# When Less is More: Can Reduced Health Monitoring Improve Medication Adherence?

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**Abstract**

Reducing the frequency of monitoring hypertension may be an efficient way of liberating scarce resources for the provision of healthcare. Mexico's single largest public healthcare provider (IMSS) recently began allowing physicians to issue multiple (automatic-refill) prescriptions to stable hypertensive patients, thus reducing the frequency of health monitoring from 30- to 90-day intervals. I use novel administrative data on more than four million hypertensive patients over three years to analyze the effects of this policy. Stable hypertensive patients with a lower frequency of monitoring experience no drawbacks in the management of their disease. In fact, I find that giving automatic-refill prescriptions actually improves medication adherence, as it reduces the number of days in which patients are out of antihypertensive medication by 2.6 days (35%). Furthermore, patients appear to value being on the low-frequency regime, as they positively modify their adherence in order to remain on it. Finally, I find evidence of positive spillovers in adherence for all hypertensive patients as clinic congestion is reduced.

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# 1 Introduction

An active area of health policy focuses on allocating scarce medical resources as efficiently as possible. Much debate has revolved around some prominent policies that seek to reallocate inputs for the production of health, such as reducing the frequency of certain procedures (i.e., consider the ongoing debate about the recommended frequency of mammograms) or allowing nurse practitioners to prescribe controlled medications. The value of these policies lies in the extent to which they can reduce the costs of providing healthcare, while not generating additional costs in terms of patients' health or general wellbeing.

These types of policies are particularly relevant for developing countries, where resources for providing healthcare are limited and health costs are increasing. As countries develop, the burden of life-long chronic conditions increases. During this epidemiological transition, the prevalence of non-communicable chronic diseases increases relative to that of communicable diseases. Low- and middle-income countries face new challenges for providing healthcare, and for allocating scarce medical resources as efficiently as possible.

Chronic conditions require constant health monitoring. However, there exists a trade-off in deciding the frequency with which this must be done. Frequent monitoring by healthcare providers may be favorable for managing chronic conditions, but it is costly in terms of resources such as clinic space and physician time. The costs of high monitoring may outweigh the benefits in certain stances.

To shed light on this trade-off, I study a recent Mexican policy that reduced the frequency of monitoring for stable hypertensive patients—patients with high blood pressure. It intended to eliminate arguably unnecessary appointments for patients whose condition was under control. This was done by allowing physicians to issue multiple refillable prescriptions, thus reducing the number of appointments necessary from one every month to one every three months.

The original motivation for the policy was to liberate resources for the provision of healthcare and reduce crowding in clinics. However, reducing the number of appointments could have either negative or positive effects on the affected patients. The reduction in care could make it more difficult for some patients to manage their condition. But the policy also lowered transaction costs of accessing treatment, which could help improve medication adherence. Moreover, if patients value the convenience of having to meet a doctor less frequently, it gave patients an incentive to improve adherence in order to remain on the low-frequency regime, and reduce the transactions costs associated with accessing medical care. In this sense, reducing hypertension monitoring could have *unintended benefits* with respect to medication adherence.

Finally, clinic congestion is reduced as the frequency of monitoring for stable patients declines. This could lead to positive spillovers for patients who were not directly affected by the policy (i.e., whose health monitoring frequency remained unchanged). I explore whether medication adherence for patients that did not receive automatic-refill prescriptions improved as clinics became less crowded.

While the lessons learned from the IMSS reform—that reducing health monitoring might positively affect patients' health behaviors and that some patients view this as a benefit for which they would actually improve the management of their disease in order to retain it—may apply to different dimensions of patient behavior, medication adherence is of interest in its own right.

Medication adherence is defined as patients' conformance with their provider's recommendations of timing, dosage, and frequency of medication-taking. Improving medication adherence could have substantial health benefits, in addition to important reductions in the costs associated with hypertension and other chronic conditions which require life-long therapeutic treatment.The costs associated with medication non-adherence—which include poor health outcomes and increased health care costs—are larger as the burden of chronic diseases increases (WHO (2003)).

While there has been increasing interest in medication adherence in developed countries—where the prevalence of chronic conditions has been historically higher—, relatively few studies (such as Case, Le Roux and Menendez (2004) and Tarozzi et al. (2009)) have addressed the phenomenon of medication non-adherence in the context of developing and middle-income countries. Understanding medication non-adherence in this context particularly relevant for middle-income countries, such as Mexico, which have experienced epidemiological transition towards chronic-degenerative diseases in recent years. From a global perspective, low- and middle-income countries that experience an increase in chronic non-communicable diseases such as hypertension or diabetes, or where where other chronic lifelong communicable diseases—namely HIV/AIDS—has high prevalence could benefit from implementing policies to promote better medication adherence, as these have been found to be cost-effective, at least in the context of developed countries (Roebuck et al. (2011), Sokol et al. (2005)).

I find that reducing the frequency of health monitoring significantly improves medication adherence. Receiving a prescription that covers treatment for 90 days (as opposed to 30) reduces the number of days a patient is out of medication by 2.6 days, a reduction of 35% with respect to the number of days patients were—on average—out of medication before the beginning of the program. The magnitude of the effect compares favorably to other interventions aimed directly at improving medication adherence. A meta-analysis of interventions to improve medication adherence in the US finds increases in adherence of only between 4 and 11% (Peterson, Takiya and Finley (2003)).

As further evidence of the role of transaction costs, I show that patients treated at the most congested clinics show a larger effect of the policy on their prescription filling behavior. Additionally, I observe positive spillovers in all patients' adherence from the general reduction in transaction costs of filling prescriptions as clinics' congestion falls. I also find evidence that patients value being on the low-frequency regime, as they improve adherence not only in response to the reduction in transaction costs when they may receive automatic-refill prescriptions, but also in order to remain on the 90-day regime.

My results show that the policy has a had a positive effect on clinic congestion, as originally intended. Additionally, patients that experience a reduction in health monitoring remain stable, and their diseases appears to remain under control. Patients' current health as measured by blood pressure does not increase. It may additionally be argued that the improvements in medication adherence will result in improved long-term health outcomes.

My research uses a specific change in policy with particular eligibility criteria which provides a clean identification strategy. I use the *Receta Resurtible* program, implemented by the Mexican Social Security Institute, IMSS (the largest social security institution in Latin America, covering around half of the Mexican population), to study the effect of prescription duration on medication adherence. In particular, drug prescriptions for patients suffering from certain chronic conditions went from covering 30 days of treatment to covering 90 days. Patients in the new regime receive three "automatic-refill" prescriptions (each covering 30 days of treatment), where one is filled at the time of the doctor's appointment, and two may be refilled in the following months without having to see a physician again.

