate the total number of visits by type, the results show that the program reduces by 5.2% the number of chronic patients' visits in clinics that had a large visit flow before the intervention. In addition, the program increases the number of non-chronic patients' visits in clinics classified as non "Large". In the online appendix, table A8 shows that most of these effects hold when we include all variables at once. The exception are the differential effects by clinic size "Large", however this is plausibly due to the collinearity with the share of chronic patients.

Discussion

Overall, the results show that reminding chronic patients the date of their visit and allowing them to confirm attendance and reallocate canceled appointments in a timely manner increases efficiency within clinics as it allows clinic management to optimize the use of physicians' time. On average, the flow of visits by chronic patients does not change, but the number of visits of patients with other conditions increases in the same clinics. This is consistent with clinics' being able to improve the timing of attendance of chronic patients so that they visit the doctor at the date or around the date scheduled and not after, once they recall that they have missed their appointment, or their health has worsened. Hence, on average, total number of visits by chronic patients does not change but the timing and organization of attendance to this population is more efficient.

Better timing of attendance to chronic patients should help clinics' management organize other activities better, including scheduling visit hours for other patients. As such, the number of visits from patients needing acute care increases as the clinics are able to accommodate more visits from this population. This evidence is further supported by the larger effects observed for clinics with a high proportion of chronic patients before the intervention, where there is an increase in 9.8% in the number of visits from non-chronic patients. Hence, efficiency gains from the program are larger in clinics that are more congested by the untimely attendance of chronic patients, as the program enables a relatively larger number of visits for ineligible patients.

The effects of the reminders increased over time, suggesting a learning period just after implementation in which clinics improved the program's implementation quality. This could be explained by a lag between collecting a patients' phone number for the SMS reminder, and the patient's next visit.

The results by population age are consistent with findings from the literature that show the use of IT technology is more effective to manage care in younger populations. One reason is that the younger population may have less severe conditions so that the relative importance that they assign to their disease is lower than among older adults and so they are more likely to forget their appointments. On the other hand, young adults are typically more connected and have less difficulty engaging in self-care programs that involve IT technologies. These stories are indistinguishable with our data, but they are both consistent with finding larger positive effects of the SMS reminder program in clinics whose population of patients is younger on average.

VI. Conclusions

In this paper we examined the effects of a nation-wide phased in SMS reminder program to manage visit adherence of patients with chronic conditions in Chile. We used this analysis to investigate whether implementing management care practices improves overall efficiency of primary care clinics. The intervention sent automatic SMS appointment reminders to patients with T2DM and/or hypertension 24-48 hours prior to the scheduled appointment with information on date, location and time of the appointment. Patients could cancel or reschedule their appointment by replying to the SMS. Using semesterly data at the clinic level on the number of visits by type of patient, we compare the quantity of visits at clinics with and without the program over time. We found that treated clinics became more efficient in managing overall patient visits, as the program helped to optimize the use of healthcare providers' time. In particular we find that the program's primary impact on patients who were not eligible to receive the SMS reminder themselves: the number of visits by these patients increased on average by 4.6%, with the effect rising to 7.4% in the second year of program implementation.

We also showed that clinics with a high burden of chronic patients in the time before the program experienced larger efficiency gains from SMS reminders, as these clinics were able to accommodate a relatively larger number of visits for non-chronic patients. In addition, the results show that while average effects for chronic patients are null, there are positive effects on visits by chronic patients below 65 years old, who are likely to have less severe chronic conditions and may be more prone to miss appointments, and who are also more likely to engage in self-care management that uses IT. Finally, as previous work in this area focuses on small pilots or studies in randomized controlled settings, the results in this paper provide the first evidence on the effects of SMS reminders at scale.

Our results have a few important policy implications. They suggest that SMS programs implemented at scale may be effective in improving efficiency in primary care clinics. The results highlight that when clinics work under tight capacity constraints, focusing on case management in particular populations can have beneficial effects to case management overall. With health costs rising swiftly, cost effective programs such as SMS reminders for case management offer countries a low-cost way to complement primary care management.

References

Abraham, S., & Sun, L. (2018). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Available at SSRN 3158747*.

Ali, Mohammed K., Seema Shah, and Nikhil Tandon. 2011. "Review of Electronic Decision-Support Tools for Diabetes Care: A Viable Option for Low- and Middle-Income Countries?" *Journal of Diabetes Science and Technology* 5 (3): 553–70. https://doi.org/10.1177/193229681100500310.

Altuwaijri, M. M., Sughayr, A. M., Hassan, M. A., & Alazwari, F. M. (2012). The effect of integrating short messaging services` reminders with electronic medical records on non-attendance rates. *Saudi Medical Journal*, *33*(2), 193–196.

Alvarez, C., Saint-Pierre, C., Herskovic, V., & Sepúlveda, M. (2018). Analysis of the Relationship between the Referral and Evolution of Patients with Type 2 Diabetes Mellitus. *International Journal of Environmental Research and Public Health*, *15*(7). https://doi.org/10.3390/ijerph15071534

Arora, S., Burner, E., Terp, S., Nok Lam, C., Nercisian, A., Bhatt, V., & Menchine, M. (2015). Improving attendance at post-emergency department follow-up via automated text message appointment reminders: A randomized controlled trial. *Academic Emergency Medicine: Official Journal of the Society for Academic Emergency Medicine*, *22*(1), 31–37. https://doi.org/10.1111/acem.12503

Athey, S., & Imbens, G. W. (2018). *Design-based analysis in difference-in-differences settings with staggered adoption*. National Bureau of Economic Research.

Baker, D. W., Brown, T., Goldman, S. N., Liss, D. T., Kollar, S., Balsley, K., Lee, J. Y., & Buchanan, D. R. (2015). Two-year follow-up of the effectiveness of a multifaceted intervention to improve adherence to annual colorectal cancer screening in community health centers. *Cancer Causes & Control: CCC*, *26*(11), 1685–1690. https://doi.org/10.1007/s10552-015-0650-0

Bangure, D., Chirundu, D., Gombe, N., Marufu, T., Mandozana, G., Tshimanga, M., & Takundwa, L. (2015). Effectiveness of short message services reminder on childhood immunization programme in Kadoma, Zimbabwe—A randomized controlled trial, 2013. *BMC Public Health*, *15*, 137. https://doi.org/10.1186/s12889-015-1470-6

Barron, W. M. (1980). Failed appointments. Who misses them, why they are missed, and what can be done. *Primary Care*, *7*(4), 563–574.

Bech, M. (2005). The economics of non-attendance and the expected effect of charging a fine on non-attendees. *Health Policy (Amsterdam, Netherlands)*, *74*(2), 181–191. https://doi.org/10.1016/j.healthpol.2005.01.001

Bedregal, P., Ferrer, J., Figueroa, B., Tellez, C., Vera, J., & Zurob, C. (2017). La espera en el sistema de salud chileno: Una oportunidad para poner a las personas al centro. In *Temas de la Agenda Pública.* Pontifica Universidad Católica de Chile.

