The Importance of Preventive Medical Care for Managing Chronic Disease

Claire Boone, Pablo Celhay, Paul Gertler, Tadeja Gracner*

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Abstract

We study how preventive medical care use affects health behaviors and outcomes for patients with chronic diseases. Leveraging variation induced by a national appointment reminder program, rolled out across 315 public primary care clinics in Chile, we use an instrumental variables approach with patient-level administrative data from over 300,000 patients with type 2 diabetes or hypertension. We find that increased preventive visits lead to more screening tests and large increases in medication adherence. Preventive care also leads to earlier detection and treatment of cardiovascular complications; we document an increase in cardiovascular hospitalizations but a reduction in in-hospital mortality.

JEL codes: I12, I18

*Boone: McGill University (email: claire.boone@mcgill.ca). Celhay: Escuela de Gobierno and Instituto de Economía, Pontificia Universidad Católica de Chile (email: pacelhay@uc.cl). Gertler: University of California, Berkeley and NBER (email: gertler@berkeley.edu). Gracner: University of Southern California (email: gracner@usc.edu). We are grateful to The Division of Primary Care at Chile's Ministry of Health, and in particular to Irma Vargas and Ximena Barros-Rubio for their expertise, suggestions, and feedback. We thank Priyanka Taneja, Madhav Nekkar, and Emma Sun for the outstanding research assistance. We thank Stefano Bertozzi, Cristóbal Otero and Becky Staiger for the helpful comments. We gratefully acknowledge research support from UC Berkeley's Center on the Economics and Demography of Aging - NIH 2P30AG012839 and the National Institute On Aging (NIA) of the National Institutes of Health (NIH) under Award Number R01AG065482. Claire Boone was supported by the Tinker Foundation, UC Berkeley's Institute for International Studies, the Center for Global Public Health, and the NIH NIA under grant award T32 AG000243 (PI: David Meltzer, MD, PhD). Pablo Celhay gratefully acknowledges financial support from ANID, FONDECYT Regular 1250440, 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 NIH/NIA. The authors declare that they have no financial or material interests in the results of this study.

I Introduction

Chronic diseases such as hypertension and type 2 diabetes are major drivers of excess mortality and health care spending, particularly among older adults (Egan et al. 2019; Piper et al. 2015). Monitoring disease status during regular preventive medical care visits with screening tests, such as blood pressure and blood glucose measurement, paired with timely treatment and behavior change, can improve disease control and reduce complications (Bodenheimer et al. 2002). Preventive medical care visits also facilitate earlier detection of complications, allowing providers to share critical information, initiate appropriate treatment, and make timely referrals to specialty care that can prevent adverse outcomes. However, many patients do not receive these benefits because they do not attend preventive care appointments; approximately 15 to 30% of these appointments are missed and sicker patients are more likely to miss them (Parsons, Bryce, and Atherton 2021; Brewster et al. 2020).

We study the effect of preventive medical care on disease monitoring and subsequent patient behavior. Specifically, we ask (1) whether patients who attend preventive care receive appropriate screening tests – a measure of the performance of their healthcare providers; (2) whether preventive care impacts patient medication adherence – a measure of patient behavior; and (3) whether preventive care leads to detection and better treatment of chronic disease complications, specifically hospitalization and in-hospital mortality for cardiovascular conditions.

The study setting is Chile's public health care system, comparable to the UK's National Health Service, that provides care to over 80% of the population (FONASA 2018). Chile provides a unique opportunity to assess how preventive care improves the management of chronic diseases at scale as the study population includes all patients recently diagnosed with diabetes or hypertension in the public health care system. The analysis sample is a panel of 316,994 newly diagnosed patients followed up to 4.5 years after diagnosis from 315 public clinics. The utilization and testing data are from electronic health records (EHR) and include 2,265,307 visits from 316,994 patients. We link EHR data at the individual level to two other administrative databases: (i) prescription and refill data from the universe of pharmacies and (ii) hospitalizations and in-hospital mortality by cause from the universe of hospitals.

We identify the effects of preventive care visits using plausibly exogenous variation in atten-

dance induced by an appointment reminder program.[1] The scale up of the reminder program was imperfect. Not all clinics adopted the reminder system. Adoption was largely driven by the technical readiness of staff to be able to enable and supervise the module, and managerial prioritization;local administrators who valued reducing no-shows and improving schedule management tended to activate earlier. Among clinics that adopted the program, the percentage of eligible appointments that sent a reminder was less than 100% due to routine operational frictions such as keeping phone numbers up to date, staff learning to monitor the module, and adjustments to scheduling workflows.

In our identification strategy, the instrument is clinic-level compliance, measured as the share of eligible patients who received a reminder, that is, the probability of being sent a reminder of an appointment. Multiple lines of evidence suggest compliance is plausibly exogenous. First, program adoption is not correlated with a large number of clinic-level characteristics, including patient health and volume measures at baseline, both individually and jointly. Second, changes in compliance over time are not correlated with changes in patient characteristics over time. Third, reminders significantly increased preventive care visits by 11% for patients with diabetes and 15% for patients with hypertension. Fourth, the effectiveness of the reminders persisted over time and did not vary by baseline patient health status. Finally, the reminder system did not induce less healthy patients to move to clinics that adopted the program because patients are administratively assigned to a single primary-care clinic based on residence.

We find that preventive visits increase disease screening and monitoring. An additional visit leads to near-universal increases in blood pressure testing (87pp for type 2 diabetes patients, 98pp for hypertension patients) and weight measurement (89pp and 93pp respectively), plus a 57pp increase in blood glucose testing among type 2 diabetes patients. These magnitudes indicate strong provider adherence to clinical guidelines that require these tests at each preventive visit, or frequently in the case of blood glucose measurment.

Visits also lead to a large increase in adherence to medication prescription, as measured by pharmacy refills. Nearly all patients who had a preventive visit filled their prescription. An ad-

[1] In (Boone et al. 2022), we examined the reminder system from a clinic-efficiency perspective, asking whether clinics expanded effective capacity after implementation. We found that integration of an automatic appointment reminder program increased clinics' ability to care for more patients, likely due to timely cancellations and rescheduling.

ditional preventive care visit is associated with a 39 pp increase in medication adherence and a 16pp increase in clinically adequate medication adherence (80%). Adherence to medication prescription is an important outcome as it is the primary therapy for controlling chronic disease for most patients.

Adherence is primarily a patient behavior, one that is typically challenging to change. It is a major problem in Chile as only 30% of patients in clinics without the reminder system filled their prescriptions and is in line with the US experience. For all conditions, 39% of new prescriptions among Medicare Part D patients were never filled (Dusetzina et al. 2022). Even highly effective, clinically necessary medications have high non-initiation rates; 21% for hepatitis C treatments and 67% for hypercholesterolemia drugs (Dusetzina et al. 2022). Likewise, among patients prescribed medications after a recent heart attack, a very salient and medically necessary treatment, only 12% achieved adequate adherence at a PDC level of 80% (Choudhry et al. 2011).

Finally, among patients with type 2 diabetes, preventive care increases cardiovascular hospitalizations (5.5 per 100 patients per semester) but reduces in-hospital cardiovascular deaths (1.0 fewer per 100 patients per semester). This reduction in mortality is consistent with evidence that elevated glucose upon hospital admission increases infections, complications, and mortality (Pasquel et al. 2021; Sharif et al. 2019; Klonoff et al. 2020). Preventive care likely operates through improved glucose control via disease monitoring and medication adherence, helping patients achieve the glycemic targets that enhance hospital care effectiveness during acute events.[2] Among hypertension patients, preventive care increases hospitalizations without reducing mortality. While well-controlled blood pressure has clear long-term health benefits (Mancia and Kjeldsen 2024), the implications on the effectiveness of inpatient treatment are less clear because blood pressure is highly variable and elevated in stressful settings like the hospital (Jacobs and Anderson 2024). The American Heart Association recommends avoiding reflexive treatment of elevated inpatient blood pressure and instead focus on long-term management (Bress et al. 2024).

One likely pathway for preventive care to increase hospitalization rates is through patient education during the preventive visit covering both personal behavioral health (e.g. diet, exercise, and medication adherence) and symptoms of complications for which patients should seek curative

[2]The American Diabetes Association recommends specific glycemic control targets that improve the effectiveness of hospital care when acute events occur.

care and treatment. Indeed, this patient education is mandated in the clinical practice guidelines for preventive visits for chronic disease patients.

On the other hand, it is also possible that preventive visits induce unnecessary or low-value hospitalizations of healthier patients. In this case, an alternative interpretation of the decrease in in-hospital mortality is due to the selection of patients that are less likely to die to be admitted to the hospital. We conduct a number of analyses to investigate the selection mechanism and conclude that selection is unlikely to explain the mortality results.

Our findings contribute to a small literature on the causal impact of preventive medical care for chronic disease patients. The Oregon Health Insurance Experiment found that the expansion of Medicaid coverage increased the probability of a diabetes diagnosis, however, unlike our context, this did not appear to translate into increased use of preventive services (Baicker et al. 2013). Similarly, Allen and Baicker (2021) show no effect of expanded coverage on diabetes patients receiving recommended preventive care screenings such as blood sugar tests, but more recent work shows benefits for some patient subpopulations (Inoue et al. 2024).

This paper also contributes to the literature on the causal impact of medical care, where identification is difficult because utilization is endogenous to prior health care use and diagnoses (Levy and Meltzer 2008). We address this challenge by leveraging a novel source of plausibly exogenous variation in utilization induced by appointment reminders, which allows us to isolate the effect of preventive care on downstream outcomes. This approach differs from most prior work, which identifies causal effects through changes in insurance coverage or patient cost-sharing (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. 2022; Aron-Dine, Einav, and Finkelstein 2013; King et al. 2009; Bradley, Neumark, and Walker 2018).

Our finding that preventive care is associated with an increase in hospitalizations is in line with the existing literature studying the causes and effects of health care use. Notably, both the Oregon and RAND health insurance experiments found that reducing the price of care through insurance led to an increased use of both primary and hospital care (Baicker et al. 2013; Taubman et al. 2014; Finkelstein et al. 2012; Manning 1987). In Oregon, the increase in hospitalizations was driven by hospital admissions not originating in the emergency department, i.e. referrals (Finkelstein et al. 2012). Similar findings have been reported in several studies using the expansion of Medicare and

Medicaid in the United States as instruments(Card, Dobkin, and Maestas 2009; Card, Dobkin, and Maestas 2008; Miller, Johnson, and Wherry 2021; Goldin, Lurie, and McCubbin 2021), and in a randomized experiment that provided cash incentives for primary care visits in a low-income US population. (Bradley, Neumark, and Walker 2018). Related, Sabety et al. 2023 show that randomly making primary care appointments for undocumented immigrants reduced emergency care use.

Our results also contribute to the therapy compliance literature. Taking medication regularly following prescriptions 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 response, a vast array of interventions to improve medication adherence have been tested. Many have been successful (e.g., Dai et al. 2017; Stecher, Mukasa, and Linnemayr 2021), but they are often complex and high-cost (Kini and Ho 2018). We contribute to this literature by demonstrating the extent to which medication adherence can be improved by simply increasing preventive care appointment compliance.

Finally, we contribute to evidence on mobile health effectiveness. Across randomized and quasi-experimental studies, SMS reminders generally increase screening, vaccination, and appointment adherence, though effects vary by setting and population (Busso, Cristia, and Humpage 2015; Gallegos et al. 2023; Gurol-Urganci et al. 2013). Individual studies range from null or small effects to sizable gains when timing and message framing are optimized.[3] We move beyond trial efficacy by exploiting a natural experiment from routine operations that captures real-world frictions —contactability/deliverability, send schedules, appointment supply, and concurrent channels. The resulting estimates are externally valid (often smaller than trial effects) and directly informative for scale-up and budgeting. The design and the length of follow-up also allow us to study what happens after the reminder (e.g., downstream health-service use), complementing recent program-scale evidence in related settings (Anderson, Dobkin, et al. 2025).

[3]Some studies include Bellucci et al. (2017), Bos, Hoogstraten, and Prahl-Andersen (2005), Clough and Casey (2014), Altuwaijri et al. (2012), Arora et al. (2015), Baker et al. (2015), Bangure et al. (2015), Berenson et al. (2016), Bourne et al. (2011), Branson, Clemmey, and Mukherjee (2013), and Hallsworth et al. (2015). For cancer screening see, for instance, Hirst et al. (2017), Kerrison et al. (2015), and Huf et al. (2020). For vaccination uptake see, for instance, Patel et al. (2022) and Regan et al. (2017). For pediatrics and primary care, see, for instance, Liew et al. (2009) and Lin et al. (2016).

II Institutional Context

Chile is a high-income country with a GDP per capita of approximately USD 17,000 and a highly educated population with a tertiary educational attainment rate of 45% for women and 37% for men (Bank 2025; OECD 2024).

II.A Health Care System

Chile has two health care systems: (i) a public system used by more than 80% of the population funded by a mandatory 7% tax on earnings and general taxes; and (ii) a private system used by the rest of the population (Goic 2015). All residents are registered in the public system by default but can opt out by purchasing private insurance. The public system guarantees access to low-cost care for all residents, and patients cannot choose where to get their services, but are administratively assigned to a single primary care clinic based on their place of residence. The public system operates as a gatekeeper model in which patients are required to first visit a general practitioner at their assigned clinic before receiving prescriptions, referrals to specialists and care in more advanced facilities.

II.B Chronic Disease Management

Chile has a high burden of chronic disease. In 2017, an estimated 57% of the population was living with at least one chronic condition; 27.6% had hypertension and 9.5% had type 2 diabetes, rates similar to those in other high-income countries such as the United States (Lanas et al. 2020; Ostchega and Nguyen 2020; Margozzini and Passi 2018). Patients with chronic diseases account for a large share of health care use, consuming 84% of health care resources (MINSAL 2017a; Martinez et al. 2019).

At the time of diagnosis with a chronic condition, including type 2 diabetes and hypertension, patients are automatically enrolled in a cardiovascular care program called PSCV (*Programa de Salud Cardiovascular*).[4] This program makes them eligible for prioritized and free care, the ability to schedule primary and preventive care appointments in advance and receive appointment re-

[4]See appendix A.1 for further details.

minders.[5] Because PSCV patients are closely monitored, there is high-quality administrative data on their healthcare utilization.

II.C Appointment Reminder Program

Patients with chronic disease miss a large number of appointments; 16.7% of scheduled appointments were missed in 2018 (Boone et al. 2022), which cost Chile approximately 180 million USD annually (Contreras 2022). Reasons for missing appointments typically 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 are a promising strategy to reduce no-shows and encourage recurring, timely preventive care visits (Jongh et al. 2012; Hamine et al. 2015; Liew et al. 2009; Leong et al. 2006).

In an effort to reduce the number of missed appointments, the Chilean Ministry of Health (MOH) offered public clinics that already used an electronic medical record (EMR) the option of adopting an automated appointment reminder system. The appointment-reminder software was integrated into the clinic's EMR system and relies on the EMR's scheduling data to trigger messages to patients prior to appointments. Due to the availability of the MOH supported reminder system, clinics did not implement their own systems.

Reminders were sent to patients enrolled in the PSCV program and provided them with the ability to confirm, cancel, or change appointment times.[6] Reminders were automatically sent 24 to 72 hours before the appointment. The system first tried to send a text message (SMS). If the patient did not respond, the system then sent an email. Finally, if the patient did not respond to SMS or email, a voice call was made. If they did not reply to any of the messages with a confirmation or cancellation, the appointment was kept.

