NBER WORKING PAPER SERIES

ENCOURAGING PREVENTATIVE CARE TO MANAGE CHRONIC DISEASE AT SCALE

Claire E. Boone
Pablo A. Celhay
Paul Gertler
Tadeja Gracner

Working Paper 31643
http://www.nber.org/papers/w31643

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2023

We gratefully acknowledge financial support from UC Berkeley's Center on the Economics and Demography of Aging - NIH 2P30AG012839. Claire Boone was supported by the Tinker Foundation, UC Berkeley's Institute for International Studies, the Center for Global Public Health, and the NIH National Institute on Aging (NIA) under grant award T32 AG000243 (PI: David Meltzer, MD, PhD). Pablo Celhay gratefully acknowledges financial support from ANID, FONDECYT Regular 1221461, and financial support from ANID, PIA/PUENTE AFB220003. The contents of this paper are solely the responsibility of the authors and do not necessarily represent the official views of the NIA. The authors declare that they have no financial or material interests. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Encouraging Preventative Care to Manage Chronic Disease at Scale
Claire E. Boone, Pablo A. Celhay, Paul Gertler, and Tadeja Gracner
NBER Working Paper No. 31643
August 2023
JEL No. I11,I12,I15

ABSTRACT

We study how reminding high-risk patients with chronic disease of their upcoming primary care appointments impacts their health care and behaviors. We leverage a natural experiment in Chile's public healthcare system that sent reminders before preventative care appointments to over 300,000 patients with type 2 diabetes and hypertension across 315 public primary care clinics between 2013 and 2018. Employing both a difference-in-differences and instrumental variables approach on national administrative patient-level data, we show that reminders increased preventative care visits, which led to more health screenings and improved medication adherence. In this at-scale program, we find substantial variation in implementation fidelity across clinics, which, once accounted for increases our estimates by over a third. Reminders also increased hospitalizations and reduced in-hospital mortality, suggesting an improvement in timely care-seeking behavior among high-risk patients. Our findings inform healthcare settings where patients must first visit their primary care provider for approval before undergoing tests, receiving medication prescriptions, or getting referrals to other specialists. Through intervening at the first step in the cascade of care, we find that a simple intervention like reminders can have large and meaningful downstream effects.

Claire E. Boone
University of Chicago
5807 S Woodlawn Ave
Chicago, IL 60637
claireboone@uchicago.edu

Pablo A. Celhay
School of Government
and Economics Institute
Pontificia Universidad Católica de Chile
Avda. Vicuña Mackenna 4860
Macul, Santiago
Chile
pablocelhay@gmail.com

Paul Gertler
Haas School of Business
University of California, Berkeley
Berkeley, CA 94720
and NBER
gertler@haas.berkeley.edu

Tadeja Gracner
RAND Corporation
1776 Main St.
Santa Monica, CA 90401
tgracner@rand.org

1 Introduction

Chronic diseases such as hypertension and type 2 diabetes are among the highest contributors to both excess mortality and health care spending globally (Egan et al. 2019; Piper et al. 2015). Regular health monitoring through screenings such as measuring blood pressure and blood glucose levels, and then appropriate treatment through medication and behavior change can improve the control of these conditions (Bodenheimer et al. 2002). However, many patients do not receive these benefits because they do not regularly attend preventative medical care appointments where such tests and treatments are administered. In fact, approximately half of all patients miss their scheduled primary care appointments (Karter et al. 2004; Schectman, Schorling, and Voss 2008; Ciechanowski et al. 2006; Hardy, O'Brien, and Furlong 2001), and between 12% and 50% drop out of care in their first year of treatment (Gucciardi 2008; Yamaguchi et al. 2017). Patients failing to keep just one primary care appointment are 70% more likely not to return to medical care within the next 18 months (Gucciardi 2008; Fullerton et al. 2012).

Patients' reasons for missing appointments include behavioral biases such as inattention, present bias, self-control issues, and a lack of salience (DellaVigna 2009; Gabaix 2019; Roberto and Kawachi 2015; Della Vigna and Malmendier 2006; Kessler and Zhang 2014). Consequently, nudges such as appointment reminders sent by text message (SMS), e-mail, or phone call are a promising strategy to reduce no-shows and encourage timely preventative care visits (Costa et al. 2010; Jongh et al. 2012; Hamine et al. 2015; Ellanti, Manecksha, and Flynn 2011; Liew et al. 2009; Leong et al. 2006). For patients with chronic diseases, nudges may be an especially promising strategy if they are sent early in the cascade of care, where they could have large effects not only on preventative visits but also on subsequent care received, patient health behaviors and outcomes.

We study (1) the impact of appointment reminders sent for preventative visits to primary care clinics, and (2) the impact of additional primary care visits on subsequent health behaviors and care received. We study these questions among patients who were recently diagnosed with type 2 diabetes and/or hypertension; a group that is typically high-risk and high cost. The setting is Chile's public healthcare system, Fonasa, which covers over 15 million individuals; approximately 80% of the county's population (FONASA 2018). We leverage two types of variation in our empirical strategy: first, spatio-temporal variation in appointment reminder program adoption by primary care clinics between 2013 and 2018. And second, variation in compliance with the program, across clinics and over time. This variation in implementation fidelity allows us to address several aspects of at-scale program implementation (List 2022).

We estimate the effect of reminders on primary care visits, health monitoring through tests, medication prescription and adherence (measured by proportion of days covered of at least 80%), and hospital care using a difference-in-differences approach. We estimate these effects over time, up to four years post-implementation. Initially, we estimate the intent to treat (ITT) effect of reminders using a difference-in-difference approach. Here we assume that after a clinic implemented appointment reminders, all chronic patients were sent an appointment reminder for their scheduled visits. Subsequently, we estimate a second set of models that consider variation in clinic-level compliance with the program over time, measured through clinics' phone records that show whether a reminder was sent. Because appointment reminders lead to plausibly exogenous variation in preventative care attendance, we then use an instrumental variable (IV) approach to estimate the impact of an additional primary care visit on subsequent care received and health behaviors.

We analyze national data, which includes 2,265,307 visits from 316,994 patients across 315 primary care clinics. These data cover the period from the time of each patient's diagnosis with hypertension (284,554 patients) or type 2 diabetes (67,619 patients) onwards. Patients are observed for an average of 4.5 years following their diagnosis. We link these data at the individual level to three datasets, all collected between 2013 and 2018: i) electronic health records (EHR) capturing information on primary care visits and screenings (2,265,307 patient-visits); ii) prescription and refill data from pharmacies nationwide; and iii) the universe of hospitalizations. Our independent variables come from two sources: i) a list from Chile's Ministry of Health documenting clinics' date of program implementation, used to estimate ITT models, and ii) phone records from clinics indicating whether patients eligible for a reminder were sent one, used to estimate clinics' program compliance.

Regarding program take-up, 208 clinics implemented the program between 2015 and 2018; 66% of clinics in our sample. Using clinics' phone records, we find large variation in implementation fidelity: while the share of eligible patients who were sent appointment reminders by text-message increases over time, on average only 53% of eligible patients were sent a reminder.

Appointment reminders increased health seeking behavior among high-risk patients when implemented at scale in a national healthcare system. Specifically, we find that reminders increased the probability that patients with type 2 diabetes visit primary care by 8.7%, and the probability that patients with hypertension visit primary care by 10.7%. Reminders were most effective for patients in middle age, and patients diagnosed relatively early in their disease progression. We also find that despite repeated nudges being sent, the average effectiveness stayed relatively constant for up to 4.5 years since patients were diagnosed.

Reminders led to an increase in the number of primary care visits as well as in the monitoring of patient blood pressure and weight. They also improved health behaviors. Patients with hypertension who received reminders were 25% more likely to pick up any medication at the pharmacy, and 43% more likely to have adequate medication adherence. Similarly, medication adherence increased by 50% among patients with type 2 diabetes. Last, we find that reminders increased cardiovascular-related hospitalizations by approximately 20% but decreased in-hospital mortality, suggesting an improvement in timely care-seeking behavior among high-risk patients. In other words, our results suggest that nudged patients sought care before their medical situation became severe.

Because appointment reminders caused variation in visits to preventative care, we estimate the effects of additional preventive care visits on downstream health care received and health behaviors using an instrumental variables approach. We estimate that an additional visit leads to an 86 and 97 percentage point (pp) increase in blood pressure tests and an 87pp and 89pp increase in weight measurement for patients with type 2 diabetes and hypertension, respectively, reflecting the fact that blood pressure and weight are measured at almost every primary care appointment. Visits also lead to a notable 20pp increase in adequate medication adherence. Finally, more visits translated into an additional 3 cardiovascular hospitalizations per 100 patients and 1.2 fewer in-hospital deaths, again suggesting the ability to treat acute complications of chronic diseases earlier.

This paper makes two major contributions. Firstly, it enhances our understanding of scaling programs, specifically the effectiveness of implementing a light-touch nudge such as appointment reminders at scale. By evaluating such programs, governments can gain valuable insights for evidence-based policy-making, as they increasingly adopt experimentation in their decision-making(List 2022)[1].

To our knowledge, the effectiveness of appointment reminders when implemented at scale by a national health system is unknown (Tomlinson et al. 2013). The current literature instead consists of small-scale trials, often lacking integration with existing health information systems (e.g. Arora et al. (2015), Lin et al. (2016), Shah et al. (2016), and Hofstetter et al. (2015)). Other studies include short-term pilots with limited follow-ups (e.g. Hamine et al. (2015), Costa et al. (2010), Hallsworth et al. (2015), and Boksmati et al. (2016)). Boksmati et al. (2016) systematically review SMS appointment reminder trials and their meta-analysis estimate from randomized controlled trials (RCTs) is approximately 20%.

The disparity between our findings' magnitude and the existing literature can be attributed to two main factors. Firstly, prior research conducted under controlled experimental conditions often yields high implementation fidelity, leading to estimates of efficacy rather than real-world effectiveness. The contrast in effect size between our comprehensive results and the broader body of literature concerning appointment reminders is in line with the conclusions drawn by DellaVigna and Linos (2022). They compared the effects of various nudge interventions implemented at scale by governments to the results found in the academic literature. They reported an average effect of 1.4pp among government-run and at-scale nudges, while the published literature showed a higher average effect of 8.7pp. DellaVigna and Linos (2022) also documented substantial publication bias in the nudging literature, with large and statistically significant effects being more likely to be published, while null effects are less likely to be reported.

A second aspect of scaling involves understanding how programs operate when variations in compliance fidelity occur, a phenomenon more prevalent in larger-scale implementation (Heckman et al. 2010; King et al. 2009; List 2022). Using phone records we provide a unique look into the implementation fidelity of this program at the clinic level and over time. On average, 53% of eligible patients at treated clinics received SMS reminders. Compliance with the reminders increased over time, rising from 46% in 2016 to 58% in 2018. Upon considering clinic-semester level compliance, we found that reminders resulted in an 8.5% increase in the probability of a visit for patients with type 2 diabetes and a 10.8% increase for patients with hypertension. These estimates are higher compared to the ITT estimates, which showed a 4.9% and 6.1% increase, respectively.

[1] Currently, there are more than 200 government nudge units, a movement that began with the UK's Behavioral Insights Team launched in 2010, in the United States the Office of Evaluation Sciences launched in 2015

We observe the same pattern in tests, medication adherence, and hospitalizations. After considering compliance, the estimated effect sizes were approximately double those obtained from the ITT analysis.

We also explored whether impacts fade out over time or with repeated use, which was possible given the long time frame of our study. Research on the effects of repeated nudges is mixed: several studies have found that the effect of the first nudge is significantly higher than subsequent nudges targeting the same behavior (Damgaard 2020; Damgaard and Gravert 2018). Our results - which show no evidence of a reduction in effectiveness over time - are aligned with Allcott, Mullainathan, and Taubinsky (2014) who find that sending repeated nudges led to sustained behavior change among the subgroup who responded positively to the initial nudge.

Our second contribution is to advance the understanding of how primary care utilization impacts health monitoring, medication adherence, and hospital admissions. Identifying the causal impact of healthcare utilization on health and behaviors is challenging because healthcare seeking behavior is usually endogenous to past utilization or diagnoses (Levy and Meltzer 2008). To address this concern, we leverage plausibly exogenous variation in primary care visit behavior resulting from appointment reminders. This allows us to examine downstream outcomes, mitigating the endogeneity concern.

Prior research has solved this problem by examining the impact of diagnosis using regression discontinuity design (Alalouf, Miller, and Wherry 2019; Moscoe, Bor, and Bärnighausen 2015; Venkataramani, Bor, and Jena 2016; O'Keeffe et al. 2014) or through leveraging an exogenous change in insurance availability or change in the prices faced by patients (Baicker et al. 2013; Finkelstein et al. 2012; Taubman et al. 2014; Card, Dobkin, and Maestas 2009; Card, Dobkin, and Maestas 2008; Adams et al. 2021; Aron-Dine, Einav, and Finkelstein 2013; King et al. 2009).

Taking medication regularly is one of the most effective ways to improve the health of patients with chronic diseases, yet many patients struggle to adhere to their prescribed therapies. In reaction, a vast array of interventions to improve medication adherence have been tested, and while many have been successful they are mostly complex and high-cost (Kini and Ho 2018; Nieuwlaat et al. 2014). We contribute to this literature by demonstrating the extent to which medication adherence can be improved by simply increasing preventative care appointments: a primary care visit increased the likelihood patients had adequate medication adherence in a given semester by 20pp.

Our finding that an increase in primary care utilization leads to an increase in hospitalizations is in line with the small economics literature studying the causes and effects of health care use. Notably, both the Oregon and RAND randomized health insurance experiments found that reducing the price of care through insurance led to an increased use of primary care and of hospitalizations (Baicker et al. 2013; Taubman et al. 2014; Finkelstein et al. 2012; Manning 1987). Similar findings have been reported in several studies using the expansion of Medicare and Medicaid in the United States as instruments for studying the impact of health care use(Card, Dobkin, and Maestas 2009; Card, Dobkin, and Maestas 2008; Miller, Johnson, and Wherry 2021). Notably, Goldin, Lurie, and McCubbin (2021) find that a reminder letter to enroll in health insurance reduced mortality especially among adults aged 45-64. We contribute to this literature by demonstrating that a non-financial instrument — appointment reminders — can yield comparable effects even when the cost of care remains constant. Additionally, we expand this body of work by showcasing similar outcomes in a non-United States context.

2 Setting

In Chile, public healthcare is low-cost and guaranteed for all residents. Primary care is received by patients at local clinics or low-complexity hospitals (if the community only has one health center), and it is centrally organized by the Ministry of Health. Going forward, we refer to all health facilities where a patient might seek primary care as 'clinics'.

The public health care system does not operate like a market where patients can choose where to get their services. Instead patients using public health insurance are assigned to one primary care clinic based on their home address. This partially addresses potential concerns about contamination bias from clinic selection in our empirical analysis that compares clinics that did and did not take up the appointment reminder program.

Chile's nationally centralized health care system allows us to link data at the individual level country-wide from primary care, pharmacies, and hospitals. This analysis therefore includes a large cross-section of patients in terms of location, socioeconomic status, wealth, and health from a population with few access to care issues.

2.1 Health and Healthcare in Chile

Chile has two health care systems: the public system, used by nearly 80% of the population that is funded primarily by a mandatory 7% tax on earnings, and the private system, used by the remainder of the population (Goic 2015; FONASA 2018). All residents are defaulted into the public system, but can opt out through purchasing private insurance. The public system is organized in a gatekeeping model where patients are required to visit a general practitioner at a primary care clinic before receiving prescriptions, referrals to specialists, or care at more advanced facilities (Rotar et al. 2018; Brekke, Nuscheler, and Straume 2007).

Patients covered by the public insurer, Fonasa, are administratively assigned to use one primary care clinic based on their place of residence. The population is divided into four groups according to their socioeconomic status: Fonasa A (19.61%, the poorest group), B (39.4%), C (16.3%), and D (24.7%, the wealthiest group).[2]

Chile's burden of chronic, non-communicable diseases is high: an estimated 57% of the population is living with at least one chronic condition (Margozzini and Passi 2018).[3] These patients

[2]Chronic condition patients in the cardiovascular program (PSCV), the population included in this analysis, must receive preventative care related to their chronic condition at public clinics where care is free and monitored by the Ministry of Health. Fonasa C and D patients, those with relatively higher socioeconomic status, can choose to receive other care such as curative or urgent care at private clinics. We do not include these kinds of visits in this analysis.

[3]Chile's 2016-2017 National Health Survey found that 27.6% of the adult population had hypertension, defined

consume 84% of healthcare resources (MINSAL 2008) and contribute to the high national rate of missed appointments: in 2018, 16.7% of scheduled appointments were missed (Boone et al. 2022). No shows are estimated to cost Chile roughly 180 million USD annually (Contreras 2022). High utilization is partly because patients with chronic conditions are prioritized for care: in 2005 Chile passed a healthcare reform that aimed to reduce wait times and guarantee access to primary care for patients with 85 priority conditions, including hypertension and type 2 diabetes (Vargas and Poblete 2008; MINSAL 2017a; FONASA 2018; Martinez et al. 2019).

Patients diagnosed with type 2 diabetes or hypertension are enrolled into a cardiovascular care program (PSCV for its acronym in Spanish) that is available nation-wide. This program makes them eligible for prioritized care including being sent appointment reminders and the ability to schedule primary care appointments in advance. Non-PSCV patients do not receive appointment reminders and for them appointments are on a first-come, first-served basis. Because PSCV patients are closely monitored, high quality administrative data exists on their visits, medication use, and hospitalizations, which we leverage in this paper. For more information on the PSCV see section A.1.

Importantly, In Chile's public health care system, patients are assigned a primary care clinic based on their home address, allowing us to assign exposure to appointment reminders to patients using their home clinic. This policy strengthens our identification strategy as selection into clinics based on patient health is limited, and reduces the likelihood of control group contamination.

In Chile, patients living with chronic conditions including hypertension and type 2 diabetes receive medications at no cost, and there are no co-payments for their health services related to their chronic diseases[4] (Aguilera, Schueller, and Leykin 2015).

2.2 Preventative Care Appointment Reminder Program

In response to low levels of disease control, and high rates of missed appointments, beginning in January 2015 the Chilean Ministry of Health offered the option for public, primary care clinics to opt-in to an appointment reminder program to reduce no-shows among patients enrolled in the PSCV (MINSAL 2017b). Clinics were eligible for this program if they had an electronic health records system. The implementation of this program was as a pilot initiative for which primary care clinics could opt into between 2015 and 2018 (Contreras 2022). The program aimed to improve patients' adherence to treatment by increasing attendance at preventative care visits,

as blood pressure $\geq$ 140/90 mmHg, and 9.5% had type 2 diabetes, both similar rates to other high-income countries such as the United States (Lanas et al. 2020; Ostchega and Nguyen 2020). Among Chileans with hypertension, 69% were aware of their condition, and 33% had controlled blood pressure (blood pressure $<$ 140/90 mmHg) (Lanas et al. 2020).