Bellucci, E., Dharmasena, L., Nguyen, L., & Calache, H. (2017). The effectiveness of SMS Reminders and the impact of patient characteristics on missed appointments in a public dental outpatient clinic. *Australasian Journal of Information Systems*, *21*. https://doi.org/10.3127/ajis.v21i0.1405

Berenson, A. B., Rahman, M., Hirth, J. M., Rupp, R. E., & Sarpong, K. O. (2016). A human papillomavirus vaccination program for low-income postpartum women. *American Journal of Obstetrics and Gynecology*, *215*(3), 318.e1-9. https://doi.org/10.1016/j.ajog.2016.02.032

Berg, M. B., Safren, S. A., Mimiaga, M. J., Grasso, C., Boswell, S., & Mayer, K. H. (2005). Nonadherence to medical appointments is associated with increased plasma HIV RNA and decreased CD4 cell counts in a community-based HIV primary care clinic. *AIDS Care*, *17*(7), 902–907. https://doi.org/10.1080/09540120500101658

Berrouiguet, S., Baca-García, E., Brandt, S., Walter, M., & Courtet, P. (2016). Fundamentals for Future Mobile-Health (mHealth): A Systematic Review of Mobile Phone and Web-Based Text Messaging in Mental Health. *Journal of Medical Internet Research*, *18*(6), e135. https://doi.org/10.2196/jmir.5066

Borusyak, K., & Jaravel, X. (2017). Revisiting event study designs. *Available at SSRN 2826228*.

Bos, A., Hoogstraten, J., & Prahl-Andersen, B. (2005). Failed appointments in an orthodontic clinic. *American Journal of Orthodontics and Dentofacial Orthopedics*, *127*(3), 355–357. https://doi.org/10.1016/j.ajodo.2004.11.014

Bourne, C., Knight, V., Guy, R., Wand, H., Lu, H., & McNulty, A. (2011). Short message service reminder intervention doubles sexually transmitted infection/HIV re-testing rates among men who have sex with men. *Sexually Transmitted Infections*, *87*(3), 229–231. https://doi.org/10.1136/sti.2010.048397

Branson, C. E., Clemmey, P., & Mukherjee, P. (2013). Text message reminders to improve outpatient therapy attendance among adolescents: A pilot study. *Psychological Services*, *10*(3), 298–303. https://doi.org/10.1037/a0026693

Callaway, B., & Sant'Anna, P. H. (2019). Difference-in-differences with multiple time periods. *Available at SSRN 3148250*.

Chaisemartin, Clément de, and Xavier D'Haultfœuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review* 110 (9): 2964–96. https://doi.org/10.1257/aer.20181169.

Chen, Z.-W., Fang, L.-Z., Chen, L.-Y., & Dai, H.-L. (2008). Comparison of an SMS text messaging and phone reminder to improve attendance at a health promotion center: A randomized controlled trial. *Journal of Zhejiang University. Science. B*, *9*(1), 34–38. https://doi.org/10.1631/jzus.B071464

Clough, B. A., & Casey, L. M. (2014). Using SMS Reminders in Psychology Clinics: A Cautionary Tale. *Behavioural and Cognitive Psychotherapy*, *42*(3), 257–268. https://doi.org/10.1017/S1352465813001173

Colubi, M. M., Pérez-Elías, M. J., Elías, L., Pumares, M., Muriel, A., Zamora, A. M., Casado, J. L., Dronda, F., López, D., Moreno, S., & SEAD Study Group. (2012). Missing scheduled visits in the outpatient clinic as a marker of short-term admissions and death. *HIV Clinical Trials*, *13*(5), 289–295. https://doi.org/10.1310/hct1305-289

Dantas, L. F., Fleck, J. L., Cyrino Oliveira, F. L., & Hamacher, S. (2018). No-shows in appointment scheduling – a systematic literature review. *Health Policy*, *122*(4), 412–421. https://doi.org/10.1016/j.healthpol.2018.02.002

DellaVigna, S. (2009). Psychology and Economics: Evidence from the Field. *Journal of Economic Literature*, *47*(2), 315–372. https://doi.org/10.1257/jel.47.2.315

Dreiher, J., Froimovici, M., Bibi, Y., Vardy, D. A., Cicurel, A., & Cohen, A. D. (2008). Nonattendance in Obstetrics and Gynecology Patients. *Gynecologic and Obstetric Investigation*, *66*(1), 40–43. https://doi.org/10.1159/000115844

Ellis, D. A., McQueenie, R., McConnachie, A., Wilson, P., & Williamson, A. E. (2017). Demographic and practice factors predicting repeated non-attendance in primary care: A national retrospective cohort analysis. *The Lancet Public Health*, *2*(12), e551–e559. https://doi.org/10.1016/S2468-2667(17)30217-7

FONASA. (2018). *Boletín Estadístico 2016-2017*. Bases de Datos, Informes y Documentos. https://www.fonasa.cl/sites/fonasa/documentos

Free, C., Phillips, G., Galli, L., Watson, L., Felix, L., Edwards, P., Patel, V., & Haines, A. (2013). The Effectiveness of Mobile-Health Technology-Based Health Behaviour Change or Disease Management Interventions for Health Care Consumers: A Systematic Review. *PLOS Medicine*, *10*(1), e1001362. https://doi.org/10.1371/journal.pmed.1001362

Gabaix, X. (2019). Behavioral inattention. In *Handbook of Behavioral Economics: Applications and Foundations 1* (Vol. 2, pp. 261–343). Elsevier. https://doi.org/10.1016/bs.hesbe.2018.11.001

Gentry, Sarah, and Padmanabhan Badrinath. n.d. "Defining Health in the Era of Value-Based Care: Lessons from England of Relevance to Other Health Systems." *Cureus* 9 (3). Accessed November 19, 2020. https://doi.org/10.7759/cureus.1079.

Geraghty, M., Glynn, F., Amin, M., & Kinsella, J. (2008). Patient mobile telephone 'text' reminder: A novel way to reduce non-attendance at the ENT out-patient clinic. *The Journal of Laryngology & Otology*, *122*(3), 296–298. https://doi.org/10.1017/S0022215107007906

Goic, A. (2015). The Chilean Health Care System: The task ahead. *Revista Médica de Chile*, *143*(6), 774–786. https://doi.org/10.4067/S0034-98872015000600011

González-Arévalo, A., Gómez-Arnau, J. I., DelaCruz, F. J., Marzal, J. M., Ramírez, S., Corral, E. M., & García-del-Valle, S. (2009). Causes for cancellation of elective surgical procedures in a Spanish general hospital. *Anaesthesia*, *64*(5), 487–493. https://doi.org/10.1111/j.1365-2044.2008.05852.x

Goodman-Bacon, A. (2018). *Difference-in-differences with variation in treatment timing*. National Bureau of Economic Research.