The appointment reminder system was rolled out between 2015 and 2018 with 83% of the take-up occurring in the first year. Of the 315 clinics in our sample, 172 adopted the program in 2015, increasing to 208 by the end of the study period (Figure 1 panel A). The adoption was likely driven by the technical readiness of staff to be able to enable and monitor the system and managerial

[5] Appointments for Non-PSCV patients are on a first-come, first-serve basis and they do not receive appointment reminders.

[6] The reminder message was as follows, in Spanish: *"Dear [Patient Name], this is a reminder that you have a medical appointment on day [date of appointment] at [time] hours at [clinic name] with the doctor [name of the doctor]. Do you confirm your time? Yes/No"*.

prioritization of reducing no-shows and improving schedule management tended to activate earlier.[7]

Activation of the system did not translate into comprehensive reminder delivery. Routine data quality and operational frictions prevented achieving 100% compliance (percentage sent reminders). These frictions include keeping phone numbers current, monitoring system performance, and scheduling workflows. The frictions only gradually decreased as facilities cleaned phone registries and stabilized processes.[8] Compliance ranged from 0 to 90% in adopter clinics in any given year and increased over time as processes stabilized (Panel (a) of Figure 1); Average compliance increased from 47% in 2016 to 55% in 2017 and 56% in 2018.

To document these dynamics, we estimate an event-study of the probability that clinic j in semester t sent an appointment reminder. Specifically, we estimate the following specification:

$$\Pr(\text{Reminder})_{jt} = \sum_{s=-4}^{6} \beta_s \cdot D_{jst} \; + \; \lambda_t \; + \; \gamma_j \; + \; \varepsilon_{jt}, \tag{1}$$

where $\Pr(\text{Reminder})_{jt}$ is the probability that a patient assigned to clinic j was sent a reminder in semester t; it is equal to zero for clinics that did not adopt the program and for clinics that did adopt, before adoption. D_{jst} are binary indicators that equal to one if clinic j is s periods away from the period of adoption in period t. We exclude $D_{j,s=-1,t}$ from the regression so that each β_s is the difference at each semester t in the probability of receiving a reminder with respect to the semester before adoption. Finally, λ_t and γ_j are semester and clinic fixed effects while ε_{jt} are unobserved random shocks that change over time within clinics.

The results, presented in panel (b) of Figure 1, show a discrete jump at the time of activation and then a monotonic increase thereafter within clinics, consistent with gradual operational scaling rather than abrupt targeting or compositional shifts. The results show that the variation in our instrument arises from (i) the clinic's adoption decision (extensive margin) and (ii) the time-varying within-clinic compliance (intensive margin). Crucially, neither margin is explained by patient self-selection of clinics or selective enrollment of PSCV patients; patients are administratively assigned to a single primary-care clinic by residence, and PSCV enrollment follows from diagnosis.

[7] These same bottlenecks, staff capabilities and managerial preferences, have limited the adoption of other mHeath technologies (Posadzki et al. 2016; Szilagyi et al. 2006; Leon, Schneider, and Daviaud 2012).

[8] Contact data quality and workflow integration frictions have limited the use of other mHealth technologies (Posadzki et al. 2016; Szilagyi et al. 2006; Leon, Schneider, and Daviaud 2012.)

III Data

III.A Electronic Medical Records

We use patient-level information from electronic health records (EHR) provided by the Division of Primary Care at Chile's Ministry of Health. The EHR data covers all visits from PSCV patients and contain a unique patient identifier, patient-level demographic information, and for each visit a unique clinic identifier, laboratory and other tests, test results, and new diagnoses for the period from January 1 2013 through December 31 2018. We use these data to construct binary indicators for if the patient received recommended preventive care in a given semester (6-month period): a preventive care visit, and if tests measuring blood pressure, weight, and blood glucose were performed.

III.B Medication Records

Information on medication prescribed and dispensed is available in administrative records from pharmacies. These records contain a unique pharmacy identifier, a unique patient identifier, prescription date, prescribed medication name, number of units prescribed, and date of medication pick-up.

Medication adherence is measured using the proportion of days covered (PDC), a standard metric in the medical literature (Osterberg and Blaschke 2005), with PDC$\geq$80% typically defined as the clinically meaningful adherent level (Kini and Ho 2018) We calculate PDC from prescription refill data: using the prescription quantity and refill dates, we infer the number of days the patient lacked sufficient medication and then compute the share of days in each semester during which the patient had enough pills to adhere to the prescription. A patient who refills on time has 100% of days covered, whereas delayed refills reduce PDC.[9] We create outcomes for the extensive margin: whether the patient filled any prescription at the pharmacy, and the intensive margin: continuous PDC, and also construct an indicator equal to one if the patient had adequate medication for at least 80% of days in the semester. These measures implicitly assume that patients take the

[9]We assume that patients with a prescribed medication at the time they were diagnosed with their chronic condition should have some active prescription going forward. Table 1 shows this is balanced between groups. This allows us to assign a PDC value of zero to patients who do not fill any prescriptions in a given semester. Medication de-prescription can occur if a patient regularly attends primary care visits and achieves substantial lifestyle improvements, but this is exceedingly rare (Oster 2018).

medication during days when they have pills available.

Medication adherence can only be calculated among patients with a prescription. 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 1 shows that the prescribing rates at patients' diagnostic visit are statistically indistinguishable between the clinics that did vs. did not implement the appointment reminder program.

III.C Hospital Admission Records

Hospital admission records include all in-patient stays (admitted and stayed at least one day in the hospital) for the universe of patients at both public and private hospitals in Chile from 2013-2018. We link these records to the EHR and medication datasets at the patient level. The data include a unique patient identifier, a unique hospital identifier, admission dates, ICD-10 codes for the primary and secondary diagnoses, and an indicator for whether the patient died in the hospital with diagnostic codes for cause of death. Importantly, because these records contain the universe of hospitalizations in Chile at both public and private hospitals, and patients will appear in these records whether they attended primary care or not, our hospitalization measures are not endogenous to primary care utilization. We do not observe the mode of arrival (e.g., walk-in vs. referral) and do not have emergency department visit records.

We classify hospitalizations as cardiovascular-related or non–cardiovascular-related using ICD-10 primary and secondary diagnostic codes. We follow the Framingham study's definition of cardiovascular disease (Kannel, McGee, and Gordon 1976; Wallisch et al. 2020), and add hospitalizations coded directly as related to type 2 diabetes or hypertension (see Table A1 for the classification of ICD-10 codes). Cardiovascular codes include hospitalizations for stroke, heart attack, heart failure, or other complications related to type 2 diabetes or hypertension (see and Table A2 for counts) (Luengo-Fernandez et al. 2023; Khokhar et al. 2016; Beckman 2014). All other codes are classified as non-cardiovascular hospitalization, which include diagnoses such as accidents, infectious diseases, and mental health concerns. We use non-cardiovascular hospitalizations as placebo outcomes as they should be unaffected by the management of chronic conditions.

For each group of hospitalizations we construct three outcomes: an indicator for any hospital

admission in the semester with relevant diagnostic codes [10], a count of total number of days spent in the hospital per semester, and an indicator for if the patient died in the hospital and had relevant diagnostic codes.[11]

III.D Analysis Sample

The clinic sample frame consists of the 506 public primary care clinics that use electronic medical records (EHR) and are therefore eligible for the appointment reminder system.[12] From this group, we exclude 92 small clinics defined as having 10 or fewer chronic disease visits in the entire pre-program period (2013 and 2014) compared to an average of 1783 visits in main sample. We also exclude 71 clinics located in extremely remote areas such as Easter Island and Patagonia. We drop two clinics that have conflicting treatment status in different sources of information. In addition, we exclude another 26 clinics that took up the reminder program but are completely missing the phone records data that are used to construct our instrument.[13] Our final sample includes 315 clinics located in 275 different counties; 79% of all counties in Chile.

Our sample of patients consists newly diagnosed with type 2 diabetes and/or hypertension between 2014 and 2018. Restricting to newly diagnosed patients reduces left-censoring and prevents over-representation of individuals with unusually high preventive-care utilization.[14] We further exclude patients younger than 35 or older than 80 at diagnosis. Those under 35 are excluded to minimize inclusion of type 1 diabetes, which is genetic and typically diagnosed earlier in life (Thomas et al. 2023), while those over 80 are excluded because clinical guidelines differ substantially for this age group (MINSAL 2017b), and the 5.0% of patients who moved clinics at any point during the

[10] Results are very similar if we use a count of number of hospital admissions in a semester rather than an indicator for any hospital admission in the semester, because only 0.2% of patient-semester observations contain more than one cardiovascular hospitalization, and only 0.7% of patient-semester observations contain more than one non-cardiovascular hospitalization.

[11] One limitation is that we are unable to observe mortality outside of the hospital. However, for patients under age 75 approximately half of all cardiovascular-related deaths occur in hospitals (Munoz and Otero 2024).

[12] There are a total of 877 public health clinics in Chile but some had not implemented EHRs by the beginning of our study period and are excluded.

[13] Baseline patient characteristics are not collectively significantly different between clinics included and excluded from the analysis. However, a few individual characteristics do differ such as the share of obese patients and BMI. This is most likely due to sampling variation, but otherwise would not surprising given the majority of excluded clinics are in remote and likely lower income regions (A6).

[14] For patients with missing diagnosis dates, we include anyone who had no chronic-disease screening visits prior to January 1, 2014 but did have one between 2014 and 2018, assigning the diagnosis date as the first screening visit after January 1, 2014. Patients present in the data on January 1, 2013 who had a second visit did so within 361 days; therefore, a patient whose next appearance occurs 362 days later is likely newly diagnosed.

study period.

For the analysis, we construct a panel of patients by semester, beginning from the visit when they were first diagnosed with a chronic disease and ending in 2018. At the time of diagnosis, patients are enrolled in the PVSC program and eligible for reminders. Each patient is represented in each semester after diagnosis. This setup allows us to code all outcomes as zero if a patient did not visit primary care or a hospital, avoiding bias related to the endogeneity of care-seeking behavior.

Following clinical guidelines that state patients should regularly attend preventive care, visits and tests are defined for each semester such that visit equals 1 if the patient had one or more preventive care visits in the semester, 0 otherwise. This is consistent with Chile's clinical guidelines that recommend a visit at least every six months for patients with diabetes or hypertension (MINSAL 2017b). It aligns with the data: among clinics without reminders, the average interval between visits is 186.7 days, or just over six months. Patients can, however, visit more frequently: 22.3% of patient-semesters contain more than one visit. For medication adherence outcomes we measure adherence over the relevant 6-month period. For hospitalization outcomes we measure whether any relevant hospitalization occurred in the semester, zero otherwise. Our final analysis sample includes 2,082,052 visits from 284,554 patients with hypertension and 439,183 visits from 67,619 patients with type 2 diabetes, all at the 315 study clinics.[15]

IV Empirical Methods

We estimate the effect of preventive care visits on the outcomes of interest using the following specification:

$$Y_{ijt} = \alpha + \beta visit_{ijt} + X'_{ijt}\delta + \lambda_t + \gamma_j + \epsilon_{ijt} \tag{2}$$

where Y_{ijt} represents the outcome for patient i at clinic j during period t, and $visit_{ijt}$ is a binary indicator denoting whether patient i visits clinic j during period t. We include fixed effects for semester-year (λ_t) and for clinic (γ_j).[16] We also include a vector of patient-level controls (X'_{ijt})

[15] A total of 35,179 patients (11%) have both conditions and are included in both sets of models.

[16] We divide each calendar year into two 6-month periods (semesters) to address trends in a more granular way than year: January to June, and July to December.

that include fixed effects for number of semesters since the patient was diagnosed, sex, 2-year age-groups (i.e. age 35-36, 37-38, 39-40, etc.) at the time of the medical visit, and body mass index (BMI) category (obese, overweight, healthy weight, underweight), and baseline health: hemoglobin A1c in two-unit intervals for patients with type 2 diabetes, and systolic blood pressure in ten-unit intervals for patients with hypertension.[17]

The unit of observation is the patient, with one observation per patient-semester after their diagnosis. Patients are nested within clinics, and eligibility for reminders varies at the clinic level over time, so we include clinic rather than patient fixed effects. We estimate all models separately for patients who were diagnosed with type 2 diabetes and hypertension.[18]

We use an instrumental variables approach to control for the possibility that $visit_{ijt}$ is correlated with unobserved patient characteristics that may also influence our outcomes of interest. The instrument for $visit_{ijt}$ is $PrReminder_{jt}$; the probability that a patient assigned to clinic j with a scheduled preventive care appointment was sent a reminder in semester t. This probability is zero for clinics that did not adopt the program, and for clinics that did adopt, before adoption. Under reasonable assumptions, our approach identifies a local average treatment effect (LATE), which is interpreted as the effect of a primary care visit on patient outcomes induced by the appointment reminder program (Angrist, Imbens, and Rubin 1996).

V Identification

The probability a patient was sent a reminder is measured using phone records that provide a comprehensive record of reminders sent by text message to individuals with appointments, as well as detailing individuals with appointments to whom a text message could not be sent. We cannot link these at the individual level to patient-EHR data. Instead, we construct a time-varying clinic-level compliance variable, defined as the share of eligible patients who were sent a text message.

Phone records are available for 90% of clinic-semesters for the years 2016-2018, but are missing for all of 2015 - the first year of adoption - and for 29 clinic-semesters in the later years in our panel. For the semesters in which they exist, the records are complete. To address this, we impute

[17] BMI is missing for 8.9% of patients at baseline; we include a fixed effect for missing BMI. Systolic blood pressure is imputed for patients missing this measure at baseline (6.1%). No patients are missing hemoglobin A1c at baseline.

[18] Pooling tests reject that the effect of appointment reminders is equal in both samples for 12 of 15 outcomes at the 10% level (Table A5).

missing observations using separate linear regressions for each clinic. Specifically, for each clinic we regress program compliance on the four quarters after the missing cell, and then use the clinic's intercept and slope to impute its program compliance. For more details on imputation including a test showing that this method is highly predictive in-sample (R^2=0.83), see Appendix section A.3. In section VI.D we present a series of robustness analyses that show that dropping imputed units does not meaningfully change our estimates but does reduce precision in few cases, likely because the number of observations is lower.

V.A Exclusion Restriction

The exclusion restriction requires that within-clinic variation over time in $PrReminder_{jt}$ is uncorrelated with unobserved within-clinic variation over time in ϵ_{ijt}. In other words, appointment reminders only affects Y_{ijt} through its impact on $visit_{ijt}$. Although this assumption cannot be directly tested, we provide supportive evidence.

Comparison of Baseline Means. We first show that adoption of the reminder program is uncorrelated with various clinic-level characteristics measured prior to the start of the program, and with patient-level characteristics measured at their initial observed visit (Table 1). Overall F-stats for joint significance are 0.07 and 1.17 among patients with hypertension and type 2 diabetes, respectively. At both types of 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 approximately 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 1). At the patient's first observed visit, the probability of a medication prescription and the probability of key tests were similar across clinics (Table 1).

Changes in Clinic Compliance Over Time. We next show that clinic-level compliance with the reminder program does not respond to shocks or changes in patient health or patient population. We regress clinic-semester compliance against lagged measures of patient health status

with clinic and calendar time fixed effects. Specifically, we estimate the following specification:

$$\Pr(\text{Reminder})_{jt} = \sum_{s=k} \beta_k \cdot x_{k,j,t-1} \; + \; \lambda_t \; + \; \gamma_j \; + \; \varepsilon_{jt}, \tag{3}$$

where the $x's$ are k clinic level indicators of patient health status at period $t-1$. By including clinic fixed effects, the $\beta's$ are interpreted as the effect of changes in the $x's$ on compliance. In Figure 2 we plot the β_k coefficients and 95% confidence intervals and find that these characteristics do not individually or jointly significantly predict compliance (joint F-statistic 0.79).