High quality administrative longitudinal data for low- and middle-income countries is rare. My research uses a novel administrative database from IMSS set up in a panel structure on patients' prescription fillings. It covers a large segment of the population as it includes the universe of hypertensive patients receiving treatment from this institution (over 4 million patients), the single largest public healthcare provider in Mexico. I directly observe every prescription filling at IMSS pharmacies.

For my empirical strategy, I use econometric models with patient fixed effects in order to assess the effect of reducing health monitoring on a variety of patient level outcomes. I additionally exploit the variation in the timing of clinics' adoption of the policy to control for potential endogeneity issues at the patient level. This also allows me to analyze whether there have been spillovers at the clinic level from reduced congestion.

My paper contributes to the literature by being one of the few which analyzes medication adherence in the context of less developed countries. It benefits from using high quality administrative panel data, covering the prescription filling history of over four million patients. I am able to exploit a specific change in policy which gives me a clean identification strategy. Additionally, given the unique policy design, I am able to explore whether patients improve adherence because of a decrease in transaction costs of accessing treatment or because of increased patient effort in order to remain on the low-cost regime (or both).

My paper speaks to the literature on the determinants of non-adherence. Although no consensus exists regarding how to improve patients' adherence, some strategies such as cost reduction (Atella et al. (2006)), health education interventions (Morisky et al. (1983), Lee, Grace and Taylor (2006)), and patient reminders (Smith et al. (2008), Piette, Weinberger and McPhee (2000)) appear to be the most effective. Improving patients' knowledge of the disease and medications, as well as of the long-term risks of hypertension appear to be key for improving adherence (Gwadry-Sridhar et al. (2013)). Volpp et al. (2008) found a daily lottery-based financial incentive to be a useful tool to improve adherence. All of the above mentioned studied were conducted in developed countries—with the exception of Atella et al. (2006) which looks at the case of Italy, and Gwadry-Sridhar et al. (2013) (which is a systematic review of the literature), all studies focus on the United States.

Reducing the cost of medications appears to have a significant effect on patient compliance, whether this reduction is monetary or nonmonetary. Changes in the co-payment structure appear to have a strong effect on the average compliance of previously low compliant patients (Atella et al. (2006)). Nonmonetary factors measured as travel time are also found to play an important role in determining the demand for medical care (Acton (1975)).

The rest of the paper is organized as follows. Section 2 presents some background information on the Mexican healthcare system and IMSS, and the *Receta Resurtible* program. Section 3 presents a theoretical model about transaction costs and adherence which yields some predictions which I will later test in the data. Section 4 describes the novel data that I use and presents some summary statistics. Section 5 discusses my empirical strategy, and Section 6 presents my main findings regarding the effects of reduced monitoring on medication adherence, health outcomes, clinic congestion, and the existence of positive spillovers, as well as some robustness checks. Section 7 concludes.

# 2 Background

## 2.1 Hypertension

This paper takes a disease specific approach, focusing on chronic hypertension for a series of reasons: (i) good medication adherence has the potential to improve health outcomes for chronic diseases; (ii) hypertensive patients are easily identifiable from their prescription fillings; (iii) health measures relevant to hypertensive patients are consistently and systematically measured; and (iv) it is highly relevant within the Mexican health context.

Hypertension is a chronic medical condition where the blood pressure in the arteries is elevated, putting strain on the heart. Uncontrolled high blood pressure can lead to heart attacks, strokes, aneurysms, and is associated with a shortened life expectancy. Hypertension is a chronic disease which generally implies life-long therapy.

In recent years, Mexico has experienced an important increase in the share of deaths occurring from non-communicable, chronic conditions, which currently represent the most serious public health issues in the country. In 2011, diabetes mellitus, cerebrovascular diseases (i.e., strokes), and hypertensive diseases—all non-communicable diseases—accounted for 29.2% of total deaths (IMSS (2012)).[1] Approximately one out of every three Mexicans over 20 in Mexico is hypertensive (ENSANUT (2012)).

Antihypertensive drugs have been found to have a major impact on health, and to be an extremely effective and highly cost-efficient treatment. Cutler et al. (2007) estimate that antihypertensive medication has a benefit-to-cost ratio of 6:1 (women) to 10:1 (men), for example. Additionally, the treatment for hypertensive patients is well defined and effective.[2] Non-adherence to cardioprotective medications ($\beta$-blockers, statins, and/or angiotensin-converting enzyme inhibitors) was associated with a 10% to 40% relative increase in risk of cardiovascular hospitalizations and a 50% to 80% relative increase in risk of mortality (Ho, Bryson and Rumsfeld (2009)).

Costs associated with hypertensive diseases have been estimated to account for at least 14% of the total health budget in Mexico (Villarreal-Ríos et al. (2002)).[3] Additionally, there exists no consensus regarding the optimal frequency of health monitoring for hypertension (Guthmann et al. (2005)).

[1] In contrast, in 1976, these same conditions accounted to less than 11% of total deaths. Communicable diseases such as pneumonia, perinatal health problems, and intestinal infectious diseases accounted for around 36.5% of total deaths in 1976, while they represented less than 8% of total deaths by 2011.

[2] It mainly consists of administering $\beta$-blockers, angiotensin-converting enzyme (ACE) inhibitors, or diuretics.

[3] In the United States hypertension affects 43-50 million adults. About 50% of those who have been diagnosed are treated, and only 51% of the treated population adheres to the prescribed treatment. Low adherence has been identified as the primary cause of unsatisfactory blood pressure control, and only 30% of those treated achieved the expected blood pressure (WHO (2003)).

## 2.2 IMSS and the *Receta Resurtible* Program

IMSS is one of the largest government institutions in Mexico and the main provider of public health services. It has a mandatory coverage of all private-sector employees, broadly corresponding to individuals in formal jobs and their families.[4] Medical benefits from IMSS are availble to approximately 58 million Mexicans (IMSS (2012)).

