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THE IMPORTANCE OF PREVENTIVE MEDICAL CARE FOR MANAGING CHRONIC DISEASE

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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 and 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.

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1 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, 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 behavior. Specifically, we ask (1) whether patients who attend preventive care receive appropriate screening tests, which is a measure of the performance of their healthcare providers; (2) whether preventive care impacts patient medication adherence, i.e. do they take medications as prescribed or, more generally, have better health behaviors; and (3) whether preventive care leads to earlier detection and treatment of chronic disease complications, specifically hospitalization and in-hospital mortality for cardio-vascular 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 is the near-universe of patients recently diagnosed with diabetes or hypertension in the public health care system. The analysis sample is a panel of patients followed up to 4.5 years after diagnosis from 315 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 by cause and in-hospital mortality from the universe of hospitals.

We identify the effects of preventive care visits using plausibly exogenous variation in attendance induced by an appointment reminder program.[1] Our instrument is clinic compliance with the reminder program, measured as the share of eligible patients who received a reminder, that is, the probability of being sent an appointment reminder. Several pieces of evidence show that compliance is plausibly exogenous. First, compliance is uncorrelated with a large number of patient- and clinic-level characteristics at baseline both individually and jointly. Second, reminders were effective in significantly increasing preventive care visits to medical care facilities. Third, the effectiveness of the reminders did not diminish over time and did not vary with baseline patient health status.

We find that preventive visits increase the use of disease screening and monitoring tests. Specifically, an additional visit leads to an 88 and 98 percentage point (pp) increase in blood pressure tests and an 88pp and 91pp increase in weight measurement for patients with type 2 diabetes and hypertension, respectively. An additional visit also leads to a 53pp increase in blood glucose tests for patients with diabetes. These large effects reflect that national clinical practice guidelines state that these tests be administered at every primary care appointment. Our results suggest providers adhere to the guidelines.

Visits also lead to a large increase in medication adherence: An additional preventive care visit is associated with a remarkable 21pp increase in adequate medication adherence, as measured by pharmacy refills. Medication adherence is an important outcome as it is a primary therapy used to control chronic disease for most patients. More generally, adherence is primarily a patient behavior, one that is typically challenging to change, and our results suggest that preventive visits do improve patient health behaviors.

Lastly, among patients with type 2 diabetes, preventive care leads to an additional 5.5 cardiovascular-related hospitalizations, but 1.1 fewer in-hospital deaths for cardiovascular disease per 100 patients per semester. These findings suggest that providers diagnosed acute complications of chronic diseases earlier than otherwise, during preventive care visits. Patients may have received referrals and better information about necessary emergency or secondary care. Placebo outcomes confirm that these effects are related to diabetes and hypertension as there were no effects on hospitalizations or in-hospital mortality for non-cardiovascular causes.

[1] 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 such as appointment reminders 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).

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 more general literature on the causal impact of medical care, for which identification can be challenging because utilization is usually endogenous to past utilization and diagnoses (Levy and Meltzer 2008). To address this concern, we leverage a novel source of plausibly exogenous variation in utilization induced by appointment reminders. This allows us to mitigate this concern when examining downstream outcomes. Previous research has largely addressed causality by leveraging an exogenous change in insurance availability or change in the prices faced by patients (Baicker et al. 2013; Finkelstein et al. 2012; Taubman et al. 2014; Card, Dobkin, and Maestas 2009; Card, Dobkin, and Maestas 2008; Adams et al. 2022; Aron-Dine, Einav, and Finkelstein 2013; King et al. 2009).

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 randomized 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 for studying the impact of health care use (Card, Dobkin, and Maestas 2009; Card, Dobkin, and Maestas 2008; Miller, Johnson, and Wherry 2021; Goldin, Lurie, and McCubbin 2021).

Finally, our work is also related 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.

2 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).

2.1 Health Care System

Chile has two modern 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. 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.

2.2 Chronic Disease

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*).[2] This program makes them eligible for prioritized free care, the ability to schedule primary care appointments in advance and receive advance appointment reminders.[3] Because PSCV patients are closely monitored, there is high-quality administrative data on their visits, medication use, and hospitalizations.

However, patients with chronic disease miss a large number of appointments; 16.7% of scheduled appointments were missed in 2018 (Boone et al. 2022), costing Chile approximately 180 million USD annually (Contreras 2022). Aiming to reduce the number of missed appointments, the Chilean Ministry of Health offered public clinics the option to adopt an automated appointment reminder system. The reminder program was available to clinics using electronic medical records and implemented through software integrated into the electronic medical record system of the clinic.

Reminders were sent to patients enrolled in the PSCV program and provide them the ability to confirm, cancel, or change appointment times.[4] A reminder was automatically sent to patients 24 to 72 hours before their 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 either the 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.

3 Data

3.1 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.

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

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

[4] The reminder message was as follows: *"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"*.

3.2 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 as the percentage of days covered (PDC), a standard metric in the medical literature (Osterberg and Blaschke 2005). PDC is calculated based on prescription refill data. From the prescription quantity and refill date, we infer the number of days the patient lacked sufficient medication. From this, we compute the proportion of days in a semester that the patient had enough pills to adhere to the prescription. If the patient refills her prescription on time then she has 100% of days covered. If she refills the prescription late, then the PDC is less than 100%.[5] We then create an indicator equal to 1 if the patient had adequate pills for at least 80% of the days in that semester. Note that this measure assumes that patients take the medication for the days that they have medication on hand.