[4]For other types of services there are co-payments depending on the household income of the beneficiary. For 2020, the Fonasa copayment groups (in 2020 US Dollars) were: group A, extreme poverty and/or unhoused (0% co-payment), group B monthly income <\$320 or on a government pension (0% co-payment), group C, monthly income \$320-465 (10% co-payment), and group D monthly income >\$465 (20% co-payment) (Salud - Gobierno de Chile 2020). In 2020 Chile's mean and median monthly income per capita were USD\$784.45 and USD\$518.74 respectively (Estadísticas 2020). As of 2023, there is national policy of no copayment for all Fonasa beneficiaries being implemented.

and by providing them with health information.

The program, which is primarily a software integrated into the clinic's electronic medical record, automatically sent a text-message (SMS, first attempt) or e-mail (second attempt) to patients 24, 48, or 72 hours before their appointment. SMS was used whenever possible, and if patients did not respond to either the SMS or the email, a voice call was made. The content of the reminder 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 [facility Name] with the doctor [name of the doctor]. Do you confirm your time? Yes/No"

This program aimed to benefit patients through reminding them of their appointment, providing them the ability to confirm or cancel, and providing notification of appointment time changes or cancellations. For clinics, the program aimed to improve schedule management and optimize appointments, to enable communication with patients about scheduling changes, and aimed to record data on reminders sent and attendance. Additionally, automating appointment reminders has the potential to free up human resources, allowing centers to attend to other critical tasks.

The appointment reminder program was a package of several nudges:

- Appointment Confirmation: Users were sent a communication as proof of their appointment shortly after scheduling.

- Reminder with Request for Confirmation: Patients were sent a reminder 24, 48, or 72 hours before the appointment. They were asked to confirm their attendance, and their response was sent to the health center for agenda updates and notification to the center manager. If they did not reply with a confirmation or cancellation request, the appointment was kept.

- Preparation: Patients were sent instructions to prepare for their appointment, such as the recommended arrival time and any required preparations specific to their appointment type (e.g. to fast if fasting blood glucose was going to be measured).

- Change of Appointment: In case of a schedule change at the clinic patients were notified about the new date or time.

- Cancellation: When the health center or the user cancelled an appointment, a communication was sent to notify the user about the cancellation.

3 Data

To evaluate the impact of appointment reminders on all subsequent visits to primary care, and medication and hospitalization outcomes, we use two datasets that measure program take-up and compliance, and three datasets that contain patient behaviors and health measures. Our sample only includes patients with a diagnosis of type 2 diabetes and/or hypertension.

3.1 Timing of Appointment Reminder Program Implementation

From the Chilean Ministry of Health, we obtained a list of public primary care clinics that had implemented the appointment reminder program, together with the date of the program initiation, between 2015 and 2018. In our analyses, 2013-2014 is included as a pre-program period. Clinics were eligible for the program if they had an electronic health record system.

Out of 877 public primary care clinics that were eligible for the program, 757 (86%) were in non-extreme geographic locations[5], and had at least one patient diagnosed with chronic conditions (Boone et al. 2022). Among these clinics, 435 (57%) used the electronic health record provider from which we could access health records data. Finally, in this analysis we include only treated clinics for which phone record data was available (N=208), as well as all control clinics (N=107), resulting in a sample of 315 clinics. These 315 clinics are in 275 different counties; 79% of all counties in Chile.

The appointment reminder program was first offered in 2015, and 172 clinics implemented the program that year. Table 1 describes take-up by semester. By the end of our study period, in 2018, 208 clinics had implemented the program, and 107 clinics did not - they remained as controls. Table 1 describes clinic-level program implementation.

3.2 Phone Records

At clinics that implemented the appointment reminder program, all patients in the PSCV program were eligible to receive appointment reminders about their upcoming primary care visits. However, as this program was implemented at scale, nationwide, there were differences in implementation fidelity or compliance. We measure clinic-level compliance using phone records, collected in 2016, 2017, and 2018. Phone records from 2015, the first year the program was offered, were not available. The dataset includes comprehensive records of SMS reminders sent to individuals with appointments. However, records for e-mail or phone call reminders are not available. To address this limitation, we make an assumption that compliance with these secondary and tertiary communication methods is correlated with SMS compliance. To measure compliance at the clinic-semester level, we construct a variable measuring the share of patients who were sent an SMS reminder, among all patients who were eligible for a reminder. In our analyses, we impute clinics' 2015 compliance as their 2016 semester 1 compliance level.

[5]We excluded 71 primary care clinics in the regions of Arica Parinacota, Aisén del General Carlos Ibáñez del Campo, the Chilean Antarctic, and Rapa Nui (Easter Island).

3.3 Electronic Health Records

To evaluate the impact of appointment reminders and of primary care on patient health-seeking behaviors and disease management, we use patient-level electronic health records (EHR) provided by the Division of Primary Care at Chile's Ministry of Health. The EHR dataset contains all visits from PSCV patients attending clinics that used a particular EHR vendor's software, the most commonly used vendor. These data contain patient-level information on patient demographics, tests, test results, new diagnoses, and self-reported health behaviors that occurred at each patient-visit to primary care, from January 1 2013 to December 31 2018.

We limit our analysis to visits from patients newly diagnosed with type 2 diabetes and/or hypertension, as this is when they become eligible for appointment reminders. We define patients as newly diagnosed if they had no diagnosis of type 2 diabetes or hypertension in the previous year in their medical record. For the majority of patients, we observe the visit where their diagnosis with type 2 diabetes or hypertension occurred, which is noted in their medical record as "initial visit". For patients where the initial visit variable was always missing we used a data driven approach to infer whether they were a new patient or not. Specifically we examine the distribution of number of days between a patient's first and second visit, among patients who were in the dataset since January 1, 2013. We found that all patients who were in the data on January 1 2013 and who had any subsequent visit, had presented for their second visit within the following 361 days. Therefore, if a patient appears in the data 362 days after January 1, 2013, they are very likely to be a new patient who is presenting at their first post-diagnosis visit. For this reason, we exclude all patients who had a visit that occurred before January 1, 2014.

We construct four binary outcomes from EHR data: an indicator for if the patient visited primary care, an indicator for if the patient's blood pressure was measured at their visit, an indicator for if the patient was weighed at their visit, and for patients with type 2 diabetes only, an indicator for if their blood sugar was measured, zero otherwise.

These testing outcomes occur if a patient visits primary care, and do not occur if a patient drops out of care and is therefore unobserved in the data. To address this, we construct outcomes at the patient-semester level for which we can assign patients a zero if they did not visit primary care. For example, we estimate the impact of appointment reminders on the probability a patient with type 2 diabetes received a blood glucose test; if the patient's EHR data shows they visited and received this test, this outcome is equal to one. If they visited and did not receive a test, or did not visit, this outcome is equal to zero. We are therefore unable to analyze patient health as measured by the results of such tests, because to do this we would have to condition on the patient having a test, which would introduce bias.

3.4 Medication Data

We measured medication adherence in administrative records from pharmacies during 2013-2018. These records contain information on pharmacy name, a unique patient identifier, prescription date, prescribed medication name, number of units prescribed, the active ingredient of the drug, and date of medication pick-up. Each prescription contains a patient identifier that can be linked to the EHR dataset. This allows us to link patients in our EHR dataset who have been prescribed a medication for their chronic condition(s) with this pharmacy dataset. During 2013-2018, that translated into 276,964 patients (79% of our patient analysis sample). These data are automatically generated at each pharmacy.

We construct two medication outcomes: first, an indicator for if the patient ever picked up any amount of medication in a given semester, zero otherwise. Second, we measure medication adherence using the proportion of days covered (PDC). We first calculate PDC, which is the ratio of medication supply the patient has collected at the pharmacy, to the amount they should have if they were taking their medication exactly as prescribed. We then create an indicator for if PDC in a given semester is at least 80%, zero otherwise. Here, we assume that a patient who has been diagnosed with type 2 diabetes and/or hypertension and who is prescribed a medication for that condition should have an active prescription going forward. Medication adherence can only be calculated among patients with a prescription. We assign a medication adherence value of zero for patients who did not fill any prescriptions in a given semester.[6]

3.5 Hospitalization Records

We use the universe of hospital admissions in Chile from 2013-2018 to examine the impact of appointment reminders on hospitalization. These records include both public and private hospitals, and can be linked to both the EHR and medication datasets with the patient identifier. These data contain hospital name and its unique identifier, as well as date of record, length of hospital stay, diagnostic codes (International Classification of Diseases 10th edition, or !CD-10) recording primary and secondary cause of admission, and an indicator for whether the patient died in the hospital. Importantly, these records contain the universe of hospitalizations in Chile at both public and private hospitals.

We separate hospitalizations into those that are cardiovascular-related and non-cardiovascular related, based on ICD-10 codes for primary and secondary diagnosis (for our classification of ICD-10 codes see table A1). For each group of hospitalizations we construct three outcomes: an indicator for if the patient was hospitalized, the length of hospital stay in days and log-transformed, and an indicator for if the patient died in the hospital.

4 Empirical Approach

The appointment reminder program was introduced by clinics at various time points over multiple years, allowing us to use a staggered adoption, difference-in-differences approach (DID) to estimate

[6]Patients may potentially experience medication de-prescription for hypertension or type 2 diabetes under specific circumstances. However, this course of action is typically considered only if the patient demonstrates regular attendance at primary care visits and has achieved significant lifestyle modifications, such as consistently adhering to a healthy diet and engaging in regular exercise. It is important to note that research indicates that only a very small proportion of patients successfully accomplish these lifestyle changes (Oster 2018).

the effects of the program. Initially, for each outcome, we employ flexible event study models, which show that the effects of the program increased over time for most outcomes. To address potential heterogeneity in effects over time, we use Borusyak (2021)'s difference-in-differences estimator for our intent to treat (ITT) models, where the treatment variable is either 0 or 1. For each outcome, we also estimate models that account for imperfect compliance at the clinic-semester level using two-way fixed effects.[7] This is our preferred specification.

Equations below represent the specification for both the ITT and compliance models, as the same control variables are included in each. We estimate all models separately for patients who were diagnosed with type 2 diabetes at baseline (N=67,619 patients), and for patients who were diagnosed with hypertension at baseline (N=249,375 patients)[8]. In pooling tests we reject that the effect of appointment reminders is equal in both samples for all outcomes other than visits (table A13) We present all models estimated separately by chronic condition.

4.1 Event Studies

To test for parallel trends and to visually examine the dynamics of the effects of appointment reminders on outcomes of interest, we estimate the model below using a non-parametric event-study approach :

$$Y_{ijt} = \sum_{\tau=-3,\tau\neq-1}^{6} \beta_\tau Q_\tau + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{ijt} \tag{1}$$

Y_{ijt} is an outcome for patient i at clinic j in semester t; we divide each calendar year into two 6-month semesters: January to June, and July to December. Q_τ are semester indicators measuring time relative to appointment reminder program adoption (at $\tau = 0$) at a clinic j. Q_{-1} is a reference or omitted category and represents a semester just before the program implementation. β_τ are coefficients on semester indicators (Q_τ) and coefficients of interest. They measures changes in outcomes at time τ relative to the first semester prior to the appointment reminder program adoption (at $\tau = -1$).

Each model is adjusted for seasonality and common temporary shocks with semester indicators (λ_t) and clinic-level fixed effects (γ_i). We also include a vector of patient-level controls (X'_{it}) that include fixed effects for semesters since the patient was diagnosed with type 2 diabetes and/or hypertension, an indicator for sex (1=male), and 2-year age fixed effects (i.e. age 40-41, vs. 42-43, vs. 44-45 etc.) at the time of a medical visit. ϵ_{ijt} is an error term correlated within clinics across time. We calculate robust standard errors, clustered at the clinic level(Abadie et al. 2020).

[7] Callaway, Goodman-Bacon, and Sant'Anna 2021 addresses estimation with a continuous treatment in a difference in differences setting but does not yet provide software.

[8] 35,179 patients (11%) were diagnosed with both type 2 diabetes and hypertension at baseline and are included in both sets of models

4.2 Difference-in-Differences Analysis

We then use a parametric, DID approach to obtain the average effect of appointment reminders on patient-level outcomes. The goal of this analysis is two-fold. Firstly, we want to understand whether sending appointment reminders increases the likelihood of patients attending preventative primary care visits. The second goal is to understand how these additional visits affect screenings, medication adherence, and hospitalizations.

We estimate the following regression model:

$$Y_{ijt} = \alpha + \beta Nudge_{jt} + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{ijt} \tag{2}$$

Y_{ijt} is an outcome for patient i at clinic j in semester t. In ITT models, $Nudge_{jt}$ is an indicator variable that takes value one for all semesters t in each clinic j after appointment reminders were implemented. In compliance models, $Nudge_{jt}$ is a number between 0-1 that measures clinic-semester compliance in each semester t in clinic j after appointment reminders were implemented. This variable is always zero for clinics that did not implement the appointment reminder program. The main coefficient of interest is β; a DID estimate that measures the impact of appointment reminders on the outcome of interest. As above, each model was adjusted for seasonality, common temporary shocks with semester indicators (λ_t), and clinic-level fixed effects (γ_i). We also included a vector of patient-level controls (X'_{it}) listed above. We again calculated robust standard errors, clustered at the clinic level.

To study whether appointment reminders increased primary care visits more for certain groups of patients we estimate heterogeneous DID models by interacting baseline patient characteristics of interest with the $Nudge_{jt}$ indicator in equation 2. We consider the duration since diagnosis and its potential implications for newly diagnosed patients, patients' health at the time of their diagnosis as a potential marker of prior healthcare utilization, and patient age.

4.3 Instrumental Variables Analysis

To understand the impact of an additional primary care visit on downstream health behaviors and outcomes, we leverage variation in clinic-level compliance with the appointment reminder program to instrument for a primary care visit. We estimate the following equations:

$$visit_{ijt} = \alpha + \beta Nudge_{jt} + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{ijt} \tag{3}$$

$$Y_{ijt} = \alpha + \beta \widehat{visit_{jt}} + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{ijt} \tag{4}$$

Where the first stage, equation (3), is the DID estimate of the impact of compliance with the appointment reminder program on visits. This is estimated separately for patients with type 2 diabetes or hypertension. The structural equation is (4), where $\widehat{visit_{jt}}$ is the predicted values from equation (3).

Both the first stage and structural equation contain the same controls: semester indicators (λ_t), and clinic-level fixed effects (γ_i). We also include a vector of patient-level controls (X'_{it}): all models include the same covariates as the DiD models.

We calculate the F-statistic from the first stage regression of program compliance on primary care visits. Several of our first stage F statistics are close to the conventional weak instruments cut off of F-stat=10. For that reason, we report Anderson-Rubin (AR) confidence intervals which are robust to weak instruments. The lower bound represents the minimum value of the coefficient that is consistent with the IV assumptions, while the upper bound represents the maximum value (Anderson and Rubin 1949). Although the AR confidence intervals may be wide in some cases, they allow us to reject the absence of an effect of the program and provide bounds on the effect size.

5 Results

We begin with an exploration of program compliance and the initial results of appointment reminders' impact on primary care visits. We then describe heterogeneity in the effects.

We next consider the effect of appointment reminders, and the preventative care visits they cause, on three set of outcomes that illustrate key pathways through which increased primary care visits could enhance patient health. First, regular health screenings received at primary care visits can aid in monitoring and early detection of health conditions, referrals to specialist care, or updates to prescriptions. We measure blood pressure, blood glucose, and weight tests received using electronic medical records.

Second, regular primary care visits are essential for patients to maintain active prescriptions for their medications, so they can obtain an adequate medication supply. We measure medication outcomes using objectively measured pharmacy refill data.

Third, increased interaction with healthcare providers during primary care visits can facilitate information exchange and patient learning. This heightened engagement can reinforce behavioral changes necessary for better management of chronic diseases, such as weight loss, physical activity, maintaining a healthy diet. These interactions may also provide patients with valuable knowledge about when to seek further medical care at a hospital, if necessary, and how to spot early-warning signs of cardiovascular problems. We measure such care-seeking behavior using hospital records.

5.1 Descriptive Statistics

A total of 315 primary care clinics were analyzed; 208 of them implemented the program between 2015 and 2018 and 107 clinics never implemented the program (table 1). Table 2 presents summary statistics by clinic's treatment status (defined as whether they reported ever having implemented the appointment reminder program by 2018) and patients' disease, at the time of their first diagnosis. At both ever and never treated clinics, 41% of patients with hypertension were male, compared to 47% of treated patients with type 2 diabetes, and 49% of control patients with type 2 diabetes. Patients were 60 years old on average. The health of patients at their time of diagnosis was similar across treated and control clinics, as measured by systolic and diastolic blood pressure, hemoglobin A1c, blood glucose, weight, and body mass index (BMI) (table 2). The probability of a medication prescription at the time of diagnosis was similar across treated and control clinics, as was the probability of key tests, suggesting that clinics with similar qualities of care did and did not take up the program (table 2).

5.2 Program compliance

We measure compliance at the clinic-semester level using phone records from 2016-2018. Figure 1 shows density plots of compliance among clinics that had implemented the program by each semester-year. In each year, there is large variation in compliance. Among treated clinics between 0 and 100% of eligible patients were sent SMS reminders. Compliance also improves over time. While average compliance in 2016 was 47%, in 2017 was 55%, and in 2018 was 56% (table 1).

We use program compliance as an instrumental variable for healthcare visits. As any instrument in a difference-in-differences setting, we have to assume that compliance with the appointment reminder program to be exogenous to trends in potential outcomes. While this assumption cannot be tested, we empirically test whether compliance has any association to baseline measures of outcomes, namely, health monitoring, medication adherence, and hospitalizations. In figure 2 we test for whether previous period compliance is associated with various measures of clinic quality. Specifically, we jointly regress clinic-semester measures such as share of patients with controlled chronic conditions, mean biomarkers, and hospitalizations on lagged compliance with appointment reminder program compliance. We find no significant association (F-test =1.37) between these measures of clinic quality and compliance, suggesting that clinics do not respond to previous semester correlates with quality by changing their level of compliance with the appointment reminder program.

5.3 Impact of appointment reminders on primary care visits

We first report results of the impact of appointment reminders on primary care visits, estimated using a flexible event study model to test for differential trends in the pre-adoption period, as well as understand the dynamic of the effects of appointment reminders over time (equation 1). Results are presented in figure 3 (see tables A2-A3 for corresponding regression analyses).

The main assumption that allows us to interpret the coefficients on the time indicators after program adoption as causal effects is that, given the program's adoption and included control variables, the potential outcome trends are not correlated with the timing of program adoption. Although it is not possible to directly test this assumption, Figure 3 demonstrates the absence of divergent trends in outcomes during the pre-adoption periods, while notable differences in outcomes emerge sharply after the program's implementation.

Additionally, we employ an F-test for all outcomes to examine whether the coefficients before the program exhibit a joint deviation from zero. The resulting p-value from this test is included at the bottom of both Table A2 and Table A3 and in most cases we reject the hypothesis of differential trends before program implementation.