Disease Salience. One potential violation of the exclusion restriction arises from the possibility that the appointment reminder program alters the salience of disease, potentially influencing the health behaviors of patients independently of primary care visits. However, the reminders focus on information regarding appointment dates and schedules. All patients in our sample are enrolled in the PSCV program in Chile, indicating that they have already been diagnosed and received information about their condition. The lack of variation in reminder effectiveness since the patient was initially diagnosed (Figure 4, panel A) also provides support against this channel.

Other Contemporaneous Interventions. Another potential violation of the exclusion restriction involves the presence of other interventions targeting the same population. For these alternative programs to confound the effects of the appointment reminder program, they would need to exhibit a similar fluctuation in intensity as the appointment reminder program. To date, we have not been made aware of any such concurrent programs.

V.B Instrument Relevance

The first stage estimates the effect of compliance with the appointment reminder program, or the probability a patient was sent a reminder, on preventive care visits:

$$visit_{ijt} = \alpha + \beta PrReminder_{jt} + X'_{ijt}\delta + \lambda_t + \gamma_j + \mu_{ijt} \tag{4}$$

As above, the model is adjusted for common temporary shocks with semester fixed effects (λ_t), and clinic fixed effects (γ_j). We also include a vector of patient-level controls (X'_{ijt}): fixed effects for semesters since the patient was diagnosed, sex, fixed effects for 2-year age groups, and health at

diagnosis (BMI category at diagnosis, hemoglobin A1c in 2-unit intervals for patients with type 2 diabetes, and systolic blood pressure in 10-unit intervals for patients with hypertension). Standard errors are clustered at the clinic level.

We find that the instrument is a strong predictor of preventive care visits: compliance with the reminder program induces a 7.4 percentage point (pp) increase in visits among patients with type 2 diabetes, and a 9.6pp increase among patients with hypertension (Table 2 columns 1-2), both statistically significant at $p < 0.01$. These correspond to respective increases of 11.3% and 14.6% in guideline-adherent preventive care.[19] Consistent with the reminders inducing more visits, mean days between visits is lower at clinics that adopted the reminder system than at those that did not adopt the system: 150.4 vs. 168.6 among diabetes patients, and 161.0 vs. 188.2 among hypertension patients, differences of 18 and 27 days, respectively, both significant at $p < 0.001$.

To characterize compilers we test whether the effect of reminders on the probability of a preventive care visit varies with important patient characteristics such as time since diagnosis, age and baseline health status by interacting baseline characteristics with the $PrReminder_{jt}$ indicator in equation 4. Figure 4, panel A, shows little heterogeneity by time since diagnosis, suggesting that the effectiveness of reminders does not fade over time. Panel B shows that the positive impact of reminders is consistent between age groups up to age 75. Figure 4, panel C shows little heterogeneity in treatment effects by hemoglobin A1c levels for diabetics, albeit the effects are not statistically significant among patients diagnosed with hemoglobin A1c levels above 12%.[20]Similarly, panel D shows little heterogeneity in treatment effects by baseline blood pressure levels, albeit the effects are not statistically significant at initial blood pressure above 170 mmHg.[21]

We also test whether the effectiveness of reminders improves as clinics gain more experience

[19](Boone et al. 2022) study the reminder system mainly as a clinic-efficiency intervention. Using longitudinal clinic-level data, they employ difference in differences to investigate whether the adoption of the reminder system changed the total number of visits to a clinic. They find that the reminder system increased the number of visits, thereby improving efficiency by reducing wasted missed appointments exploiting excess capacity. The increase in visits did not come through visits from patients with chronic disease, but rather by patients with acute illnesses waiting for appointments. This paper asks a different question. Using patient-level linked administrative data and an IV strategy to estimate the causal effect of an additional preventive visit on subsequent outcomes. The estimand is a LATE for patients whose preventive-care attendance changes with reminder compliance. In a capacity-constrained system, reminders can raise preventive-visit completion among some patients even if the total number of chronic visits at the clinic does not move much, because clinics can reorganize schedules and use the freed capacity for other patients.

[20]Hemoglobin A1c reflects long-term blood glucose levels. Chilean guidelines define type 2 diabetes as A1c $\geq$7% (MINSAL 2017b).

[21]Hypertension is defined in Chile as blood pressure $\geq$140/90 mmHg (MINSAL 2017b).

with the reminder system, or, conversely, whether reminders became less effective the longer they were implemented at clinics. We estimate an event-history version of equation (4) allowing the coefficient on *PrReminder*to change based on the time since the clinic adopted the reminder system. The results, presented in (Figure 3), show that the effect of *PrReminder* on the probability of a visit increases between the semester of adoption (period 0) and the semester immediately following and then remains relatively stable thereafter. Figure 3 also shows parallel trends in the period prior to adoption, consistent with the assumption that program take-up is not correlated with trends in potential outcomes.

VI Results

In this section, we report the results of model (1) estimated by 2SLS. The key parameter of interest is the effect of a preventive care visit on the outcome of interest. For comparison, we estimate the same models by OLS, reported in Appendix tables A8-A11, and find that the 2SLS coefficient estimates are significantly lower than the OLS. We also report the estimation results of reduced form models by substituting (4) into (2) and the key parameter of interest in these models is the effect of clinic-level compliance on the outcome. Finally, we estimate event study versions of the reduced form that allow the coefficients on clinic compliance to vary by time since the clinic adopted the reminder system and report those results in Appendix Figures A3-A6.

The first stage F-statistic is above 10, the usual threshold for instrument strength, in 11 of the 17 main models. However, the first stage F-statistics are about 8.5 in the other 6 models, raising concern over the possibility of weak instruments. To address this issue, as recommended by Keane and Neal (2024), we report Anderson-Rubin (AR) 95% confidence intervals that are robust to weak instruments (Anderson and Rubin 1949). The AR bounds represent the minimum and maximum values of the coefficient that are consistent with the IV assumptions and provide bounds on the effect size. We also test the hypothesis that the lower AR bound is zero, which is a test of the absence of an effect.

For robustness, we also estimate models using limited-information maximum likelihood (LIML), the results of which are reported in Appendix Tables A12–A15. LIML may, in some cases, perform better than 2SLS in the presence of weak instruments, especially in the case of multiple weak

instruments. However, in our just identified case of a single instrument, the LMIL results change very little from the 2SLS results, consistent with theoretical expectations (Keane and Neal 2024).

VI.A Disease monitoring

An additional preventive care visit produces near-universal uptake of recommended health monitoring tests. Specifically, an additional visit leads to an 87.4pp and 97.5pp increase in the probability of a blood pressure test for patients with type 2 diabetes and hypertension, respectively (Table 2 panel B, columns 3-4). A visit also leads to an 89.1pp and 92.8pp increase in the probability of weight measurement (Table 2 panel B, columns 5-6). For patients with type 2 diabetes, an additional visit leads to a 56.9pp increase in the likelihood of having a blood glucose test (Table 2 panel B, column 7). The AR confidence intervals reject null effects for all outcomes.

Chile's clinical practice guidelines require blood pressure and weight at each primary care encounter, and regular blood sugar monitoring.The large effects suggest strong provider adherence: patients who attend preventive care are extremely likely to receive these tests.

In line with these results, reduced form estimates in panel A of Table 2 show that compliance with the appointment reminder system is positively associated with receipt of blood pressure, weight, and blood glucose or hemoglobin A1c monitoring. Event study estimates of the reduced form in Appendix Figure A3 show the absence of differential pre-intervention trends and demonstrate sustained effects over time since the clinic adopted the reminder system.

VI.B Medication adherence

Preventive visits substantially increased patient medication use. Patients who attended a preventive visit were more likely to fill their prescriptions (Table 3, Panel B, models 1–2). In contrast, only 30% of patients in clinics without the reminder system filled their medication the semester it was prescribed, despite the fact that medication is free and readily available at the clinic pharmacy. These positive effects partially reflect the institutional setting in which patients must visit their healthcare provider to have an active medication prescription.

Preventive visits also improved adherence on both continuous coverage and the clinically relevant 80% threshold. Specifically, a visit increases continuous medication adherence by roughly 39pp and adequate adherence by 16pp for both conditions (Table 3, panel B, models 3-6). The AR

confidence intervals again reject null effects for all outcomes. These results likely reflect both provider counseling on medication importance during the visit and the heightened salience of that message from the visit.

Reduced-form estimates similarly show that higher clinic compliance increases adherence. Complete compliance increases the probability of filling a prescription by 7.7pp for patients with type 2 diabetes and by 8.0pp for patients with hypertension; increases the likelihood of continuous adherence by roughly 3pp; and adequate adherence by 1.2–1.4pp and (Table 3, panel A). Event history specifications of the reduced form, presented in Appendix Figure A4, show sustained effects over time since the clinic adopted the reminder system and no differences in pre-intervention trends.

VI.C Hospitalization and in-hospital mortality

We find that preventive care increases hospitalizations for cardiovascular disease. For every 100 patients with diabetes, preventive care results in 5.5 additional cardiovascular admissions; for hypertensive patients, the increase is 2.7 admissions (Table 4, Panel B, columns 1-2). In contrast, in-hospital cardiovascular mortality decreases by 1.0 deaths per 100 patients with type 2 diabetes (Table 4, Panel B, column 5). For hypertensive patients, the in-hospital mortality effect is smaller at -0.11 and is not statistically significant. We find no impact on the length of stay for cardiovascular outcomes. The AR confidence intervals reject null effects for admission and mortality for diabetic patients and for admission of patients with hypertension.[22]

Admissions: Why do preventive visits increase cardiovascular admissions? Clinical practice guidelines require comprehensive patient education that covers both behavioral health management (diet, exercise, medication adherence) and the recognition of symptom for complications that require immediate medical attention. This education likely improves the ability og patient ability to identify and act on warning signs.

The notion is not one of a simple passive transfer of information, but rather that a preventive visit is a clinical trigger that can shift the behavioral threshold of a patient for seeking acute care. During a preventive visit, providers conduct risk assessments, reinforce recognition and interpretation of symptoms, and provide explicit instruction as to when symptoms warrant urgent evaluation

[22]Again, the reduced form results reported in Panel A are consistent with the structural results and the event study results reported in the Appendix show that effects are sustained over the role out of the reminder system.

and treatment. So, actions taking place at each medical visit are not merely information, they are more clinical assessments and communication that can improve patient engagement as they interact with physicians.

These results are consistent with the existing literature, which shows large downstream utilization responses to improved access to primary care, especially for chronic diseases. In the Oregon Health Insurance Experiment, Medicaid coverage increased the probability of hospital admission by 30%, (Finkelstein et al. 2012). Heart failure patients often delay seeking care because they do not correctly recognize the symptoms of a worsening condition, and education together with better outpatient chronic-disease management reduces such delays (Gravely-Witte et al. 2010). The REACT community public health campaign on acute myocardial infarction symptoms increased the use of emergency medical services (EMS) and reduced morality by patients with coronary heart disease (Luepker 2000). Empowerment-based chronic-care education improves perception of symptoms and self-care management by patients with heart-failure (Yu et al. 2022). Related evidence from COPD shows that action plans combined with patient education help patients recognize disease exacerbation and initiate treatment earlier (Howcroft et al. 2016). Structured chronic disease self-management programs have been shown to alter patient behavior and healthcare utilization (Lorig et al. 1999), and outcomes (DeWalt et al. 2006).

Taken together, this supports a common mechanism: meaningful engagement in chronic-disease care can change the way patients perceive, interpret, and respond to symptoms. Getting patients into substantive chronic-care preventive visits improves symptom recognition and reduces delays in seeking appropriate care, making higher short-term hospitalization rates a plausible consequence of better detection and response to disease progression rather than a simple effect of generic information.

Mortality: The lower in-hospital mortality of patients with diabetes is consistent with the hypothesis that patients who have better control of their blood glucose when they arrive at the hospital respond better to treatment. Preventive care improves glucose control through more disease monitoring and improved medication adherence. This pathway is supported by the medical literature that shows that higher blood glucose upon admission is associated with more infections, complications and higher in-hospital mortality (Pasquel et al. 2021; Sharif et al. 2019; Klonoff et al. 2020). Reflecting this, the American Diabetes Association recommends specific glycemic control

targets that enhance the effectiveness of hospital care when acute events occur (American Diabetes Association Professional Practice Committee 2023).

In contrast, while well-controlled blood pressure has clear long-term health benefits, especially for cardiovascular health (Mancia and Kjeldsen 2024), the implications of blood pressure control on the effectiveness of inpatient treatment are less clear because blood pressure is highly variable and is elevated in stressful settings like the hospital (Jacobs and Anderson 2024). Reflecting this, the American Heart Association recommends avoiding reflexive treatment of elevated inpatient blood pressure and instead focusing on long-term management (Bress et al. 2024).

Selection: An alternative explanation is that preventive visits induce unnecessary or low-value hospitalizations of healthier patients with diabetes, creating spurious mortality reductions through patient selection. Indeed, we observe that preventive care increases cardiovascular hospitalizations, which could change the patient mix. However, multiple lines of evidence contradict this selection-based interpretation.

First, unlike the US, there are no financial incentives for providers to recommend more care than medically needed. In Chile's public system, hospitals operate under fixed budgets and clinicians are paid fixed salaries.

Second, there is no difference in the number of days hospitalized (Table 4 columns 1-4). If healthier patients are being hospitalized, we would expect that less time in the hospital would be needed. However, there was no effect on length of stay suggesting that the conditions were not less severe.

Third, while there is an effect on mortality for patients with diabetes, there is no effect on mortality for patients with hypertension. If the main channel were compositional (i.e., admitting "healthier" cases), we would expect a similar pattern for hypertension patients as well, not a null effect.

Fourth, we find no correlation between the appointment reminder compliance and patient baseline health status (blood glucose, blood pressure and BMI) among those who later have cardiovascular-related hospitalizations (Figure 5). This suggests that we are not detecting an increase in hospitalizations among those who were relatively healthier at baseline.

Fifth, we also find that in subgroups that do not experience an increase in cardiovascular admissions, reductions in in-hospital cardiovascular mortality still appear, helping to alleviate concerns

about selection. Table 5 shows that among middle-aged patients (ages 50–75) with diabetes, there is no statistically significant increase in cardiovascular hospitalizations, but we still observe a reduction of 1.1 in-hospital deaths per 100 patients.[23]

Sixth, the increase in hospitalizations occurs entirely in cardiovascular conditions, with no corresponding change in other types of admissions: Table 6 shows no impact of either reminders or visits on non-cardiovascular hospitalizations, length of non-cardiovascular stay, or in-hospital mortality. If preventive visits were broadly inducing unnecessary hospital use, we might expect increases in all types of diagnoses; both cardiovascular and non-cardiovascular.

Seventh, the conditions driving the increase – acute cardiovascular events such as stroke and myocardial infarction (see Tables A1 and A2 for details) – are not typically influenced by provider discretion. Long wait times at Chilean hospitals also make it unlikely that patients would seek inpatient care unless necessary (Martinez et al. 2019).

Finally, we can rule out direct referrals as the primary mechanism. Two findings contradict this explanation: (1) only 0.12% of hospitalizations occur within one day and 1.42% within seven days of preventive appointments (Figure 6, Table A7)—too few to drive the overall increase; (2) referrals would increase both cardiovascular and non-cardiovascular admissions, yet we observe increases only for cardiovascular conditions.