As a public health provider, IMSS delivers a number of medical services. Services are provided to formal workers (insured individuals) and other beneficiaries (family members also covered by IMSS) free of charge.[5] Medical prescriptions are issued by attending physicians and are then filled at IMSS pharmacies free of charge.[6]

Most outpatients receive medical care in Family Medicine Units (*Unidades de Medicina Familiar*, UMF), which represent the most basic level of care provided by IMSS. These are often referred to as primary care centers, and there are 1,118 UMF's across the country. Finally, IMSS administers 1,347 pharmacies nationwide where drug prescriptions issued by IMSS may be filled free of charge by patients.[7] Availability of medications at IMSS compares favorably to that of other public healthcare providers in the country, as 86% of patients reported to have completely filled their prescription at the place where they received outpatient care (ENSANUT (2012))

Although almost 80% of patients describe the healthcare services provided by IMSS as 'good' or 'very good', waiting times are often cited as a problem. In particular, attending a doctor's appointment may be a time consuming activity, as the mean waiting time for outpatient care at IMSS is 75 minutes, a high number relative to other public and private healthcare providers in Mexico (ENSANUT (2012)).

This paper uses a recent policy change in Mexico's public healthcare system. In an attempt to increase the efficiency in the provision of healthcare, IMSS reduced the frequency of health monitoring for chronic stable patients by changing the length of treatment covered by prescriptions for medications treating a number of chronic diseases, among these hypertension.[8] Medical prescriptions are issued by the patient's physician. They traditionally covered the treatment for the following 30 days, at which point the patient had to attend a new appointment in order to get a new prescription. As of August 2013, patients considered to be 'stable patients' became eligible to receive

[4]The other main public health provider in Mexico is *Seguro Popular*, which provides healthcare to individuals not covered by IMSS, thus providing access to health services to individuals working in informal sectors of the economy.

[5]Benefits include general healthcare, maternity, and specialist care, surgery, hospitalization or care in a convalescent home, medicine, laboratory services, and dental care.

[6]IMSS doctors are salaried workers who earn a monthly wage, and receive no additional benefits depending on the number of patients they receive or their health outcomes, or on the type of treatment prescribed.

[7]All pharmacies are located at an IMSS healthcare unit. A pharmacy can be found at every UMF.

[8]The chronic conditions for which automatic refill prescriptions may be issued are hypertension, diabetes, arthritis, back and waist pain, long-term skin conditions, seizures, chronic bronchitis, asthma, colitis, ulcerative colitis, and thyroid disease.

special prescriptions covering 90 days of treatment. These are called *Recetas Resurtibles*, or automatic refill prescriptions: patients actually receive three prescription, each covering a month's worth of treatment, which should be filled at an IMSS pharmacy every 30 days. The program takes its name from these automatic-refill prescriptions, and is simply known as the *Receta Resurtible* program.

Therefore, a patient on the 30-day prescription regime must go to doctor's appointments and fill prescriptions once every month, while a patient on the automatic refill regime must also fill prescriptions on a monthly basis at a pharmacy—with short waiting times and no scheduling restrictions—, but must attend a doctor's appointment *only once every three months*. In general, a patient on the *Receta Resurtible* program should see a doctor only four times a year, while a patient who is not in this program should do so twelve times a year. Figures A.1 and A.2 in the Appendix help illustrate the way in which the policy was designed.[9]

It has been estimated by IMSS that this policy may free up clinic space and physician time. *Receta Resurtible* prescriptions are given to chronic patients who are considered to be stable and who arguably need not be meeting with a physician on a monthly basis for health reasons. Estimates made by IMSS suggest that the program will imply a reduction of 7 million 'unnecessary' doctor's appointments per year.

The *Receta Resurtible* officially started in August 2013, although the actual implementation in some clinics started a few months later. Additionally, a small share of clinics (less than 3%) started issuing automatic refill prescriptions before the nationwide program started. By December 2014, over 90% of clinics were issuing Recetas Resurtibles (see Figure 1). The clinics that issue automatic refills prescriptions are scattered throughout the country (see Figures A.3 and A.4 in the Appendix). In August 2013, an official announcement was made by IMSS when the program was launched. The announcement received limited media coverage across the country and the *Receta Resurtible* Program is advertised on IMSS's webpage.

Both the number of automatic refill prescriptions and the share that these represent from the total number of prescriptions issued by IMSS has increased since the implementation of the program. By December 2014, around 15% of prescriptions for medications for treating hypertension were automatic refill prescriptions. This share was 6% during August 2013, the month when the program started.[10] The way in which

[9]Waiting times at IMSS are high for outpatient care, with a mean of 75.1 minutes and a 75th percentile of 2 hours. Additionally, transportation costs may also be quite elevated—Mexico City, where around 18% of the Mexican population lives, was ranked as the worst city for commuting in IBM's Global Commuter Pain Survey, 2011, for example. Receiving an automatic refill prescription reduces the number of doctor's appointments a patient must make by a factor of three. Patients must still fill their prescriptions every month, but this task is much easier as (i) waiting time in pharmacies is shorter, (ii) no appointment is necessary, and (iii) prescriptions may be filled by other individuals besides the patient.

[10]It is estimated that around 20% (and no more than 30%) of hypertensive patients are stable at IMSS

automatic refill prescriptions have evolved can be seen in Figure 2.

# 3 The Model

## 3.1 Baseline Model

I begin with a simple three-stage model, where individual $i$ choses a health-related action in order to maximize utility. In the model, the health-related action refers to the agent's non-adherence as measured by his treatment gap, or how long he will wait to fill a new prescription once he finishes his current stock of medication.

### 3.1.1 Timing

$\mathbf{s = 0}$. *(pre-policy)* . This stage merely establishes a baseline. It begins when patient $i$ runs out of medication and must decide when to restart treatment, implicitly choosing a treatment gap. To do so, he must attend a doctor's appointment at a clinic at a cost of $c_i$. The patient receives medication from his physician to cover his treatment for a fixed time interval.

Patients receive patient-specific health benefits from restarting treatment, which we will denote by $M_i$.[11] Therefore, we may define the net benefits of filling a prescription for an agent as $b_i = M_i - c_i$.

Every day (referred to as a period $t$ within the stage) after he has run out of medication, a patient must decide whether to restart treatment or wait until next period. Each period the patient draws an idiosyncratic cost $\varepsilon_{i,t}$ of getting his medication, from the same cost distribution $F(E) = Prob\{\varepsilon < E\}$, with $F(0) = 0$ and $F(B) = 1$. We may think of this additional cost as some factor that makes it relatively more or less costly to get the medication (for example, a deadline at work, or a friend offering a ride, respectively). A patient who decides to fill his prescription will therefore receive $u_{i,t} = b_i - \varepsilon_{i,t}$, and alternatively, one who decides to wait, will receive $u_{i,t} = 0$. A rational patient will restart treatment whenever the benefits exceed the costs. He will therefore choose:

$$w_{i,t} = \begin{cases} 0 \text{ (restart treatment)} & \text{if } \varepsilon_{i,t} \leq b_i \\ 1 \text{ (wait)} & \text{if } \varepsilon_{i,t} \geq b_i. \end{cases}$$

Once the patient sees the doctor, a patient may be assigned to a new low-frequency regime. We will denote this new, automatic-refill regime by $RR$ (for *Receta Resurtible*).

clinics.