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. However, this does not appear to be a problem, since receiving a prescription is uncorrelated with whether the patients is assigned to a clinic that uses the reminder system, our instrument. Appendix table A6 shows that the prescribing rates at patients' baseline visit are statistically indistinguishable between the clinics that did vs. did not implement the appointment reminder program.

3.3 Hospitalization Records

Hospital admission records from both public and private hospitals in Chile are available from 2013-2018. We link these records to both the EHR and medication datasets at the patient level. The data contain a unique patient identifier, a unique hospital identifier, the date of visit, ICD-10 diagnostic codes for the primary and secondary cause of admission, and an indicator for whether the patient

[5]We assume that a patient who has been prescribed a medication will have an active prescription going forward. We assign a medication adherence value of zero for patients who did not fill any prescriptions in a given future semester. Patients may potentially experience medication de-prescription if the patient demonstrates regular attendance at primary care visits and has achieved significant lifestyle modifications. However, this is very rare (Oster 2018).

died in the hospital. Importantly, 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, which means that hospitalization measures are not endogenous to primary care utilization.

We separate hospitalizations into those that are cardiovascular-related and non-cardiovascular related, based on ICD-10 codes for primary and secondary diagnosis.[6] Cardiovascular codes include hospitalizations with type 2 diabetes or hypertension ICD codes in the reason for visit, or closely related complications such as heart attack, stroke, and heart failure (Luengo-Fernandez et al. 2023; Khokhar et al. 2016; Beckman 2014). We use non-cardiovascular related hospitalizations as placebo outcomes, which include diagnoses such as accidents, infectious diseases, and mental health concerns. For each group of hospitalizations we construct two outcomes: an indicator for if the patient was hospitalized and an indicator for if the patient died in the hospital.[7]

3.4 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.[8] 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. Finally, we drop two clinics that have conflicting treatment status in different sources of information and another 26 clinics that took up the reminder program but are completely missing the phone records data that are used to construct our instrument. We perform a balance test in appendix table A5 and find that baseline patient characteristics are similar between clinics included and excluded from the analysis. Our final sample includes 315 clinics located in 275 different counties; 79% of all counties in Chile.

The patient sample includes those newly diagnosed with type 2 diabetes and/or hypertension between 2014 and 2018. We limit the sample to those newly diagnosed to reduce left censoring and

[6] See appendix table A1 for the classification of ICD-10 codes.

[7] 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).

[8] 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.

avoid over-representing patients who have high attendance at preventive care.[9] We also exclude patients under 35 years of age and over 80 years of age at the time of diagnosis. We exclude those below 35 to minimize inclusion of type 1 diabetic patients as type 1 is genetic and typically occurs earlier in life (Thomas et al. 2023). We exclude those over 80 as the clinical practice guidelines for them are different than for younger patients (MINSAL 2017b). 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 with visits to the 315 study clinics.

4 Empirical Methods

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

$$Y_{ijt} = \alpha + \beta visit_{ijt} + X'_{it}\delta + \lambda_t + \gamma_i + \epsilon_{ijt} \tag{1}$$

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_i).[10] We also include a vector of patient-level controls (X'_{it}) that include fixed effects for number of semesters since the patient was diagnosed, gender, and 2-year age-groups (i.e. age 35-36, 37-38, 39-40, etc.) at the time of the medical visit. We estimate all models separately for patients who were diagnosed with type 2 diabetes and hypertension.[11]

4.1 Estimation

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

[9] For patients whose date of diagnosis was missing, we include anyone who did not have a chronic disease screening visit prior to January 1, 2014 but did have one between 2014 and 2018, and label their date of diagnosis as the time of the first screening visit after January 1, 2014. Patients who were in the data on January 1 2013 and had a second visit, had the second visit within the following 361 days. Therefore, if a patient appears in the data 362 days after January 1, 2013, they are likely to be a new patient at their first post-diagnosis visit.

[10] 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.

[11] Pooling tests reject that the effect of appointment reminders is equal in both samples for 8 of our 10 main outcomes (appendix table A4).

a scheduled preventive care appointment was sent a reminder in semester t. It is always zero for clinics that did not implement the appointment reminder program.

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. Phone records are available for 90% of clinic-semesters for the years 2016-2018, but are missing for all of 2015 and for 29 clinic-semesters in the later years in our panel. However, records are complete for the semesters that they are available. We impute missing observations using linear regressions for each clinic. Specifically, for each clinic we separately regress program compliance for the year-semesters that they are available on year-semester date, and then use the clinic's intercept and slope to impute its program compliance in missing cells. For more details on imputation, see appendix section A.2. In section 5.4 we describe a series of robustness analyses showing that dropping imputed units does not change our estimates, but does reduce precision in some cases as the number of observations is reduced.