Taken together, our findings suggest that preventive care increases clinically appropriate cardiovascular hospitalizations. Preventive visits likely improve disease control and symptom awareness such that patients are hospitalized at stages when acute interventions are most effective—earlier in disease progression or with better baseline health status—thereby reducing in-hospital mortality.

VI.D Robustness to Imputation

We perform several analyses to asses the robustness of our results to the influence of imputing clinic-semester compliance for clinic-semesters with missing phone records data on our results.[24] Table A3 details the number of imputed cells by semester-year. In Figures A7 and A8 we first re-estimate our main results excluding all observations with imputed compliance. While our statistical power is slightly reduced, point estimates remain similar for all outcomes. Second, we impute compliance for

[23] The largest increases in cardiovascular hospitalizations occur in the elderly: those 75 and older.
[24] Section A.3 provides more details about the imputation.

2016, a year for which we have compliance data, and re-estimate our main results including imputed 2016 compliance and excluding 2015 compliance. We find that using imputed 2016 compliance or true 2016 compliance, alongside true compliance data, yields similar results, providing support for our imputation methods. Overall, we find that imputation does not meaningfully affect the point estimates or direction of the effect, but does increase precision in some cases, likely because it allows us to include a larger number of observations in the analyses.

VII Conclusion

Controlling chronic diseases such as type 2 diabetes and hypertension is a global issue. In the Chilean context, we have shown that receipt of preventive medical care substantially improved the monitoring of patients' chronic conditions, health behaviors, and the diagnosis and treatment of complications. Our findings are important for settings with gatekeeper healthcare models in which patients must visit primary care providers before being referred to specialty care, approve diagnostic tests or prescribe medication. This model is common in other countries such as Canada, the United Kingdom, Spain, and integrated health systems in the United States that focus on prevention and case management, such as Kaiser Permanente (Reibling and Wendt 2012).

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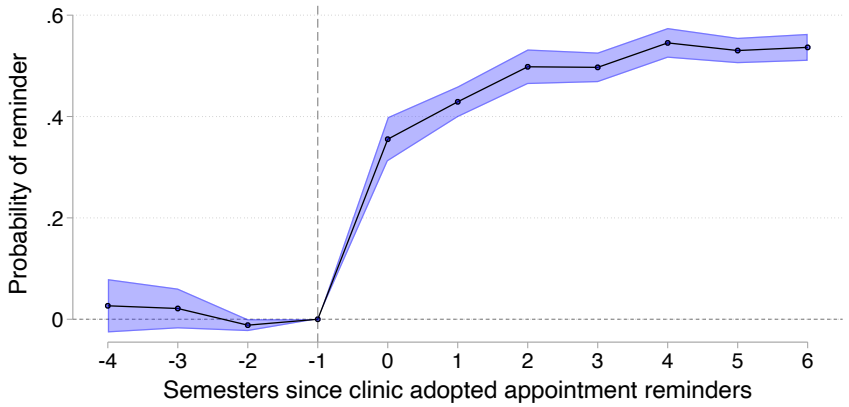
VIII Tables and Figures

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

(a) Take-up and compliance summary by semester

Date	Clinics with Reminders	Clinics without Reminders	Compliance		
			Mean	Min.	Max.
S1 2014	0	315	-	-	-
S2 2014	0	315	-	-	-
S1 2015*	168	147	42.5%	0.0%	79.8%
S2 2015*	172	143	45.2%	0.0%	72.8%
S1 2016	203	112	45.0%	0.0%	76.1%
S2 2016	208	107	48.7%	10.4%	75.7%
S1 2017	208	107	55.4%	14.1%	83.5%
S2 2017	208	107	52.8%	14.6%	80.8%
S1 2018	208	107	57.1%	5.7%	84.9%
S2 2018	208	107	53.0%	0.0%	87.2%
Total	208	107	50.3%	0.0%	87.2%

(b) Event study: Compliance relative to program take-up



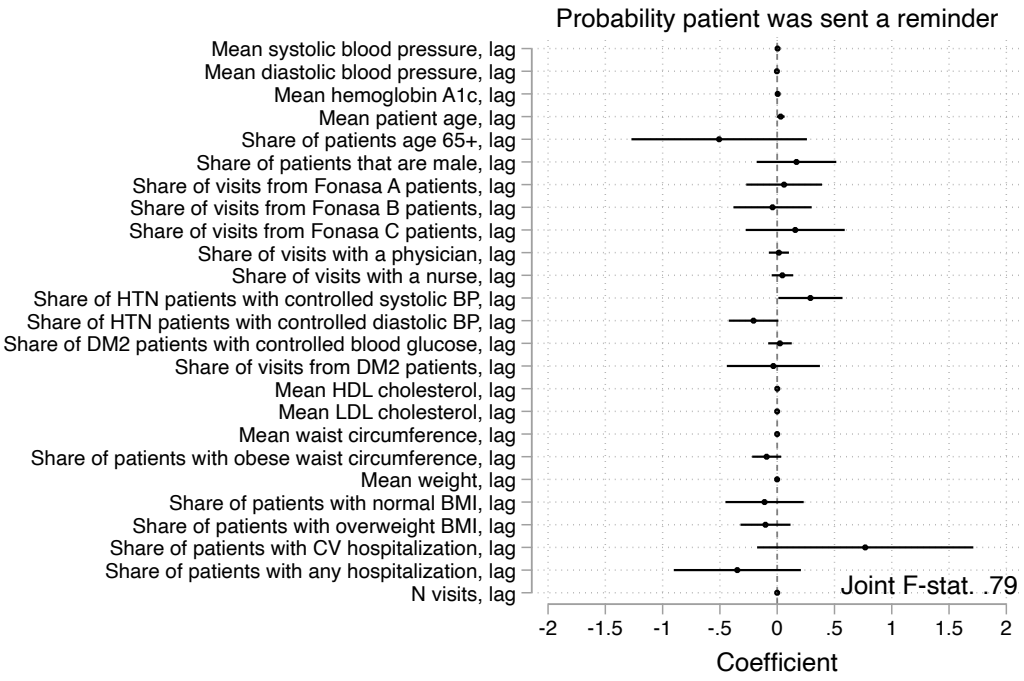
Note: Panel A: Compliance is the share of patients sent an appointment reminder using text messages, among eligible patients in a clinic-semester cell and was measured using phone records. The asterisk denotes semesters with imputed compliance data: compliance data was unavailable in 2015, so 2015 semester 1 and semester 2 were imputed using clinic-level linear regression. Panel B: displays coefficients and 95% confidence intervals from an event study where the outcome is clinic-semester compliance, or the probability of a reminder being sent: $PrReminder_{jt} = \sum_{\tau=-3}^{6} \beta_\tau Q_\tau + \lambda_t + \gamma_i + \epsilon_{ijt}$, for clinic j in semester t. β_τ are coefficients on semester indicators (Q_τ) for time relative to reminder program adoption, λ_t are semester fixed effects, and γ_j are clinic fixed effects, and robust standard errors are clustered at the clinic level.

Table 1: Balance of patient characteristics at baseline in main analysis sample

	Reminder program		No reminder program			
	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
F-stat for test of joint significance						0.07
N Clinics	207		103		Total	310
N Patients	191,293		93,261		Total	284,554
N Visits	1,408,820		673,232		Total	2,082,052
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
Glucose test, at DM2 primary care visit	1.00	0.00	1.00	0.01	0.000	0.71
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
F-stat for test of joint significance						1.17
N Clinics	207		107		Total	314
N Patients	42,609		25,010		Total	67,619
N Visits	280,602		158,581		Total	439,183

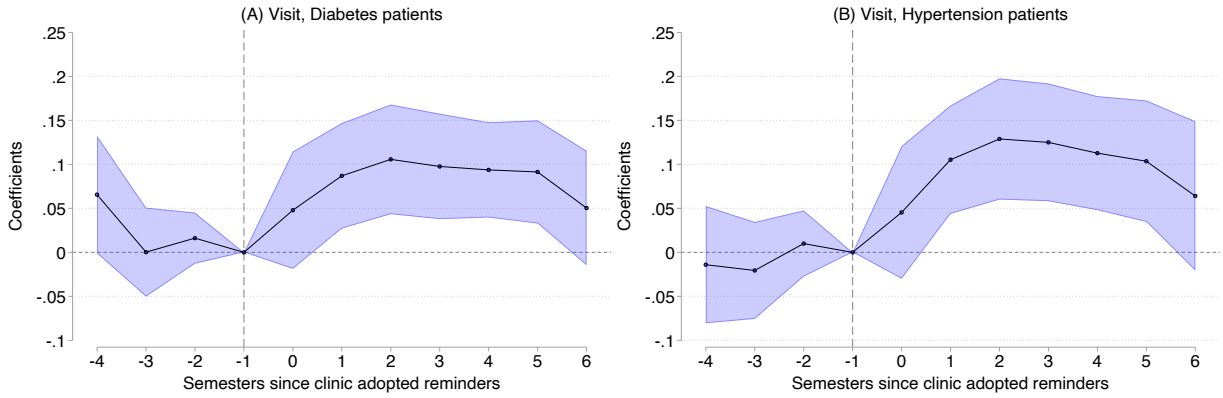
Note: Patient health and characteristics measured at patient's primary care visit when diagnosis with type 2 diabetes and/or hypertension occurred, referred to as their baseline visit, comparing means between patients at clinics that ever vs. never implemented the appointment reminder program. Hemoglobin 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



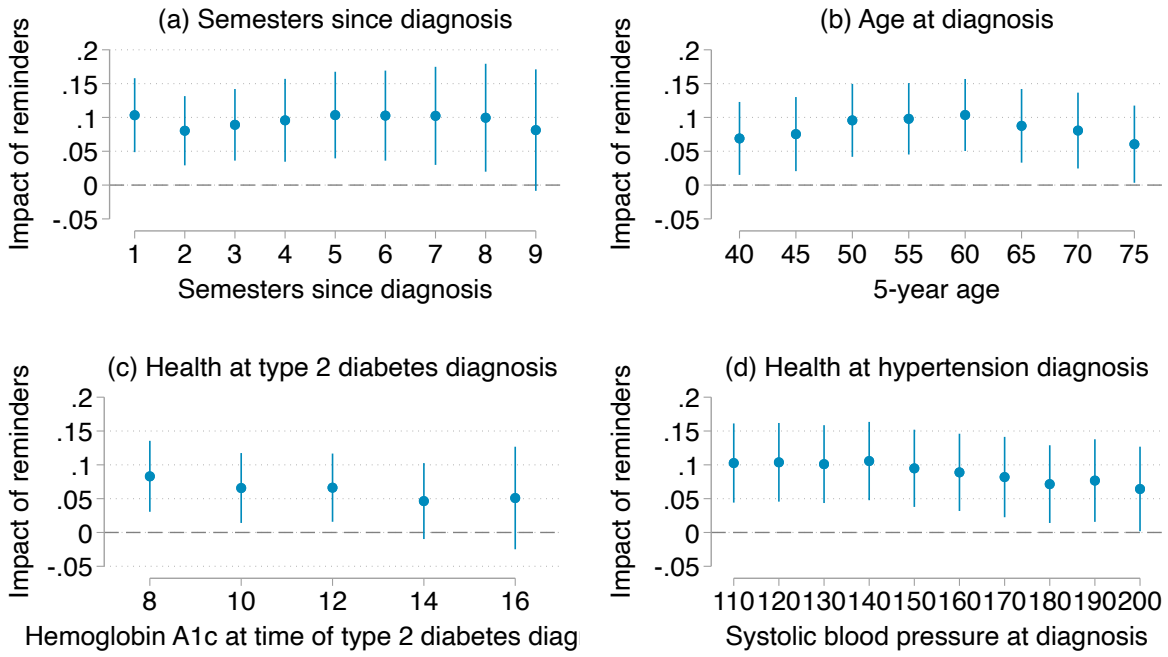
Note: Coefficients and 95% confidence intervals from a multivariate regression of the probability a patient was sent a reminder, or clinic-semester compliance with the appointment reminder program: $\Pr(\text{Reminder})_{jt} = \alpha + \mathbf{X}'_{j,t-1}\boldsymbol{\beta} + \lambda_t + \gamma_j + \mu_{jt}$, on a set of lagged patient characteristics ($\mathbf{X}_{j,t-1}$), with semester (λ_t) and clinic fixed effects (γ_j), with robust standard errors clustered at the clinic level. Regression includes both clinics that did and did not implement reminders. Lagged coefficients were measured in the previous semester. The joint F-statistic is shown on the figure (F=0.79, p-val=0.75).

Figure 3: Event study: impact of appointment reminders on preventive care visits



Note: Figures show two-way fixed effect event study regression estimates: $visit_{ijt} = \sum_{\tau=-4}^{6} \beta_\tau Q_\tau + X'_{it}\delta + \lambda_t + \gamma_j + \epsilon_{ijt}$, for patient i at clinic j in semester t. β_τ are coefficients on semester indicators (Q_τ) for time relative to reminder program adoption, λ_t are semester fixed effects, and γ_j are clinic fixed effects, X'_{ijt} is a vector of patient-level controls: fixed effects for the number of semesters since the patient was diagnosed, sex, 2-year age-group fixed effects, BMI category at diagnosis, and baseline health at diagnosis—hemoglobin A1c in 2-unit intervals for patients with type 2 diabetes, and systolic blood pressure in 10-unit intervals for patients with hypertension. Robust standard errors are clustered at the clinic level. The shaded areas denote 95% confidence intervals. The x-axis is the number of semesters relative to when the clinic implemented appointment reminders.

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



Note: Figures display coefficients and 95% confidence intervals from difference-in-difference heterogeneity models. Each point is the main effect of appointment reminders + the coefficient on the interaction term between compliance with the appointment reminder program and the dimension of heterogeneity. Reference groups are (a) semester of diagnosis (0), (b), age 35-39, (c) hemoglobin a1c under 8%, (d) systolic blood pressure under 110 mmHg. F-statistics and p-values from joint F-test of equality of interaction coefficients: (a) F=0.87, p-val=0.54, (b) F=3.1, p-val=0.004, (c) F=1.1, p-val=0.36, (d) F=2.0, p-val=0.03.