[11] We may think of these benefits as the benefits as perceived by the patient, as in Baicker, Mullainathan and Schwartzstein (2012), where these may differ from the true benefits of adhering as they may be affected by 'behavioral biases'.

Patients on this regime will receive an additional prescription which may be filled at a pharmacy in the following stage, once his current medication is exhausted. Hence, they do not need to see the doctor in stage $s = 1$ for renewing prescriptions, and may simply do so directly at the pharmacy (we will assume that patients get only one automatic-refill prescription). Patients that remain in the general regime need to renew prescriptions at a doctor's appointment in every stage.

$\mathbf{s = 1}$. Once the agent runs out of medications from the previous stage ($s = 0$), the agent must decide when to get his medication for stage $s = 1$. Depending on whether the patient is on the $RR$ regime, he must fill his prescription directly at a pharmacy or attend a doctor's appointment to renew it.

We will express the cost of filling a prescription at a pharmacy as a fraction of renewing it with a doctor, and denote it by $\delta_i c_i$, with $0 < \delta_i < 1$. Let us define $\Delta c_i = (1 - \delta_i)c_i > 0$.[12] We may think that this reduction in costs $\delta_i$ may vary across individuals due to patients facing different congestion for scheduling appointments, transportations costs, or opportunity cost of time, for example.

We can express the net benefit of patients on the automatic-refill regime as $b_i^{RR} = M_i - \delta_i c_i = M_i - c_i + (1 - \delta_i)c_i = b_i + (1 - \delta_i)c_i = b_i + \Delta c_i > b_i$. Therefore, patients on the low-frequency regime ($RR$) will act according to:

$$w_{i,t}^{RR} = \begin{cases} 0 \text{ (restart treatment)} & \text{if } \varepsilon_{i,t} \leq b_i + \Delta c_i \\ 1 \text{ (wait)} & \text{if } \varepsilon_{i,t} \geq b_i + \Delta c_i \end{cases}$$

while patients that remained on the general regime will continue to act as in stage $s = 0$. Hence, we may define the difference in utilities for patients on either regime for stage $s$, as $\Delta U_{i,s} = (b_i^{RR} - \varepsilon_{i,s}^{RR}) - (b_i - \varepsilon_{i,s}) = (1 - \delta_i)c_i - (\varepsilon_{i,s}^{RR} - \varepsilon_{i,s}) > 0$, where $\varepsilon_{i,s}$ represents the actual idiosyncratic shock incurred by the patient on the period when he chooses to restart treatment.

$\mathbf{s = 2}$. Once a patient exhausts the medication received in stage $s = 1$, he must again decide when to get his next prescription. All patients—independently of the regime they have been assigned to—must go to the clinic for a doctor's appointment to receive a new prescription, at a cost of $c_i$ (therefore receiving net benefits of $b_i$). They will follow the same rule as in stage $s = 0$, and will restart treatment when $\varepsilon \leq b_i$.

[12] I will additionally assume at this point that the idiosyncratic shock $\varepsilon$ is relatively small, such that $B < \Delta c_i = (1 - \delta)c_i$ for any $c_i$.

### 3.1.2 Treatment Gaps

We may derive the probability distribution of the waiting time until a patient restarts treatment.[13] Let $a_{i,s}$ be the random variable "length of time until patient restarts treatment" (for patient $i$ in stage $s$) and denote $a_{i,s} = 1$ if the patient restarts treatment on the first day after he ran out of his previous prescription (i.e., a treatment gap of zero). I will define the probability of *not* restarting treatment (waiting) as $\lambda_{i,s} = \int_{b_i}^{B} dF(\varepsilon)$. Therefore, $Prob\{a_{i,s} = 1\} = (1 - \lambda_{i,s})$, and $Prob\{a_{i,s} = 2\} = (1 - \lambda_{i,s})\lambda_{i,s}$. In general, we find that $Prob\{a_{i,s} = k\} = (1 - \lambda_{i,s})\lambda_{i,s}^{k-1}$, so the treatment gap is geometrically distributed.[14] The average treatment gap for patient $i$ at stage $s$ is thus denoted by $\bar{a}_{i,s}$, and is given by:

$$\bar{a}_{i,s} = \sum_{k=1}^{\infty} k \cdot Prob\{a_{i,s} = k\} = (1 - \lambda_{i,s})^{-1}. \tag{1}$$

We may then compare the expected treatment gap for a given patient $i$ who is in the automatic-refill regime, when he must fill a prescription at pharmacy ($RR$) or renew it by attending a doctor's appointment. It is straightforward to see that treatment gaps will be lower when costs are lower:

$$\lambda_{i,1}^{RR} = \int_{b_i+\Delta c_i}^{B} dF(\varepsilon) < \int_{b_i}^{B} dF(\varepsilon) = \lambda_{i,s}, \tag{2}$$

for $s \in \{0, 2\}$, which implies,

$$\bar{a}_{i,1}^{RR} < \bar{a}_{i,0},$$
$$\bar{a}_{i,1}^{RR} < \bar{a}_{i,2}.$$

In this sense, in $s = 2$ the expected treatment gap will be the same as it was before the introduction of the policy, $\bar{a}_{i,2}^{RR} = \bar{a}_{i,0} = \bar{a}_{i,2} = (1 - \lambda_{i,0})^{-1}$, as transaction costs are identical in both $s = 0$ and $s = 2$. It will also be equal to the patient $i$'s expected treatment gap had he not been assigned to the automatic-refill regime, as in both cases the patient must visit the doctor. Therefore, in this baseline model:

$$\bar{a}_{i,1}^{RR} < \bar{a}_{i,2}^{RR} = \bar{a}_{i,0},$$
$$\bar{a}_{i,1} = \bar{a}_{i,2} = \bar{a}_{i,0}.$$

It is important to note that comparisons are made within patients and across stages.

[13] I follow Ljungqvist and Sargent (2004) to derive this probability and to characterize average waiting times in the model.

[14] This generalization holds as long as successive draws are independent of one another.

I make no assumptions about how patients are assigned to the automatic-refill regime (which could potentially be correlated to $b_i$), nor about whether the reduction in costs is experienced in the same way by all patients (as $\delta_i$ is patient specific).

## 3.2 Retaining the Benefits

I extend the baseline model to allow for physicians to evaluate patients on the automatic-refill regime and allow them to stay (or remove them) from the low-frequency setup contingent on their observed adherence.