Gucciardi, E. (2008). A Systematic Review of Attrition from Diabetes Education Services: Strategies to Improve Attrition and Retention Research. *Canadian Journal of Diabetes*, *32*(1), 53–65. https://doi.org/10.1016/S1499-2671(08)21011-7

Gupta, D., & Wang, W.-Y. (2012). Patient Appointments in Ambulatory Care. In R. Hall (Ed.), *Handbook of Healthcare System Scheduling* (pp. 65–104). Springer US. https://doi.org/10.1007/978-1-4614-1734-7_4

Gurol-Urganci, I., Jongh, T. de, Vodopivec-Jamsek, V., Atun, R., & Car, J. (2013). Mobile phone messaging reminders for attendance at healthcare appointments. *Cochrane Database of Systematic Reviews*, *12*. https://doi.org/10.1002/14651858.CD007458.pub3

Hamine, Saee, Emily Gerth-Guyette, Dunia Faulx, Beverly B. Green, and Amy Sarah Ginsburg. 2015. "Impact of MHealth Chronic Disease Management on Treatment Adherence and Patient Outcomes: A Systematic Review." *Journal of Medical Internet Research* 17 (2): e52. https://doi.org/10.2196/jmir.3951.

Hashim, M. J., Franks, P., & Fiscella, K. (2001). Effectiveness of telephone reminders in improving rate of appointments kept at an outpatient clinic: A randomized controlled trial. *The Journal of the American Board of Family Practice*, *14*(3), 193–196.

Husain-Gambles, M., Neal, R. D., Dempsey, O., Lawlor, D. A., & Hodgson, J. (2004). Missed appointments in primary care: Questionnaire and focus group study of health professionals. *British Journal of General Practice*, *54*(499), 108–113.

Iacobucci, G. (2019). Sixty seconds on. . . Missed GP appointments. *BMJ*, *364*. https://doi.org/10.1136/bmj.l69

InterSystems Corporation. (n.d.). *Chilean Health Providers and Patients Benefit from Better, More Coordinated Care*.

Jongh, Thyra de, Ipek Gurol-Urganci, Vlasta Vodopivec-Jamsek, Josip Car, and Rifat Atun. 2012. "Mobile Phone Messaging for Facilitating Self-management of Long-term Illnesses." *Cochrane Database of Systematic Reviews*, no. 12. https://doi.org/10.1002/14651858.CD007459.pub2.

Kannisto, K. A., Koivunen, M. H., & Välimäki, M. A. (2014). Use of Mobile Phone Text Message Reminders in Health Care Services: A Narrative Literature Review. *Journal of Medical Internet Research*, *16*(10), e222. https://doi.org/10.2196/jmir.3442

Kruse, Clemens Scott, Nicole Krowski, Blanca Rodriguez, Lan Tran, Jackeline Vela, and Matthew Brooks. 2017. "Telehealth and Patient Satisfaction: A Systematic Review and Narrative Analysis." *BMJ Open* 7 (8): e016242. https://doi.org/10.1136/bmjopen-2017-016242.

Lacy, N. L., Paulman, A., Reuter, M. D., & Lovejoy, B. (2004). Why We Don't Come: Patient Perceptions on No-Shows. *The Annals of Family Medicine*, *2*(6), 541–545. https://doi.org/10.1370/afm.123

LaGanga, L. R., & Lawrence, S. R. (2007). Clinic Overbooking to Improve Patient Access and Increase Provider Productivity*. *Decision Sciences*, *38*(2), 251–276. https://doi.org/10.1111/j.1540-5915.2007.00158.x

Lee, C. S., & McCormick, P. A. (2003). Telephone reminders to reduce non-attendance rate for endoscopy. *Journal of the Royal Society of Medicine*, *96*(11), 547–548.

Lieu, T. A., Capra, A. M., Makol, J., Black, S. B., Shinefield, H. R., & Group‖, for the I. M. S. (1998). Effectiveness and Cost-effectiveness of Letters, Automated Telephone Messages, or Both for Underimmunized Children in a Health Maintenance Organization. *Pediatrics*, *101*(4), e3–e3. https://doi.org/10.1542/peds.101.4.e3

Manfredi, R. (2017, July 10). *SMS Reminders Reduce Missed Medical Appointments for Providers*. https://mgage.com/knowledge-share/case-studies/sms-reminders-reduce-missed-medical-appointments-providers/

Margozzini, P., & Passi, A. (2018). Encuesta Nacional de Salud, ENS 2016-2017: Un aporte a la planificación sanitaria y politicas públicas en Chile. *Ars Medica Revista de Ciencias Médicas*, *43*(1), 30–34.

Martínez, D. A., Zhang, H., Bastias, M., Feijoo, F., Hinson, J., Martinez, R., Dunstan, J., Levin, S., & Prieto, D. (2019). Prolonged wait time is associated with increased mortality for Chilean waiting list patients with non-prioritized conditions. *BMC Public Health*, *19*(1), 233. https://doi.org/10.1186/s12889-019-6526-6

MDS. (2013). *Encuesta CASEN 2013*. Ministerio de Desarrollo Social, Gobierno de Chile. http://observatorio. ministeriodesarrollosocial. gob. cl/casen/casen-documentos. php. 2013.

Ministerio de Salud de Chile. (2014). *Implementación y Avances*. E-Salud/Proyecto Sidra. http://www.salud-e.cl/sidra-home/avance/

MINSAL. (2008). *Informe final: Estudio de carga de enfermedad y carga atribuible*. Ministerio de Salud de Chile.

MINSAL. (2018). *Evaluación de Programas Gubernamentales: Fondo de Farmacia para Enfermedades Crónicas No Transmisibles en Atención Primaria de Salud*.

Moore, C. G., Wilson-Witherspoon, P., & Probst, J. C. (2001). Time and money: Effects of no-shows at a family practice residency clinic. *Family Medicine*, *33*(7), 522–527.