Figure 3, shows that the impact of appointment reminders on primary care visits becomes more pronounced as time passes since the program was adopted, a trend that is also evident in our compliance data (see Figure 1). In event studies shown in panels (a) and (b), where we explore the effects of clinic-level compliance on primary care visits, coefficients exhibit an up to two-fold increase across all periods, compared to intent to treat (ITT) estimates (panels c-f), except for semester 6. Second, the temporal pattern becomes even more pronounced. For instance, after two years of program implementation (semester 4), the effect of reminders is substantially larger compared to the first year (see Figure 3). Notably, similar patterns are observed in the ITT event studies when employing BJS and TWFE models (refer to Figure 3, panels (c) and (e) for type 2 diabetes patients, and panels (d) and (f) for hypertension patients). This suggests minimal bias in our TWFE compliance models.

Furthermore, the impact dynamics closely mirror the compliance patterns observed among clinics, as depicted in Figure 1. The effects gradually diminish during the final semester of our data, aligning with the decrease in clinic compliance observed notably in the last semester of 2018. This decline in effects also corresponds to the program's final active semester, as the pilot ended in 2018.

Table 3 provides an overview of the average impact of appointment reminders on primary care visits using the difference-in-differences (DID) approach, pooling all post-treatment periods. Among patients with type 2 diabetes, we observe that, on average, the adoption of the appointment reminder program increases the likelihood of a primary care visit in a given semester by 5.7 percentage points (pp) (see Table 3, column 1, panels A). Similarly, for patients with hypertension, the average effect is an increase of 7.0 pp (see Table 3, column 1, panels B). Effects are significant at conventional levels.

When estimating the effects using the intention-to-treat (ITT) models (see Table 3, columns 2-3), the estimates are predictably smaller. Specifically, among patients with type 2 diabetes, the ITT models indicate an increase of 2.6 (TWFE) and 3.2 (BJS) percentage points in the probability of a visit. For patients with hypertension, the effects are also 2.6 (TWFE) and 3.2 (BJS) percentage points.

5.4 Heterogeneity in the impact of appointment reminders on visits

Next, we investigate how appointment reminders affect primary care visits, considering potential heterogeneity. Time since a patient's chronic disease diagnosis could influence outcomes, with recently diagnosed patients having higher disease salience, less information, and limited treatment adherence experience. As a result, new diagnoses might gain greater intervention benefits initially, but the effect of repeated reminders could fade over time as patients become eligible. Our findings indicate this is not the case, as the effect of reminders on visits remains consistent throughout the first four years after a patient's diagnosis (see Figure 4, panel (a)).

The impact of appointment reminders may vary by age of the recipients. Older adults are more likely to have more severe health conditions that necessitate regular medical appointments, potentially leading to a higher number of scheduled visits. Moreover, older adults may exhibit greater awareness of their healthcare needs compared to younger individuals. Alternatively, younger patients may benefit more from reminders sent by phone due to their better average technological literacy and greater likelihood of using mobile phones (Parikh et al. 2010; Zhang et al. 2015). Consequently, the effectiveness of appointment reminder programs in relation to age remains an empirical question. Figure 4 panel (b) shows that there is a positive and statistically significant impact of reminders on visits only for patients less than 75 years old. Reminders do not increase primary care visits among patients age 75 years or older.

Last, we investigate whether the impact of reminders differs depending on patients' health, as measured by biomarkers at the time of their diagnosis, referred to as their baseline visit. Individuals with more severe health conditions may already have established effective routines or systems to manage their healthcare appointments. They might have more experience navigating the healthcare system and exhibit better organizational skills, resulting in a reduced reliance on appointment reminders for visit adherence. Panel (c) in figure 4 shows that there is a positive and statistically significant effect of appointment reminders only among patients diagnosed with relatively low hemoglobin A1c values, at less than 12%. Reminders were not statistically significant among patients diagnosed when their hemoglobin A1c was very elevated, hemoglobin A1c>12%. In Chile, the clinical guidelines stipulate that patients should be diagnosed with type 2 diabetes mellitus (type 2 diabetes) if their hemoglobin A1c level[9] is at least 7% (MINSAL 2017b). Similarly, the effect of reminders is not statistically significant among patients diagnosed with hypertension at very elevated blood pressure levels (refer to Figure 4, Panel (d)). As per Chile's clinical guidelines, hypertension should be diagnosed when the blood pressure reading is equal to or exceeds 140/90 mmHg (MINSAL 2017b). Our findings indicate that reminders are effective when patients are diagnosed with hypertension below or slightly above the diagnostic threshold (systolic blood pressure <170 mmHg), but they do not exhibit effectiveness at very high levels of systolic blood pressure.

5.5 What happens at each visit? Impacts of appointment reminders and visits on health monitoring

The impact of appointment reminders on the likelihood of undergoing health monitoring tests is illustrated in Table 4. The measurement of blood pressure, weight, and blood sugar can only take place if the patient visits primary care. Therefore, for patients who do not attend these visits, we can infer that their corresponding values for these tests are zero.

In our sample, we observe that a high proportion of patients receive blood pressure tests (95%) and are weighed (94%) during their primary care visits (refer to Table 2). Consequently, the testing rates once a patient visits a health center for these conditions are high. When estimating the effect of appointment reminders on the probability of undergoing these tests, unsurprisingly, we find that

[9]Hemoglobin A1c is expressed as a percentage and measures the share of red blood cells that have sugar-coated hemoglobin

the dynamics closely resemble the impact estimates on visit attendance. Specifically, for patients with type 2 diabetes, the probability of being tested for blood pressure increases by 4.9 percentage points (pp), and for patients with hypertension, it increases by 6.9 pp (refer to Table 4, columns 1 and 2). Similarly, the impact of reminders on the likelihood of being weighed is 5.0 pp for patients with type 2 diabetes and 6.3 pp for patients with hypertension (refer to Table 4, panel A, columns 3 and 4). We find no statistically significant effect of reminders on the probability of a blood glucose or hemoglobin A1c test for patients with type 2 diabetes (table 4, panel (a) column (2).

Table 4 includes findings from instrumental variables models that estimate the influence of an additional primary care visit on health monitoring. In these models, compliance is employed as an instrumental variable to capture the probability of visiting primary care. Because appointment reminders caused plausibly exogenous variation in the use of primary, preventative care, these estimates give us a benchmark of the impact of a visit on downstream care received. We provide Anderson-Rubin confidence intervals (see First stage F-stat in table 4). Aligned with our DID estimates, a visit leads to an 86.2pp and 97.2pp increase in BP test for patients with type 2 diabetes and hypertension, respectively (table 4) panel B, columns 1-2). A patient being weighed is also very likely: a visit leads to an 87.4pp and 88.9pp increase in weight measurement (table 4) panel B, columns 3-4).

5.6 Does patient behavior change? Impact of appointment reminders and primary care visits on medication adherence

In this section we test for whether appointment reminders and visits impacted medication adherence. We find that 55% of patients with type 2 diabetes, and 59% of patients with hypertension were prescribed a medication for their disease at their diagnostic visit. Table 2 shows that prescribing rates at patients' baseline visit are statistically indistinguishable between clinics that did vs. did not implement the appointment reminder program: p-value=0.3 for patients with hypertension, and p=0.5 for patients with type 2 diabetes.

We proceed by estimating medication adherence outcomes among patients with any hypertension or type 2 diabetes prescription at the time of their diagnosis. We find that reminders increased the probability a patient picking up any medication from the pharmacy in a semester by 8.1pp, a relative increase of 27.4%. Similarly, among patients with hypertension, we find a 7.5pp increase in pick up, or a relative increase of 25.4% (table 5, panel A columns 1-2).

Our instrumental variables approach shows that an additional primary care visit has a large positive effect on the probability of any medication refill. This could be because in Chile's gatekeeper health care system a prescription can only be obtained through visiting primary care.

In addition to increasing any medication pick up rates, our empirical findings indicate that appointment reminders have a positive impact on improving adequate medication adherence among hypertensive patients. Adequate medication adherence is defined as maintaining a coverage ratio of days equal to or exceeding 80%, following established conventions within the medical literature (refer to Table 5, panel (a), columns 3-4). Specifically, reminders resulted in a 1.2 pp increase in the likelihood of achieving adequate medication adherence for all patients. The impact of a visit on adequate medication adherence is statistically significant among patients with hypertension, where we find a substantial 20.2pp increase.

5.7 Impact of appointment reminders and visits on cardiovascular hospitalizations

We now examine the last pathway through which additional visits to primary care might improve patient health: information and referrals. We hypothesize that through more frequent interaction with clinicians, patients may have more information or a better understanding of how to manage their chronic condition. We test this hypothesis using the objectively measured outcome of hospitalizations. We hypothesize that more visits to primary care would lead to *more* hospitalizations, due to increased testing and referrals from their primary care clinician, and patient knowledge of when to seek care.

We find that appointment reminders led to an increased probability of hospitalization for cardiovascular-related conditions during a given semester, but not for non-cardiovascluar related conditions. Specifically, we observe an additional 2.8 hospitalizations per 1000 patients with type 2 diabetes and 2.1 hospitalizations per 1000 patients with hypertension. However, this effect was only statistically significant for patients with hypertension, representing a notable increase of 19.0% (see Table 6, panel (a), columns 1-2). We found no significant effect of appointment reminders on the length of stay for these hospitalized patients (columns 3-4).

When we explore in-hospital mortality, our results indicate that the program reduces in-hospital deaths by 0.7 per 1000 patients with type 2 diabetes, resulting in a relative effect of 1% (column 5, Table 6). Although we did not observe significant effects on in-hospital mortality for patients with hypertension, the direction of the effect is consistent.

Taken together, these findings indicate that patients who received appointment reminders exhibited a higher likelihood of seeking hospital care at an earlier stage. This could suggest less severe health conditions upon arrival, possibly attributed to factors such as referrals, enhanced medication adherence, or guidance from healthcare providers regarding appropriate care-seeking.

Our instrumental variables analysis supports these conclusions, as we observed a positive effect of visits on hypertension-related hospitalizations and a positive effect of visits on in-hospital mortality for patients with type 2 diabetes. We find no statistically significant effects of reminders on non-cardiovascular hospitalizations (Table A12).

6 Discussion

In this study, we investigate the impact of appointment reminders on high-risk patients' visits to primary, preventative healthcare clinics, subsequent care received, and health behaviors in Chile's public healthcare system. Using data for more than 300,000 patients we employ a difference-in-difference empirical design to measure the impact of sending appointment reminders on healthcare utilization, and an instrumental variables approach to understand the impact of additional primary, preventative care visits on health behaviors.

Conducting this study in the Chilean setting presents three key advantages. First, the nationwide scaling of appointment reminders enables us to assess their effectiveness using variation in clinic-level compliance and so address several aspects of at-scale program implementation (List 2022). This goes beyond previous studies that instead measured the efficacy of reminders using only intention to treat models. Second, with approximately 80% of the population utilizing Chile's public healthcare system, we have access to a substantial individual-level dataset, allowing us to examine the impact of additional primary care visits on downstream health behaviors and outcomes. The dataset includes over 2.5 million health care visits from patients followed for an average of 4.5 years, affording us a third advantage: the ability to comprehend the dynamic effects of appointment reminders over multiple periods and providing sufficient statistical power to detect even minor effects on medication adherence, hospitalization, and in-hospital mortality. Last, In Chile's public healthcare system patients are assigned a primary care clinic based on their home address, reducing contamination between the treatment and control group.

We find that patients who received reminders attended 8.7 to 10.7% more primary care visits. Contrary to studies in other settings, we do not find that the effectiveness of this repeated reminder decreased over time: the impact of the nudge was just as large in the first semester patients were eligible for it and more than 4 years later.[10] Where we do find variation in the effectiveness of nudges is the age and health of patients at the time of their diagnosis with a chronic condition. Reminders sent primary by text-message were more effective in middle age, and are ineffective for patients aged 75 and above perhaps because patients do not own a cell phone or do not understand how to use it effectively.

We also show that more primary care visits led to increased screenings, improved medication adherence, and timely hospital use, with the latter particularly benefiting patients with type 2 diabetes.We identified three pathways through which primary care visits might lead to improved health: increased screenings, medication availability and adherence, and hospital referrals and information. First, we find that at additional visits patients were more likely to be weighed and received more blood pressure screenings. We do not find a statistically significant change in blood glucose (hemoglobin A1c) screenings among patients with type 2 diabetes. Hemoglobin A1c serves as a long-term indicator of blood glucose levels. It is plausible that physicians determined blood glucose unnecessary to remeasure at the additional visits caused by appointment reminders. This finding is also in line with Allen and Baicker (2021) who find that access to insurance through Oregon's Medicaid lottery does not increase blood sugar monitoring among patients with diabetes. In contrast, blood pressure is recommended to be assessed at each primary care visit because of its short term variability, and regardless of the patient's health status (MINSAL 2017b).

Visits improved medication refill behaviors, as measured by the probability a patient ever visited

[10]For instance see Arora et al. (2015), Boksmati et al. (2016), Costa et al. (2010), Hallsworth et al. (2015), Hamine et al. (2015), Hofstetter et al. (2015), Lin et al. (2016), Shah et al. (2016).

a pharmacy during a given semester, and the probability they had adequate medication adherence. A vast majority of patients in the control group failed to achieve adequate medication adherence, with less than 3% meeting the target. Our estimates therefore translate into a 50% and 43% relative increase in adequate adherence for patients with type 2 diabetes and hypertension, respectively.

Recent research has shed light on the issue of medication non-initiation, whereby patients fail to pick up a new prescription soon after receiving it, leading to a lack of medication use long-term. Here, we observe that only 30% of patients in the control group picked up their medication the semester it was prescribed, even though medication is free. This is in line with recent findings from the US showing that 39% of new prescriptions among Medicare Part D patients were never initiated (Dusetzina et al. 2022). This phenomenon persists even for highly effective and necessary medications, with non-initiation rates ranging from 21% for hepatitis C drugs to 67% for hypercholesterolemia drugs (Dusetzina et al. 2022). Similarly, a study focusing on patients prescribed medications after a recent heart attack (i.e., a very salient and medically necessary treatment) found that only 12% of patients achieved adequate medication adherence (Choudhry et al. 2011).

Within Chile's public healthcare system, medication prescriptions are typically valid for a short duration, ranging from 1 to 6 months. While this practice encourages more frequent primary care visits to obtain updated prescriptions, it may also lead to reduced medication adherence if patients run out of valid refills before obtaining a new prescription.

Appointment reminders and visits also increased cardiovascular hospitalizations, which could be due to referrals or information gained at primary care visits. The reduction in in-hospital mortality, which is larger and statistically significant only for patients with type 2 diabetes, suggests that the value of additional preventative care visits is higher for these patients compared to patients with hypertension. This is in line with the medical literature that shows type 2 diabetes is a more severe and more costly condition than hypertension, both per capita and overall despite hypertension being more prevalent in the United States (American Diabetes Association 2018; Wang, Grosse, and Schooley 2017).

In terms of magnitude, back of the envelope calculations suggest that the appointment reminder program led to one additional cardiovascular hospitalization for every 470 treated patients (among patients with hypertension), and led to one fewer in-hospital mortality for every 1428 treated patients (among patients with type 2 diabetes). In comparison, in their analysis of the impact of health insurance on mortality, Goldin, Lurie, and McCubbin 2021 find that Medicaid take-up led to one fewer death for every 1587 treated individuals.

Taken together, our results demonstrate that interventions to improve attendance at primary care appointments can not only cause patients to receive necessary medical care such as screening tests, but can also change patient health behaviors such as medication adherence and the timing of seeking acute care. This finding is important because improving health through costly behavior change is a challenge for many individuals. This is well known in the context of patients with type 2 diabetes and hypertension: many behavior change programs fail, and many patients who could control their condition with improved diet and exercise struggle to do so (Oster 2018; Delamater

2006; Wang, Min, et al. 2020; Raj et al. 2018).

Our analysis has limitations, the first being that while we show that health behaviors improve, we cannot produce an unbiased estimate of the effect of appointment reminders on intermediate health outcomes, such as blood pressure, weight, or blood sugar. This is because we find that appointment reminders increase the probability of health screening, meaning estimates of the impact of reminders on the results of those screening tests would be biased. This is a common challenge faced by studies with exogenous variation in healthcare utilization (Adams et al. 2021; Fan et al. 2019; King et al. 2009; Manning 1987; Pan, Lei, and Liu 2016; Oster 2020). Second, we do not observe medication ingestion, and instead must rely on refill behavior from pharmacy claims. Third, while we are able to use compliance with reminders as an instrument for visits, our estimates of the impact of visits are imprecise and we focus more on bounds of the effect rather than a precise coefficient. This may be in part due to the fact that our instrument only includes reminders sent by SMS, which was the primary mode of communication but not the only mode.

Our findings have several implications for policy. First, we show that appointment reminders are effective at scale, even if implemented with large variation in compliance. We show that in the context of public, government run health care clinics in Chile, implementation fidelity improved over time suggesting clinic-level learning. As a result, we see that the impacts of the program on outcomes downstream of appointment reminders also increased over time. Our results suggest that interventions to improve attendance at primary care appointments can not only cause patients to receive necessary medical care such as screening tests, but can also change patient health behaviors such as medication adherence and the timing of seeking acute care, reinforcing attendance at preventative care as an important policy lever.

Control of chronic conditions like type 2 diabetes and hypertension is a global issue. Our findings are particularly important for other settings with a gate-keeper healthcare model where patients must first visit their primary care provider or general practitioner before being referred to speciality care, approved for tests, or prescribed new medication. This model is common in other OECD countries with public health care systems, such as Canada, the United Kingdom, Spain, and Italy (Reibling and Wendt 2012; Brekke, Nuscheler, and Straume 2007; Rotar et al. 2018; Watt 1987; Blöndal and Ásgeirsdóttir 2019). As we have demonstrated in Chile, in such gate-keeper health care systems a light touch intervention such as nudging patients to attend primary care can have potentially large and meaningful impacts as it intervenes in the first step in the cascade of care. Nudges such as appointment reminders are increasingly used by governments to encourage constituents to take-up programs. Here, we have shown how these nudges can be used to also study the downstream effects of program take up, and that they are a promising strategy to promote treatment adherence among high-risk patients living with chronic diseases.

References

Abadie, Alberto et al. (2020). "Sampling-Based versus Design-Based Uncertainty in Regression Analysis". en. In: *Econometrica* 88.1, pp. 265–296. ISSN: 0012-9682. DOI: 10.3982/ECTA12675. URL: https://www.econometricsociety.org/doi/10.3982/ECTA12675 (visited on 12/26/2021).

Adams, Alyce S. et al. (Sept. 2021). *The Impact of Financial Assistance Programs on Health Care Utilization*. Working Paper 29227. Series: Working Paper Series. National Bureau of Economic Research. DOI: 10.3386/w29227. URL: https://www.nber.org/papers/w29227 (visited on 04/30/2022).

Aguilera, Adrian, Stephen M. Schueller, and Yan Leykin (Apr. 2015). "Daily mood ratings via text message as a proxy for clinic based depression assessment". en. In: *Journal of Affective Disorders* 175, pp. 471–474. ISSN: 01650327. DOI: 10.1016/j.jad.2015.01.033. URL: https://linkinghub.elsevier.com/retrieve/pii/S0165032715000373 (visited on 04/01/2020).