To model this new element, I will assume that the basic setup of the model will be repeated in the future, and that patients are forward-looking. Therefore, being allowed to stay on the automatic-refill regime after $s = 2$ will give a higher future utility of $U_{i,} = \Delta c_i - (\bar{\varepsilon}^{RR}_{i,3} - \bar{\varepsilon}_{i,3}) > 0$ if he remains on the $RR$ regime versus going back to the general regime (in stages $s = 1, 3$), yields a additional future expected utility equal to:

$$
\begin{aligned}
\Delta U_i &= \mathbb{E}[u^{RR}_i - u_i] = (M_i - \delta_i c_i - \mathbb{E}[\varepsilon^{RR}_i]) - (M_i - c_i - \mathbb{E}[\varepsilon_i]) \\
\Delta U_i &= \Delta c_i - (\mathbb{E}[\varepsilon^{RR}_i] - \mathbb{E}[\varepsilon_i]). \qquad (3)
\end{aligned}
$$

Given that $0 \leq \varepsilon \leq B \leq (1 - \delta_i)c_i = \Delta c_i$, it is necessarily the case that $\Delta U_i \geq 0$.[15]

Stage $s = 2$ is modified: patients on the automatic-refill regime decide when to resume treatment, by choosing whether to wait longer ($a_{RR,2}$). However, they know that doctors will evaluate them to determine if they can stay on the low-frequency regime or if they should be transferred back to the general regime.

Patients are aware that lower treatment gaps will increase the probability that they will be allowed to stay on the automatic-refill regime. Therfore, there exist additional costs of waiting longer to resume treatment as a patient risks loosing the automatic-refill prescription benefits. In this setup, patients will decide to wait according to:

$$
w_{RR,t} = \begin{cases} 0 \text{ (restart treatment)} & \text{if } \varepsilon_t \leq b_{RR} + \alpha \Delta U \\ 1 \text{ (wait)} & \text{if } \varepsilon_t \geq b_{RR} + \alpha \Delta U \end{cases}
$$

where $0 < \alpha < 1$ is the perceived increase in the probability that the doctor will allow the patient to remain in the automatic-refill regime if he restarts treatment.

In this setup, the expected treatment gap for an individual in the automatic-refill regime in stage $s = 2$ will be given by $\bar{a}^{RR}_{i,2} = (1 - \lambda^{RR}_{i,2})^{-1}$. Comparing to their behavior before the frequency was reduced:

[15] Given the decision rule followed by patients in the baseline model, we can express the expected value of the idiosyncratic cost $\varepsilon$ as $\mathbb{E}[\varepsilon^*_j] = \mathbb{E}[\varepsilon | \varepsilon > b_j] = \frac{\int_{b_j}^{B} \varepsilon f(\varepsilon) d\varepsilon}{1 - F(b_j)}$.

$$\lambda_{i,2}^{RR} = \int_{b_i+\alpha\Delta U}^{B} dF(\varepsilon) < \int_{b_i}^{B} dF(\varepsilon) = \lambda_{i,0}. \tag{4}$$

Patients on the automatic-refill regime will exhibit improved adherence than they did before the policy was adopted in $s = 0$. However, the model cannot predict how the expected gap will compare in stages 1 and 2.

Therefore, in this extension of the model, patients on the automatic-refill regime will have expected treatment gaps such that:

$$\bar{a}_{i,1}^{RR} < \bar{a}_{i,0}^{RR},$$
$$\bar{a}_{i,2}^{RR} < \bar{a}_{i,0}^{RR}.$$

which reflects that—even when cost of filling their prescriptions are the same in stage $s = 2$ as they were before the policy—patients on the automatic-refill regime exhibit a lower expected treatment gap, as they try to increase their probability of staying on the low-cost regime.

The main conclusions from the model are:

1. A patient on the automatic-refill will have a lower expected treatment gap when he may fill his prescriptions at a pharmacy than when in the high-monitoring regime, $\bar{a}_{i,1}^{RR} < \bar{a}_{i,0}^{RR}$.
2. If patients value the low-frequency regime (i.e., $\Delta U > 0$), a patient on the automatic-refill regime will also have a lower expected treatment gap when he must renew a prescription with a doctor than when he is in the high-monitoring regime, $\bar{a}_{i,2}^{RR} < \bar{a}_{i,0}^{RR}$.
3. The magnitude of the difference between expected treatment gaps when on and off the automatic-refill regime will be greater the larger the reduction in transaction costs from avoiding a doctor's appointment,

$$\frac{\partial|\Delta a_{i,s}|}{\partial\delta_i} = \frac{\partial|(\bar{a}_{i,0}^{RR} - \bar{a}_{i,s}^{RR})|}{\partial\delta_i} > 0, \text{for } s \in \{1, 2\}.$$

I will empirically test these predictions. In particular—and as I will discuss in further detail in Section 5—I will first check whether patients assigned improve adherence once they are assigned to the automatic-refill *Receta Resurtible* program. I will assess whether there are heterogeneous effects for different subgroups of the population (which could arguably have different $\delta_i$'s). In this same spirit, I will analyze whether the magnitude of the effect is greater when congestion is high (again, arguably higher $\delta_i$), as predicted by the model.

I will additionally explore whether there is an improvement in adherence not only when patients on the automatic-refill, $RR$, regime may fill prescriptions at a pharmacy ("non-costly" fillings, stage $s = 1$), but also when they must renew them at a doctor's appointment ("costly" fillings, stage $s = 2$), in order to assess whether patients seem to value remaining on the low-frequency regime (i.e., evidence that $\Delta U > 0$).

# 4 Data

I use a novel and original database that uses administrative data from pharmaceutical records from IMSS. Additionally, I have clinical records for a subsample of the patients in this database. The dataset which uses pharmaceutical records includes detailed information at the patient level and has a panel structure which allows me to test the hypotheses that longer prescription improves adherence by reducing transaction costs, and to explore the effects of the *Receta Resurtible* program on patient behavior. Refill records of computerized pharmacy systems are used increasingly as a source of compliance information (Steiner and Prochazka (1997)). My data compares favorably to that which is used in most studies, as it comes from a public health provider that allows me to observe a large sample of around 4.3 million hypertensive patients in a semi-closed pharmacy system (where patients consistently get their medication from the same system) using reliable administrative data.