Mugavero, M. J., Lin, H.-Y., Willig, J. H., Westfall, A. O., Ulett, K. B., Routman, J. S., Abroms, S., Raper, J. L., Saag, M. S., & Allison, J. J. (2009). Missed visits and mortality among patients establishing initial outpatient HIV treatment. *Clinical Infectious Diseases: An Official Publication of the Infectious Diseases Society of America*, *48*(2), 248–256. https://doi.org/10.1086/595705

Murdock, A., Rodgers, C., Lindsay, H., & Tham, T. C. K. (2002). Why Do Patients not Keep their Appointments? Prospective Study in a Gastroenterology Outpatient Clinic. *Journal of the Royal Society of Medicine*, *95*(6), 284–286. https://doi.org/10.1177/014107680209500605

Neal, R. D., Hussain-Gambles, M., Allgar, V. L., Lawlor, D. A., & Dempsey, O. (2005). Reasons for and consequences of missed appointments in general practice in the UK: Questionnaire survey and prospective review of medical records. *BMC Family Practice*, *6*(1), 47. https://doi.org/10.1186/1471-2296-6-47

NHS. (2018). *Appointments in General Practice*. https://digital.nhs.uk/data-and-information/publications/statistical/appointments-in-general-practice/oct-2018#resources

Nuti, L. A., Lawley, M., Turkcan, A., Tian, Z., Zhang, L., Chang, K., Willis, D. R., & Sands, L. P. (2012). No-shows to primary care appointments: Subsequent acute care utilization among diabetic patients. *BMC Health Services Research*, *12*, 304. https://doi.org/10.1186/1472-6963-12-304

Oliver, D. (2019). David Oliver: Missed GP appointments are no scandal. *BMJ*, *364*. https://doi.org/10.1136/bmj.l545

Parikh, A., Gupta, K., Wilson, A. C., Fields, K., Cosgrove, N. M., & Kostis, J. B. (2010). The Effectiveness of Outpatient Appointment Reminder Systems in Reducing No-Show Rates. *The American Journal of Medicine*, *123*(6), 542–548. https://doi.org/10.1016/j.amjmed.2009.11.022

Reekie, D., & Devlin, H. (1998). Preventing failed appointments in general dental practice: A comparison of reminder methods. *British Dental Journal*, *185*(9), 472–474. https://doi.org/10.1038/sj.bdj.4809840

Reti, S. (2003). Improving outpatient department efficiency: A randomized controlled trial comparing hospital and general-practice telephone reminders. *The New Zealand Medical Journal*, *116*(1175), U458.

Roberto, C. A., & Kawachi, I. (2015). *Behavioral economics and public health*. Oxford University Press.

Sawyer, S. M., Zalan, A., & Bond, L. M. (2002). Telephone reminders improve adolescent clinic attendance: A randomized controlled trial. *Journal of Paediatrics and Child Health*, *38*(1), 79–83. https://doi.org/10.1046/j.1440-1754.2002.00766.x

Schectman, J. M., Schorling, J. B., & Voss, J. D. (2008). Appointment adherence and disparities in outcomes among patients with diabetes. *Journal of General Internal Medicine*, *23*(10), 1685–1687. https://doi.org/10.1007/s11606-008-0747-1

Scheitel, Marianne R., Maya E. Kessler, Jane L. Shellum, Steve G. Peters, Dawn S. Milliner, Hongfang Liu, Ravikumar Komandur Elayavilli, et al. 2017. “Effect of a Novel Clinical Decision Support Tool on the Efficiency and Accuracy of Treatment Recommendations for Cholesterol Management.” *Applied Clinical Informatics* 8 (1): 124–36. https://doi.org/10.4338/ACI-2016-07-RA-0114.

Schwebel, F. J., & Larimer, M. E. (2018). Using text message reminders in health care services: A narrative literature review. *Internet Interventions*, *13*, 82–104. https://doi.org/10.1016/j.invent.2018.06.002

Shipman, S. A., & Sinsky, C. A. (2013). Expanding Primary Care Capacity By Reducing Waste And Improving The Efficiency Of Care. *Health Affairs*, *32*(11), 1990–1997. https://doi.org/10.1377/hlthaff.2013.0539

Spikmans, F. J. M., Brug, J., Doven, M. M. B., Kruizenga, H. M., Hofsteenge, G. H., & Schueren, M. A. E. V. B. der. (2003). Why do diabetic patients not attend appointments with their dietitian? *Journal of Human Nutrition and Dietetics*, *16*(3), 151–158. https://doi.org/10.1046/j.1365-277X.2003.00435.x

Tompkins, Christopher P., Aparna R. Higgins, and Grant A. Ritter. 2009. “Measuring Outcomes And Efficiency In Medicare Value-Based Purchasing.” *Health Affairs* 28 (Supplement 2): w251–61. https://doi.org/10.1377/hlthaff.28.2.w251.

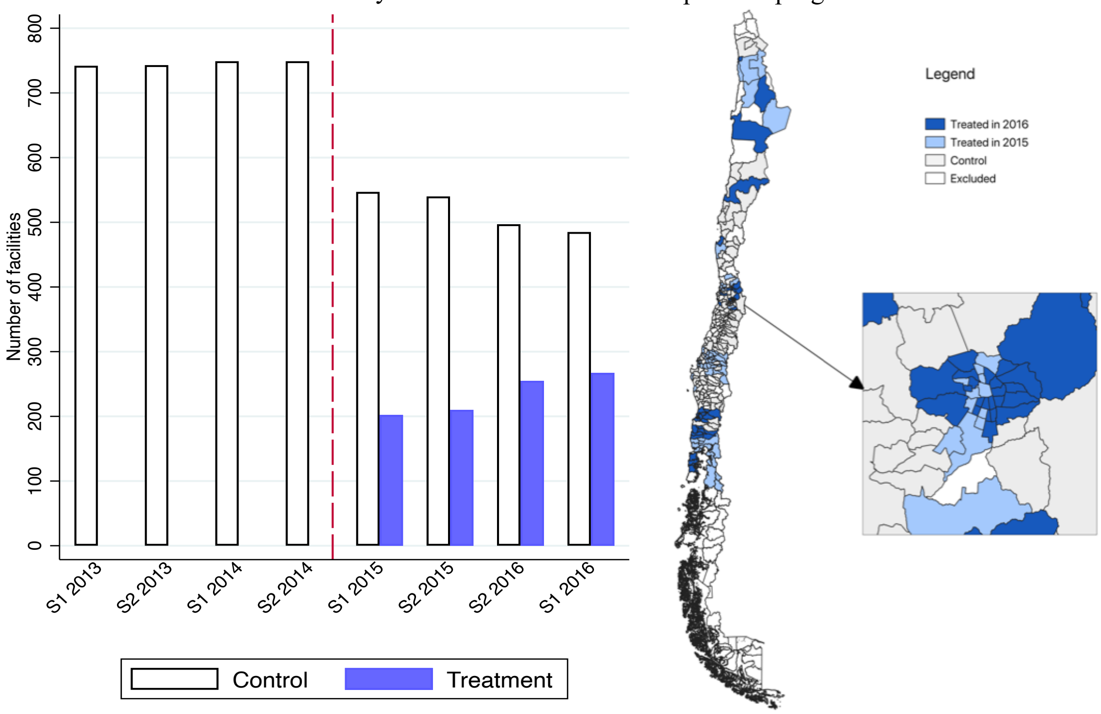
Walburn, A., Swindells, S., Fisher, C., High, R., & Islam, K. M. (2012). Missed visits and decline in CD4 cell count among HIV-infected patients: A mixed method study. *International Journal of Infectious Diseases: IJID: Official Publication of the International Society for Infectious Diseases*, *16*(11), e779-785. https://doi.org/10.1016/j.ijid.2012.06.004

TABLES AND FIGURES

Figure 1: Program Implementation Across Primary Care Clinics 2013-2016.