Alalouf, Mattan, Sarah Miller, and Laura Wherry (Oct. 2019). *What Difference Does a Diagnosis Make? Evidence from Marginal Patients*. en. Tech. rep. w26363. Cambridge, MA: National Bureau of Economic Research, w26363. DOI: 10.3386/w26363. URL: http://www.nber.org/papers/w26363.pdf (visited on 09/25/2020).

Allcott, Hunt, Sendhil Mullainathan, and Dmitry Taubinsky (Apr. 2014). "Energy policy with externalities and internalities". en. In: *Journal of Public Economics* 112, pp. 72–88. ISSN: 00472727. DOI: 10.1016/j.jpubeco.2014.01.004. URL: https://linkinghub.elsevier.com/retrieve/pii/S004727271400005X (visited on 05/04/2021).

Allen, Heidi and Katherine Baicker (Oct. 2021). *The Effect of Medicaid on Care and Outcomes for Chronic Conditions: Evidence from the Oregon Health Insurance Experiment*. en. Tech. rep. w29373. Cambridge, MA: National Bureau of Economic Research, w29373. DOI: 10.3386/w29373. URL: http://www.nber.org/papers/w29373.pdf (visited on 08/25/2023).

American Diabetes Association (Mar. 2018). "Economic Costs of Diabetes in the U.S. in 2017". In: *Diabetes Care* 41.5, pp. 917–928. ISSN: 0149-5992. DOI: 10.2337/dci18-0007. URL: https://doi.org/10.2337/dci18-0007 (visited on 07/12/2023).

Anderson, T. W. and Herman Rubin (Mar. 1949). "Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations". In: *The Annals of Mathematical Statistics* 20.1. Publisher: Institute of Mathematical Statistics, pp. 46–63. ISSN: 0003-4851, 2168-8990. DOI: 10.1214/aoms/1177730090. URL: https://projecteuclid.org/journals/annals-of-mathematical-statistics/volume-20/issue-1/Estimation-of-the-Parameters-of-a-Single-Equation-in-a/10.1214/aoms/1177730090.full (visited on 03/02/2023).

Aron-Dine, Aviva, Liran Einav, and Amy Finkelstein (Feb. 2013). "The RAND Health Insurance Experiment, Three Decades Later". en. In: *Journal of Economic Perspectives* 27.1, pp. 197–222. ISSN: 0895-3309. DOI: 10.1257/jep.27.1.197. URL: https://pubs.aeaweb.org/doi/10.1257/jep.27.1.197 (visited on 05/02/2022).

Arora, Sanjay et al. (2015). "Improving Attendance at Post–Emergency Department Follow-up Via Automated Text Message Appointment Reminders: A Randomized Controlled Trial". en. In: *Academic Emergency Medicine* 22.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/acem.12503, pp. 31–37. ISSN: 1553-2712. DOI: 10.1111/acem.12503. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/acem.12503 (visited on 07/12/2023).

Baicker, Katherine et al. (May 2013). "The Oregon Experiment — Effects of Medicaid on Clinical Outcomes". In: *New England Journal of Medicine* 368.18. Publisher: Massachusetts Medical Society _eprint: https://doi.org/10.1056/NEJMsa1212321, pp. 1713–1722. ISSN: 0028-4793. DOI: 10.1056/NEJMsa1212321. URL: https://doi.org/10.1056/NEJMsa1212321 (visited on 04/29/2022).

Blöndal, Björn and Tinna Laufey Ásgeirsdóttir (2019). "Costs and efficiency of gatekeeping under varying numbers of general practitioners". en. In: *The International Journal of Health Planning and Management* 34.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hpm.2601, pp. 140–156. ISSN: 1099-1751. DOI: 10.1002/hpm.2601. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/hpm.2601 (visited on 04/30/2022).

Bodenheimer, Thomas et al. (Nov. 2002). "Patient Self-management of Chronic Disease in Primary Care". In: *JAMA* 288.19, pp. 2469–2475. ISSN: 0098-7484. DOI: 10.1001/jama.288.19.2469. URL: https://doi.org/10.1001/jama.288.19.2469 (visited on 07/05/2023).

Boksmati, Nasim et al. (Feb. 2016). "The Effectiveness of SMS Reminders on Appointment Attendance: a Meta-Analysis". en. In: *Journal of Medical Systems* 40.4, p. 90. ISSN: 1573-689X. DOI: 10.1007/s10916-016-0452-2. URL: https://doi.org/10.1007/s10916-016-0452-2 (visited on 12/17/2018).

Boone, Claire E et al. (Mar. 2022). "How scheduling systems with automated appointment reminders improve health clinic efficiency". en. In: *Journal of Health Economics* 82, p. 102598. ISSN: 01676296. DOI: 10.1016/j.jhealeco.2022.102598. URL: https://linkinghub.elsevier.com/retrieve/pii/S0167629622000182 (visited on 02/18/2022).

Borusyak, Kirill (2021). "Revisiting Event Study Designs: Robust and Efficient Estimation". en. In: p. 48.

Brekke, Kurt R., Robert Nuscheler, and Odd Rune Straume (Jan. 2007). "Gatekeeping in health care". en. In: *Journal of Health Economics* 26.1, pp. 149–170. ISSN: 0167-6296. DOI: 10.1016/j.jhealeco.2006.04.004. URL: https://www.sciencedirect.com/science/article/pii/S0167629606000531 (visited on 04/30/2022).

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro H. C. Sant'Anna (July 2021). *Difference-in-Differences with a Continuous Treatment*. en. arXiv:2107.02637 [econ]. URL: http://arxiv.org/abs/2107.02637 (visited on 07/24/2023).

Card, David, Carlos Dobkin, and Nicole Maestas (Nov. 2008). "The Impact of Nearly Universal Insurance Coverage on Health Care Utilization: Evidence from Medicare". en. In: *American Economic Review* 98.5, pp. 2242–2258. ISSN: 0002-8282. DOI: 10.1257/aer.98.5.2242. URL: https://pubs.aeaweb.org/doi/10.1257/aer.98.5.2242 (visited on 05/02/2022).

— (May 2009). "Does Medicare Save Lives?*". In: *The Quarterly Journal of Economics* 124.2, pp. 597–636. ISSN: 0033-5533. DOI: 10.1162/qjec.2009.124.2.597. URL: https://doi.org/10.1162/qjec.2009.124.2.597 (visited on 05/02/2022).

Choudhry, Niteesh K. et al. (Dec. 2011). "Full Coverage for Preventive Medications after Myocardial Infarction". In: *New England Journal of Medicine* 365.22. Publisher: Massachusetts Medical Society _eprint: https://doi.org/10.1056/NEJMsa1107913, pp. 2088–2097. ISSN: 0028-4793. DOI: 10.1056/NEJMsa1107913. URL: https://doi.org/10.1056/NEJMsa1107913 (visited on 04/18/2023).

Ciechanowski, Paul et al. (Feb. 2006). "Where is the patient? The association of psychosocial factors and missed primary care appointments in patients with diabetes". eng. In: *General Hospital Psychiatry* 28.1, pp. 9–17. ISSN: 0163-8343. DOI: 10.1016/j.genhosppsych.2005.07.004.

Contreras, José Luis (2022). *Eficiencia en la Gestión de Atención Primaria de Salud (APS)*. Tech. rep. Comisión Nacional de Evaluación y Productividad. URL: https://www.cnep.cl/wp-content/uploads/2022/06/Informe-final.pdf (visited on 07/05/2023).

Costa, Thiago Martini da et al. (Jan. 2010). “Hallsworth”. eng. In: *International Journal of Medical Informatics* 79.1, pp. 65–70. ISSN: 1872-8243. DOI: 10.1016/j.ijmedinf.2009.09.001.

Damgaard, Mette T (2020). “A decade of nudging: What have we learned?” en. In.

Damgaard, Mette Trier and Christina Gravert (Jan. 2018). “The hidden costs of nudging: Experimental evidence from reminders in fundraising”. en. In: *Journal of Public Economics* 157, pp. 15–26. ISSN: 0047-2727. DOI: 10.1016/j.jpubeco.2017.11.005. URL: https://www.sciencedirect.com/science/article/pii/S0047272717301895 (visited on 02/25/2023).

Delamater, Alan M. (Apr. 2006). “Improving Patient Adherence”. In: *Clinical Diabetes* 24.2, pp. 71–77. ISSN: 0891-8929. DOI: 10.2337/diaclin.24.2.71. URL: https://doi.org/10.2337/diaclin.24.2.71 (visited on 02/25/2023).

Della Vigna, Stefano and Ulrike Malmendier (May 2006). “Paying Not to Go to the Gym”. en. In: *American Economic Review* 96.3, pp. 694–719. ISSN: 0002-8282. DOI: 10.1257/aer.96.3.694. URL: https://pubs.aeaweb.org/doi/10.1257/aer.96.3.694 (visited on 04/30/2022).

DellaVigna, Stefano (May 2009). “Psychology and Economics: Evidence from the Field”. en. In: *Journal of Economic Literature* 47.2, pp. 315–372. ISSN: 0022-0515. DOI: 10.1257/jel.47.2.315. URL: http://pubs.aeaweb.org/doi/10.1257/jel.47.2.315 (visited on 05/18/2020).

DellaVigna, Stefano and Elizabeth Linos (2022). “RCTs to Scale: Comprehensive Evidence From Two Nudge Units”. en. In: *Econometrica* 90.1, pp. 81–116. ISSN: 0012-9682. DOI: 10.3982/ECTA18709. URL: https://www.econometricsociety.org/doi/10.3982/ECTA18709 (visited on 04/28/2022).

Dusetzina, Stacie B. et al. (Apr. 2022). “Many Medicare Beneficiaries Do Not Fill High-Price Specialty Drug Prescriptions”. en. In: *Health Affairs* 41.4, pp. 487–496. ISSN: 0278-2715, 1544-5208. DOI: 10.1377/hlthaff.2021.01742. URL: http://www.healthaffairs.org/doi/10.1377/hlthaff.2021.01742 (visited on 04/28/2022).

Egan, Brent M. et al. (June 2019). “The global burden of hypertension exceeds 1.4 billion people: should a systolic blood pressure target below 130 become the universal standard?” en-US. In: *Journal of Hypertension* 37.6, pp. 1148–1153. ISSN: 0263-6352. DOI: 10.1097/HJH.0000000000002021. URL: https://journals.lww.com/jhypertension/Fulltext/2019/06000/The_global_burden_of_hypertension_exceeds_1_4.6.aspx (visited on 03/10/2021).

Ellanti, P., R. P. Manecksha, and R. Flynn (Jan. 2011). “The use of text messaging to reduce non-attendance at outpatients clinic–a departmental experience”. eng. In: *Irish Medical Journal* 104.1, pp. 28–29. ISSN: 0332-3102.

Estadísticas, Insituto Nacional de (2020). *Síntesis de Resultados Encuesta Suplementaria de Ingresos*. Tech. rep. URL: http://www.ine.cl/prensa/2021/08/24/ingreso-laboral-promedio-mensual-en-chile-fue-de-$635.134-en-2020 (visited on 09/30/2021).

Fan, Hongli et al. (Apr. 2019). “Does Public Health Insurance Coverage Lead to Better Health Outcomes? Evidence From Chinese Adults”. In: *Inquiry: A Journal of Medical Care Organization, Provision and Financing* 56, p. 0046958019842000. ISSN: 0046-9580. DOI: 10.1177/0046958019842000. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6463230/ (visited on 04/30/2022).

Finkelstein, Amy et al. (Aug. 2012). “The Oregon Health Insurance Experiment: Evidence from the First Year*”. In: *The Quarterly Journal of Economics* 127.3, pp. 1057–1106. ISSN: 0033-5533. DOI: 10.1093/qje/qjs020. URL: https://doi.org/10.1093/qje/qjs020 (visited on 04/29/2022).

FONASA (2018). *Bases de datos, informes y documentos*. URL: https://www.fonasa.cl/sites/fonasa/documentos (visited on 04/21/2022).

Fullerton, Birgit et al. (Jan. 2012). "Predictors of dropout in the German disease management program for type 2 diabetes". eng. In: *BMC health services research* 12, p. 8. ISSN: 1472-6963. DOI: 10.1186/1472-6963-12-8.

Gabaix, Xavier (Jan. 2019). "Chapter 4 - Behavioral inattention". en. In: *Handbook of Behavioral Economics: Applications and Foundations 1*. Ed. by B. Douglas Bernheim, Stefano DellaVigna, and David Laibson. Vol. 2. Handbook of Behavioral Economics - Foundations and Applications 2. North-Holland, pp. 261–343. DOI: 10.1016/bs.hesbe.2018.11.001. URL: http://www.sciencedirect.com/science/article/pii/S2352239918300216 (visited on 05/04/2020).

Goic, Alejandro (2015). "The Chilean Health Care System: The task ahead". In: 1. URL: https://www.scielo.cl/scielo.php?script=sci_arttext&pid=S0034-98872015000600011&lng=en&nrm=iso&tlng=en (visited on 04/21/2022).

Goldin, Jacob, Ithai Z Lurie, and Janet McCubbin (Feb. 2021). "Health Insurance and Mortality: Experimental Evidence from Taxpayer Outreach". In: *The Quarterly Journal of Economics* 136.1, pp. 1–49. ISSN: 0033-5533. DOI: 10.1093/qje/qjaa029. URL: https://doi.org/10.1093/qje/qjaa029 (visited on 09/19/2022).

Gucciardi, Enza (Mar. 2008). "A Systematic Review of Attrition from Diabetes Education Services: Strategies to Improve Attrition and Retention Research". In: *Canadian Journal of Diabetes* 32, pp. 53–65. DOI: 10.1016/S1499-2671(08)21011-7.

Hallsworth, Michael et al. (Sept. 2015). "Stating Appointment Costs in SMS Reminders Reduces Missed Hospital Appointments: Findings from Two Randomised Controlled Trials". en. In: *PLOS ONE* 10.9, e0137306. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0137306. URL: http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0137306 (visited on 06/12/2018).

Hamine, Saee et al. (2015). "Impact of mHealth Chronic Disease Management on Treatment Adherence and Patient Outcomes: A Systematic Review". en. In: *Journal of Medical Internet Research* 17.2, e52. DOI: 10.2196/jmir.3951. URL: https://www.jmir.org/2015/2/e52/ (visited on 01/31/2020).

Hardy, K. J., S. V. O'Brien, and N. J. Furlong (Dec. 2001). "Information given to patients before appointments and its effect on non-attendance rate". eng. In: *BMJ (Clinical research ed.)* 323.7324, pp. 1298–1300. ISSN: 0959-8138. DOI: 10.1136/bmj.323.7324.1298.

Heckman, James et al. (2010). "Analyzing social experiments as implemented: A reexamination of the evidence from the HighScope Perry Preschool Program". en. In: *Quantitative Economics* 1.1. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/QE8, pp. 1–46. ISSN: 1759-7331. DOI: 10.3982/QE8. URL: https://onlinelibrary.wiley.com/doi/abs/10.3982/QE8 (visited on 05/02/2022).

Hemann, Brian A., William F. Bimson, and Allen J. Taylor (2007). "The Framingham Risk Score: An Appraisal of Its Benefits and Limitations". en. In: *American Heart Hospital Journal* 5.2. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1541-9215.2007.06350.x, pp. 91–96. ISSN: 1751-7168. DOI: 10.1111/j.1541-9215.2007.06350.x. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1541-9215.2007.06350.x (visited on 07/05/2023).

Hofstetter, Annika M. et al. (Oct. 2015). "Text message reminders for timely routine MMR vaccination: A randomized controlled trial". en. In: *Vaccine* 33.43, pp. 5741–5746. ISSN: 0264-410X. DOI: 10.1016/j.vaccine.2015.09.042. URL: https://www.sciencedirect.com/science/article/pii/S0264410X15013183 (visited on 07/12/2023).

Jongh, Thyra de et al. (2012). "Mobile phone messaging for facilitating self-management of long-term illnesses". en. In: *Cochrane Database of Systematic Reviews* 12. Publisher: John Wiley & Sons, Ltd. ISSN: 1465-1858. DOI: 10.1002/14651858.CD007459.pub2. URL: https://www.

cochranelibrary.com/cdsr/doi/10.1002/14651858.CD007459.pub2/full (visited on 08/26/2020).

Karter, Andrew J. et al. (2004). "Missed Appointments and Poor Glycemic Control: An Opportunity to Identify High-Risk Diabetic Patients". In: *Medical Care* 42.2, pp. 110–115. ISSN: 0025-7079. URL: https://www.jstor.org/stable/4640707 (visited on 12/14/2018).

Kessler, Judd and C. Zhang (Jan. 2014). "Behavioral Economics and Health". In.

King, Gary et al. (Apr. 2009). "Public policy for the poor? A randomised assessment of the Mexican universal health insurance programme". eng. In: *Lancet (London, England)* 373.9673, pp. 1447–1454. ISSN: 1474-547X. DOI: 10.1016/S0140-6736(09)60239-7.

Kini, Vinay and P. Michael Ho (Dec. 2018). "Interventions to Improve Medication Adherence: A Review". en. In: *JAMA* 320.23, p. 2461. ISSN: 0098-7484. DOI: 10.1001/jama.2018.19271. URL: http://jama.jamanetwork.com/article.aspx?doi=10.1001/jama.2018.19271 (visited on 08/25/2023).

Lanas, Fernando et al. (Aug. 2020). "May Measurement Month 2018: an analysis of blood pressure screening results from Chile". In: *European Heart Journal Supplements* 22.Supplement_H, H37–H39. ISSN: 1520-765X. DOI: 10.1093/eurheartj/suaa023. URL: https://doi.org/10.1093/eurheartj/suaa023 (visited on 01/18/2021).

Leong, Kwok Chi et al. (Dec. 2006). "The use of text messaging to improve attendance in primary care: a randomized controlled trial". eng. In: *Family Practice* 23.6, pp. 699–705. ISSN: 0263-2136. DOI: 10.1093/fampra/cml044.

Levy, Helen and David Meltzer (Apr. 2008). "The Impact of Health Insurance on Health". en. In: *Annual Review of Public Health* 29.1, pp. 399–409. ISSN: 0163-7525, 1545-2093. DOI: 10.1146/annurev.publhealth.28.021406.144042. URL: https://www.annualreviews.org/doi/10.1146/annurev.publhealth.28.021406.144042 (visited on 05/02/2022).

Liew, Su-May et al. (Dec. 2009). "Text messaging reminders to reduce non-attendance in chronic disease follow-up: a clinical trial". eng. In: *The British Journal of General Practice: The Journal of the Royal College of General Practitioners* 59.569, pp. 916–920. ISSN: 1478-5242. DOI: 10.3399/bjgp09X472250.