Attrition may represent a problem for my identification strategy which uses patient fixed effects, as patients that leave the database may do so for non-random reasons which may imply different effects for non-adherence.[16] Namely, the most probable events that would cause a patient to disappear from the data are (i) if the insured individual stops working in the formal sector; (ii) if the individual willingly discontinues treatment; and (iii) if the individual dies. To address these issues I can focus exclusively on patients that are considered persistent patients ("continuous users" in Van Wijk et al. (2006)): patients that never have a gap between prescription fillings of over 90 days. This allows me to study a type of non-adherence called non-conformance.[17] By restricting my analysis to only persistent users, the sample of patients I use is limited to arounds 1.2 million patients. However, this allows me to better identify actual hypertensive chronic patients (as opposed to patients that were prescribed one of the medications for treating hypertension for some other reason—for example, diuretics for

[16] Around 24% of patients "dropout" of the panel. A patient is considered a dropout if he has a gap between prescription filling of over 180 days.

[17] Non-adherence may be classified as follows: (i) Primary non adherence, where the provider writes a prescription, but medication is never filled or initiated; (ii) Non persistence, where the patient decides to stop taking medication after starting it, without being advised to do so; and (iii) Non conformance, where otherwise persistent patients fail to take medications as prescribed by their health provider (Jimmy and Jose (2011)).

treating tissue swelling). Additionally, I can verify if my results are robust to picking a different window to 90 days.

From an empirical point of view, it is interesting to focus on non-conformance since refill records of computerized pharmacy systems are used increasingly as a source of compliance information. It has been found that they show a significant association with other measures of medication adherence and that they are a suitable measure for evaluating patient compliance to therapeutic treatment (Steiner and Prochazka (1997)). Rates of refilling prescriptions are an accurate measure of overall adherence in a closed pharmacy system since refills are measured at several points in time (Jimmy and Jose (2011)).

Additionally, I can see if my results change significantly when I exclusively analyze the effect of the *Receta Resurtible* Program on retired patients, as these individuals cannot leave the dataset due to a change in their employment situation (as they are entitled to IMSS benefits for life).

The database uses IMSS administrative data on prescriptions filled at IMSS pharmacies. This database contains anonymized patient identifiers which allow me to follow patients in time, information on the physician who issued prescription, the pharmacy where it was dispensed, the date when prescription was issued, whether the prescription is a *Receta Resurtible* (i.e., prescription duration: 30- vs automatic refill), and a product identifier or medication code. Additionally, it includes patient information such as year of birth, gender, relationship to insured individual (self, spouse, parent, child), and retirement status. The data starts in January 2012 and goes through December 2014. This database comprises information on the universe of prescriptions filled in IMSS pharmacies with digital records.

The source of this database is administrative data collected by IMSS, the single largest public health provider in Mexico. As discussed in Atella et al. (2006), administrative data implies a series of advantages over survey data, such as not being affected by item unit and item non-response, measurement errors and bias effects due to interaction with interviewers. Additionally, it contains extremely rich information on patient medication purchasing history for a very large population for a period of three years. The panel structure of the data allows me to follow patients in time, which is fundamental for my empirical strategy as I use patient fixed-effects in order to control for observable and unobservable time-unvarying patient characteristics.

Finally, I constructed a database that includes clinical information for a subset of patients and provides relevant medical information and health outcomes for 3,000 patients. These were randomly chosen from all the individuals that filled at least one prescription in August 2013. The random sample was stratified by whether the patient received an automatic refill prescription during this month, so that half of the patients in the random sample actually received prescriptions covering 90 days of treatment, while the remaining half did not. This dataset includes information collected by the attending physician at the Family Medicine Units (*Unidades de Medicina Familiar*, UMF) during the doctor's appointment and provides information on the patient's blood pressure reading (systolic and diastolic in mmHg), heart rate, height, and weight. It also provides a diagnostic using the ICD (International Classification of Diseases) diagnostic codes, in addition to the doctor's notes on the description of the diagnostic. Just as in the pharmacy records database, the clinical dataset allows me to follow patients over time thanks to anonymized patient identifiers, and provides information about the date of the appointment, its location, and the attending physician. I merged this database with the prescription database and am thus able to perform a more extensive analysis for a sample of patients.

## 4.1 Summary Statistics

To identify hypertensive patients, I consider only those individuals that filled a prescription for any of the 20 products which are used to treat chronic hypertension at IMSS clinics, as determined by their own clinical guidelines.[18] Although some of these medications may be used to treat other conditions (most importantly diuretics which are used for treating certain kidney diseases), they may only be prescribed as automatic refill prescription medications if they are intended for treating hypertension (the *Receta Resurtible* program only applies for 10 specific conditions). Additionally, as I focus on persistent users (those who fill prescriptions for treating hypertension recurrently), this approach allows me to effectively identify chronic hypertensive patients. The total number of patients that filled at least one prescription at an IMSS pharmacy during August, 2013 was approximately 5.2 million.[19]

Table 1 shows some patient characteristics for individuals that received at least one automatic refill prescription during August 2013 (which I refer to as 'eligible' individuals) and those that received only 30-day prescriptions ('non-eligible' individuals). There exist eligibility criteria to determine whether a patient can receive a *Receta Resurtible* to ensure that only 'stable' patients get long prescriptions, as it would be desirable for 'unstable' patients to continue attending to regular doctor's appointments on a monthly basis to keep their condition under control. These criteria are based on

[18] These mainly consist of $\beta$-blockers, angiotensin-converting enzyme (ACE) inhibitors, diuretics, and calcium channel blockers. The specific medications are Amlodipine, Candesartan Cilexetil-Hydrochlorothiazide, Captopril, Chlorthalidone, Diazoxide, Enalapril, Felodipine, Furosemide, Hydralazine, Hydrochlorothiazide, Losartan, Methyldopa, Metoprolol, Nifedipine, Prazosin, Propranolol, Spironolactone, Telmisartan, Valsartan, and Verapamil.

[19] Of these patients, 42% filled a prescription for at least one medication for treating hypertension, of which approximately 6.5% were automatic refill prescriptions. See tables A.1, A.2 and A.3 in the Appendix for greater detail.

the patient's hypertension and general health status.[20] However, I also find that empirically stable patients that originally get assigned to the low frequency regime and exhibit bad medication adherence (namely, high treatment gaps), are reassigned back to the general 30-day regime.