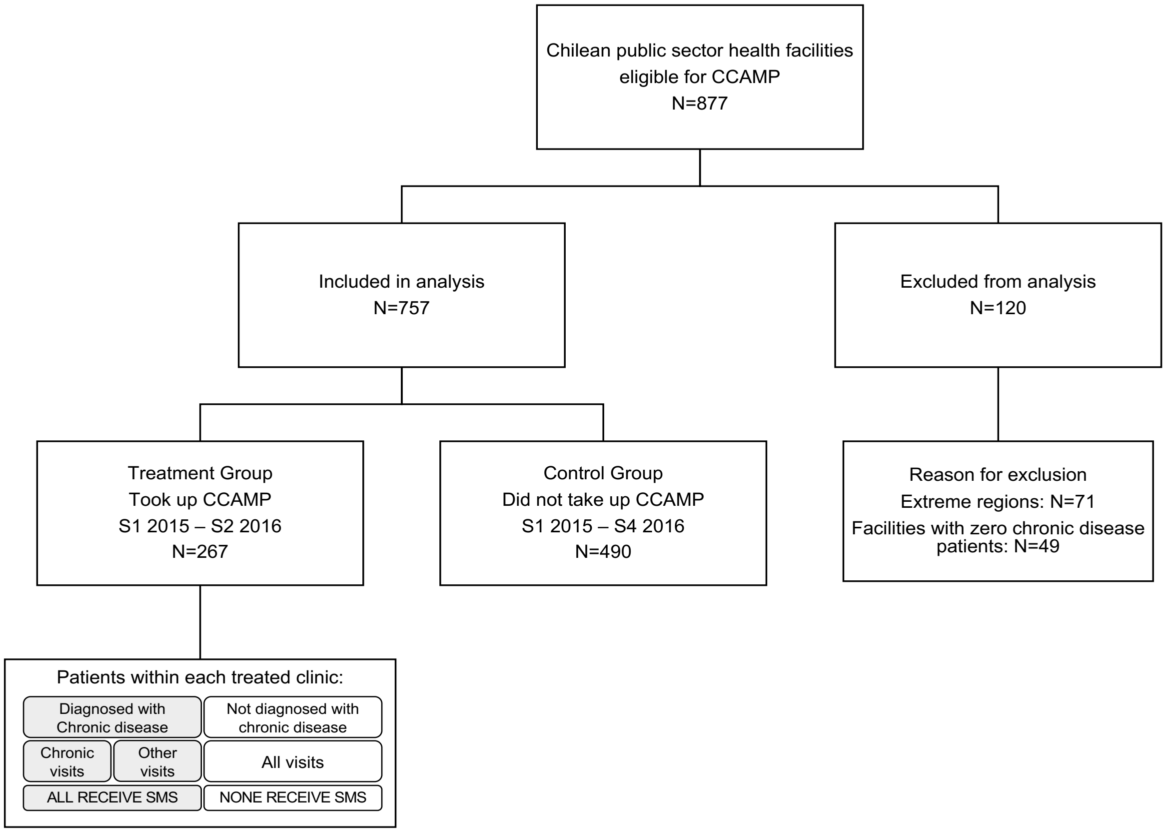
i) Program implementation by semester and year.

ii) Map of municipalities in which clinics adopted the program in 2015 and 2016.



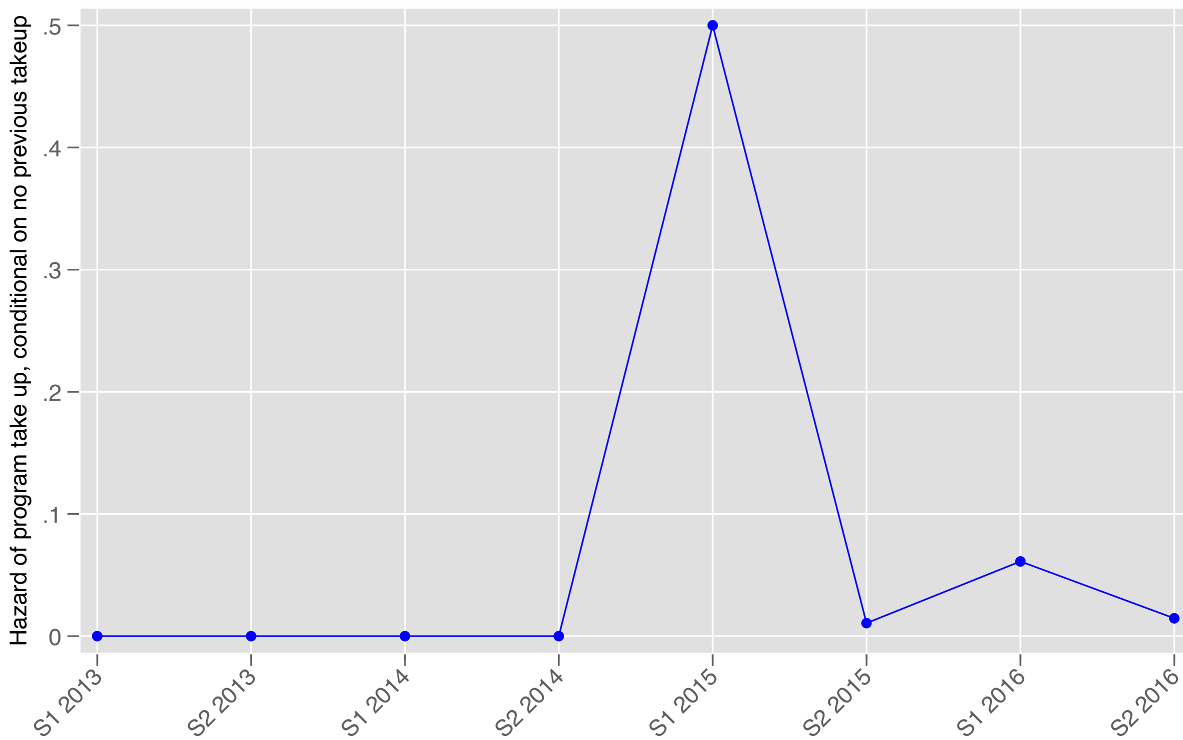
Notes: Authors' calculations based on data obtained from the Ministry of Health, Chile.