Table 2: Impact of appointment reminders and visits on health monitoring

		Visit		Blood pressure test		Weighed		Blood sugar test
		Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Reduced form: impact of appointment reminders								
Pr(Reminder)	β	0.074	0.096	0.065	0.094	0.066	0.089	0.042
	SE	(0.025)	(0.029)	(0.024)	(0.028)	(0.026)	(0.029)	(0.025)
	p-val	[0.003]	[0.001]	[0.006]	[0.001]	[0.011]	[0.002]	[0.094]
Panel B. Instrumental variables: impact of primary care visit								
Visit	β	-	-	0.874	0.975	0.891	0.928	0.569
	SE	-	-	(0.080)	(0.040)	(0.192)	(0.103)	(0.211)
	p-val	-	-	[0.000]	[0.000]	[0.000]	[0.000]	[0.007]
	AR CI	-	-	[0.64, 1.06]	[0.89, 1.08]	[0.42, 1.40]	[0.67, 1.16]	[-0.20, 0.92]
	AR p-val	-	-	0.006	0.001	0.011	0.003	0.094
	Observations	439,183	2,082,052	439,183	2,082,052	439,183	2,082,052	439,183
	Clinics	314	310	314	310	314	310	314
Mean Y | Pr(SMS)=0		0.654	0.656	0.626	0.629	0.613	0.616	0.565
Mean Y | Visit=0		-	-	0.000	0.000	0.000	0.000	0.000
First stage F-stat		-	-	8.663	10.980	8.663	10.980	8.663

Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of health monitoring in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of health monitoring in a given semester. IV models were estimated using equation (1). Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. For IV estimates, Anderson-Rubin (AR) confidence intervals and p-values are also presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Table 3: Impact of appointment reminders and visits on medication outcomes

		Filled any prescription		Medication adherence (%)		Medication adherence≥ 80%	
		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							
Pr(Reminder)	β	0.077	0.080	0.029	0.033	0.012	0.014
	SE	(0.030)	(0.027)	(0.015)	(0.013)	(0.007)	(0.005)
	p-val	[0.010]	[0.003]	[0.060]	[0.013]	[0.072]	[0.008]
Panel B. Instrumental variables: impact of primary care visit							
Visit	β	1.044	0.912	0.394	0.386	0.168	0.157
	SE	(0.420)	(0.336)	(0.215)	(0.172)	(0.100)	(0.071)
	p-val	[0.013]	[0.007]	[0.067]	[0.025]	[0.094]	[0.027]
	AR CI	[0.26, 2.41]	[0.35, 2.07]	[-0.01, 1.05]	[0.10, 0.95]	[-0.02, 0.49]	[0.04, 0.42]
	AR p-val	0.016	0.007	0.073	0.021	0.080	0.012
	Observations	238,198	1,098,176	238,198	1,098,176	238,198	1,098,176
	Clinics	312	309	312	309	312	309
Mean Y | Pr(SMS)=0		0.301	0.300	0.119	0.124	0.024	0.028
Mean Y | Visit=0		0.215	0.222	0.075	0.083	0.011	0.015
First stage F-stat		10.405	11.096	10.405	11.096	10.405	11.096

Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of medication adherence in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of medication adherence in a given semester. IV models were estimated using equation (1). Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. For IV estimates, Anderson-Rubin (AR) confidence intervals and p-values are also presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis. Note that the estimate of the effect of visits on any medication pick up is over 1 because we use a linear probability model.

Table 4: Impact of appointment reminders and visits on cardiovascular hospitalizations

		Any cardiovascular hospitalization per 100 patients		N days admitted for cardiovascular hospitalizations		In-hospital CV mortality per 100 patients	
		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							
Pr(Reminder)	β	0.405	0.263	-0.001	0.016	-0.077	-0.011
	SE	(0.204)	(0.090)	(0.035)	(0.015)	(0.029)	(0.012)
	p-val	[0.048]	[0.004]	[0.978]	[0.277]	[0.007]	[0.375]
Panel B. Instrumental variables: impact of primary care visit							
Visit	β	5.462	2.729	-0.013	0.164	-1.041	-0.109
	SE	(2.829)	(1.161)	(0.467)	(0.161)	(0.499)	(0.127)
	p-val	[0.054]	[0.019]	[0.977]	[0.307]	[0.038]	[0.389]
AR 95% CI		[0.15, 15.25]	[1.01, 6.97]	[-1.35, 1.05]	[-0.14, 0.66]	[-3.16, -0.30]	[-0.47, 0.13]
AR p-val		0.053	0.005	0.977	0.281	0.010	0.372
Observations		439,183	2,082,052	439,183	2,082,052	439,183	2,082,052
Clinics		314	310	314	310	314	310
Mean Y | Pr(SMS)=0		1.809	1.192	0.247	0.150	0.053	0.037
Mean Y | Visit=0		2.011	1.325	0.319	0.186	0.120	0.085
First stage F-stat		8.663	10.980	8.663	10.980	8.663	10.980

Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of cardiovascular hospital outcomes in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of cardiovascular hospital outcomes in a given semester. IV models were estimated using equation (1). Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. For IV estimates, Anderson-Rubin (AR) confidence intervals and p-values are also presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Table 5: Impact of appointment reminders and visits on cardiovascular hospitalizations, among patients with type 2 diabetes, by age group.

	Any cardiovascular hospitalization per 100 patients with diabetes			In-hospital CV mortality per 100 patients with diabetes		
	Age< 50	Age 50-74	Age≥ 75	Age< 50	Age 50-74	Age≥ 75
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Reduced form: impact of appointment reminders						
Pr(Reminder)	0.509	0.256	1.527	-0.092	-0.086	0.011
	(0.380)	(0.251)	(0.769)	(0.052)	(0.037)	(0.148)
	[0.182]	[0.308]	[0.048]	[0.076]	[0.019]	[0.943]
Panel B. Instrumental variables: impact of primary care visit						
Visit	8.227	3.233	26.149	-1.495	-1.092	0.191
	(7.164)	(3.044)	(17.793)	(1.027)	(0.560)	(2.551)
	[0.252]	[0.289]	[0.143]	[0.146]	[0.052]	[0.940]
AR 95% CI	[-3.81, 48.57]	[-4.29, 10.75]	[NA]	[-7.68, 0.03]	[-3.36, -0.26]	[NA]
AR p-val	0.184	0.315	0.043	0.078	0.023	0.940
Observations	70,070	323,655	45,454	70,070	323,655	45,454
Clinics	311	314	298	311	314	298
Mean Y | Pr(SMS)=0	1.030	1.887	2.567	0.015	0.050	0.141
Mean Y | Visit=0	0.902	2.102	3.113	0.047	0.108	0.309
First stage F-stat	6.220	8.705	3.665	6.220	8.705	3.665

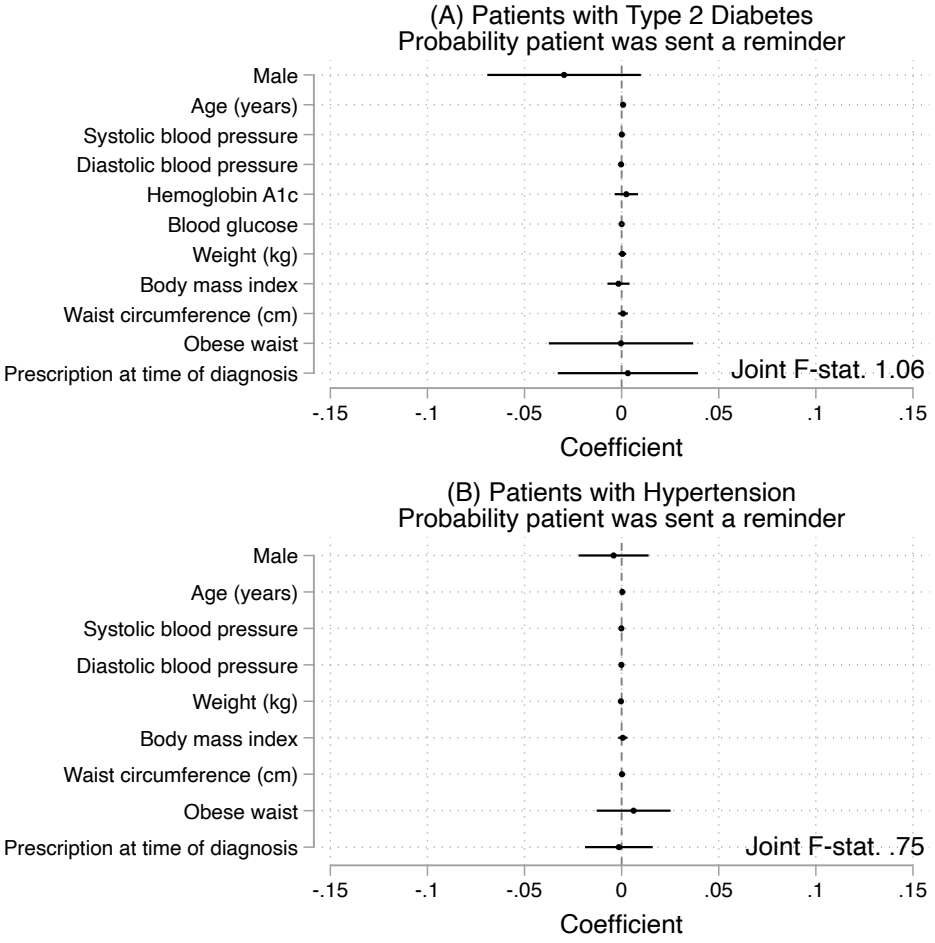
Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of cardiovascular hospital outcomes in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of cardiovascular hospital outcomes in a given semester. IV models were estimated using equation (1). Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. For IV estimates, Anderson-Rubin (AR) confidence intervals and p-values are also presented to account for a weak first stage, however for patients age 70 and over, estimates could not be bounded. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, and sex.

Table 6: Impact of appointment reminders and visits on placebo outcomes: non-cardiovascular hospitalizations

		Any non-cardiovascular hospitalization per 100 patients		N days admitted for non-cardiovascular hospitalizations		In-hospital non-CV mortality per 100 patients	
		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							
Pr(Reminder)	β	0.031	0.233	-0.046	-0.003	0.012	0.017
	SE	(0.394)	(0.199)	(0.058)	(0.021)	(0.042)	(0.017)
	p-val	[0.936]	[0.244]	[0.427]	[0.893]	[0.775]	[0.322]
Panel B. Instrumental variables: impact of primary care visit							
Visit	β	0.357	2.423	-0.627	-0.028	0.161	0.177
	SE	(5.310)	(2.299)	(0.826)	(0.218)	(0.569)	(0.191)
	p-val	[0.946]	[0.293]	[0.448]	[0.897]	[0.778]	[0.353]
AR 95% CI		[-14.86, 12.43]	[-1.44, 9.92]	[-3.49, 0.92]	[-0.65, 0.42]	[-1.13, 1.79]	[-0.18, 0.80]
AR p-val		0.946	0.256	0.417	0.896	0.775	0.320
Observations		439,183	2,082,052	439,183	2,082,052	439,183	2,082,052
Clinics		314	310	314	310	314	310
Mean Y | Pr(SMS)=0		4.387	3.844	0.443	0.323	0.154	0.090
Mean Y | Visit=0		5.215	4.766	0.630	0.485	0.315	0.215
First stage F-stat		8.663	10.980	8.663	10.980	8.663	10.980

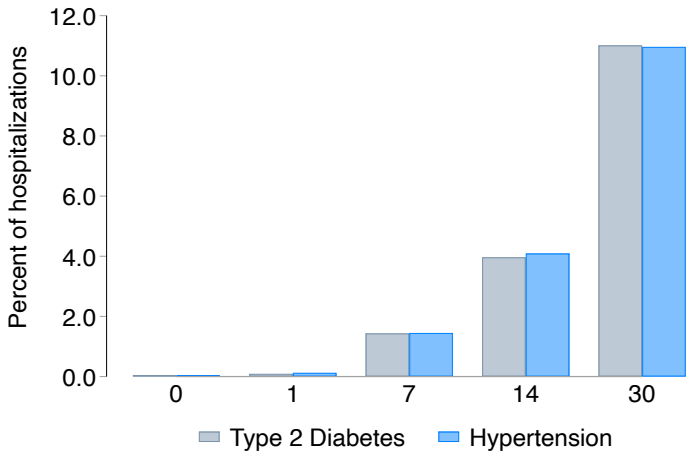
Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of non-cardiovascular hospital outcomes in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of non-cardiovascular hospital outcomes in a given semester. IV models were estimated using equation (1). Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. For IV estimates, Anderson-Rubin (AR) confidence intervals and p-values are also presented to account for a weak first stage. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Figure 5: Balance in baseline health characteristics among patients with cardiovascular hospitalizations



Note: Coefficients and 95% confidence intervals of regressions of clinic-semester compliance with the reminder program on baseline characteristics, among patients who were later hospitalized for cardiovascular reasons.

Figure 6: Days between preventive visit and hospitalization



Note: Share of hospitalizations, by baseline diagnosis, that were within 0 (same day), 0-1, 0-7, 0-14, or 0-30 days after the same patient had a preventive care visit.

A Online Appendices

For **The Importance of Preventive Medical Care for Managing Chronic Disease**

Claire Boone, Pablo Celhay, Paul Gertler, Tadeja Gracner

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 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.

A.2 Cardiovascular vs. Non-Cardiovascular Hospitalizations

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

Condition	**ICD-10 Codes**
Diabetes mellitus, type 2	E 11.X, E 13.X, E 14.X
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
Angina pectoris	I 20.0, I 20.1, I 20.2, I 20.8, I20.9
Acute myocardial infarction	I 21.0, I 21.1, I21.2, I 21.3, I 21.4, I 21.9
Ischaemic heart disease	I 24.9, I25.0
Heart failure	I 50.0, I 50.1, I 50.9
Hemorrhage	I 60.X, I 61.X, 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
Stroke	I 64.X
Occlusion and stenosis of arteries	I 65.X, I 66.X
Other cerebrovascular diseases	I 67.X
Atherosclerosis of arteries of extremities	I 70.2
Peripheral vascular disease	I 73.9
Transient cerebral ischaemic attacks	G 45.9

Note: ICD-10 codes listed are included in outcomes cardiovascular-related hospitalization and in-hospital cardiovascular mortality, based on the Framingham study definition of cardiovascular disease (Kannel, McGee, and Gordon 1976; Wallisch et al. 2020), with the addition of codes directly related to type 2 diabetes or hypertension. All other ICD-10 codes are included in non cardiovascular-related hospitalization and non cardiovascular-related mortality outcomes. A decimal of X indicates all integers were used.

Table A2: Cardiovascular hospitalizations, by patient diagnosis at baseline

Patients:	Type 2 Diabetes		Hypertension	
	N	%	N	%
Diabetes mellitus, type 2	4240	43.8	5904	21.6
Heart failure	1340	13.9	4479	16.4
Acute myocardial infarction	1214	12.5	4338	15.9
Other cerebrovascular diseases	738	7.6	3177	11.6
Angina pectoris	457	4.7	2052	7.5
Stroke	443	4.6	1891	6.9
Hemorrhage	300	3.1	1764	6.5
Cerebral infarction	195	2.0	846	3.1
Transient cerebral ischemic attacks	155	1.6	652	2.4
Primary hypertension	151	1.6	827	3.0
Hypertensive heart disease	98	1.0	343	1.3
Occlusion and stenosis of arteries	90	0.9	316	1.2
Ischaemic heart disease	74	0.8	243	0.9
Peripheral vascular disease	73	0.8	219	0.8
Atherosclerosis of arteries of extremities	66	0.7	133	0.5
Hypertensive chronic kidney disease	41	0.4	97	0.4
Cardiovascular hospitalization	9675	100.0	27281	100.0

A.3 Imputation of missing phone records

Overall, 10.3% of observations have missing compliance data:

Table A3: Number of imputed cells

Semester-Year	Observations with imputed compliance		Total Observations
	N	%	
S1 2014	0	0.0%	67,439
S2 2014	0	0.0%	122,479
S1 2015	91,160	54.7%	166,756
S2 2015	115,124	56.2%	204,832
S1 2016	0	0.0%	235,024
S2 2016	0	0.0%	257,812
S1 2017	3960	1.4%	279,290
S2 2017	4723	1.6%	298,912
S1 2018	4849	1.6%	308,805
S2 2018	11,535	3.7%	314,072
Total	231,596	10.3%	2,255,421

Phone records were missing for all clinics in 2015, the first year the program was offered. 29 clinics were additionally missing one or more semesters of phone records, explained in the following table:

Table A4: Missing phone records

Missing semesters (S) of phone records	N clinics	% of ever treated clinics
2018 S2	14	6.7%
2018 S1, 2018 S2	1	0.5%
2017 S2, 2018 S1, 2018 S2	2	1.0%
2017 S1, 2017 S2, 2018 S1, 2018 S2	12	5.8%

For each clinic, j, with any missing phone records data we estimate the following linear regression using quarterly compliance data:

$$PrReminder_{j,t} = \alpha_j + \beta_j Quarter_t + \epsilon_{j,t}$$

Where $PrReminder_{j,t}$ is the share of patients who were sent an SMS reminder in clinic j during quarter t, also called the clinic's compliance with the program. $Quarter_t$ is a count variable taking values 1, 2, 3, ... representing 2014 quarter 1, 2014 quarter 2, 2014 quarter 3 etc. To impute missing

values, we use the four quarters closest in time to the missing semester, which improves precision compared to using all available data.