Since the assignment to automatic refill prescriptions is therefore non-random, we would expect to see patients that are *ex-ante* healthier to receive automatic-refill prescriptions as these prescriptions are only given to stable patients. If these patients also exhibit different behaviors as far as medical adherence go, our empirical strategy must take this into account to avoid the selection bias which may arise from the fact that patients on the 30- and automatic refill regime are different. To address this issue, I use patient-fixed effects which effectively allows me to compare a patient's own adherence when he is on the low- or high-frequency regime. I additionally exploit the variation in the *timing* of the adoption of the *Receta Resurtible* program at the clinic level. Finally, I look at the differential effect of the policy on patients who are *ex-ante* more likely to receive automatic refill prescriptions, as the identifying assumption for the fixed effects model to be correctly specified is more likely satisfied for these patients (no omitted patient specific characteristic correlated with receiving an automatic-refill prescription and with the patient's adherence). These empirical strategies are discussed in greater detail below.

Table 1 allows us to compare eligible and non-eligible patients on a series of observable characteristics. It shows that patients on the automatic refill regime are younger and healthier (as they are taking fewer medications) on average, and that these differences are statistically significantly different from zero. It is interesting, however, that the share of persistent users in both types of patients is not significantly different and accounts to around 40% of all hypertensive patients (most of the analysis performed in this paper focuses on persistent patients exclusively).

## 4.2 Measuring Adherence

Pharmacy refill data is best suited to analyze non-conformance, where persistent patients fails to take medications as prescribed. Primary non-adherence cannot be observed in this kind of data as patients never enter pharmacy records. Non-persistence would be possible to analyze by establishing a threshold to determine how long a patient must be absent from the data to be considered as a 'dropout'. However, due to the time span after the offset of the *Receta Resurtible* program covered in my data it

[20] In the case of hypertension, a patient is considered to be a stable patient, and is thus eligible for an automatic refill prescription if (i) his systolic pressure $\leq$130 mmHg; (ii) diastolic pressure $\leq$80 mmHg; (iii) he suffers from no additional comorbidities; and (iv) he has not experienced previous acute complications derived from hypertension.

is not yet possible to perform an adequate analysis of non-persistence.

The variable that I use to measure non-adherence is the treatment gap. Treatment gaps are calculated as the number of days in the interval between prescription fillings minus the number of days' supply obtained at the beginning of the interval. For instance, if a patient fills a prescription which provides treatment for 30 days and fills his next prescription after 38 days, then he is be considered to have a treatment gap of 8 days. A negative treatment gap occurs when a patient fills his next prescription before he is out of stock of medication.[21] Additionally, I measure adherence using different thresholds, where patients are considered non-adherent if the number of days they are out of medication exceeds a certain number of days.

### 4.3 Preliminary Evidence

Figure 3 shows the monthly mean treatment gap for eligible and non-eligible patients (markers, primary axis). Before the nationwide offset of the program in August 2013, both groups of patients have very similar measures of adherence, as measured by the treatment gap. However, once the *Receta Resurtible* program began, adherence for eligible patients improved significantly with respect to non-eligible patients. Additionally, it shows the difference in treatment gaps for eligible and non-eligible individuals (solid line, secondary axis). The graph shows that before the start of the program, the differences fluctuated around zero, and became significantly negative after the adoption of automatic refill prescriptions.[22]

The preliminary evidence presented above suggests that the *Receta Resurtible* Program had an effect on the behavior of patients that experienced a reduction in the monitoring of healthcare. Patients who received automatic-refill prescriptions appear to have improved adherence as they are on average out of medication for fewer days than patients with shorter prescriptions.

## 5 Empirical Strategy

### 5.1 Patient-Level Variation

To assess the impact of reduced healthcare monitoring on various outcomes, among these medication adherence, I use a fixed effects model at the patient level. Intuitively, this allows us to compare the medication purchasing behavior of an individual patient

[21] Part of the analysis ignores negative treatment gaps (or truncates treatment gaps at zero) to ensure that these observations are not driving the results, as they might not actually be a measure of better adherence.

[22] Figure A.5 in the Appendix shows how the distribution of treatment gap for continuous users changed before and after the implementation of the *Receta Resurtible* program.

with automatic refill prescription to his behavior with a regular 30-day prescription.

Additionally, I estimate the aggregate effects of the implementation of the policy at the clinic level and exploit the variation in the timing of the adoption of the policy in order to address the fact that patients are assigned to the 30- and automatic refill prescriptions non-randomly.

The baseline fixed effects model at the individual level will give estimates for the effect of being assigned to the low-frequency regime on patients' adherence as we are effectively looking at patients that changed from one prescription regime to another, and comparing their behavior before and after this change. The estimated coefficient will show how—on average—the number of days between appointments changes for a particular patient when he is on the 90- versus the 30-day regime. The equation I estimate is

$$y_{i,t,c} = \beta_0 + \beta_1 RR_{i,t,c} + \beta_2 \mathbf{X}_{i,t,c} \alpha_i + \gamma_{ym} + \varepsilon_{i,t,c}, \tag{5}$$

where $y_{i,t}$ represents the outcome of interest, such as the treatment gap, whether a patient was out of medication for a given number of days, or some health outcome for patient $i$, at date $t$, in clinic $c$.[23] $\alpha_i$'s are patient fixed effects, $\gamma_{ym}$ are year/month dummies, and $\mathbf{X}_{i,t,j}$ are controls, which may vary at the patient or at the clinic level, and will only be included in some of my specifications. $RR_{i,t,c}$ is a dummy variable equal to one if the patient is on the low monitoring, automatic-refill regime. The coefficient of interest is $\beta_1$. If the *Receta Resurtible* program is indeed improving medication adherence we would expect $\beta_1$ to be negative, as a lower treatment gap indicates improved compliance.

Recall that the theoretical model predicts $\beta_1 < 0$ since it predicts that average treatment gaps decrease for patients that go on the low-monitoring regime, as can be seen in $\Delta a^{RR} = \bar{a}^{RR}_{i,1} - \bar{a}^{RR}_{i,0} < \bar{a}_{i,1} - \bar{a}_{i,0} = \Delta a = 0$.

Since the panel ends in December, 2014, I include year/month dummies to control for mechanical effects that could affect my results due to right censoring. In particular, given that the treatment gap only takes a real value contingent on whether the patient actually makes a future purchase, it will take smaller values the closer it is to the end date of the period covered in the data by construction.

The underlying assumption for this model to be correctly specified is that there are no omitted time-varying patient specific characteristics which are correlated with receiving an automatic refill *Receta Resurtible* prescription, which seems like a plausible assumption, as there were no other health policy changes at IMSS. In any case, the

[23]It is important to remember that patients on the automatic refill regime still have to purchase their medication on a monthly basis. The automatic refill regime implies a 90-day time period between doctor's appointment in order to receive a new prescription, but monthly visits to the pharmacy.

rest of my empirical strategy relies on analysis at the clinic level and uses arguably exogenous variation in the timing and intensity with which the policy was adopted to address any concerns about the patient fixed effects methodology.