Figure 2: CCAMP eligibility and inclusion in the final sample for the analysis.



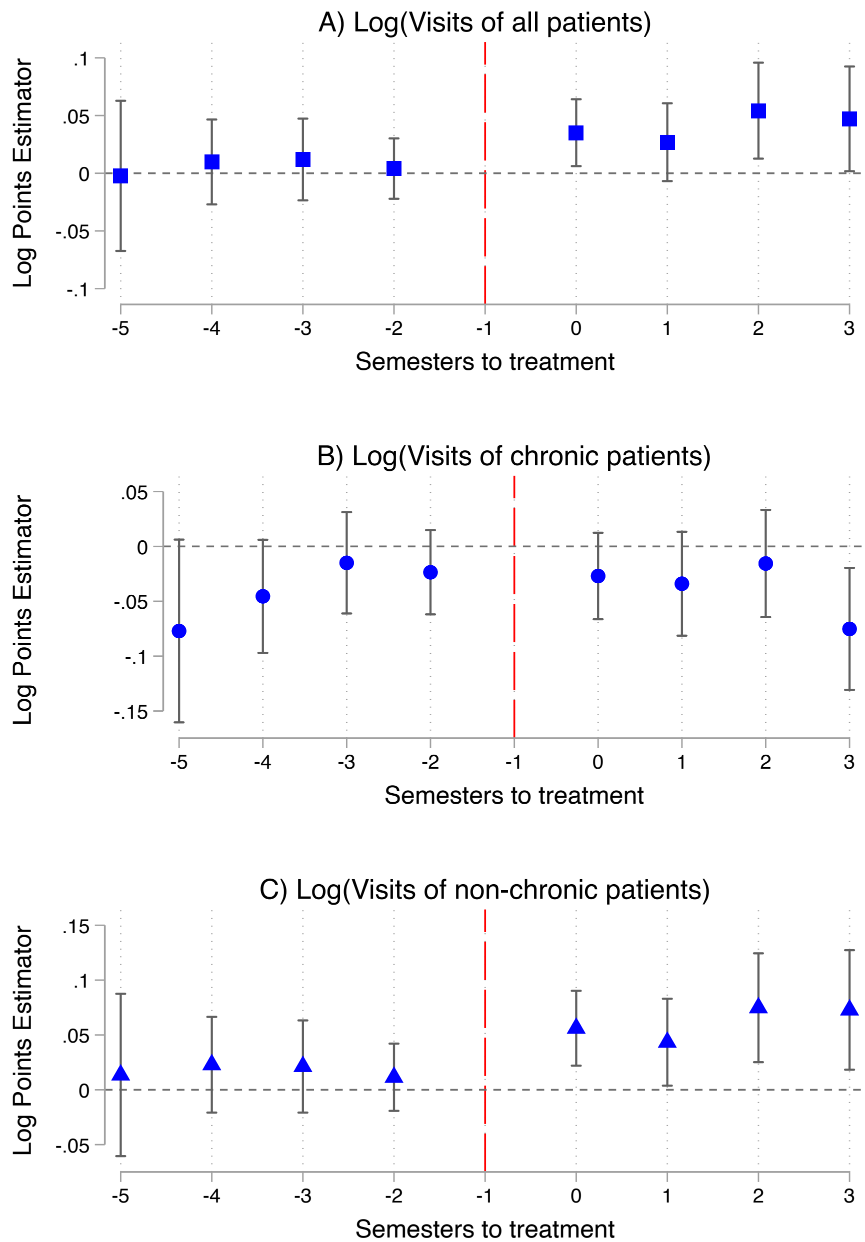
Notes: CCAMP is the Critical Care Appointment Management Program (Mensajería para la Gestión de Citas en Pacientes Crónicos). HTN refers to hypertension, and DM to T2DM. Extreme regions are De Arica Parinacota, Aisén del General Carlos Ibáñez del Campo, the Chilean Antarctic, and Easter Island.

Figure 3: Discrete Time Hazard Model: Probability of Program Take-Up by Semester



Note: Plotted are coefficients from a discrete time hazard model, where the outcome is clinic take-up of CCAMP in a given semester, where the predictors are time indicators.

Figure 4: Changes in Total Number of Visits per Clinic per Semester Over Time.



Notes: Figures show regression estimates based on equation (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.

Table 1: Descriptive statistics

	(1) Treated Clinics Mean (SD)		(2) Control Clinics Mean (SD)		(3) 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
Non-chronic clinic population (1000s)	15.22	(0.75)	14.37	(0.54)	0.85
Chronic clinic population (1000s)	2.89	(0.14)	2.74	(0.11)	0.15
Share of chronic 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		

*** 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 socio-economic 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 services.

Table 2. Discrete time hazard estimate of the probability of program take up by municipality and clinic characteristics

	Mean (SD)	Model (1)	Model (2)
Time invariant municipality characteristics			
Mean household income per capita (log USD)	5.857	-0.063	-0.067
	(0.251)	(0.223)	(0.224)
Proportion male	0.476	0.989	1.051
	(0.018)	(2.569)	(2.573)
Mean age	36.908	-0.024	-0.024
	(2.506)	(0.025)	(0.025)
Time invariant clinic characteristics			
Type of facility: urban primary care clinic	0.750	**0.397****	**0.398****
	(0.433)	**(0.164)**	**(0.164)**
Baseline average total visits (log)	8.588	-0.003	-0.001
	(0.922)	(0.071)	(0.071)
Baseline average share of visits by chronic patients	0.207	**-2.489*****	**-2.514*****
	(0.100)	**(0.719)**	**(0.715)**
Time varying clinic characteristics			
Total visit shocks (deviations from pre-treatment mean)	8.766	-	-8.75E-05
	(296.42)		(0.000)
Time Dummies			
Semester 2 2015	0.125	**-3.559*****	**-3.556*****
	(0.331)	**(0.371)**	**(0.372)**
Semester 1 2016	0.126	**-1.758*****	**-1.748*****
	(0.331)	**(0.186)**	**(0.190)**
Semester 2 2016	0.126	**-3.241*****	**-3.244*****
	(0.331)	**(0.322)**	**(0.321)**
Number of clinics	754	754	754
Observations	3003	3003	3003

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses clustered at clinic level. All semesters where no clinic took up the program are omitted. Models 1 and 2 show coefficient, and standard errors in parentheses from two separate discrete time hazard models, where the outcome is clinic take-up of CCAMP in a given semester. Three clinics are only present in the pre-treatment period leaving n=754 clinics out of total of 757. Time dummies are included, and semester 1 2015 is the reference level.

Table 3. Clinic-level results for the impact of CCAMP on visits by patient type.