Variation in the probability a patient was sent a reminder comes from both the extensive (take-up) and intensive margins. The appointment reminder system was rolled out between 2015 and 2018. 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). Among those that took up the program, there is both cross-sectional and time series variation in the probability a patient was sent a reminder. Figure 1 panel A shows that in each year, there is large variation in compliance: among clinics that took up the program, between 0 and 90% of eligible patients were sent SMS reminders. Over time, an increasing number of eligible patients were sent reminders: while average compliance in 2016 was 47%, in 2017 it was 55%, and in 2018 it was 56%. Figure 1 panel B is an event study plot where the outcome is the clinic-semester probability a patient was sent a reminder, shows that within-clinics, compliance increased with time since program adoption.

4.2 Identification

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).

4.2.1 Instrument Relevance

In our first stage we estimate the effect of compliance with the appointment reminder program, or the probability a patient was sent a reminder, on preventive care visits:

$$visit_{ijt} = \alpha + \beta PrReminder_{jt} + X'_{it}\delta + \lambda_t + \gamma_i + \mu_{ijt} \tag{2}$$

As above, each model is adjusted for common temporary shocks with semester fixed effects (λ_t), and clinic fixed effects (γ_i). We also include a vector of patient-level controls (X'_{it}): fixed effects for semesters since the patient was diagnosed, gender, and 2-year age-group fixed effects. Standard errors are clustered at the clinic level.

We find that our instrument is a strong predictor of preventive care visits: compliance with the reminder program induces a 6.2 percentage point (pp) increase in visits among patients with type 2 diabetes, and a 7.7pp increase among patients with hypertension (table 1 columns 1-2), both significant at p<0.05. These results indicate meaningful changes in the likelihood of attending primary care following program implementation, supporting the strength of our instrument.

Heterogeneity. We test whether the effect of the reminders varies with important patient characteristics by interacting baseline patient characteristics with the $PrReminder_{jt}$ indicator in equation 2. We first test for heterogeneity by time since diagnosis. Figure A2, panel (a), shows little variation, suggesting the effectiveness of reminders does not fade over time. Second, we test for heterogeneity by age. Figure A2, panel B shows the positive impact of reminders on visits is consistent across age groups up to age 75. Finally, we test for heterogeneity by health status at diagnosis, measured using biomarkers. Figure A2, panel C shows little heterogeneity in treatment effects by hemoglobin A1c levels, albeit the effects are not statistically significant among patients diagnosed with hemoglobin A1c levels above 12%.[12] 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.[13]

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

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

4.2.2 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 (Appendix table A6). 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) (Appendix table A6). At the patient's first observed visit, the probability of a medication prescription and the probability of key tests were similar across clinics (table A6).

Changes in Clinic Compliance Over Time. We next show that clinic-semester level compliance with the reminder program does not respond to shocks in patient health or patient population. In appendix figure A1 we plot coefficients and 95% confidence intervals from a multivariate regression of lagged clinic and patient characteristics on compliance. We find these characteristics do not significantly predict compliance (F-statistic 1.04).

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 (A2, panel A) also provides support.

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.

5 Results

In general, the first stage F-statistics are below 10 indicating weak instruments. To address this issue, we report Anderson-Rubin (AR) 95% confidence intervals which are robust to weak instruments (Anderson and Rubin 1949). The lower bound represents the minimum value of the coefficient that is consistent with the IV assumptions, while the upper bound represents the maximum value. AR confidence intervals allow us to reject the absence of an effect of the program and provide bounds on the effect size.

5.1 Health monitoring

We find that an additional preventive care visit at a primary care clinic has large impacts on the likelihood of receiving health monitoring tests. An additional visit leads to an 87.7pp and 98.5pp increase in the probability of a blood pressure test for patients with type 2 diabetes and hypertension, respectively (table 1 panel B, columns 3-4). A visit also leads to an 88.1pp and 91.2pp increase in the probability of weight measurement (table 1 panel B, columns 5-6). For patients with type 2 diabetes, an additional visit leads to a 53.3pp increase the likelihood of having a blood glucose test (table 1 panel B, column 7). The Anderson-Rubin confidence intervals reject null effects for all outcomes.

In line with these results, reduced form estimates in panel A of Table 1 shows that variation in compliance with the appointment reminder is positively associated with the likelihood of a patient being monitored for blood pressure, weight, and blood glucose or hemoglobin A1c.

Chile's clinical practice guidelines state that blood pressure and weight should be measured at each primary care encounter, and blood sugar should be regularly monitored.[14] The large effects

[14]Patients may also be monitoring their health on their own, outside of clinics, but this is not observable in our data, nor are these test values used for updates to the patients care plan, medications or diagnoses.

we find suggest strong guideline adherence among providers, so that if patients attend preventive care, they are extremely likely to receive these tests.

5.2 Medication adherence

Preventive visits also substantially increase adequate medication adherence, defined as maintaining a coverage ratio of days of at least 80%. Specifically, a visit increases the probability of adequate medication adherence by 21pp for both patient types (table 2, panel B). The reduced form estimates also show that program compliance at the clinic level increases the likelihood of adequate medication adherence, by 1.3-1.4pp (table 2, panel B).