Lin, Chia-Lei et al. (Dec. 2016). "Text Message Reminders Increase Appointment Adherence in a Pediatric Clinic: A Randomized Controlled Trial". en. In: *International Journal of Pediatrics* 2016. Publisher: Hindawi, e8487378. ISSN: 1687-9740. DOI: 10.1155/2016/8487378. URL: https://www.hindawi.com/journals/ijpedi/2016/8487378/ (visited on 07/12/2023).

List, John A. (Feb. 2022). *The Voltage Effect: How to Make Good Ideas Great and Great Ideas Scale*. en. Google-Books-ID: 34JXEAAAQBAJ. Crown. ISBN: 978-0-593-23948-3.

Manning, Willard G. (1987). "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment". In: *American Economic Review* 77.3, pp. 251–77. URL: https://econpapers.repec.org/article/aeaaecrev/v_3a77_3ay_3a1987_3ai_3a3_3ap_3a251-77.htm.

Margozzini, Paula and Álvaro Passi (June 2018). "Encuesta Nacional de Salud, ENS 2016-2017: un aporte a la planificación sanitaria y políticas públicas en Chile". es. In: *ARS MEDICA Revista de Ciencias Médicas* 43.1. Number: 1, pp. 30–34. ISSN: 0719-1855. DOI: 10.11565/arsmed.v43i1.1354. URL: https://173.236.243.65/index.php/MED/article/view/1354 (visited on 04/21/2022).

Martinez, Diego A. et al. (Feb. 2019). "Prolonged wait time is associated with increased mortality for Chilean waiting list patients with non-prioritized conditions". In: *BMC Public Health* 19. ISSN: 1471-2458. DOI: 10.1186/s12889-019-6526-6. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6390314/ (visited on 02/06/2020).

Miller, Sarah, Norman Johnson, and Laura R Wherry (June 2021). "Medicaid and Mortality: New Evidence From Linked Survey and Administrative Data". en. In: *The Quarterly Journal of Economics* 136.3, pp. 1783–1829. ISSN: 0033-5533, 1531-4650. DOI: 10.1093/qje/qjab004. URL: https://academic.oup.com/qje/article/136/3/1783/6124639 (visited on 09/19/2022).

MINSAL (2008). *INFORME FINAL ESTUDIO DE CARGA DE ENFERMEDAD Y CARGA ATRIBUIBLE*. Tech. rep. URL: http://www.repositoriodigital.minsal.cl/bitstream/handle/2015/602/3895.pdf?sequence=1 (visited on 04/21/2022).

— (May 2017a). *DISPONE CREACIÓN DE COMISIÓN MÉDICA ASESORA PARA ANALIZAR LA SITUACIÓN DE PERSONAS QUE FALLECEN HABIENDO ESTADO EN UNA LISTA DE ESPERA O CON UNA GARANTÍA DE OPORTUNIDAD GES RETRASADA*. es. URL: https://www.bcn.cl/leychile (visited on 04/21/2022).

— (2017b). *Orientación Técnica Programa de Salud Cardiovascular*. URL: https://www.u-cursos.cl/medicina/2017/0/DPPAEF/1/foro/r/OT-PROGRAMA-DE-SALUD-CARDIOVASCULAR_05.pdf (visited on 10/17/2018).

Moscoe, Ellen, Jacob Bor, and Till Bärnighausen (Feb. 2015). "Regression discontinuity designs are underutilized in medicine, epidemiology, and public health: a review of current and best practice". en. In: *Journal of Clinical Epidemiology* 68.2, pp. 132–143. ISSN: 08954356. DOI: 10.1016/j.jclinepi.2014.06.021. URL: https://linkinghub.elsevier.com/retrieve/pii/S0895435614003990 (visited on 02/10/2020).

Nieuwlaat, Robby et al. (2014). "Interventions for enhancing medication adherence". en. In: *Cochrane Database of Systematic Reviews* 11. Publisher: John Wiley & Sons, Ltd. ISSN: 1465-1858. DOI: 10.1002/14651858.CD000011.pub4. URL: https://www.cochranelibrary.com/cdsr/doi/10.1002/14651858.CD000011.pub4/full (visited on 08/25/2023).

O'Keeffe, A. G. et al. (Sept. 2014). "Regression discontinuity designs: an approach to the evaluation of treatment efficacy in primary care using observational data". en. In: *BMJ* 349.sep08 3, g5293–g5293. ISSN: 1756-1833. DOI: 10.1136/bmj.g5293. URL: http://www.bmj.com/cgi/doi/10.1136/bmj.g5293 (visited on 02/10/2020).

Ostchega, Yechiam and Duong T Nguyen (2020). "Hypertension Prevalence Among Adults Aged 18 and Over: United States, 2017–2018". en. In: 364, p. 8.

Oster, Emily (Oct. 2018). "Diabetes and Diet: Purchasing Behavior Change in Response to Health Information". en. In: *American Economic Journal: Applied Economics* 10.4, pp. 308–348. ISSN: 1945-7782. DOI: 10.1257/app.20160232. URL: https://www.aeaweb.org/articles?id=10.1257/app.20160232 (visited on 04/01/2019).

— (June 2020). "Health Recommendations and Selection in Health Behaviors". en. In: *American Economic Review: Insights* 2.2, pp. 143–160. ISSN: 2640-205X, 2640-2068. DOI: 10.1257/aeri.20190355. URL: https://pubs.aeaweb.org/doi/10.1257/aeri.20190355 (visited on 07/24/2023).

Pan, Jay, Xiaoyan Lei, and Gordon G. Liu (2016). "Health Insurance and Health Status: Exploring the Causal Effect from a Policy Intervention". en. In: *Health Economics* 25.11. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.3225, pp. 1389–1402. ISSN: 1099-1050. DOI: 10.1002/hec.3225. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/hec.3225 (visited on 05/02/2022).

Parikh, Amay et al. (June 2010). "The Effectiveness of Outpatient Appointment Reminder Systems in Reducing No-Show Rates". en. In: *The American Journal of Medicine* 123.6, pp. 542–548. ISSN: 00029343. DOI: 10.1016/j.amjmed.2009.11.022. URL: https://linkinghub.elsevier.com/retrieve/pii/S0002934310001087 (visited on 08/25/2021).

Piper, Margaret A. et al. (Feb. 2015). "Diagnostic and Predictive Accuracy of Blood Pressure Screening Methods With Consideration of Rescreening Intervals: A Systematic Review for the

U.S. Preventive Services Task Force". In: *Annals of Internal Medicine* 162.3. Publisher: American College of Physicians, pp. 192–204. ISSN: 0003-4819. DOI: 10.7326/M14-1539. URL: https://www.acpjournals.org/doi/10.7326/M14-1539 (visited on 11/09/2020).

Raj, Gayathiri Durai et al. (Feb. 2018). "Adherence to Diabetes Dietary Guidelines Assessed Using a Validated Questionnaire Predicts Glucose Control in Adults With Type 2 Diabetes". en. In: *Canadian Journal of Diabetes* 42.1, pp. 78–87. ISSN: 1499-2671. DOI: 10.1016/j.jcjd.2017.04.006. URL: https://www.sciencedirect.com/science/article/pii/S1499267116306086 (visited on 02/25/2023).

Reibling, Nadine and Claus Wendt (July 2012). "Gatekeeping and provider choice in OECD healthcare systems". en. In: *Current Sociology* 60.4, pp. 489–505. ISSN: 0011-3921, 1461-7064. DOI: 10.1177/0011392112438333. URL: http://journals.sagepub.com/doi/10.1177/0011392112438333 (visited on 04/30/2022).

Roberto, Christina A. and Ichiro Kawachi (Sept. 2015). *Behavioral Economics and Public Health*. en. Google-Books-ID: WXQ_CgAAQBAJ. Oxford University Press. ISBN: 978-0-19-939847-8.

Rotar, Alexandru M. et al. (June 2018). "Shared decision making between patient and GP about referrals from primary care: Does gatekeeping make a difference?" In: *PLoS ONE* 13.6, e0198729. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0198729. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5995363/ (visited on 04/30/2022).

Salud - Gobierno de Chile, Ministerio de (2020). *FONASA*. URL: https://www.fonasa.cl/sites/fonasa/documentos (visited on 02/03/2021).

Schectman, Joel M., John B. Schorling, and John D. Voss (July 2008). "Appointment Adherence and Disparities in Outcomes Among Patients with Diabetes". en. In: *Journal of General Internal Medicine* 23.10, p. 1685. ISSN: 1525-1497. DOI: 10.1007/s11606-008-0747-1. URL: https://doi.org/10.1007/s11606-008-0747-1 (visited on 04/30/2022).

Shah, Sachin J. et al. (Dec. 2016). "Targeted Reminder Phone Calls to Patients at High Risk of No-Show for Primary Care Appointment: A Randomized Trial". en. In: *Journal of General Internal Medicine* 31.12, pp. 1460–1466. ISSN: 1525-1497. DOI: 10.1007/s11606-016-3813-0. URL: https://doi.org/10.1007/s11606-016-3813-0 (visited on 07/12/2023).

Taubman, Sarah L. et al. (Jan. 2014). "Medicaid Increases Emergency-Department Use: Evidence from Oregon's Health Insurance Experiment". In: *Science* 343.6168. Publisher: American Association for the Advancement of Science, pp. 263–268. DOI: 10.1126/science.1246183. URL: https://www.science.org/doi/full/10.1126/science.1246183 (visited on 04/29/2022).

Tomlinson, Mark et al. (Feb. 2013). "Scaling Up mHealth: Where Is the Evidence?" en. In: *PLOS Medicine* 10.2. Publisher: Public Library of Science, e1001382. ISSN: 1549-1676. DOI: 10.1371/journal.pmed.1001382. URL: https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1001382 (visited on 11/22/2020).

Vargas, Verónica and Sergio Poblete (June 2008). "Health prioritization: the case of Chile". eng. In: *Health Affairs (Project Hope)* 27.3, pp. 782–792. ISSN: 1544-5208. DOI: 10.1377/hlthaff.27.3.782.

Venkataramani, Atheendar S, Jacob Bor, and Anupam B Jena (Mar. 2016). "Regression discontinuity designs in healthcare research". en. In: *BMJ*, p. i1216. ISSN: 1756-1833. DOI: 10.1136/bmj.i1216. URL: http://www.bmj.com/lookup/doi/10.1136/bmj.i1216 (visited on 02/10/2020).

Wang, Guijing, Scott D. Grosse, and Michael W. Schooley (Dec. 2017). "Conducting Research on the Economics of Hypertension to Improve Cardiovascular Health". English. In: *American Journal of Preventive Medicine* 53.6. Publisher: Elsevier, S115–S117. ISSN: 0749-3797, 1873-2607. DOI: 10.1016/j.amepre.2017.08.005. URL: https://www.ajpmonline.org/article/S0749-3797(17)30440-3/fulltext (visited on 07/12/2023).

Wang, Youfa, Jungwon Min, et al. (Apr. 2020). "Effectiveness of Mobile Health Interventions on Diabetes and Obesity Treatment and Management: Systematic Review of Systematic Reviews". EN. In: *JMIR mHealth and uHealth* 8.4. Company: JMIR mHealth and uHealth Distributor: JMIR mHealth and uHealth Institution: JMIR mHealth and uHealth Label: JMIR mHealth and uHealth Publisher: JMIR Publications Inc., Toronto, Canada, e15400. DOI: 10.2196/15400. URL: https://mhealth.jmir.org/2020/4/e15400 (visited on 02/25/2023).

Watt, W. Donald (May 1987). "The Family Physician: Gatekeeper to the Health-Care System". In: *Canadian Family Physician* 33, pp. 1101–1104. ISSN: 0008-350X. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2218510/ (visited on 04/30/2022).

Yamaguchi, Satoko et al. (July 2017). "Previous dropout from diabetic care as a predictor of patients' willingness to use mobile applications for self-management: A cross-sectional study". In: *Journal of Diabetes Investigation* 8.4, pp. 542–549. ISSN: 2040-1116. DOI: 10.1111/jdi.12613. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5497048/ (visited on 04/30/2022).

Zhang, Xiaojun et al. (Feb. 2015). "Using diffusion of innovation theory to understand the factors impacting patient acceptance and use of consumer e-health innovations: a case study in a primary care clinic". eng. In: *BMC health services research* 15, p. 71. ISSN: 1472-6963. DOI: 10.1186/s12913-015-0726-2.

7 Tables and Figures

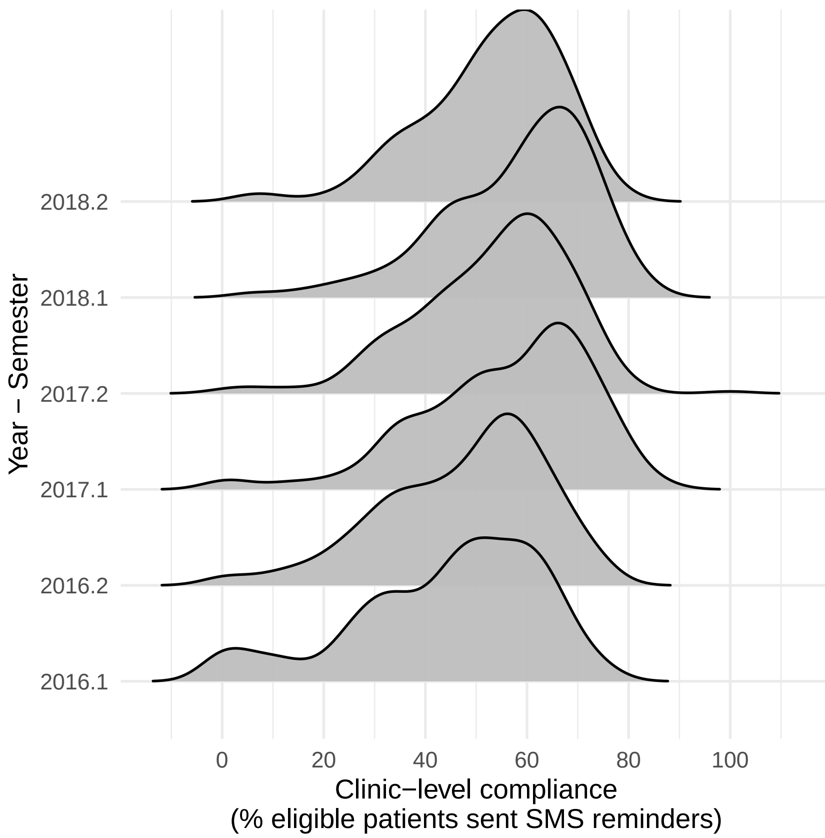
Table 1: Take-up and compliance with appointment reminder program among public primary care clinics

Date	N Treated Clinics	N Control Clinics	Compliance Mean	Compliance Min.	Compliance Max.
S1 2014	0	315	-	-	-
S2 2014	0	315	-	-	-
S1 2015*	168	147	46%	0%	76%
S2 2015*	172	143	46%	0%	76%
S1 2016	203	112	46%	0%	76%
S2 2016	208	107	49%	10%	76%
S1 2017	208	107	56%	14%	83%
S2 2017	208	107	53%	16%	81%
S1 2018	208	107	58%	18%	85%
S2 2018	208	107	54%	20%	78%
Total	208	107	53%	0%	85%

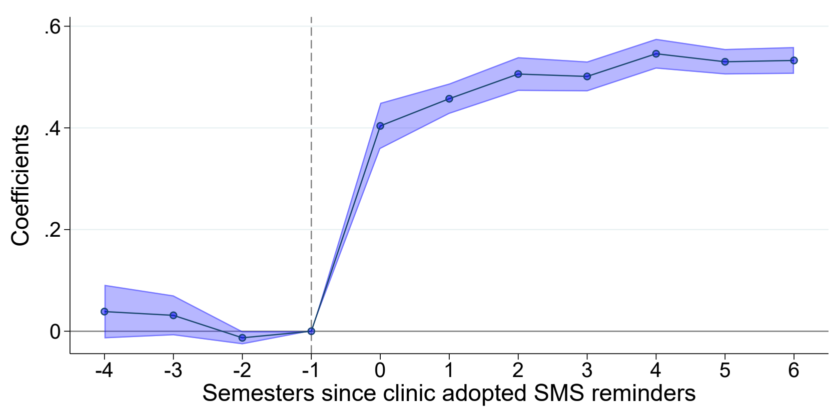
Note: Number of clinics that did and did not take up the appointment reminder program. Compliance was measured among treated clinics only using phone records. It is the share of patients sent an SMS reminder, among eligible patients in a clinic-semester cell. Compliance data was unavailable in 2015, so semester 1 2016 numbers were used.

Figure 1: Change in compliance over time: share of eligible patients sent reminders

(a) Variation in appointment reminder program compliance



(b) Change clinic-level compliance since program start



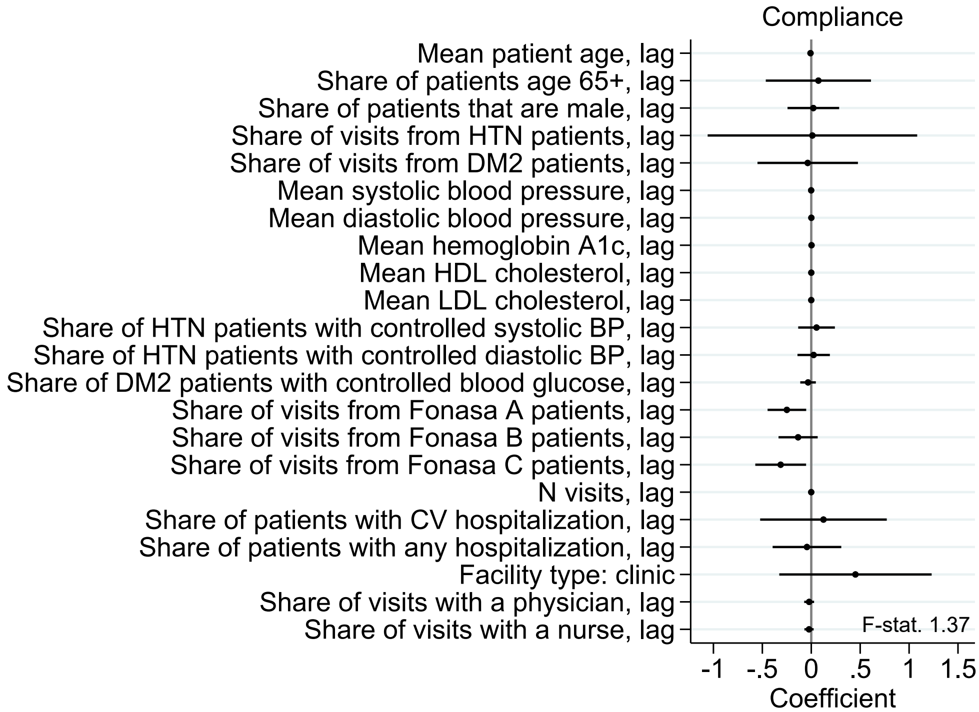
Note: Compliance was measured among ever treated clinics only using phone records. It is the share of patients sent an SMS reminder, among eligible patients in a clinic-semester cell.