We then use the clinic-specific intercept and slope to impute missing compliance values using the following formula:

$$\widehat{PrReminder}_{j,t} = \alpha_j + \beta_j Quarter_t$$

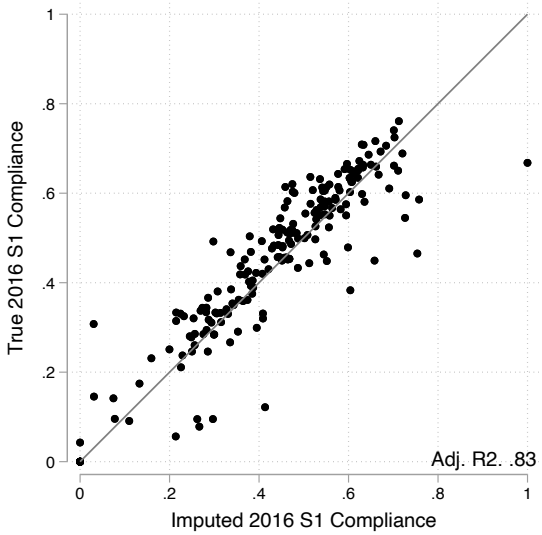
For example, if a clinic began sending reminders in 2015 S2, which corresponds to $Quarter_t = 7, 8$, but was missing phone records for that semester, we would impute it 2015 S2 compliance as 2015 $\alpha_j + \beta_j * 7.5$. Table A3 details the number of imputed cells per year-semester.

To examine the precision of our imputation method we conduct a placebo imputation exercise: we predict compliance in the first semester of 2016 using data from 2016 quarters 3-4 and 2017 quarters 1-2. Figure A1 below plots true versus imputed compliance for 2016 semester 1, showing that most observations lie tightly along the 45-degree line, indicating a strong correlation between true and predicted values. In addition, the adjusted R^2 of these *out-of-sample* imputations is 0.83, and the distribution of prediction errors is symmetric and centered close to zero (see Figure A2 below).

The instrument itself, including imputations, is balanced with no evidence of systematic bias across clinic size, urban/rural classification, or many baseline patient demographics and health measures; in Figure 2 we show that clinic-semester level compliance with the reminder program does not respond to shocks in patient health or patient population. Furthermore, after applying this refined imputation approach, the F-statistics from the first stage increased suggesting reduced noise from measurement error in the construction of the instrument.

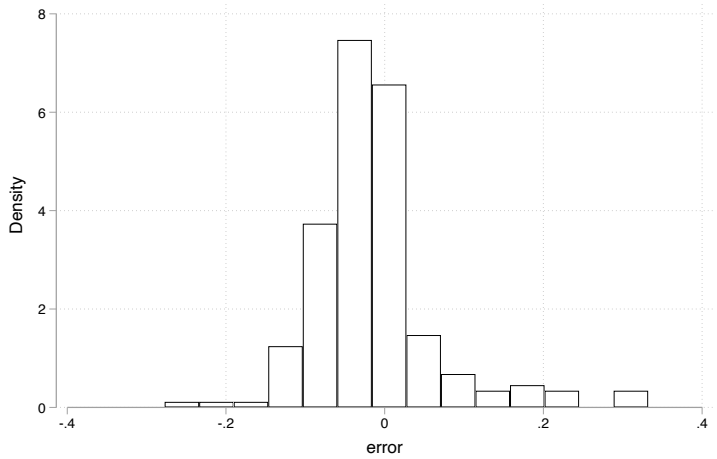
In addition, to test for if our main results are sensitive to this imputation, figures **??-??** present results where all of 2015 and the 29 clinic-semesters missing phone records in 2017 semester 1 or later are removed from the analyses.

Figure A1: Placebo imputation: compare true to imputed 2016 semester 1 compliance



Note: Placebo compliance in 2016 semester 1 imputed using 2016S2 and 2017S1 and clinic-level linear regressions, compared to actual 2016 S1 compliance. Overall adjusted R^2 is 0.83.

Figure A2: Placebo imputation: distribution of errors



Note: Errors (imputed minus true compliance) from imputing placebo compliance in 2016 semester 1.

A.4 Additional Tables and Figures

Table A5: Testing the equality of regression coefficients: impact of appointment reminders among type 2 diabetes patients vs. hypertension patients

Outcome	**F stat**	**P-val**
Visit	1.93	0.15
Blood pressure test	2.55	0.08
Weighed	0.58	0.56
Blood sugar test	-	-
Any medication pick up	60.35	0.00
Medication adherence (%)	0.72	0.49
Medication adherence ($\geq$80%)	25.43	0.00
Any cardiovascular hospitalization	228.98	0.00
N days admitted for cardiovascular hospitalization	173.43	0.00
In-hospital cardiovascular mortality	11.86	0.00
Any non-cardiovascular hospitalization	83.8	0.00
N days admitted for non-cardiovascular hospitalization	178.42	0.00
In-hospital non-cardiovascular mortality	56.51	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 receive 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.

Table A6: Compare baseline patient characteristics between clinics included and excluded from the analysis

	Excluded Clinics		Included Clinics			
	Mean	SD	Mean	SD	Diff.	P-val
Panel A: Patients with hypertension						
Male	0.40	0.49	0.41	0.49	-0.007	0.38
Age (years)	61.82	10.66	60.97	10.87	0.858	0.06
Systolic blood pressure	137.02	19.84	136.82	19.98	0.196	0.88
Diastolic blood pressure	79.22	12.08	80.74	12.07	-1.516	0.01
Weight (kg)	76.73	15.20	77.20	15.19	-0.468	0.10
Body mass index	30.59	5.50	30.87	5.54	-0.282	0.06
Waist circumference (cm)	100.51	11.96	101.00	12.03	-0.496	0.29
Obese waist	0.43	0.50	0.39	0.49	0.046	0.55
Blood pressure test	0.96	0.19	0.96	0.20	0.006	0.53
Weighed	0.94	0.24	0.94	0.24	0.002	0.93
Prescription at time of diagnosis	0.46	0.50	0.59	0.49	-0.124	0.10
F-stat for test of joint significance						1.51
N Clinics	26		310		Total	336
N Patients	27,598		284,554		Total	312,152
N Visits	214,389		2,082,052		Total	2,296,441
Panel B: Patients with type 2 diabetes						
Male	0.47	0.50	0.48	0.50	-0.011	0.27
Age (years)	60.48	10.85	59.65	10.81	0.834	0.28
Systolic blood pressure	134.15	20.17	132.10	19.61	2.047	0.30
Diastolic blood pressure	77.20	11.44	78.25	11.21	-1.058	0.02
Hemoglobin A1c	8.01	2.44	8.21	2.48	-0.198	0.02
Blood glucose	162.66	72.39	167.78	74.51	-5.112	0.07
Weight (kg)	78.55	15.36	78.56	15.36	-0.011	0.97
Body mass index	30.77	5.54	30.82	5.63	-0.055	0.71
Waist circumference (cm)	102.66	12.05	101.90	12.13	0.763	0.11
Obese waist	0.42	0.49	0.36	0.48	0.064	0.54
Glucose test, at DM2 primary care visit	1.00	0.00	1.00	0.01	0.000	0.15
Blood pressure test	0.96	0.19	0.95	0.22	0.014	0.03
Weighed	0.95	0.22	0.93	0.25	0.017	0.11
Prescription at time of diagnosis	0.38	0.48	0.55	0.50	-0.177	0.02
F-stat for test of joint significance						1.58
N Clinics	26		314		Total	340
N Patients	7,542		67,619		Total	75,161
N Visits	53,526		439,183		Total	492,709

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 included vs excluded from our analysis, because they did vs. did not have phone records data. 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.

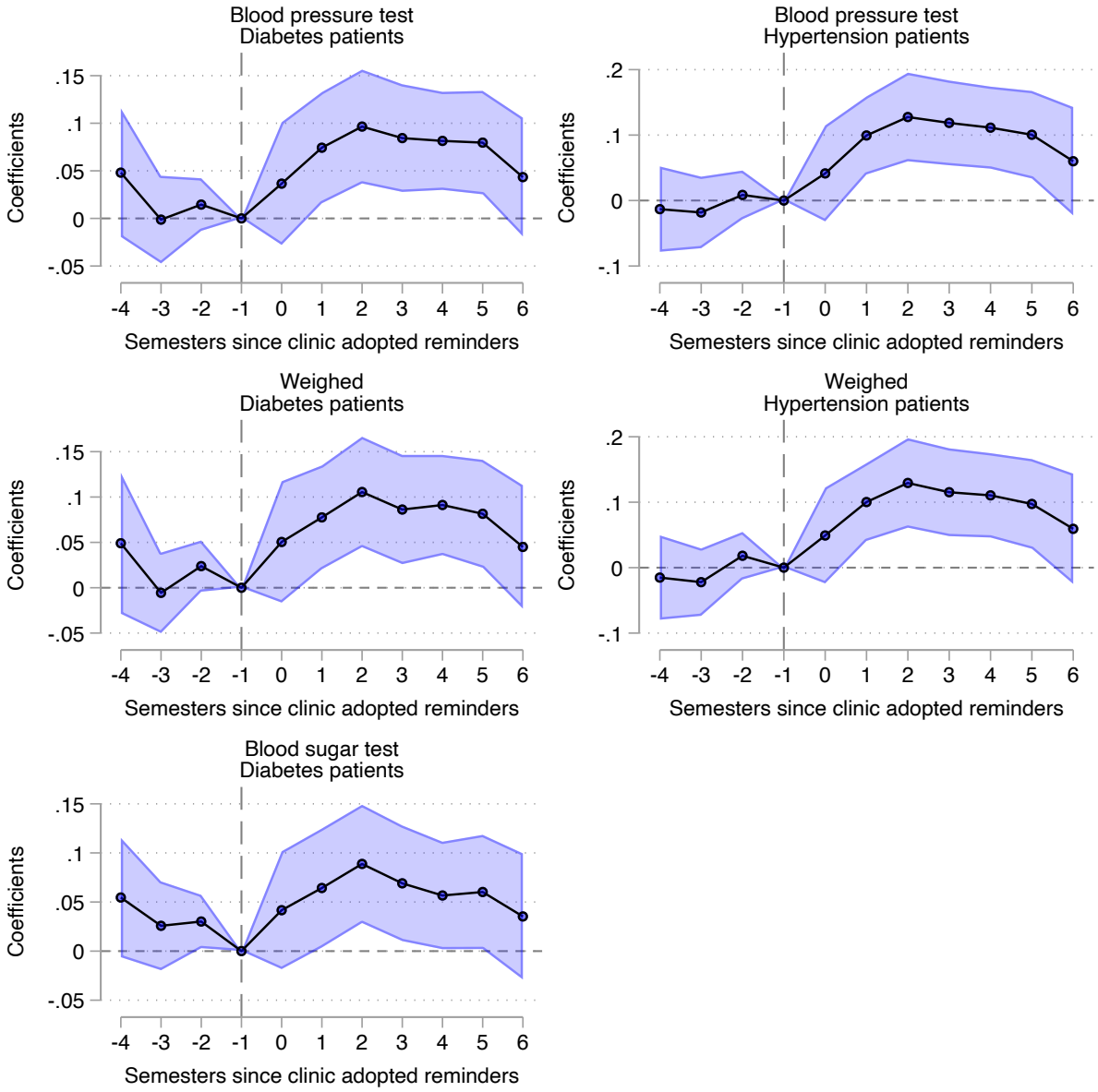
A.5 Event Studies

To examine dynamics of the reminder program roll out, we estimate event study models for our main outcomes using the following two-way fixed effects specification:

$$Y_{ijt} = \sum_{\tau=-4}^{6} \beta_\tau Q_\tau + X'_{it}\delta + \lambda_t + \gamma_j + \epsilon_{ijt} \tag{5}$$

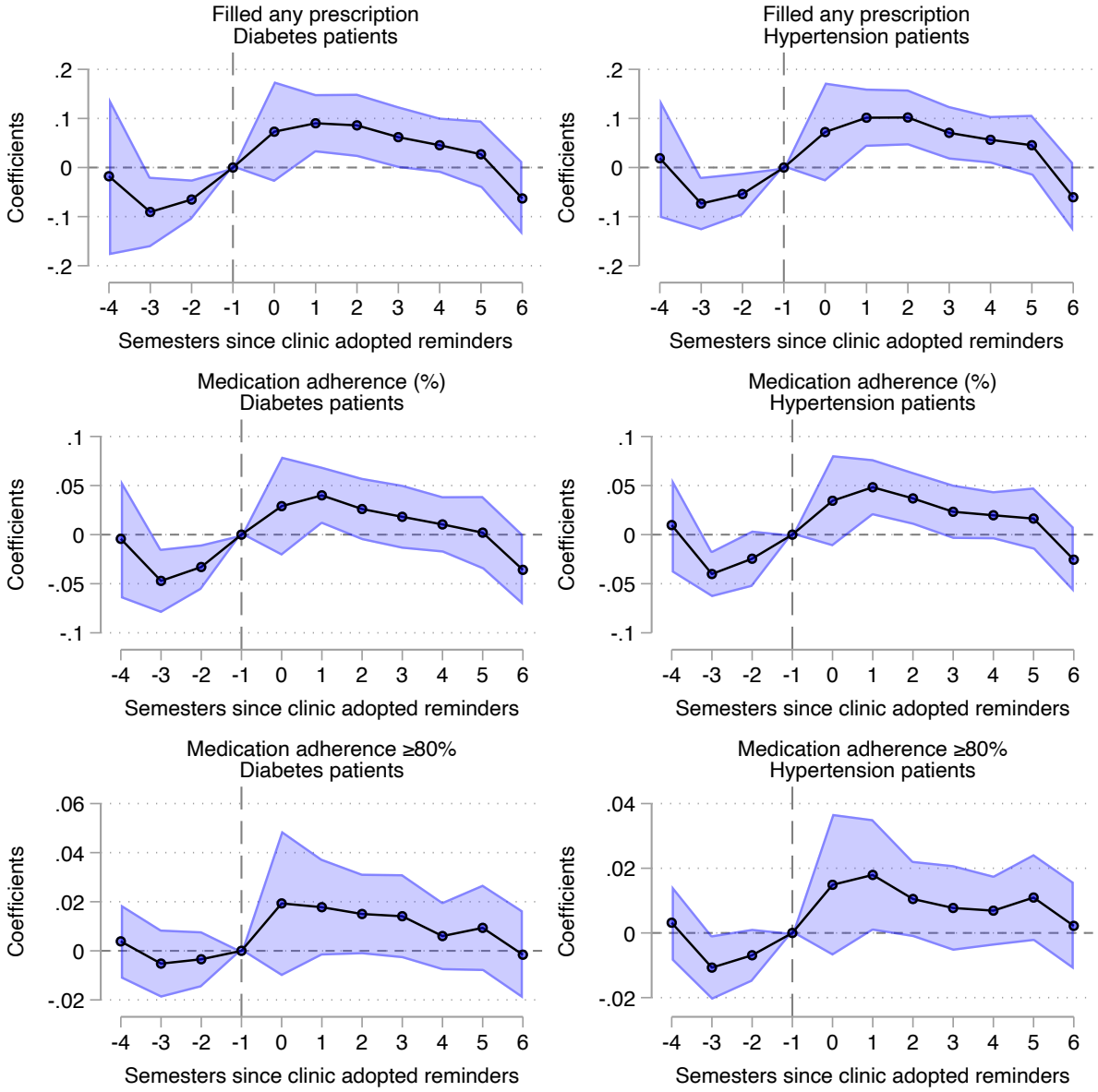
Where Y_{ijt} is an outcome for patient i at clinic j in semester t. β_τ are coefficients on semester indicators (Q_τ) for time relative to the previous period of program adoption, Q_{-1}. As in our instrumental variables analyses, each model is adjusted for common temporary shocks with semester fixed effects (λ_t), and for time-invariant clinic characteristics with clinic fixed effects (γ_j). We also include a vector of patient-level controls X'_{ijt}: fixed effects for the number of semesters since the patient was diagnosed, sex, 2-year age-group fixed effects, BMI category at diagnosis, and baseline health at diagnosis—hemoglobin A1c in 2-unit intervals for patients with type 2 diabetes, and systolic blood pressure in 10-unit intervals for patients with hypertension. Robust standard errors are clustered at the clinic level. As in our other analyses, we estimate all models separately for patients diagnosed with type 2 diabetes and with hypertension.