5.3 Hospitalizations and in-hospital mortality

We find that an additional preventive care visit leads to an increased rate of hospitalization for cardiovascular-related conditions of 5.5 per 100 patients with type 2 diabetes and 3.0 per 100 patients with hypertension, per semester (table 3, columns 1-2). An additional preventive visit also reduces the in-hospital mortality rate by 1.1 per 100 patients with type 2 diabetes per semester (table 3 columns 5). For patients with hypertension, the in-hospital mortality effect is smaller at -0.19 and is not statistically significant.

Together, these findings indicate that more preventive care led to a higher likelihood of seeking hospital care at an earlier stage. This could suggest that patients hospitalized for cardiovascular conditions are have less severe health conditions upon arrival, possibly attributed to factors such as referrals, enhanced medication adherence or other healthy habits, or guidance from healthcare providers regarding appropriate care-seeking.

Placebo outcomes. As a placebo test, we run the same analyses on non-cardiovascular hospitalizations; all hospital visits without hypertension or type 2 diabetes-related ICD codes such as accidents, broken bones, and mental health conditions. We find no statistically significant relationship between reminders or visits and hospitalizations for non-cardiovascular related conditions or in-hospital mortality attributed to non-cardiovascular causes (table 4). In all cases, our estimates are not statistically significant and most are near zero.

5.4 Robustness checks

We perform several analyses to check the robustness of our results to the influence of imputing clinic-semester compliance for clinic-semesters with missing phone records data on our results.[15] Appendix table A3 details the number of imputed cells by semester-year. Overall, we find that imputation does not meaningfully affect the point estimates or direction of effect, but does increase precision in some cases, likely because it allows us to include a larger number of observations in the analyses.

In the first test, reported in appendix tables A7-A10, we 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, in appendix tables A11-A14 we impute compliance for 2016, a year for which we have compliance data, and re-estimate our main results including imputed 2016 compliance and excluding 2015 compliance. This allows us to compare these estimates to appendix table A7-A10, which also exclude 2015 imputed values. We find that using imputed 2016 compliance or true 2016 compliance, alongside true compliance data, yields similar results, providing support for our imputation methods.

6 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).

[15] Section A.2 provides more details about the imputation.

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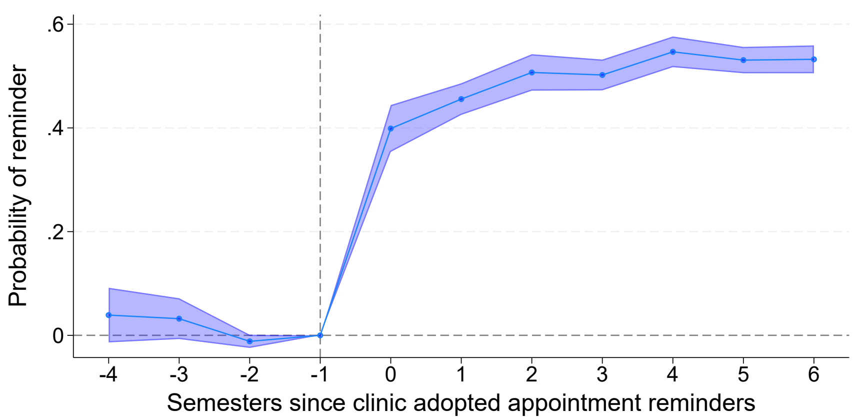
7 Tables and Figures

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

(a) Take-up and compliance summary by semester

	Clinics with	Clinics without	Compliance		
Date	Reminders	Reminders	Mean	Min.	Max.
S1 2014	0	315	-	-	-
S2 2014	0	315	-	-	-
S1 2015*	168	147	48.2%	0.0%	83.4%
S2 2015*	172	143	49.1%	0.0%	81.1%
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%	13.9%	83.5%
S2 2017	208	107	52.9%	9.3%	80.8%
S1 2018	208	107	57.2%	4.7%	85.1%
S2 2018	208	107	53.1%	0.0%	90.3%
Total	208	107	51.3%	0.0%	90.3%

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



Note: Panel A: Compliance is the share of patients sent an appointment reminder using text message, 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.

Table 1: 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)	0.062	0.077	0.055	0.076	0.055	0.070	0.033
	(0.024)	(0.027)	(0.022)	(0.026)	(0.025)	(0.027)	(0.024)
	[0.010]	[0.005]	[0.016]	[0.004]	[0.029]	[0.011]	[0.175]
Panel B. Instrumental variables: impact of primary care visit							
Visit	-	-	0.877	0.985	0.881	0.912	0.533
	-	-	(0.095)	(0.052)	(0.237)	(0.131)	(0.253)
	-	-	[0.000]	[0.000]	[0.000]	[0.000]	[0.036]
AR CI	-	-	[0.57, 1.13]	[0.87, 1.14]	[0.25, 1.61]	[0.54, 1.24]	[-0.69, 0.96]
AR p-val	-	-	0.015	0.004	0.028	0.011	0.174
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	0.657	0.654	0.626	0.629	0.614	0.617	0.566
Mean Y | Visit=0	-	-	0.000	0.000	0.000	0.000	0.000
First stage F-stat	-	-	6.708	8.140	6.708	8.140	6.708

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, and sex.