	(1)	(2)	(3)
	Log visits by patient type		
	Total	**Chronic**	**Non-chronic**
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	5,986	5,986	5,986
Adjusted R-squared	0.965	0.923	0.958
Control group mean visits	5,214	957	4,071
Number of clinics	757	757	757
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

*** 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 2x2 comparisons. A switcher is a clinic that took up the program in a given semester. 100 bootstrap replications used.

Table 4. Clinic-level results for the impact of CCAMP on visits by patient type by semester.

	(1)	(2)	(3)
	Log visits by patient type		
	Total	**Chronic**	**Non-chronic**
Treated (β) semester of treatment	**0.035****	-0.028	**0.056*****
	(0.015)	(0.020)	**(0.017)**
Treated (β) 1 semester after treatment	0.027	0.032	**0.043****
	(0.017)	(0.024)	**(0.020)**
Treated (β) 2+ semesters after treatment	**0.051****	**-0.044***	**0.074*****
	(0.021)	**(0.024)**	**(0.025)**
Observations	5,986	5,986	5,986
Adjusted R-squared	0.965	0.923	0.958
Control group mean visits	5,214	957	4,071
Number of clinics	757	757	757
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

*** 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.

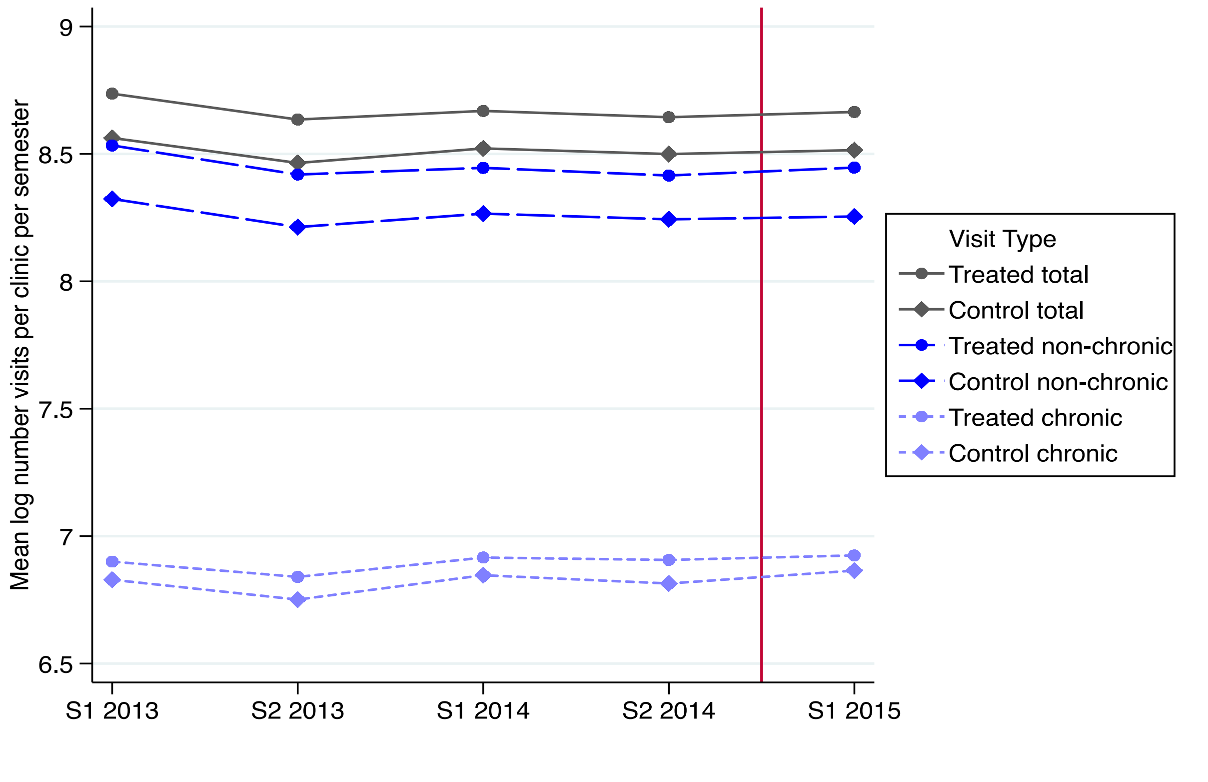
Table 5. Heterogeneity in clinic-level results for the impact of CCAMP on visits by patient type.

	(1)	**(2)**	**(3)**
	Y = Log visits by patient type.		
	Total	**Chronic**	**Non-chronic**
Panel A: Heterogeneity by share of chronic patients			
Treated (β)	0.018	-0.015	0.025
	(0.015)	(0.023)	(0.017)
Treated x Specialized Clinic (ξ1)	**0.071***	0.003	**0.098****
	(0.037)	(0.043)	**(0.049)**
β + ξ1	**0.088*****	-0.013	**0.123*****
	(0.034)	(0.038)	**(0.046)**
Panel B: Heterogeneity by relative share of chronic patients <65 years			
Treated (β)	0.024	**-0.029***	**0.037****
	(0.015)	**(0.017)**	**(0.018)**
Treated x Young Population (ξ2)	**0.036***	**0.055***	0.035
	(0.019)	**(0.031)**	(0.022)
β + ξ2	**0.059*****	0.027	**0.072*****
	(0.018)	(0.031)	**(0.021)**
Panel C: Heterogeneity by clinic size: large			
Treated (β)	**0.035****	0.000	**0.047****
	(0.016)	(0.023)	**(0.019)**
Treated x Large Clinic (ξ3)	-0.009	-0.052	-0.003
	(0.022)	(0.032)	(0.026)
β + ξ3	0.026	**-0.052***	**0.044****
	(0.018)	**(0.028)**	**(0.022)**
Observations	5,986	5,986	5,986
Control group mean visits	5,214	957	4,071
Number of clinics	757	757	757
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

*** 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. Treated is an indicator equal to 1 in the semesters on and after a clinic adopted CCAMP, 0 otherwise. β + ξ 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 visits is in the top quartile. Young population is an indicator for it the clinic's share of chronic patients that are over 65 years old is in the top 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).

ONLINE APPENDIX: TABLES AND FIGURES

Figure A1: Trends in outcome variable: mean log number of visits per clinic, by patient type.



Note: We present here the clinic-specific mean number of visits per semester, in the period before any clinic implemented the CCAMP program.

Table A1: Number of clinics Implementing the CCAMP over time.

Semester, Year	Control	Treated	Total
S1 2013	742	0	742
S2 2013	743	0	743
S1 2014	749	0	749
S2 2014	749	0	749
S1 2015	547	202	749
S2 2015	540	210	750
S1 2016	497	255	752
S2 2016	485	267	752
Ever	490	267	757

Note: The last row shows clinics that ever or never implemented CCAMP.