Figure A3: Event study estimates of the impact of appointment reminders on health monitoring



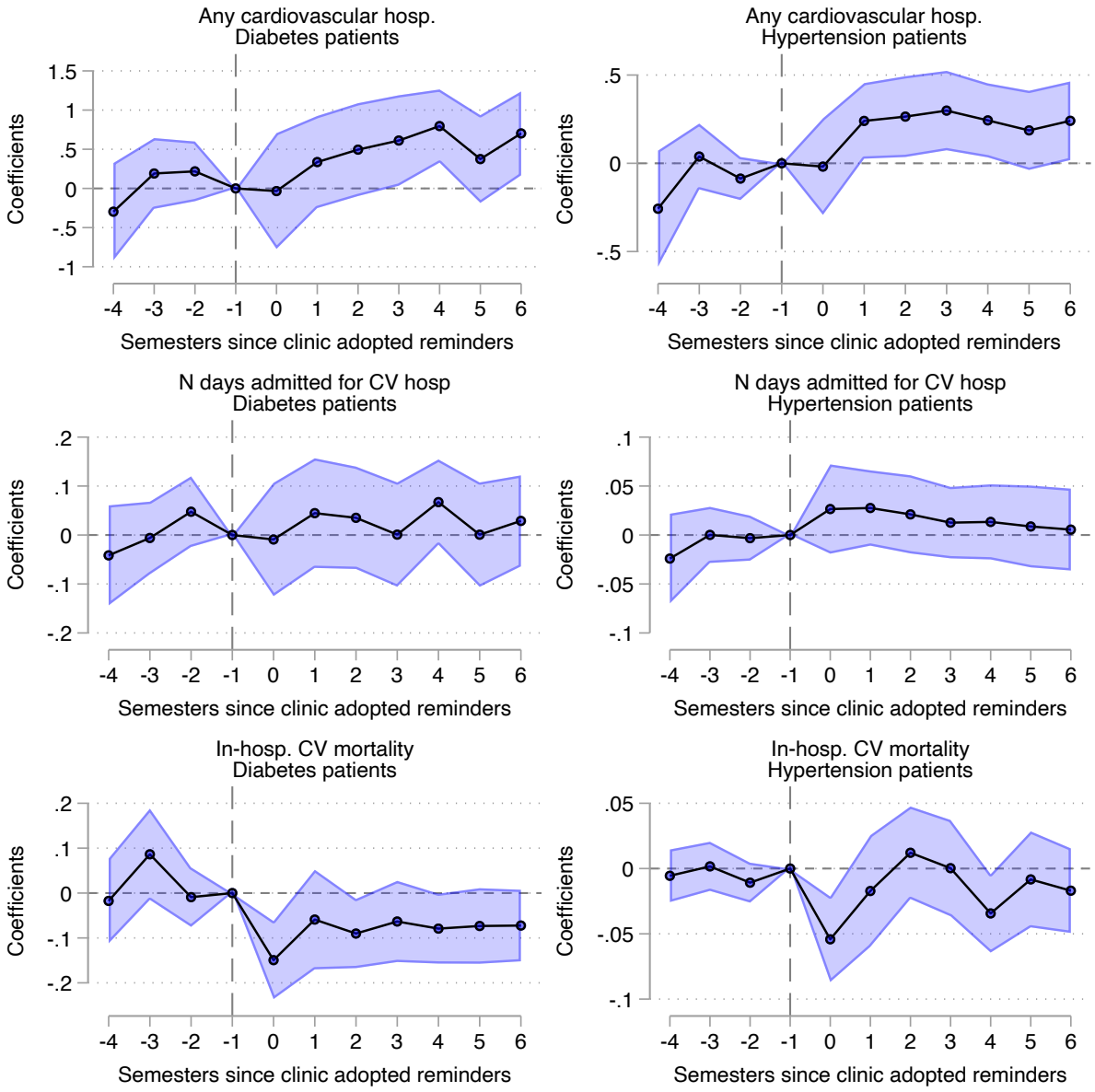
Note: Figures show two-way fixed effect regression estimates. The shaded areas denote 95% confidence intervals. The x-axis is the number of semesters relative to when the clinic implemented appointment reminders. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis. Robust standard errors were clustered at the clinic level.

Figure A4: Event study estimates of the impact of appointment reminders on medication outcomes



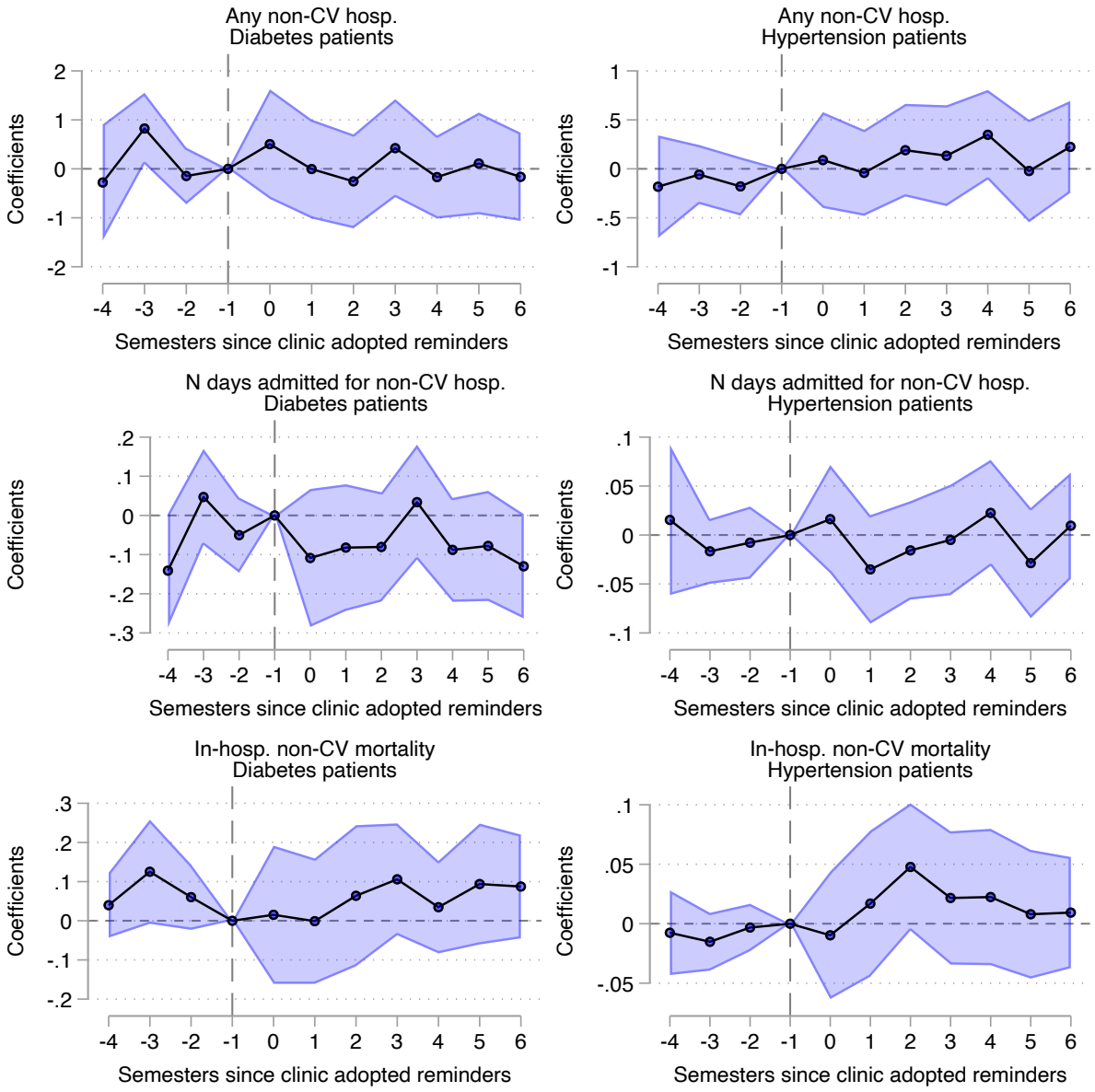
Note: Figures show two-way fixed effect regression estimates. The shaded areas denote 95% confidence intervals. The x-axis is the number of semesters relative to when the clinic implemented appointment reminders. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis. Robust standard errors were clustered at the clinic level.

Figure A5: Event study estimates of the impact of appointment reminders on cardiovascular hospitalization outcomes



Note: Figures show two-way fixed effect regression estimates. The shaded areas denote 95% confidence intervals. The x-axis is the number of semesters relative to when the clinic implemented appointment reminders. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis. Robust standard errors were clustered at the clinic level.

Figure A6: Event study estimates of the impact of appointment reminders on non-cardiovascular hospitalization outcomes



Note: Figures show two-way fixed effect regression estimates. The shaded areas denote 95% confidence intervals. The x-axis is the number of semesters relative to when the clinic implemented appointment reminders. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis. Robust standard errors were clustered at the clinic level.

A.6 Time between preventive visits and hospitalizations

Table A7: Days between preventive visit and hospitalization

Days between preventive visit and hospitalization	Type 2 Diabetes N	Type 2 Diabetes %	Hypertension N	Hypertension %
0 days	17	0.05%	52	0.04%
1 days	32	0.09%	170	0.13%
7 days	493	1.43%	1950	1.45%
14 days	1363	3.97%	5501	4.09%
30 days	3785	11.01%	14742	10.96%
Total hospitalizations	34372		134457	

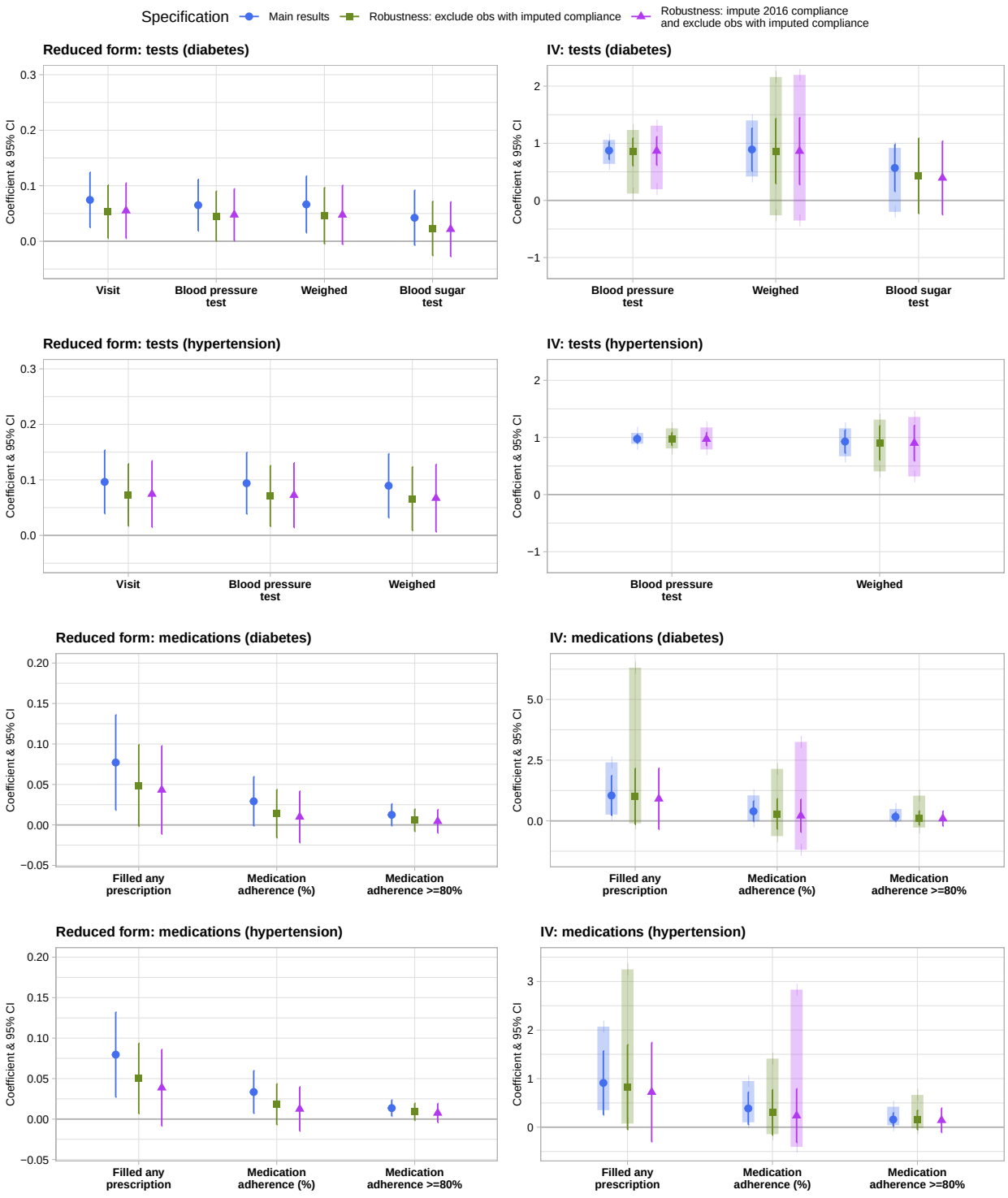
Note: This table describes the number and share of hospitalizations that were 0 (same day), 0-1, 0-7, 0-14, and 0-30 days after the same patient had a preventive care visit (inclusive). The denominator is 146,565 total hospitalizations among patients included in our sample.

A.7 Robustness to imputation of missing clinic-level program compliance

In figures A7 and A8 we plot the first stage and instrumental variables estimates, comparing our main specification to two sets of robustness results. For the first stage, coefficients and 95% confidence intervals are plotted. For IV results, coefficients and both 95% Wald confidence intervals (lines) and Anderson-Rubin 95% confidence intervals (thicker bars) are plotted.