Table 2: Impact of appointment reminders and visits on medication outcomes

	Medication adherence $\geq$ 80%	
	Type 2 Diabetes	Hyper-tension
	(1)	(2)
Panel A. Reduced form: impact of appointment reminders		
Pr(Reminder)	0.013	0.014
	(0.006)	(0.005)
	[0.048]	[0.002]
Panel B. Instrumental variables: impact of primary care visit		
Visit	0.216	0.211
	(0.127)	(0.097)
	[0.089]	[0.030]
AR CI	[0.01, 0.80]	[0.07, 0.75]
AR p-val	0.058	0.006
Observations	238,198	1,098,176
Clinics	312	309
Mean Y | Pr(SMS)=0	0.024	0.028
Mean Y | Visit=0	0.011	0.015
First stage F-stat	7.373	7.541

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, and sex.

Table 3: Impact of appointment reminders and visits on cardiovascular hospitalizations

	Cardiovascular hospitalization per 100 patients		In-hospital CV mortality per 100 patients	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Panel A. Reduced form: impact of appointment reminders				
Pr(Reminder)	0.342	0.233	-0.069	-0.015
	(0.198)	(0.085)	(0.029)	(0.011)
	[0.086]	[0.006]	[0.018]	[0.192]
Panel B. Instrumental variables: impact of primary care visit				
Visit	5.492	3.030	-1.111	-0.193
	(3.288)	(1.376)	(0.610)	(0.157)
	[0.096]	[0.028]	[0.070]	[0.219]
AR 95% CI	[-0.681, 19.463]	[0.990, 9.42]	[-4.549, -0.206]	[-0.798, 0.102]
AR p-val	0.089	0.009	0.022	0.188
Observations	439,183	2,082,052	439,183	2,082,052
Clinics	314	310	314	310
Mean Y | Pr(SMS)=0	1.687	1.122	0.053	0.037
Mean Y | Visit=0	1.831	1.216	0.120	0.085
First stage F-stat	6.708	8.140	6.708	8.140

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, and sex.

Table 4: Impact of appointment reminders and visits on placebo outcomes: non-cardiovascular (CV) hospitalizations

	Non-cardiovascular hospitalization per 100 patients		In-hospital non-CV mortality per 100 patients	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Panel A. Reduced form: impact of appointment reminders				
Pr(Reminder)	0.005	0.168	0.001	0.015
	(0.356)	(0.186)	(0.042)	(0.017)
	[0.989]	[0.365]	[0.982]	[0.371]
Panel B. Instrumental variables: impact of primary care visit				
Visit	0.010	2.200	0.014	0.202
	(5.753)	(2.606)	(0.671)	(0.236)
	[0.999]	[0.399]	[0.983]	[0.394]
AR 95% CI	[-19.890, 14.225]	[-2.693, 11.729]	[-1.909, 1.938]	[-0.242, 1.066]
AR p-val	0.999	0.373	0.983	0.367
Observations	439,183	2,082,052	439,183	2,082,052
Clinics	314	310	314	310
Mean Y | Pr(SMS)=0	4.223	3.753	0.153	0.090
Mean Y | Visit=0	4.990	4.632	0.315	0.215
First stage F-stat	6.708	8.140	6.708	8.140

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, and sex.

A Online Appendices

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.

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

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

Note: ICD-10 codes listed are included in outcomes cardiovascular-related hospitalization and in-hospital cardiovascular mortality. All other ICD-10 codes are included in non cardiovascular-related hospitalization and non cardiovascular-related mortality outcomes. A decimal of X indicates all integers were used.

A.2 Imputation of missing phone records

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 A2: 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:

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

Where $PrReminder_{j,t}$ is the share of patients who were sent an SMS reminder in clinic j during semester t, also called the clinic's compliance with the program. $Semester_t$ is a count variable taking values 1, 2, ... 10 representing 2014 semester 1, 2014 semester 2, ... through 2018 semester 2.

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

$$Pr\widehat{Reminder}_{j,t} = \alpha_j + \beta_j Semester_t$$

For example, if a clinic began sending reminders in 2015 S2, which corresponds to $Semester_t =$ 4, but was missing phone records for that semester, we would impute it 2015 S2 compliance as 2015 $\alpha_j + \beta_j * 4$. Table A3 details the number of imputed cells per year-semester.

To test for if our main results are sensitive to this imputation, tables A7-A9 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.

Table A3: Number of imputed cells

Semester-Year	Observations with imputed compliance N	%	Total Observations
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

A.3 Additional Tables and Figures

Table A4: Testing the equality of regression coefficients: impact of appointment reminders among type 2 diabetes patients vs. hypertension patients

Outcome	**F stat**	**P-val**
Visit	1.18	0.31
Blood pressure test	3.16	0.04
Weighed	1.70	0.18
Blood sugar test	-	-
Medication adherence	25.27	0.00
Cardiovascular hospitalization	212.00	0.00
In-hospital cardiovascular mortality	13.04	0.00
Non-cardiovascular hospitalization	79.1	0.00
In-hospital non-cardiovascular mortality	61.04	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 A5: 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	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	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