Table A2. Event Study Estimates of the Impact of CCAMP Over Time

	(1)	(2)	(3)
	Log visits by patient type		
	Total	**Chronic**	**Non-chronic**
Semesters to CCAMP implementation			
5+ before	-0.002	**-0.077***	0.014
	(0.033)	**(0.042)**	(0.038)
4 before	0.010	**-0.045***	0.023
	(0.019)	**(0.026)**	(0.022)
3 before	0.012	-0.015	0.021
	(0.018)	(0.024)	(0.021)
2 before	0.004	-0.024	0.011
	(0.013)	(0.020)	(0.016)
0 after	**0.035****	-0.027	**0.056*****
	(0.015)	(0.020)	**(0.017)**
1 after	0.027	-0.034	**0.043****
	(0.017)	(0.024)	**(0.020)**
2 after	**0.054****	-0.016	**0.075*****
	(0.021)	(0.025)	**(0.025)**
3 after	**0.047****	**-0.075*****	**0.073*****
	(0.023)	**(0.028)**	**(0.028)**
Observations	5,986	5,986	5,986
Number of clinics	757	757	757
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses clustered at clinic level. Each column shows coefficients from a separately estimated event study 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. Shown are coefficients on semester indicators for time relative to the CCAMP program adoption. These estimate the difference in outcomes at a clinic at a given time, relative to the omitted category (1 semester before implementation).

Table A3. Weights used for de Chaisemartin & D'Haultfoeille Estimation in sharp difference-in-differences designs with multiple groups and periods

	Evenly weighted	**Weighted by N switchers**
Semesters to CCAMP implementation		
0 after	0.25	0.287
1 after	0.25	0.275
2 after	0.25	0.224
3 after	0.25	0.215

Estimated using de Chaisemartin and D'Haultfoeille weighted difference in differences estimator, which is a weighted combination of 2x2 comparisons. A switcher is a clinic that took up the program in a given semester. 100 bootstrap replications used.

Table A4. de Chaisemartin & D'Haultfoeille diagnostic check: Correlation between two-way fixed effect ATT weights and semester-year variable.

	(1)
Dependent variable	**Weights**
Semester-Year	-0.413**
SE	(0.184)
t-stat	-2.248
correlation	-0.094

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses clustered at clinic level. Coefficient from the regression of variables possibly correlated with the treatment effect, the semester-year indicators, on the de Chaisemartin and D'Haultfoeuille weights from a two-way fixed effect DiD estimation.

Table A5. Chaisemartin and D'Haultfoeille Event Study Estimates of the Impact of CCAMP Over Time

	(1)	(2)	(3)
	Log visits by patient type		
	Total	**Chronic**	**Non-chronic**
Semesters to CCAMP implementation			
4+ before	0.028	-0.010	0.031
	(0.025)	(0.036)	(0.027)
3 before	0.007	0.040	0.005
	(0.014)	(0.024)	(0.016)
2 before	-0.013	-0.023	-0.012
	(0.015)	(0.023)	(0.016)
1 before	-0.003	0.016	-0.009
	(0.014)	(0.021)	(0.016)
0 after	**0.032****	-0.019	**0.050****
	(0.016)	(0.024)	**(0.019)**
1 after	0.025	-0.032	**0.037***
	(0.016)	(0.026)	**(0.019)**
2 after	**0.060*****	0.000	**0.079*****
	(0.021)	(0.025)	**(0.024)**
3 after	**0.048****	-0.041	**0.070*****
	(0.022)	(0.026)	**(0.026)**
Observations	5937	5937	5937
Number of clinics	757	757	757
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses clustered at clinic level. Each column shows coefficients from a separately estimated event study 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. Shown are coefficients on semester indicators for time relative to the CCAMP program adoption, estimated using the unweighted Chaisemartin and D'Haultfoeuille multiple groups and periods difference-in-differences estimator with 4 placebo periods and 4 post periods, and estimated with 100 bootstrap repetitions. These estimate the difference in outcomes at a clinic at a given time.

Table A6. Clinic-level results for the impact of CCAMP on number of patients by type

	(1)	(2)	(3)
	Log number of patients		
	Total	**Chronic**	**Non-chronic**
Treated (β)	0.000	**-0.020***	-0.016
	(0.011)	**(0.010)**	(0.019)
Observations	5,912	5,986	5,907
Adjusted R-squared	0.983	0.986	0.963
Control group mean patients	12,147	1,845	9,826
Number of clinics	750	757	750
Clinic fixed effects	Y	Y	Y
Time fixed effects	Y	Y	Y

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. 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 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. Total and non-chronic population only available annually; models 1 and 3 include year fixed effects. Model 2 includes semester effects. 7 clinics were missing N total and non-chronic patients and are excluded from models 1 and 3.

Table A7. Placebo Test: Clinic-level results for the impact of CCAMP on number of patients by type using lead treatment variable

	(1)	(2)	(3)
	Log visits by patient type		
	Total	**Chronic**	**Non-chronic**
Treated (lead)	-0.001	0.013	-0.004
	(0.014)	(0.021)	(0.016)
Observations	4,469	4,469	4,469
Adjusted R-squared	0.969	0.923	0.962
Control group mean visits	5,181	941	4,051
Number of clinics	753	753	753
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses clustered at clinic level. Treatment indicator was moved earlier in time by 2 semesters. For treated clinics all semesters before program implementation are included, and for control clinics all semesters are included. 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.

Table A8. Heterogeneity in clinic-level results for the impact of CCAMP on visits by patient type

	(1)	(2)	(3)
	Log visits by patient type		
	Total	**Chronic**	**Non-chronic**
Treated (β)	0.006	-0.021	0.011
	(0.019)	(0.020)	(0.022)
Treated x Specialized Clinic (ξ1)	**0.072***	0.009	**0.098****
	(0.037)	**(0.038)**	**(0.049)**
Treated x Young Population (ξ2)	**0.044****	**0.054***	**0.046****
	(0.019)	(0.031)	**(0.021)**
Treated x Large Clinic (ξ3)	0.004	-0.032	0.010
	(0.022)	(0.025)	(0.027)
$\beta + \xi 1$	**0.077****	-0.012	**0.110****
	(0.033)	(0.036)	**(0.045)**
$\beta + \xi 2$	**0.049*****	0.033	**0.057*****
	(0.019)	(0.034)	**(0.021)**
$\beta + \xi 3$	0.010	**-0.053****	0.022
	(0.020)	**(0.024)**	(0.023)
Observations	5,986	5,986	5,986
Control group mean visits	5,214	957	4,071
Number of clinics	757	757	757
Clinic fixed effects	Y	Y	Y
Semester fixed effects	Y	Y	Y

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses clustered at clinic level. Each column shows coefficients from a separately estimated 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. 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 visits is in the top quartile. Young population is an indicator for it 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 the pre-treatment period.