Table 2: Balance of patient characteristics at baseline

	Reminders		Control			
	Mean	SD	Mean	SD	Diff.	P-val
Panel A: Patients with hypertension						
Male	0.41	0.49	0.41	0.49	-0.003	0.71
Age (years)	61.01	10.73	60.88	11.16	0.130	0.76
Systolic blood pressure	136.90	20.05	136.65	19.84	0.250	0.73
Diastolic blood pressure	80.49	12.08	81.25	12.01	-0.753	0.07
Weight (kg)	77.18	15.16	77.22	15.27	-0.043	0.87
Body mass index	30.89	5.54	30.84	5.56	0.055	0.61
Waist circumference (cm)	101.12	11.96	100.74	12.19	0.382	0.23
Obese waist	0.40	0.49	0.37	0.48	0.025	0.39
Blood pressure test	0.96	0.20	0.95	0.21	0.004	0.45
Weighed	0.94	0.24	0.93	0.26	0.014	0.22
Prescription at time of diagnosis	0.58	0.49	0.60	0.49	-0.022	0.30
N Patients	191,293		93,261		Total	284,554
N Visits	1,414,540		675,883		Total	2,090,423
Panel B: Patients with type 2 diabetes						
Male	0.47	0.50	0.49	0.50	-0.021	0.02
Age (years)	59.82	10.66	59.35	11.06	0.473	0.34
Systolic blood pressure	132.35	19.72	131.67	19.41	0.682	0.20
Diastolic blood pressure	77.95	11.20	78.78	11.21	-0.828	0.00
Hemoglobin A1c	8.22	2.51	8.20	2.44	0.024	0.71
Blood glucose	167.76	74.28	167.81	74.90	-0.053	0.98
Weight (kg)	78.49	15.37	78.69	15.34	-0.195	0.37
Body mass index	30.87	5.65	30.75	5.60	0.121	0.35
Waist circumference (cm)	102.06	12.08	101.66	12.18	0.396	0.21
Obese waist	0.35	0.48	0.38	0.49	-0.036	0.28
Blood glucose test	0.84	0.36	0.84	0.36	0.000	1.00
Blood pressure test	0.95	0.22	0.95	0.22	-0.001	0.92
Weighed	0.94	0.25	0.93	0.26	0.006	0.69
Prescription at time of diagnosis	0.55	0.50	0.56	0.50	-0.012	0.50
N Patients	42,609		25,010		Total	67,619
N Visits	282,700		159,622		Total	442,322

Note: Patient health and characteristics measured at patient's primary care visit when diagnosis with type 2 diabetes and/or hypertension occurred, referred to as their baseline visit, comparing means between patients at clinics that ever vs. never implemented appointment reminders. Hemoglobin A1c, blood glucose, and glucose test are measured only among patients diagnosed with type 2 diabetes at their initial visit. All other characteristics are measured for all patients. SD stands for standard deviation, and diff. stands for difference between treatment and control groups. P-val is the p-value on a two-sided t-test of whether the difference=0.

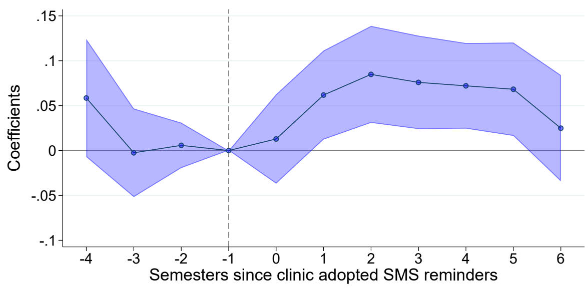
Figure 2: Association between clinic characteristics and semesterly compliance



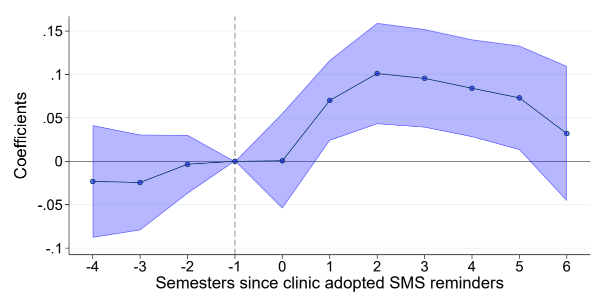
Note: Coefficients and 95% confidence intervals from a multivariate regression of clinic-semester compliance with the appointment reminder program on a set of lagged patient characteristics and contemporaneous clinic-level characteristics. Compliance was measured among treated clinics only using phone records. It is the share of patients sent an SMS reminder, among eligible patients in a clinic-semester cell. 95% confidence intervals were constructed from robust standard errors clustered at the clinic level. The regression includes clinic-semesters at treated clinics after reminders were adopted. Lagged coefficients were measured in the previous semester. The joint F-statistic is shown on the figure.

Figure 3: First stage: event study effect of appointment reminders on primary care visits

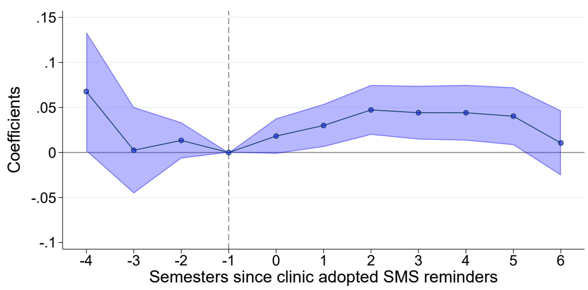
(a) Type 2 Diabetes Visits (Compliance TWFE)



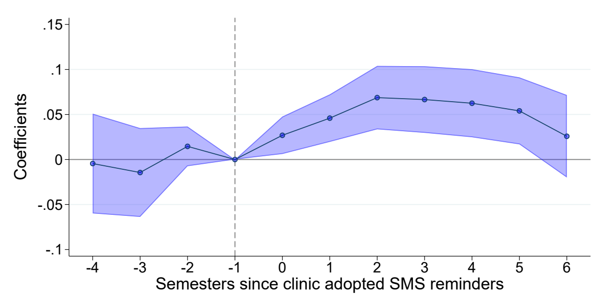
(b) Hypertension Visits (Compliance TWFE)



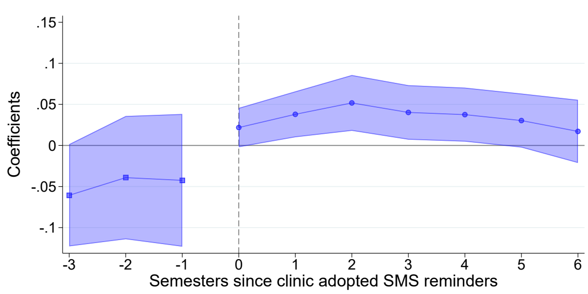
(c) Type 2 Diabetes Visits (ITT TWFE)



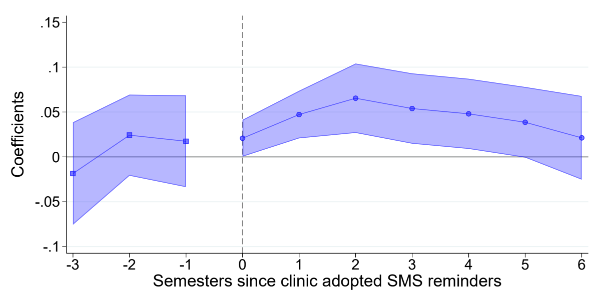
(d) Hypertension Visits (ITT TWFE)



(e) Type 2 Diabetes Visits (ITT BJS)



(f) Hypertension Visits (ITT BJS)



Note: Figures show regression estimates based on equation 1. The shaded areas denote 95% confidence intervals. The x-axis is number of semesters until or since the clinic adopted the appointment reminder program. ITT stands for intent to treat, and BJS stands for Borusyak, Jaravel, and Spiess. The coefficients in panel a were estimated using a two-way fixed effects event study model where the independent variable is clinic-semester compliance with the appointment reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. The independent variables in panels b and c are indicators equal to one in the semester of, and after a clinic implemented reminders and zero otherwise. The coefficients in panel b were estimated using a two-way fixed effects DiD model, and the coefficient in panel c were estimated using the Borusyak, Jaravel, and Spiess (2021) estimator for staggered policy adoption. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

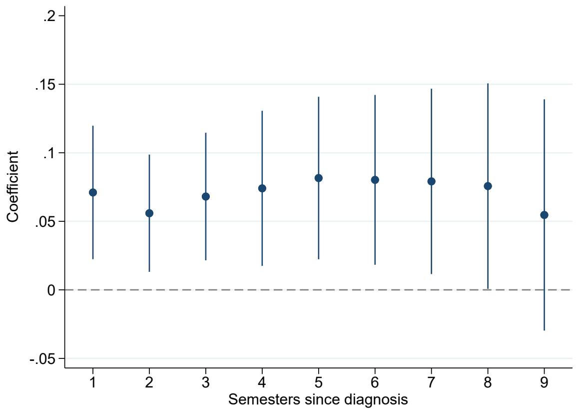
Table 3: First stage: effect of appointment reminders on primary care visits by baseline diagnosis

	Y = Primary Care Visit		
Specification	Compliance TWFE (1)	ITT TWFE (2)	ITT BJS (3)
Panel A: Patients with type 2 diabetes			
Reminders	0.057	0.026	0.032
	(0.023)	(0.012)	(0.015)
	[0.013]	[0.035]	[0.035]
Mean dep. var.	0.653	0.654	0.653
Observations	442,322	442,322	442,225
Clinics	314	314	313
Panel B: Patients with hypertension			
Reminders	0.070	0.043	0.040
	(0.025)	(0.016)	(0.018)
	[0.006]	[0.007]	[0.023]
Mean dep. var.	0.652	0.653	0.652
Observations	2,090,423	2,090,423	2,090,423
Clinics	310	310	310

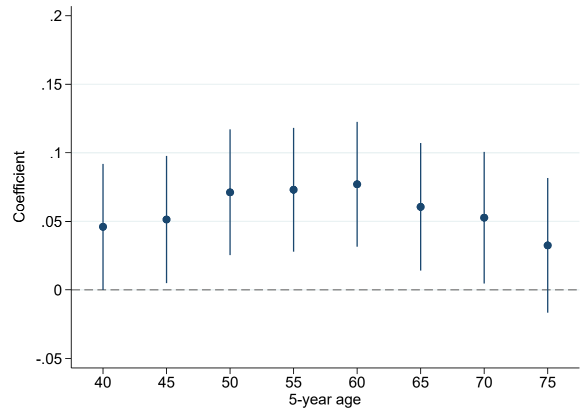
Note: *p<0.1; **p<0.05; ***p<0.01. This table presents our first stage: difference-in-differences (DiD) estimates of the effect of appointment reminders on the probability of a patient-visit in a given semester. ITT stands for intent to treat, and BJS stands for Borusyak, Jaravel, and Spiess. The coefficient in column 1 was estimated using a two-way fixed effects DiD model where the independent variable is clinic-semester compliance with the appointment program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. The independent variable in columns 2 and 3 is an indicator equal to one in the semester of, and after a clinic implemented SMS reminders and zero otherwise. The coefficient in model 2 was estimated using a two-way fixed effects DiD model, and the coefficient in model 3 was estimated using the Borusyak, Jaravel, and Spiess (2021) estimator for staggered policy adoption. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

Figure 4: Heterogeneity in the effect of appointment reminders on primary care visits

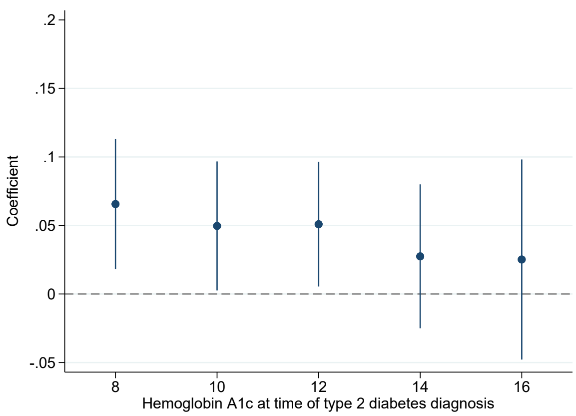
(a) Semesters since diagnosis



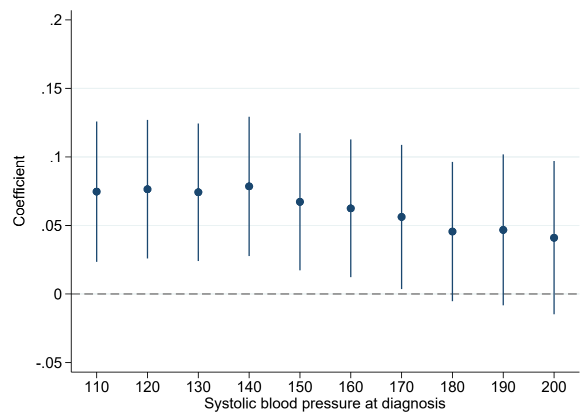
(b) Age at diagnosis



(c) Health at type 2 diabetes diagnosis



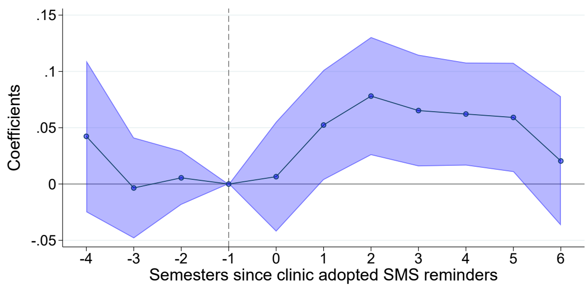
(d) Health at hypertension diagnosis



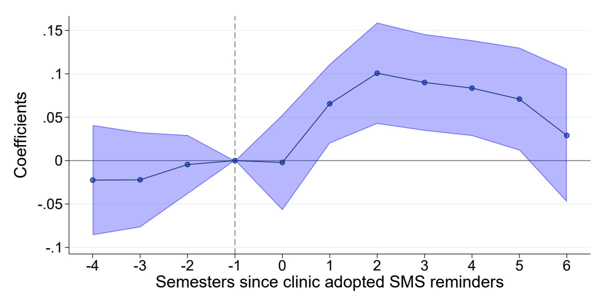
Note: Figures display coefficients and 95% confidence intervals from difference-in-difference heterogeneity models. Each dot is the main effect of appointment reminders + the coefficient on the interaction term between appointment reminders and the dimension of heterogeneity.

Figure 5: Event study estimates of the impact of appointment reminders on health monitoring

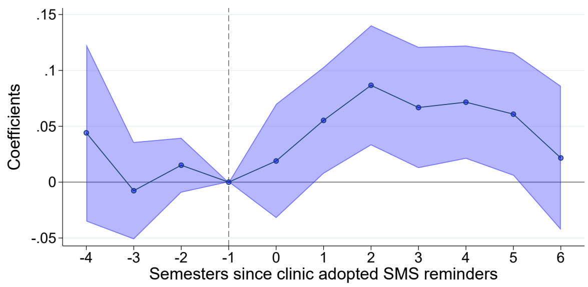
(a) Blood pressure test (DM2)



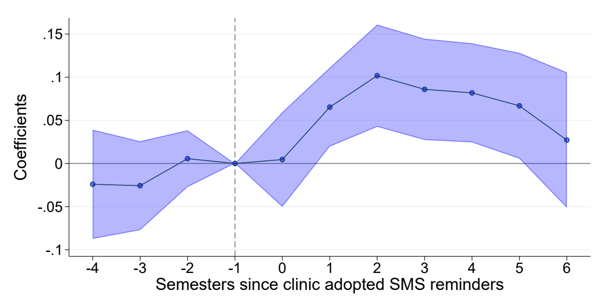
(b) Blood pressure test (HTN)



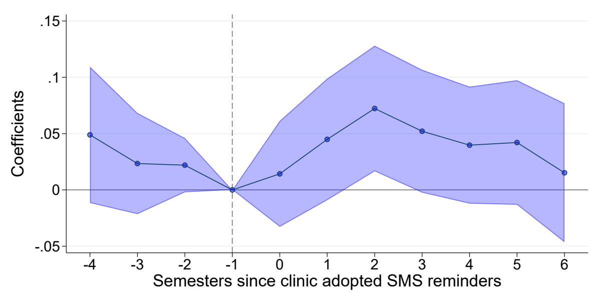
(c) Weighed (DM2)



(d) Weighed (HTN)



(e) Blood sugar test (DM2)



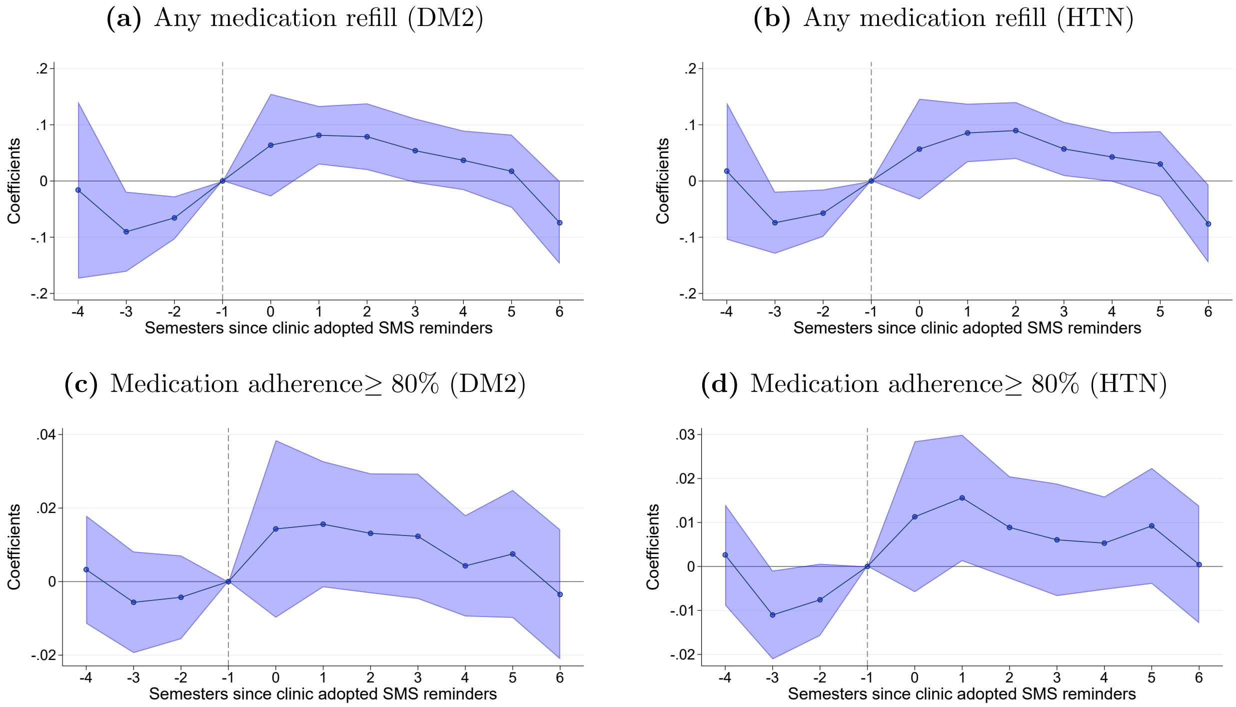
Note: Figures show regression estimates based on equation 1. The shaded areas denote 95% confidence intervals. The x-axis is number of semesters until or since the clinic implemented appointment reminders. Estimated using a two-way fixed effects event study model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