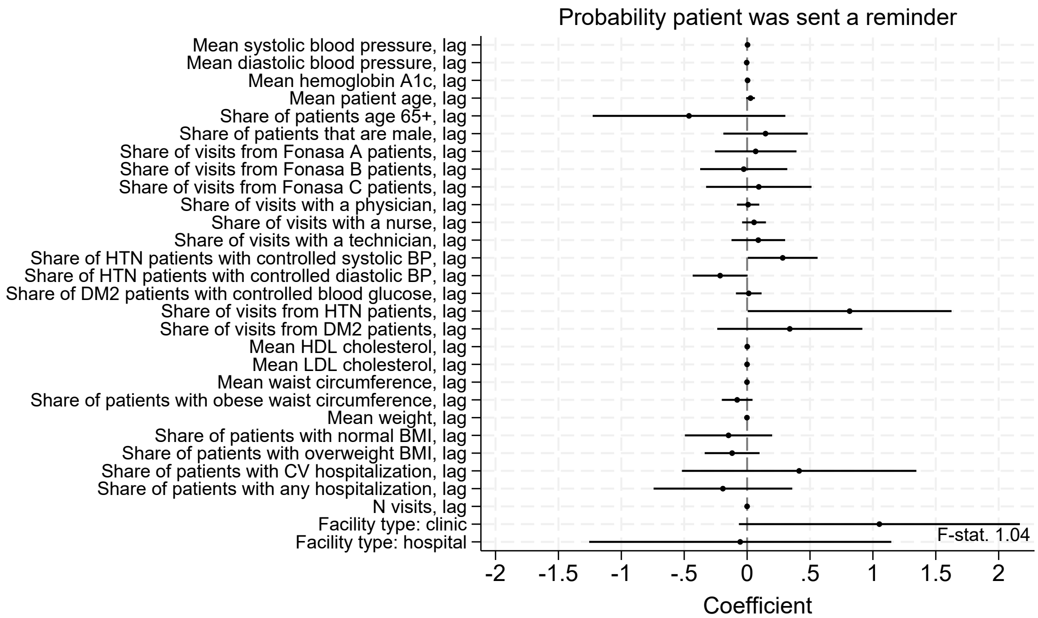
Note: Patient health and characteristics measured at patient's primary care visit when diagnosis with type 2 diabetes and/or hypertension occurred, referred to as their baseline visit, comparing means between patients at clinics included vs excluded from our analysis, because they did vs. did not have 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.

Table A6: 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	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	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.

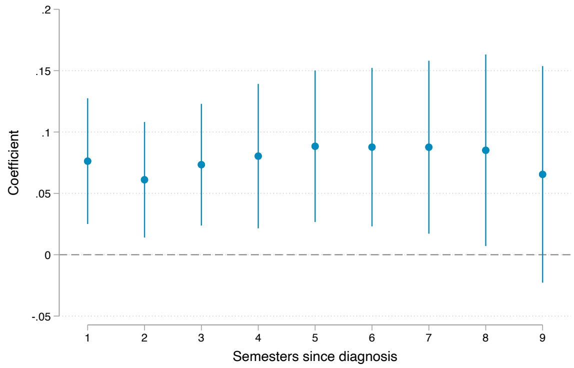
Figure A1: Association between clinic characteristics and semesterly compliance



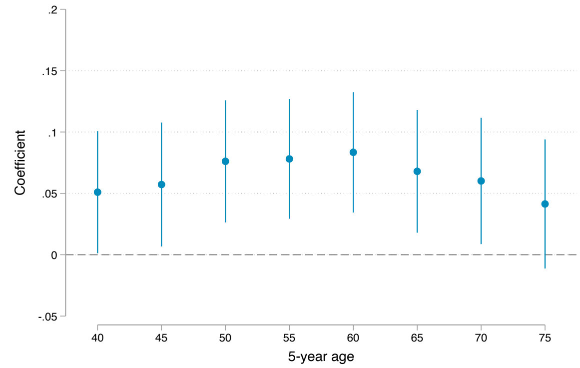
Note: Coefficients and 95% confidence intervals from a multivariate regression of clinic-semester compliance with the appointment reminder program on a set of lagged patient characteristics and contemporaneous clinic-level characteristics. The outcome is the probability a patient was sent a reminder, or compliance, in a given clinic-semester and was measured using phone records. 95% confidence intervals were constructed from robust standard errors clustered at the clinic level. Lagged coefficients were measured in the previous semester. The joint F-statistic is shown on the figure (p=0.26).

Figure A2: Heterogeneity in the effect of appointment reminders on primary care visits