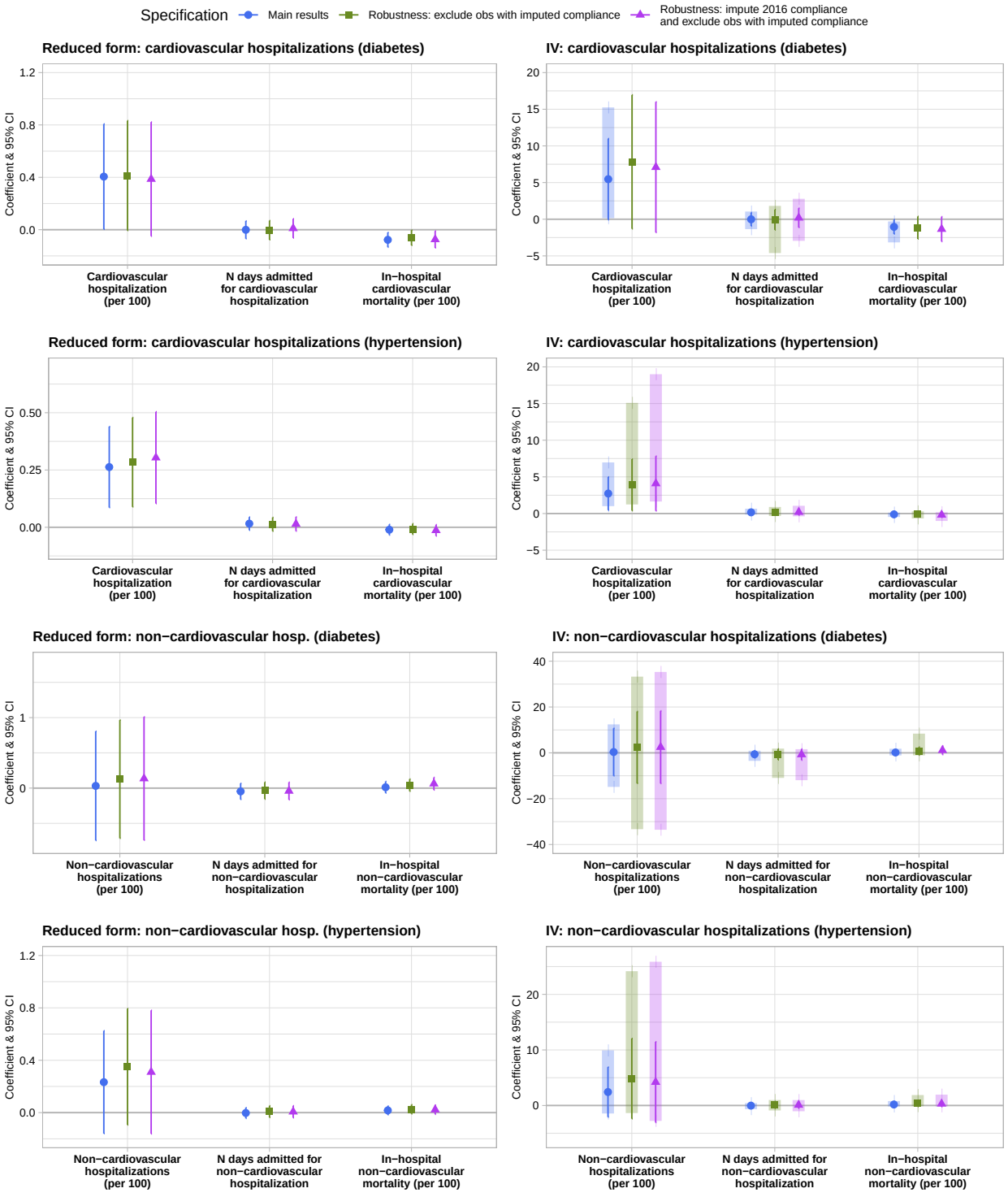
We estimate two sets of robustness results: (1) we exclude all observations with imputed compliance (estimates and 95% CIs in green), and (2) to understand how imputing clinic-semesters that are missing phone records (mostly 2015) impacts our results, we impute 2016 (even though we have it), and also exclude observations with imputed compliance (estimates and 95% CIs in purple). Comparing our main results (in blue) to (1) allows for understanding how cells with imputed compliance affect our results, and comparing (1) and (2) allows for understanding of how our imputation method affects results.

Figure A7: Comparison of reduced form and instrumental variables results across main and robustness specifications for visits and medication outcomes



Note: Figures comparing main (tables 1-4) to robustness specifications: excluding all observations with imputed compliance (tables A7-A10), and imputing 2016 compliance and excluding all observations with imputed compliance (tables A11-A14). In IV results, Wald 95% CIs are shown in solid lines, and Anderson-Rubin 95% CIs are shown in thick shaded regions. AR CIs would not compute for two outcomes: cardiovascular hospitalization and in-hospital cardiovascular mortality in the specification that excludes all observations with imputed compliance.

Figure A8: Comparison of reduced form and instrumental variables results across main and robustness specifications for hospitalization outcomes



Note: Figures comparing main (tables 1-4) to robustness specifications: excluding all observations with imputed compliance (tables A7-A10), and imputing 2016 compliance and excluding all observations with imputed compliance (tables A11-A14). In IV results, Wald 95% CIs are shown in solid lines, and Anderson-Rubin 95% CIs are shown in thick shaded regions. AR CIs would not compute for two outcomes: cardiovascular hospitalization and in-hospital cardiovascular mortality in the specification that excludes all observations with imputed compliance.

A.8 OLS Models

To benchmark our findings, we also report OLS regressions of visits on testing, medication, and hospitalization outcomes. Because these estimates rely on patient-level variation in preventive care use, they may conflate the causal effect of visits with underlying differences in patients' health or behavior that drive preventive care uptake. The OLS models are as follows:

$$Y_{ijt} = \alpha + \beta\, visit_{ijt} + X'_{ijt}\delta + \lambda_t + \gamma_j + \varepsilon_{ijt}. \tag{1}$$

Where Y_{ijt} is the outcome for patient i at clinic j in semester t, and $visit_{ijt}$ is an indicator equal to one if patient i visited clinic j during that semester. We include semester fixed effects (λ_t) to account for common temporal shocks and clinic fixed effects (γ_j) to absorb time-invariant clinic characteristics. Consistent with our reduced form and IV models, we also include a vector of patient-level controls X'_{ijt}: fixed effects for the number of semesters since the patient was diagnosed, sex, 2-year age-group fixed effects, BMI category at diagnosis, and baseline health at diagnosis—hemoglobin A1c in 2-unit intervals for patients with type 2 diabetes, and systolic blood pressure in 10-unit intervals for patients with hypertension. Robust standard errors are clustered at the clinic level. As in our other analyses, we estimate all models separately for patients diagnosed with type 2 diabetes and with hypertension.

Table A8: OLS: Impact of 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)
Visit	0.950	0.963	0.936	0.946	0.759
	(0.003)	(0.002)	(0.005)	(0.004)	(0.010)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	439,183	2,082,052	439,183	2,082,052	439,183
Clinics	314	310	314	310	314
Mean Y | Visit=0	0.000	0.000	0.000	0.000	0.000

Note: OLS estimates of the effect of a preventive care visit on health monitoring outcomes in a given semester. Robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Table A9: OLS: Impact of visits on medication outcomes

	Any medication pickup		Medication adherence (%)		Medication adherence≥ 80%	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)	(5)	(6)
Visit	0.269	0.268	0.108	0.110	0.019	0.022
	(0.017)	(0.014)	(0.007)	(0.006)	(0.002)	(0.002)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	238,198	1,098,176	238,198	1,098,176	238,198	1,098,176
Clinics	312	309	312	309	312	309
Mean Y | Visit=0	0.215	0.222	0.075	0.083	0.011	0.015

Note: OLS estimates of the effect of a preventive care visit on medication outcomes in a given semester. Robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Table A10: OLS: Impact of visits on cardiovascular hospitalizations

	Any cardiovascular hospitalization per 100 patients		N days admitted for cardiovascular hospitalizations		In-hospital CV mortality per 100 patients	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)	(5)	(6)
Visit	-0.584	-0.346	-0.146	-0.078	-0.095	-0.066
	(0.054)	(0.022)	(0.013)	(0.005)	(0.010)	(0.004)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	439,183	2,082,052	439,183	2,082,052	439,183	2,082,052
Clinics	314	310	314	310	314	310
Mean Y | Visit=0	2.011	1.325	0.319	0.186	0.120	0.085

Note: OLS estimates of the effect of a preventive care visit on the probability of cardiovascular hospital outcomes in a given semester, among all patients. Robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Table A11: OLS: Impact of visits on placebo outcomes: non-cardiovascular (CV) hospitalizations

	Any non-cardiovascular hospitalization per 100 patients		N days admitted for non-cardiovascular hospitalizations		In-hospital non-CV mortality per 100 patients	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)	(5)	(6)
Visit	-1.529	-1.278	-0.332	-0.241	-0.252	-0.172
	(0.093)	(0.048)	(0.017)	(0.010)	(0.019)	(0.008)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	439,183	2,082,052	439,183	2,082,052	439,183	2,082,052
Clinics	314	310	314	310	314	310
Mean Y | Visit=0	5.215	4.766	0.630	0.485	0.315	0.215

Note: OLS estimates of the effect of a preventive care visit on the probability of non-cardiovascular hospital outcomes in a given semester. Robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

A.9 LIML IV Estimation

Table A12: Impact of appointment reminders and visits on health monitoring (LIML)

		Visit		Blood pressure test		Weighed		Blood sugar test
		Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Reduced form: impact of appointment reminders								
Pr(Reminder)	β	0.074	0.096	0.065	0.094	0.066	0.089	0.042
	SE	(0.025)	(0.029)	(0.024)	(0.028)	(0.026)	(0.029)	(0.025)
	p-val	[0.003]	[0.001]	[0.006]	[0.001]	[0.011]	[0.002]	[0.094]
Panel B. Instrumental variables: impact of primary care visit								
Visit		-	-	0.874	0.975	0.891	0.928	0.569
		-	-	(0.080)	(0.040)	(0.192)	(0.103)	(0.210)
		-	-	[0.000]	[0.000]	[0.000]	[0.000]	[0.007]
Observations		439,183	2,082,052	439,183	2,082,052	439,183	2,082,052	439,183
Clinics		314	310	314	310	314	310	314
Mean Y | Pr(SMS)=0		0.654	0.656	0.626	0.629	0.613	0.616	0.565
Mean Y | Visit=0		-	-	0.000	0.000	0.000	0.000	0.000
First stage F-stat		-	-	8.657	10.979	8.657	10.979	8.657

Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of health monitoring in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of health monitoring in a given semester. IV models were estimated using equation (1) and the limited information maximum likelihood. Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Table A13: Impact of appointment reminders and visits on medication outcomes (LIML)

		Filled any prescription		Medication adherence (%)		Medication adherence≥ 80%	
		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							
Pr(Reminder)	β	0.077	0.080	0.029	0.033	0.012	0.014
	SE	(0.030)	(0.027)	(0.015)	(0.013)	(0.007)	(0.005)
	p-val	[0.010]	[0.003]	[0.060]	[0.013]	[0.072]	[0.008]
Panel B. Instrumental variables: impact of primary care visit							
Visit		1.044	0.912	0.394	0.386	0.168	0.157
		(0.419)	(0.335)	(0.214)	(0.171)	(0.100)	(0.071)
		[0.013]	[0.007]	[0.066]	[0.024]	[0.092]	[0.026]
Observations		238,198	1,098,176	238,198	1,098,176	238,198	1,098,176
Clinics		312	309	312	309	312	309
Mean Y | Pr(SMS)=0		0.301	0.300	0.119	0.124	0.024	0.028
Mean Y | Visit=0		0.215	0.222	0.075	0.083	0.011	0.015
First stage F-stat		10.391	11.093	10.391	11.093	10.391	11.093

Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of medication adherence in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of medication adherence in a given semester. IV models were estimated using equation (1) and the limited information maximum likelihood. Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis. Note that the estimate of the effect of visits on any medication pick up is over 1 because we use a linear probability model.

Table A14: Impact of appointment reminders and visits on cardiovascular hospitalizations (LIML)

	Any cardiovascular hospitalization per 100 patients		N days admitted for cardiovascular hospitalizations		In-hospital CV mortality per 100 patients	
	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						
Pr(Reminder) β	0.405	0.263	-0.001	0.016	-0.077	-0.011
SE	(0.204)	(0.090)	(0.035)	(0.015)	(0.029)	(0.012)
p-val	[0.048]	[0.004]	[0.978]	[0.277]	[0.007]	[0.375]
Panel B. Instrumental variables: impact of primary care visit						
Visit	5.462	2.729	-0.013	0.164	-1.041	-0.109
	(2.825)	(1.159)	(0.466)	(0.160)	(0.498)	(0.126)
	[0.053]	[0.019]	[0.977]	[0.305]	[0.037]	[0.388]
Observations	439,183	2,082,052	439,183	2,082,052	439,183	2,082,052
Clinics	314	310	314	310	314	310
Mean Y | Pr(SMS)=0	1.809	1.192	0.247	0.150	0.053	0.037
Mean Y | Visit=0	2.011	1.325	0.319	0.186	0.120	0.085
First stage F-stat	8.657	10.979	8.657	10.979	8.657	10.979

Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of cardiovascular hospital outcomes in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of cardiovascular hospital outcomes in a given semester. IV models were estimated using equation (1) and the limited information maximum likelihood. Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.

Table A15: Impact of appointment reminders and visits on placebo outcomes: non-cardiovascular (CV) hospitalizations (LIML)

	Any non-cardiovascular hospitalization per 100 patients		N days admitted for non-cardiovascular hospitalizations		In-hospital non-CV mortality per 100 patients	
	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						
Pr(Reminder) β	0.031	0.233	-0.046	-0.003	0.012	0.017
SE	(0.394)	(0.199)	(0.058)	(0.021)	(0.042)	(0.017)
p-val	[0.936]	[0.244]	[0.427]	[0.893]	[0.775]	[0.322]
Panel B. Instrumental variables: impact of primary care visit						
Visit	0.357	2.423	-0.627	-0.028	0.161	0.177
	(5.301)	(2.295)	(0.825)	(0.218)	(0.568)	(0.190)
	[0.946]	[0.291]	[0.447]	[0.896]	[0.778]	[0.352]
Observations	439,183	2,082,052	439,183	2,082,052	439,183	2,082,052
Clinics	314	310	314	310	314	310
Mean Y | Pr(SMS)=0	4.387	3.844	0.443	0.323	0.154	0.090
Mean Y | Visit=0	5.215	4.766	0.630	0.485	0.315	0.215
First stage F-stat	8.657	10.979	8.657	10.979	8.657	10.979

Note: Panel A presents reduced form estimates of the effect of compliance with appointment reminders on the probability of non-cardiovascular hospital outcomes in a given semester. Reduced form models were estimated using equation (2), where the independent variable was Pr(Reminder), the probability a patient was sent a reminder in a given semester, or clinic-semester level compliance. Panel B presents instrumental variables (IV) (second-stage) estimates of the effect of a primary care visit on the probability of non-cardiovascular hospital outcomes in a given semester. IV models were estimated using equation (1) and the limited information maximum likelihood. Panels A and B include robust standard errors, clustered at the clinic level in parentheses, and p-values in brackets. All models include fixed effects for semester, clinic, semesters since the patient's diagnosis, age in 2-year increments, sex, BMI at diagnosis, and systolic blood pressure or hemoglobin A1c at diagnosis.