Table 4: Impact of appointment reminders and visits on health monitoring

	Blood pressure test		Weighed		Blood sugar test
	Type 2 Diabetes	Hyper- tension	Type 2 Diabetes	Hyper- tension	Type 2 Diabetes
	(1)	(2)	(3)	(4)	(5)
Panel A. Reduced form: impact of appointment reminders					
Program Compliance	0.049	0.069	0.050	0.063	0.027
	(0.021)	(0.025)	(0.024)	(0.026)	(0.024)
	[0.022]	[0.006]	[0.041]	[0.018]	[0.252]
Panel B. Instrumental variables: impact of primary care visit					
Visit	0.862	0.972	0.874	0.889	0.483
	(0.108)	(0.058)	(0.270)	(0.152)	(0.292)
	[0.000]	[0.000]	[0.001]	[0.000]	[0.099]
AR CI	[0.48, 1.15]	[0.82, 1.14]	[0.12, 1.76]	[0.43, 1.26]	[-1.09, 0.99]
AR p-val	0.020	0.006	0.039	0.016	0.250
Observations	442,322	2,090,423	442,322	2,090,423	442,322
Clinics	314	310	314	310	314
Mean Y | Pr(SMS)=0	0.622	0.627	0.610	0.615	0.562
Mean Y | Visit=0	0.000	0.000	0.000	0.000	0.000
First stage F-stat	6.305	7.697	6.305	7.697	6.305

Note: Panel A presents difference-in-differences (DiD) estimates of the effect of compliance with appointment reminders on the probability of a health monitoring tests. DiD models were estimated using a two-way fixed effects DiD model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. Panel B presents instrumental variables estimates of the effect of a primary care visit on tests. Anderson-Rubin (AR) confidence intervals and p-value are presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

Figure 6: Event study estimates of the impact of appointment reminders on medication adherence



Note: Figures show regression estimates based on equation 1. The shaded areas denote 95% confidence intervals. The x-axis is number of semesters until or since the clinic implemented appointment reminders. Estimated using a two-way fixed effects event study model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

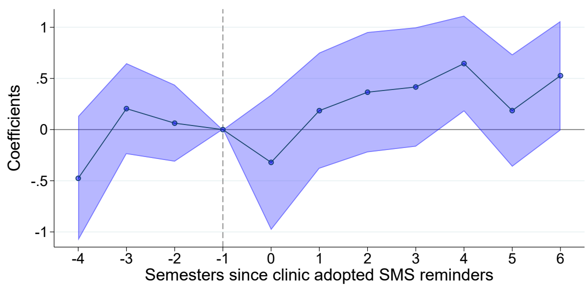
Table 5: Impact of appointment reminders and visits on medication outcomes

	Any medication refill		Medication adherence $\geq$ 80%	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Panel A. Reduced form: impact of appointment reminders				
Program Compliance	0.081	0.075	0.012	0.012
	(0.029)	(0.026)	(0.007)	(0.005)
	[0.006]	[0.004]	[0.087]	[0.018]
Panel B. Instrumental variables: impact of primary care visit				
Visit	1.462	1.254	0.210	0.202
	(0.665)	(0.593)	(0.140)	(0.111)
	[0.029]	[0.035]	[0.136]	[0.069]
AR CI	[0.340, 5.21]	[0.37, 5.06]	[-0.05, 0.90]	[0.04,0.89]
AR p-val	0.013	0.010	0.100	0.028
Observations	239,626	1,102,554	239,626	1,102,554
Clinics	312	309	312	309
Mean Y | Pr(SMS)=0	0.295	0.295	0.024	0.028
Mean Y | Visit=0	0.212	0.219	0.011	0.015
First stage F-stat	6.926	6.525	6.926	6.525

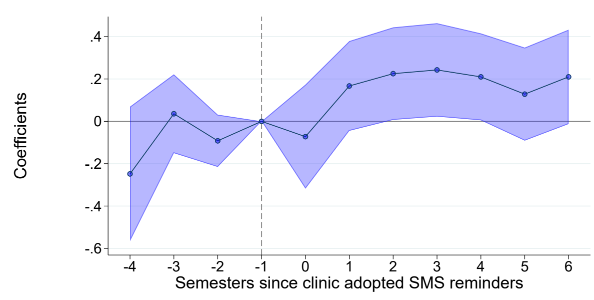
Note: Panel A presents difference-in-differences (DiD) estimates of the effect of compliance with appointment reminders on the probability of medication outcomes. DiD models estimated using a two-way fixed effects DiD model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. Panel B presents instrumental variables estimates of the effect of a primary care visit on medication. Anderson-Rubin (AR) confidence intervals and p-value are presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

Figure 7: Event study estimates of the impact of appointment reminders on cardiovascular hospitalisation

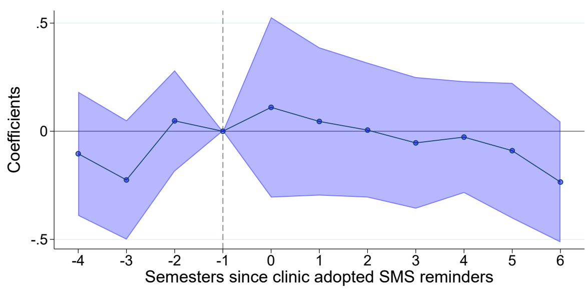
(a) Cardiovascular hospitalization (DM2)



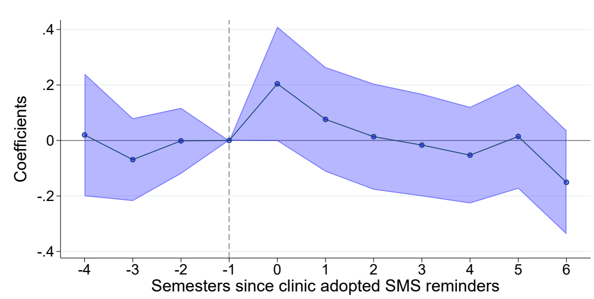
(b) Cardiovascular hospitalization (HTN)



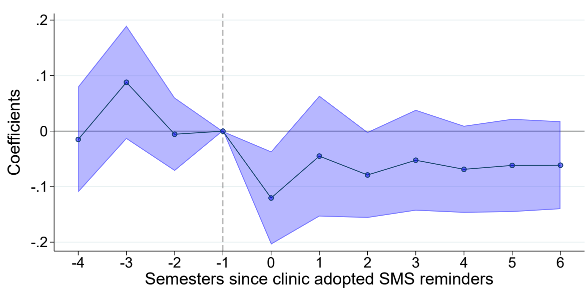
(c) Log days CV hospitalization (DM2)



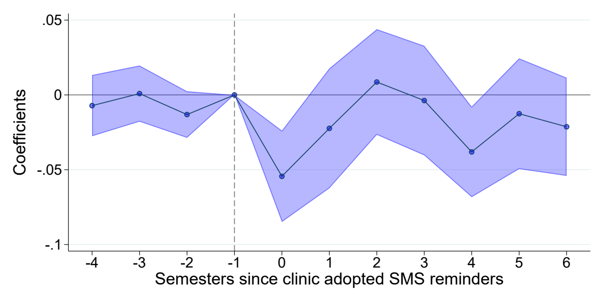
(d) Log days CV hospitalization (HTN)



(e) In-hospital CV mortality (DM2)



(f) In-hospital CV mortality (HTN)



Note: Figures show regression estimates based on equation 1. The shaded areas denote 95% confidence intervals. The x-axis is number of semesters until or since the clinic implemented appointment reminders. Estimated using a two-way fixed effects event study model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

Table 6: Impact of appointment reminders and visits on cardiovascular hospitalizations

	Cardiovascular hospitalization (per 100)		Log days CV hospitalization		In-hospital CV mortality (per 100)	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Reduced form: impact of appointment reminders						
Program Compliance	0.285	0.213	-0.040	0.018	-0.070	-0.015
	(0.203)	(0.088)	(0.104)	(0.071)	(0.029)	(0.012)
	[0.162]	[0.016]	[0.699]	[0.802]	[0.016]	[0.221]
Panel B. Instrumental variables: impact of primary care visit						
Visit	5.011	3.024	-0.465	0.261	-1.223	-0.208
	(3.595)	(1.455)	(1.233)	(1.044)	(0.703)	(0.177)
	[0.164]	[0.038]	[0.707]	[0.803]	[0.083]	[0.242]
AR CI	[-2.88, 20.15]	[0.69, 9.67]	[-6.52, 2.38]	[-4.13, 5.27]	[-5.74, -0.32]	[-0.87, 0.14]
AR p-val	0.164	0.019	0.697	0.802	0.021	0.218
Observations	442,322	2,090,423	7,510	24,053	442,322	2,090,423
Clinics	314	310	291	305	314	310
Mean Y | Pr(SMS)=0	1.689	1.124	1.929	1.848	0.053	0.037
Mean Y | Visit=0	1.796	1.203	2.020	1.919	0.118	0.084
First stage F-stat	6.305	7.697	5.920	4.781	6.305	7.697

Note: Panel A presents difference-in-differences (DiD) estimates of the effect of compliance with appointment reminders on the probability of hospitalization outcomes. DiD models estimated using a two-way fixed effects DiD model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. Panel B presents instrumental variables estimates of the effect of a primary care visit on hospitalizations. Anderson-Rubin (AR) confidence intervals and p-value are presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level. Log length of hospital stay is conditional on any CV hospitalization in a given semester.

A Appendix Tables and Figures

Table A1: ICD-10 Codes included in cardiovascular hospitalization outcomes

Condition	ICD-10 Codes
Diabetes mellitus	E 10.0, E 10.1, E 10.2, E 10.3, E 10.4, E 10.5, E 10.6, E 10.7, E 10.8, E 10.9, E 11.0, E 11.1, E 11.2, E 11.3, E 1.4, E 11.5, E 11.6, E 11.7, E 11.8, E 11.9
Primary hypertension	I 10.X
Hypertensive heart disease	I 11.0, I 11.9
Hypertensive chronic kidney disease	I 12.0, I 12.9, I 13.0, I 13.1, I 13.2, I 13.9
Acute myocardial infarction	I 21.0, I 21.1, I 21.2, I 21.3, I 21.4, I 21.9
Acute ischaemic heart disease	I 24.9
Heart failure	I 50.0, I 50.1, I 50.9
Hemorrhage	I 60.0, I 60.1, I 60.2, I 60.3, I 60.4, I 60.5, I 60.6, I 60.7, I 60.8, I 60.9, I 61.0, I 61.1, I 61.2, I 61.3, I 61.4, I 61.5, I 61.6, I 61.8, I 61.9, I 62.0, I 62.1, I 62.9
Cerebral infarction	I 63.0, I 63.1, I 63.2, I 63.3, I 63.4

Note: ICD-10 codes listed are included in outcomes cardiovascular-related hospitalization and in-hospital cardiovascular mortality. All other ICD-10 codes are included in non cardiovascular-related hospitalization and non cardiovascular-related mortality outcomes.

Table A2: First stage: event study estimates of the effect of appointment reminders on primary care visits among patients with type 2 diabetes

	Y = Primary Care Visit		
Specification	Compliance TWFE (1)	ITT TWFE (2)	ITT BJS (3)
Pre 4	0.059	0.068	–
	(0.033)	(0.034)	
Pre 3	-0.003	0.002	-0.061
	(0.025)	(0.024)	(0.032)
Pre 2	0.006	0.013	-0.039
	(0.013)	(0.010)	(0.038)
Pre 1	–	–	-0.042
			(0.041)
Post 0	0.013	0.018	0.022
	(0.025)	(0.010)	(0.012)
Post 1	0.062	0.030	0.038
	(0.025)	(0.012)	(0.014)
Post 2	0.085	0.047	0.052
	(0.027)	(0.014)	(0.017)
Post 3	0.076	0.044	0.040
	(0.026)	(0.015)	(0.017)
Post 4	0.072	0.044	0.038
	(0.024)	(0.016)	(0.017)
Post 5	0.068	0.040	0.030
	(0.026)	(0.016)	(0.017)
Post 6	0.025	0.011	0.017
	(0.030)	(0.018)	(0.020)
Pre-trends p-val	0.220	0.107	0.248
Mean dep. var.	0.653	0.654	0.654
Observations	442,322	442,322	442,225
Clinics	314	314	313

Note: This table presents event study estimates of the effect of appointment reminders on the probability of a patient-visit in a given semester. ITT stands for intent to treat, and BJS stands for Borusyak, Jaravel, and Spiess. The coefficients in column 1 were estimated using a two-way fixed effects DiD model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. The independent variable in columns 2 and 3 is an indicator equal to one in the semester of, and after a clinic implemented appointment reminders and zero otherwise. The coefficient in model 2 was estimated using a two-way fixed effects DiD model, and the coefficient in model 3 was estimated using the Borusyak, Jaravel, and Spiess (2021) estimator for staggered policy adoption. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level. Pre-trends p-val is from an joint F-test that all pre-reminder program coefficients are zero.

Table A3: Event study estimates of the effect of appointment reminders on primary care visits among patients with hypertension

	Y = Primary Care Visit		
Specification	Compliance TWFE (1)	ITT TWFE (2)	ITT BJS (3)
Pre 4	-0.023	-0.004	–
	(0.033)	(0.028)	
Pre 3	-0.024	-0.014	-0.019
	(0.028)	(0.025)	(0.029)
Pre 2	-0.003	0.015	0.024
	(0.017)	(0.011)	(0.023)
Pre 1	–	–	0.017
			(0.026)
Post 0	0.001	0.027	0.021
	(0.028)	(0.011)	(0.010)
Post 1	0.070	0.046	0.047
	(0.024)	(0.013)	(0.014)
Post 2	0.101	0.069	0.065
	(0.030)	(0.018)	(0.020)
Post 3	0.096	0.067	0.054
	(0.029)	(0.019)	(0.020)
Post 4	0.084	0.062	0.048
	(0.029)	(0.019)	(0.020)
Post 5	0.073	0.054	0.039
	(0.031)	(0.019)	(0.020)
Post 6	0.032	0.026	0.021
	(0.040)	(0.023)	(0.024)
Pre-trends p-val	0.610	0.083	0.034
Mean dep. var.	0.652	0.653	0.653
Observations	2,090,423	2,090,423	2,090,423
Clinics	310	310	310

Note: This table presents event study estimates of the effect of appointment reminders on the probability of a patient-visit in a given semester. ITT stands for intent to treat, and BJS stands for Borusyak, Jaravel, and Spiess. The coefficients in column 1 were estimated using a two-way fixed effects DiD model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. The independent variable in columns 2 and 3 is an indicator equal to one in the semester of, and after a clinic implemented appointment reminders and zero otherwise. The coefficient in model 2 was estimated using a two-way fixed effects DiD model, and the coefficient in model 3 was estimated using the Borusyak, Jaravel, and Spiess (2021) estimator for staggered policy adoption. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level. Pre-trends p-val is from an joint F-test that all pre-reminder program coefficients are zero.

Table A4: Heterogeneity in the effect of appointment reminders by semesters since diagnosis with type 2 diabetes or hypertension

	Visit (1)
Program Compliance	0.059 (0.023)
Semesters since diagnosis=0	Ref.
Semesters since diagnosis=1	-0.445 (0.010)
Semesters since diagnosis=2	-0.424 (0.009)
Semesters since diagnosis=3	-0.432 (0.010)
Semesters since diagnosis=4	-0.429 (0.011)
Semesters since diagnosis=5	-0.423 (0.012)
Semesters since diagnosis=6	-0.405 (0.013)
Semesters since diagnosis=7	-0.388 (0.014)
Semesters since diagnosis=8	-0.363 (0.016)
Semesters since diagnosis=9	-0.354 (0.018)
Semesters since diagnosis=0 × Program Compliance	Ref.
Semesters since diagnosis=1 × Program Compliance	0.012 (0.024)
Semesters since diagnosis=2 × Program Compliance	-0.004 (0.020)
Semesters since diagnosis=3 × Program Compliance	0.009 (0.022)
Semesters since diagnosis=4 × Program Compliance	0.015 (0.025)
Semesters since diagnosis=5 × Program Compliance	0.022 (0.027)
Semesters since diagnosis=6 × Program Compliance	0.021 (0.028)
Semesters since diagnosis=7 × Program Compliance	0.020 (0.031)
Semesters since diagnosis=8 × Program Compliance	0.016 (0.035)
Semesters since diagnosis=9 × Program Compliance	-0.005 (0.040)
Mean dep. var.	0.647
Observations	2,265,307
Clinics	315

Note: Table corresponds to figure 4, panel A.

Table A5: Heterogeneity in the effect of appointment reminders by age at diagnosis

	Visit (1)
Program Compliance	0.049 (0.024)
Age=40	Ref.
Age=50	0.031 (0.003)
Age=60	0.056 (0.004)
Age=70	0.074 (0.005)
Age=80	0.047 (0.008)
Age=40 × Program Compliance	Ref.
Age=50 × Program Compliance	0.026 (0.007)
Age=60 × Program Compliance	0.035 (0.008)
Age=70 × Program Compliance	0.017 (0.011)
Age=80 × Program Compliance	-0.008 (0.016)
Mean dep. var.	0.647
Observations	2,265,307
Clinics	315

Note: Table corresponds to figure 4, panel B.

Table A6: Heterogeneity in the effect of appointment reminders by hemoglobin A1c at diagnosis with type 2 diabetes

	Visit (1)
Program Compliance	0.060 (0.024)
Hemoglobin A1c=6	Ref.
Hemoglobin A1c=8	0.007 (0.004)
Hemoglobin A1c=10	-0.013 (0.005)
Hemoglobin A1c=12	-0.023 (0.006)
Hemoglobin A1c=14	-0.021 (0.008)
Hemoglobin A1c=16	-0.016 (0.012)
Hemoglobin A1c=6 × Program Compliance	Ref.
Hemoglobin A1c=8 × Program Compliance	0.004 (0.011)
Hemoglobin A1c=10 ×Program Compliance	-0.009 (0.013)
Hemoglobin A1c=12 ×Program Compliance	-0.008 (0.014)
Hemoglobin A1c=14 ×Program Compliance	-0.033 (0.021)
Hemoglobin A1c=16 ×Program Compliance	-0.033 (0.033)
Mean dep. var.	0.647
Observations	442,322
Clinics	314

Note: Table corresponds to figure 4, panel C.