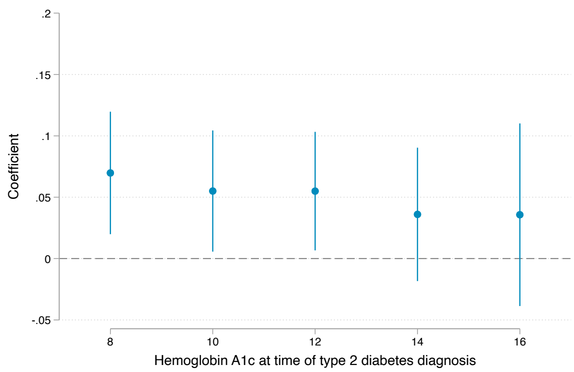
(a) Semesters since diagnosis



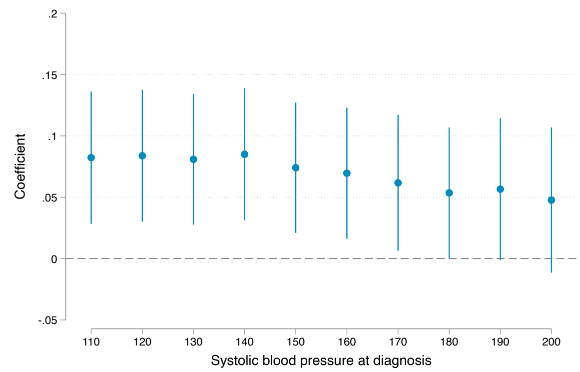
(b) Age at diagnosis



(c) Health at type 2 diabetes diagnosis



(d) Health at hypertension diagnosis



Note: Figures display coefficients and 95% confidence intervals from difference-in-difference heterogeneity models. Each 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, (c) hemoglobin a1c of 6%, (d) systolic blood pressure 100 mmHg.

A.4 Robustness

A.4.1 Robustness to Excluding Semesters with Imputed Compliance

Table A7: Impact of appointment reminders and visits on health monitoring, excluding semesters with imputed compliance

	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)	0.053	0.073	0.045	0.071	0.045	0.065	0.022
	(0.024)	(0.028)	(0.023)	(0.028)	(0.026)	(0.029)	(0.025)
	[0.030]	[0.011]	[0.050]	[0.011]	[0.086]	[0.028]	[0.372
Panel B. Instrumental variables: impact of primary care visit							
Visit	-	-	0.846	0.975	0.854	0.895	0.419
	-	-	(0.129)	(0.062)	(0.308)	(0.161)	(0.341)
	-	-	[0.000]	[0.000]	[0.006]	[0.000]	[0.221]
Observations	400,587	1,863,197	400,587	1,863,197	400,587	1,863,197	400,587
Clinics	314	310	314	310	314	310	314
Mean Y | Pr(SMS)=0	0.657	0.654	0.626	0.629	0.614	0.617	0.566
Mean Y | Visit=0	-	-	0.000	0.000	0.000	0.000	0.000
First stage F-stat	-	-	4.781	6.577	4.781	6.577	4.781

Note: This table presents the main results with the additional exclusion of clinic-semester cells where compliance data is missing. 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.

Table A8: Impact of appointment reminders and visits on medication outcomes, excluding semesters with imputed compliance

	Medication adherence ≥ 80%	
	Type 2 Diabetes	Hyper-tension
	(1)	(2)
Panel A. Reduced form: impact of appointment reminders		
Pr(Reminder)	0.006	0.009
	(0.007)	(0.005)
	[0.411]	[0.097]
Panel B. Instrumental variables: impact of primary care visit		
Visit	0.120	0.150
	(0.151)	(0.104)
	[0.426]	[0.152]
Observations	218,826	994,115
Clinics	312	309
Mean Y | Pr(SMS)=0	0.024	0.028
Mean Y | Visit=0	0.011	0.015
First stage F-stat	5.118	6.926

Note: This table presents the main results with the additional exclusion of clinic-semester cells where compliance data is missing. 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.

Table A9: Impact of appointment reminders and visits on cardiovascular hospitalizations, excluding semesters with imputed compliance

	Cardiovascular hospitalization		In-hospital CV mortality	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Panel A. Reduced form: impact of appointment reminders				
Pr(Reminder)	0.375	0.250	-0.060	-0.008
	(0.210)	(0.096)	(0.029)	(0.012)
	[0.075]	[0.010]	[0.040]	[0.521]
Panel B. Instrumental variables: impact of primary care visit				
Visit	7.118	3.446	-1.142	-0.104
	(4.434)	(1.679)	(0.783)	(0.161)
	[0.109]	[0.041]	[0.146]	[0.520]
Observations	400,587	1,863,197	400,587	1,863,197
Clinics	314	310	314	310
Mean Y | Pr(SMS)=0	1.687	1.122	0.053	0.037
Mean Y | Visit=0	1.819	1.224	0.116	0.089
First stage F-stat	4.781	6.577	4.781	6.577

Note: This table presents the main results with the additional exclusion of clinic-semester cells where compliance data is missing. 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.

Table A10: Impact of appointment reminders and visits on non-cardiovascular (CV) hospitalizations, excluding semesters with imputed compliance

	Non-cardiovascular hospitalization		In-hospital non-CV mortality	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Panel A. Reduced form: impact of appointment reminders				
Pr(Reminder)	0.164	0.323	0.040	0.025
	(0.394)	(0.220)	(0.044)	(0.018)
	[0.678]	[0.142]	[0.364]	[0.159]
Panel B. Instrumental variables: impact of primary care visit				
Visit	3.061	4.472	0.758	0.352
	(7.475)	(3.554)	(0.907)	(0.284)
	[0.682]	[0.209]	[0.404]	[0.216]
Observations	400,587	1,863,197	400,587	1,863,197
Clinics	314	310	314	310
Mean Y | Pr(SMS)=0	4.224	3.753	0.153	0.090
Mean Y | Visit=0	4.930	4.620	0.321	0.227
First stage F-stat	4.781	6.577	4.781	6.577

Note: This table presents the main results with the additional exclusion of clinic-semester cells where compliance data is missing. 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.

A.4.2 Robustness to Excluding Semesters with Imputed Compliance & Imputing 2016 Compliance

To understand how imputing clinic-semesters that are missing phone records (mostly 2015) impacts our results, here we impute 2016 (even though we have it) and compare results to the previous section, which includes true 2016 numbers. Tables in this and the previous section do not include imputed 2015.

Table A11: Impact of appointment reminders and visits on health monitoring (Imputed 2016 compliance)

	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)ˆ	0.070	0.077	0.061	0.076	0.061	0.070	0.031
	(0.025)	(0.030)	(0.023)	(0.029)	(0.027)	(0.030)	(0.024)
	[0.006]	[0.010]	[0.009]	[0.008]	[0.023]	[0.021]	[0.198]
Panel B. Instrumental variables: impact of primary care visit							
Visit	-	-	0.877	0.992	0.875	0.909	0.451
	-	-	(0.096)	(0.062)	(0.231)	(0.152)	(0.235)
	-	-	[0.000]	[0.000]	[0.000]	[0.000]	[0.056]
Observations	400,587	1,863,197	400,587	1,863,197	400,587	1,863,197	400,587
Clinics	314	310	314	310	314	310	314
Mean Y | Pr(SMS)=0	0.657	0.654	0.626	0.629	0.614	0.617	0.566
Mean Y | Visit=0	-	-	0.000	0.000	0.000	0.000	0.000
First stage F-stat	-	-	7.673	6.755	7.673	6.755	7.673

Note: This table presents the main results but excluding clinic-semester cells where compliance data is missing, and using imputed 2016 compliance ($\widehat{Pr(Reminder))}$. 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.

Table A12: Impact of appointment reminders and visits on medication outcomes (Imputed 2016 compliance)

	Medication adherence $\geq$ 80%	
	Type 2 Diabetes	Hyper-tension
	(1)	(2)
Panel A. Reduced form: impact of appointment reminders		
$\widehat{\text{Pr(Reminder)}}$	0.003	0.007
	(0.007)	(0.006)
	[0.649]	[0.216]
Panel B. Instrumental variables: impact of primary care visit		
Visit	0.052	0.121
	(0.114)	(0.105)
	[0.645]	[0.248]
Observations	218,826	994,115
Clinics	312	309
Mean Y | Pr(SMS)=0	0.024	0.028
Mean Y | Visit=0	0.011	0.015
First stage F-stat	7.323	5.739

Note: This table presents the main results but excluding clinic-semester cells where compliance data is missing, and using imputed 2016 compliance ($\widehat{Pr(Reminder)}$). 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.

Table A13: Impact of appointment reminders and visits on cardiovascular hospitalizations (Imputed 2016 compliance)

	Cardiovascular hospitalization		In-hospital CV mortality	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Panel A. Reduced form: impact of appointment reminders				
Pr(Reminder)ˆ	0.344	0.219	-0.061	-0.003
	(0.214)	(0.098)	(0.034)	(0.011)
	[0.109]	[0.027]	[0.070]	[0.790]
Panel B. Instrumental variables: impact of primary care visit				
Visit	4.948	2.861	-0.874	-0.038
	(3.114)	(1.469)	(0.594)	(0.143)
	[0.113]	[0.052]	[0.142]	[0.789]
Observations	400,587	1,863,197	400,587	1,863,197
Clinics	314	310	314	310
Mean Y | Pr(SMS)=0	1.687	1.122	0.053	0.037
Mean Y | Visit=0	1.819	1.224	0.116	0.089
First stage F-stat	7.673	6.755	7.673	6.755

Note: This table presents the main results but excluding clinic-semester cells where compliance data is missing, and using imputed 2016 compliance ($\widehat{Pr(Reminder)}$). 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.

Table A14: Impact of appointment reminders and visits on non-cardiovascular hospitalizations (Imputed 2016 compliance)

	Non-cardiovascular hospitalization		In-hospital non-CV mortality	
	Type 2 Diabetes	Hyper-tension	Type 2 Diabetes	Hyper-tension
	(1)	(2)	(3)	(4)
Panel A. Reduced form: impact of appointment reminders				
Pr(Reminder)ˆ	0.082	0.291	0.040	0.026
	(0.400)	(0.233)	(0.039)	(0.016)
	[0.839]	[0.212]	[0.304]	[0.107]
Panel B. Instrumental variables: impact of primary care visit				
Visit	1.154	3.821	0.578	0.346
	(5.714)	(3.356)	(0.609)	(0.257)
	[0.840]	[0.256]	[0.343]	[0.180]
Observations	400,587	1,863,197	400,587	1,863,197
Clinics	314	310	314	310
Mean Y | Pr(SMS)=0	4.224	3.753	0.153	0.090
Mean Y | Visit=0	4.930	4.620	0.321	0.227
First stage F-stat	7.673	6.755	7.673	6.755

Note: This table presents the main results but excluding clinic-semester cells where compliance data is missing, and using imputed 2016 compliance ($\widehat{Pr(Reminder))}$. 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 SMS Compliance, or the share of a clinic's eligible patients sent an SMS reminder in a given semester. 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, and sex.