Table A7: Heterogeneity in the effect of appointment reminders by systolic blood pressure at the time of diagnosis with hypertension

	Visit (1)
Program Compliance	0.068 (0.027)
Systolic BP=100	Ref.
Systolic BP=110	0.016 (0.005)
Systolic BP=120	0.016 (0.005)
Systolic BP=130	0.016 (0.005)
Systolic BP=140	0.008 (0.005)
Systolic BP=150	0.006 (0.005)
Systolic BP=160	-0.002 (0.006)
Systolic BP=170	-0.011 (0.006)
Systolic BP=180	-0.018 (0.006)
Systolic BP=190	-0.023 (0.007)
Systolic BP=200	-0.046 (0.008)
Systolic BP=100 × Program Compliance	Ref.
Systolic BP=110 × Program Compliance	0.007 (0.013)
Systolic BP=120 × Program Compliance	0.009 (0.012)
Systolic BP=130 × Program Compliance	0.006 (0.012)
Systolic BP=140 × Program Compliance	0.011 (0.012)
Systolic BP=150 × Program Compliance	-Ref. (0.013)
Systolic BP=160 × Program Compliance	-0.005 (0.014)
Systolic BP=170 × Program Compliance	-0.012 (0.014)
Systolic BP=180 × Program Compliance	-0.022 (0.016)
Systolic BP=190 × Program Compliance	-0.021 (0.017)
Systolic BP=200 × Program Compliance	-0.027 (0.019)
Mean dep. var.	0.647
Observations	1,964,313
Clinics	310

Note: Table corresponds to figure 4, panel D.

Table A8: Event study: Impact of appointment reminders on health monitoring

	Blood pressure test		Weighed		Blood sugar test
Patients:	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes
	(1)	(2)	(3)	(4)	(5)
Pre 4	0.042	-0.022	0.044	-0.024	0.049
	(0.034)	(0.032)	(0.040)	(0.032)	(0.031)
Pre 3	-0.003	-0.022	-0.008	-0.026	0.023
	(0.023)	(0.028)	(0.022)	(0.026)	(0.023)
Pre 2	0.006	-0.005	0.015	0.006	0.022
	(0.012)	(0.017)	(0.012)	(0.017)	(0.012)
Pre 1	-	-	-	-	-
Post 0	0.007	-0.002	0.019	0.005	0.014
	(0.025)	(0.028)	(0.026)	(0.028)	(0.024)
Post 1	0.052	0.066	0.055	0.065	0.045
	(0.025)	(0.023)	(0.024)	(0.023)	(0.027)
Post 2	0.078	0.101	0.087	0.102	0.072
	(0.027)	(0.030)	(0.027)	(0.030)	(0.028)
Post 3	0.065	0.090	0.067	0.086	0.052
	(0.025)	(0.028)	(0.028)	(0.030)	(0.028)
Post 4	0.062	0.084	0.072	0.082	0.040
	(0.023)	(0.028)	(0.026)	(0.029)	(0.026)
Post 5	0.059	0.071	0.061	0.067	0.042
	(0.025)	(0.030)	(0.028)	(0.031)	(0.028)
Post 6	0.020	0.029	0.022	0.027	0.015
	(0.029)	(0.039)	(0.033)	(0.040)	(0.031)
Observations	442,322	2,090,423	442,322	2,090,423	442,322
Clinics	314	310	314	310	314
Mean Y | Pr(SMS)=0	0.621	0.621	0.610	0.610	0.562
Pre-trends p-value	0.507	0.713	0.315	0.195	0.244

Note: Event study estimates of the impact of appointment reminders on health monitoring (estimated using two-way fixed effects and equation 1). Standard errors, clustered at the clinic level are shown in parentheses, and p-values are shown in brackets. Table corresponds to figure 5.

Table A9: Event Study: Impact of appointment reminders on medication outcomes

	Any medication refill		Medication adherence $\geq$ 80%	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Pre 4	-0.016	0.018	0.003	0.003
	(0.080)	(0.062)	(0.007)	(0.006)
Pre 3	-0.090	-0.074	-0.006	-0.011
	(0.036)	(0.028)	(0.007)	(0.005)
Pre 2	-0.066	-0.057	-0.004	-0.008
	(0.019)	(0.021)	(0.006)	(0.004)
Pre 1	-	-	-	-
Post 0	0.064	0.057	0.014	0.011
	(0.046)	(0.045)	(0.012)	(0.009)
Post 1	0.081	0.085	0.016	0.016
	(0.026)	(0.026)	(0.009)	(0.007)
Post 2	0.079	0.090	0.013	0.009
	(0.030)	(0.026)	(0.008)	(0.006)
Post 3	0.054	0.057	0.012	0.006
	(0.029)	(0.024)	(0.009)	(0.006)
Post 4	0.037	0.043	0.004	0.005
	(0.027)	(0.022)	(0.007)	(0.005)
Post 5	0.017	0.030	0.008	0.009
	(0.033)	(0.030)	(0.009)	(0.007)
Post 6	-0.074	-0.076	-0.003	0.000
	(0.037)	(0.035)	(0.009)	(0.007)
Observations	239,626	1,102,554	239,626	1,102,554
Clinics	312	309	312	309
Mean Y | Pr(SMS)=0	0.292	0.292	0.027	0.027
Pre-trends p-value	0.000	0.000	0.400	0.005

Note: Event study estimates of the impact of appointment reminders on medication outcomes (estimated using two-way fixed effects and equation 1). Standard errors, clustered at the clinic level are shown in parentheses, and p-values are shown in brackets. Table corresponds to figure 6.

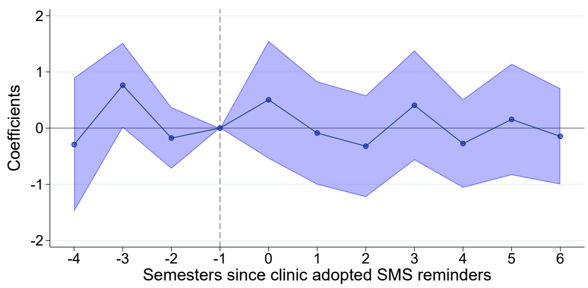
Table A10: Event Study: Impact of appointment reminders on cardiovascular hospitalizations

	Cardiovascular hospitalization (per 100)		Log days CV hospitalization		In-hospital CV mortality (per 100)	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)	(5)	(6)
Pre 4	-0.476	-0.248	-0.104	0.020	-0.015	-0.007
	(0.309)	(0.161)	(0.146)	(0.112)	(0.048)	(0.010)
Pre 3	0.205	0.036	-0.225	-0.069	0.088	0.001
	(0.226)	(0.095)	(0.140)	(0.076)	(0.052)	(0.010)
Pre 2	0.063	-0.092	0.048	-0.001	-0.006	-0.013
	(0.191)	(0.063)	(0.119)	(0.060)	(0.034)	(0.008)
Pre 1	-	-	-	-	-	-
Post 0	-0.320	-0.072	0.111	0.204	-0.120	-0.054
	(0.336)	(0.125)	(0.212)	(0.105)	(0.043)	(0.016)
Post 1	0.185	0.167	0.045	0.076	-0.045	-0.022
	(0.288)	(0.108)	(0.174)	(0.096)	(0.055)	(0.020)
Post 2	0.366	0.225	0.005	0.014	-0.079	0.009
	(0.299)	(0.111)	(0.158)	(0.097)	(0.039)	(0.018)
Post 3	0.416	0.243	-0.054	-0.017	-0.052	-0.004
	(0.296)	(0.112)	(0.154)	(0.094)	(0.046)	(0.019)
Post 4	0.646	0.210	-0.027	-0.053	-0.069	-0.038
	(0.238)	(0.104)	(0.131)	(0.088)	(0.040)	(0.015)
Post 5	0.186	0.128	-0.090	0.015	-0.062	-0.013
	(0.279)	(0.112)	(0.159)	(0.096)	(0.043)	(0.019)
Post 6	0.527	0.210	-0.235	-0.151	-0.061	-0.021
	(0.272)	(0.113)	(0.142)	(0.095)	(0.040)	(0.017)
Observations	442,322	2,090,423	7,510	24,053	442,322	2,090,423
Clinics	314	310	291	305	314	310
Mean Y | Pr(SMS)=0	1.146	1.146	1.861	1.861	0.039	0.039
Pre-trends p-value	0.200	0.279	0.195	0.760	0.288	0.278

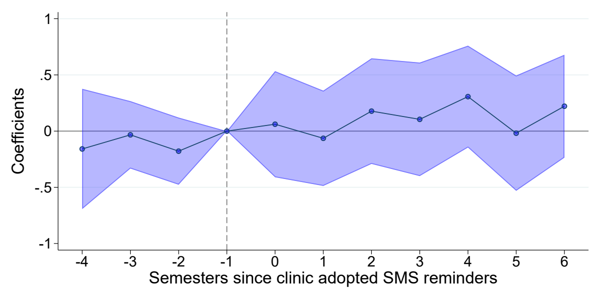
Note: Event study estimates of the impact of appointment reminders on CV hospitalizations (estimated using two-way fixed effects and equation 1). Standard errors, clustered at the clinic level are shown in parentheses, and p-values are shown in brackets. Table corresponds to figure 7.

Figure A1: Event study estimates of the impact of appointment reminders on non-cardiovascular hospitalisation

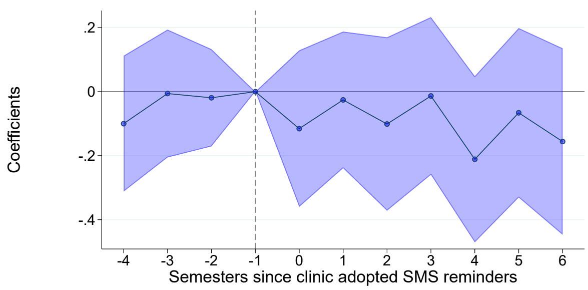
(a) Non-CV hospitalization (DM2)



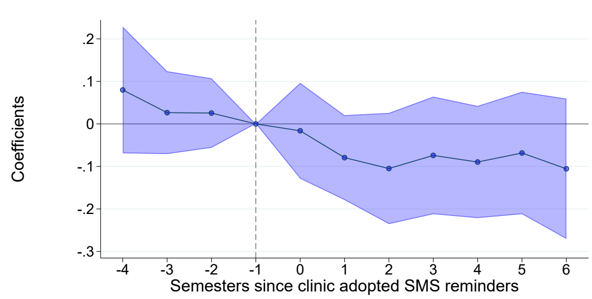
(b) Non-CV hospitalization (HTN)



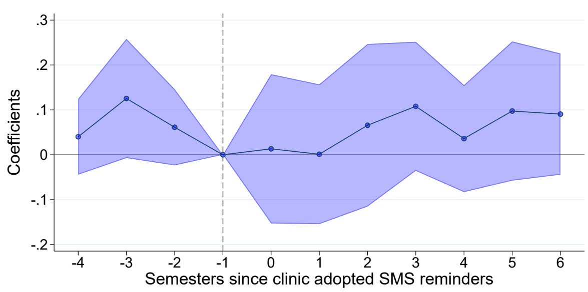
(c) Log days non-CV hospitalization (DM2)



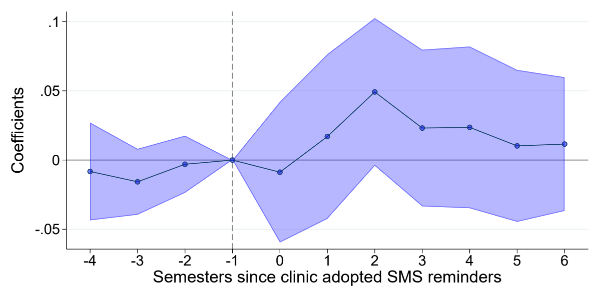
(d) Log days non-CV hospitalization (HTN)



(e) In-hospital non-CV mortality (DM2)



(f) In-hospital non-CV mortality (HTN)



Note: Figures show regression estimates based on equation 1. The shaded areas denote 95% confidence intervals. The x-axis is number of semesters until or since the clinic implemented appointment reminders. Estimated using a two-way fixed effects event study model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level.

Table A11: Event Study: Impact of appointment reminders on non-cardiovascular hospitalizations

	Non-cardiovascular hospitalization (per 100)		Log days non-CV hospitalization		In-hospital non-CV mortality (per 100)	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)	(5)	(6)
Pre 4	-0.293	-0.159	-0.100	0.080	0.040	-0.008
	(0.605)	(0.272)	(0.108)	(0.076)	(0.043)	(0.018)
Pre 3	0.763	-0.033	-0.006	0.026	0.125	-0.016
	(0.383)	(0.152)	(0.101)	(0.049)	(0.067)	(0.012)
Pre 2	-0.176	-0.178	-0.019	0.026	0.061	-0.003
	(0.278)	(0.152)	(0.077)	(0.042)	(0.043)	(0.010)
Pre 1	-	-	-	-	-	-
Post 0	0.504	0.061	-0.116	-0.016	0.013	-0.009
	(0.532)	(0.240)	(0.124)	(0.057)	(0.084)	(0.026)
Post 1	-0.087	-0.064	-0.026	-0.079	0.001	0.017
	(0.467)	(0.215)	(0.108)	(0.051)	(0.079)	(0.030)
Post 2	-0.321	0.178	-0.101	-0.105	0.066	0.049
	(0.460)	(0.239)	(0.138)	(0.066)	(0.092)	(0.027)
Post 3	0.406	0.105	-0.014	-0.074	0.108	0.023
	(0.496)	(0.257)	(0.125)	(0.070)	(0.073)	(0.029)
Post 4	-0.275	0.307	-0.211	-0.090	0.036	0.024
	(0.400)	(0.230)	(0.132)	(0.067)	(0.061)	(0.030)
Post 5	0.155	-0.018	-0.066	-0.068	0.097	0.010
	(0.503)	(0.261)	(0.134)	(0.073)	(0.079)	(0.028)
Post 6	-0.146	0.222	-0.156	-0.106	0.091	0.012
	(0.434)	(0.233)	(0.148)	(0.084)	(0.069)	(0.025)
Observations	442,322	2,090,423	18,980	82,704	442,322	2,090,423
Clinics	314	310	309	310	314	310
Mean Y | Pr(SMS)=0	3.783	3.783	1.324	1.324	0.096	0.096
Pre-trends p-value	0.179	0.708	0.833	0.746	0.147	0.091

Note: Event study estimates of the impact of appointment reminders on non-CV hospitalizations (estimated using two-way fixed effects and equation 1). Standard errors, clustered at the clinic level are shown in parentheses, and p-values are shown in brackets. Table corresponds to figure A1.

Table A12: Impact of appointment reminders and visits on non-cardiovascular hospitalizations

	Non-cardiovascular hospitalization (per 100)		Log days non-CV hospitalization		In-hospital non-CV mortality (per 100)	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Reduced form: impact of appointment reminders						
Program Compliance	0.053	0.221	-0.093	-0.093	0.013	0.021
	(0.368)	(0.191)	(0.099)	(0.061)	(0.042)	(0.017)
	[0.885]	[0.249]	[0.348]	[0.125]	[0.754]	[0.204]
Panel B. Indirect least squares: impact of primary care visit						
Visit	0.940	3.137	12.894	-1.422	0.230	0.302
	(6.440)	(2.982)	(58.520)	(0.987)	(0.740)	(0.259)
	[0.884]	[0.294]	[0.826]	[0.151]	[0.756]	[0.245]
AR CI	[-22.35, 17.36]	[-2.70, 14.63]	NA	[-5.81, 0.51]	[-1.83, 2.64]	[-0.17, 1.36]
AR p-val	0.885	0.264	0.352	0.133	0.755	0.204
Observations	442,322	2,090,423	18,980	82,704	442,322	2,090,423
Clinics	314	310	309	310	314	310
Mean Y — Pr(SMS)=0	4.226	3.753	1.479	1.309	0.153	0.089
Mean Y — Visit=0	4.895	4.583	1.600	1.432	0.309	0.213
First stage F-stat	6.305	7.697	0.053	6.783	6.305	7.697

Note: Panel A presents difference-in-differences (DiD) estimates of the effect of appointment reminder program compliance on the probability of hospitalization outcomes. DiD models estimated using a two-way fixed effects DiD model where the independent variable is clinic-semester compliance with the reminder program for treated clinics, and zero for control clinics. Compliance is the share of a clinic's eligible patients sent an SMS reminder in a given semester. Panel B presents instrumental variables estimates of the effect of a primary care visit on hospitalizations. Anderson-Rubin (AR) confidence intervals and p-value are presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, 2-year age, and male. Robust standard errors are clustered at the clinic level. Log length of hospital stay is conditional on any CV hospitalization in a given semester.

Table A13: Testing the equality of regression coefficients: impact of appointment reminders among type 2 diabetes patients vs. hypertension patients

Outcome	**F stat**	**P-val**
Visit	0.47	0.63
Blood pressure test	5.49	0.00
Weighed	3.66	0.03
Blood sugar test	-	-
Any medication refill	46.82	0.00
Medication adherence	25.60	0.00
Cardiovascular hospitalization	208.20	0.00
Log days cardiovascular hospitalization	32.64	0.00
In-hospital cardiovascular mortality	12.78	0.00
Non-cardiovascular hospitalization	74.20	0.00
Log days non-cardiovascular hospitalization	147.84	0.00
In-hospital non-cardiovascular mortality	61.00	0.00

Note: F-statistics and p-values from tests of whether the effect of appointment reminders is equivalent among patients with type 2 diabetes vs. those with hypertension. Only patients with type 2 diabetes recieve blood sugar tests, so no values are included here. A p-value <0.05 indicates we reject the null hypothesis that the two regression coefficients are equal.

A.1 Chile's Cardiovascular Health Program

In line with international recommendations, Chile's public healthcare system integrated care for patients with hypertension and type 2 diabetes in 2002, resulting in the creation of the Cardiovascular Health Program (PSCV for its acronym in Spanish: Programa Salud Cardiovascular) for in primary care. The primary objectives of the PSCV are to prevent and reduce morbidity, disability, and premature mortality associated with cardiovascular diseases, as well as to prevent complications arising from type 2 diabetes. This program focuses on assessing the overall cardiovascular risk in individuals, rather than considering risk factors separately. To determine patients' cardiovascular risk the PSCV utilizes the Framingham Tables (see Hemann, Bimson, and Taylor 2007), adapted to the Chilean population. Patients are eligible if they meet at least one of the following criteria:

1. Personal history of atherosclerotic cardiovascular disease, including coronary artery disease, cerebrovascular disease, peripheral arterial disease, atherosclerotic aortic disease, renovascular disease, and carotid disease.
2. High blood pressure: defined, for individuals aged 15 and above as systolic blood pressure $\geq$140 mmHg and/or a diastolic blood pressure $\geq$90 mmHg.
3. Type 2 Diabetes Mellitus: defined as venous glycemia >200 mg/dl at any time, two consecutive 8-hour fasting venous glycemia readings $\geq$126 mg/dl, or blood glucose $\geq$200 mg/dL two hours after a 75g oral glucose load.
4. Dyslipidemia: defined as total cholesterol $\geq$240 mg/dl and LDL cholesterol $\geq$160 mg/dl.
5. Smoking: defined as individuals aged 55 and above who currently smoke tobacco.

For individuals who don't meet the admission criteria but have other risk factors, such as high blood pressure (but not above 140/90 mmHg), pre-diabetes, metabolic syndrome, obesity or overweight, and risky alcohol consumption, annual check-ups, education on healthy lifestyles, and referral to the Vida Sana Program (a preventative and healthy lifestyle program in the public health care system) is recommended.