I use the patient fixed-effects model to further explore the mechanisms through which longer prescriptions may be improving adherence. In order to do so, I can run Equation 5 separately for (i) different subgroups (male, female, employed, non-employed, retired, younger, older) of patients within my sample; and (ii) patients from different clinics (classified by congestion as measured by doctor-workload).

Finally, the model predicts a higher effect for patients with higher $\delta_i$'s. I will use clinic congestion (as measured by the number of appointments per doctor per month) as a factor which affects $\delta_i$ to test whether the effect of *Receta Resurtible* is larger in more congested clinics.

## 5.2 Clinic-Level Variation

The remainder of my analysis focuses on the effects—both direct and indirect—of decreasing the frequency of health monitoring for stable patients. It relies on the heterogeneity in the timing and intensity of the adoption of the *Receta Resurtible* program by IMSS clinics. I analyze the direct impact the policy had on clinic congestion (as measured by the number of appointments per doctor), and on the indirect effect it had on medication adherence, *both* for patients whose health monitoring was decreased (on the automatic-refill regime) and for those who remained on the original 30-day regime. An effect on the latter type of patients would suggest additional spillovers of the policy, most obviously via decreased congestion.

This strategy allows me to exploit the variation in prescription duration. In this way I can address endogeneity concerns regarding changes in patients' behavior which may be correlated with being eligible for an automatic refill prescription (which would violate the assumption needed for a patient fixed effects model to be correctly specified). The key assumption of the fixed effects model—no omitted time-varying patient-specific characteristics which are correlated with receiving an automatic refill prescription—is more likely to hold shortly after the policy was implemented (i.e., patients have not changed adherence in order to go on the low-monitoring regime). Therefore, by using a *clinic's* adoption of the automatic-refill regime (timing or intensity), I can address endogeneity concerns at the *individual* level.

As mentioned above, although the *Receta Resurtible* program officially started in August 2013, some clinics began issuing automatic refill prescriptions before this date, while others took a few months to adopt the program. Therefore, there exists geographical variation in the timing of uptake of the program which allows me to explore the causal effect of prescription duration on medication adherence. To assess the impact of longer (automatic refill) prescriptions on medication adherence I will now look at the impact of adopting the *Receta Resurtible* program on aggregate measures of medication adherence at the clinic level. The general equation I estimate is

$$y_{c,t} = \beta_0 + \beta_1 RR_{c,t} + \alpha_c + \gamma_{ym} + \varepsilon_{c,t}, \tag{6}$$

where $y_{c,t}$ represents either a measure of clinic congestion or an aggregate measure of medication adherence (such as the treatment gap) for clinic $c$. $\alpha_c$'s are clinic fixed effects and $\gamma_{ym}$ are year/month dummies. $RR_{c,t}$ is a variable which measures the adoption of the *Receta Resurtible* program at the clinic level and defined in different ways for several specifications: $RR_{c,t}$ may represent (i) the share of hypertensive medication prescriptions in a clinic which are automatic refill prescriptions, (ii) or a dummy variable indicating the "start date" on which a clinic adopted the policy.[24] The coefficient of interest is $\beta_1$. If the *Receta Resurtible* program is indeed improving medication adherence we would expect $\beta_1$ to be negative, as a lower treatment gap indicates improved aggregate compliance.

The validity of this strategy would be compromised if clinics' adoption of the *Receta Resurtible* program had an effect on the composition of its patients. In order to test whether the composition of patients receiving care from clinics appears to have changed as a result of the *Receta Resurtible* program, I additionally estimate Equation 6 using measures of aggregate patient characteristics, such as the share of hypertensive patients visiting a clinic, mean age, and gender composition, as the dependent variable, $y_{c,t}$. If the adoption of the clinic has not had an effect on the clinics' composition of patients, we would expect $\beta_1$ to be statistically undistinguishable from zero, which would address this concern on the validity of the empirical strategy. Table A.4 in the Appendix presents some evidence to suggest that clinics did not change the composition of the patients they treat as they adopted the *Receta Resurtible* program (which is fundamental for the validity of my identification strategy).[25]

Finally, in order to assess the impact of longer automatic refill prescription on

[24] The start dates are defined as follows: (A) the first month in which the share of automatic refill prescriptions is equal or greater than 5%; (B) the first month in which the share of automatic refill prescriptions is equal or greater than 3%; and (C) the month on which the number of automatic refill prescriptions increased the most with respect to the previous month.

[25] This table shows that we cannot find evidence to suggest that the number of diabetic patients treated in a clinic, the male-female composition, or the share of patients who are retired changed as a result of a clinics adoption of the *Receta Resurtible* policy. I find a slightly significant effect on the share of hypertensive patients in clinics, although the magnitude is negligible, and a small but significant effect on age. However, as the analysis focuses on persistent patients and since newly diagnosed hypertensive patients cannot get automatic refill prescriptions, the aging of the population in the clinic is partially driven by a mechanical time-trend effect. Patients in clinics with a higher share of automatic refill prescriptions being issued also appear to receive a greater number of hypertensive medications on average. The magnitude of the coefficient is small.

medication adherence I exploit the richness of my data by including patient fixed effects and using measures of the clinics' adoption of the *Receta Resurtible* program, and try to identify the effect on patients who are more likely to receive automatic refill prescriptions. With this kind of model, I first use the variation in the adoption of the *Receta Resurtible* program at the clinic level and analyze the effect on patients, focusing on the patients that are more likely to receive an automatic refill prescription. The fixed effects model allows me to control for time-invariant observable and non-observable individual characteristics. By defining the treatment variable at the clinic level, I alleviate concerns about endogeneity of assignment at the individual level.

I can analyze the differential effect for patients that are likely to be eligible for longer prescriptions by adding an interaction term with patients' diabetes status.[26] This allows me to effectively identify whether the reduction in aggregate adherence measures does in fact come from the patients who are receiving the longer prescriptions. Additionally, by using clinic level data for my independent variable, I am able to address potential endogeneity concerns which may bias my results.

This model also allows me to explore whether there may be spillovers to patients that remain on the 30-day regime. Since patients on diabetic medications are less likely to be on the low-monitoring regime, finding an improvement in the adherence of these patients would be evidence of positive spillovers.

The regressions I estimate are of the form:

$$y_{i,c,t} = \beta_0 + \beta_1 RR_{c,t} + \beta_2 RR_{c,t} * NonDiabetic_i + \alpha_i + \gamma_{ym} + \varepsilon_{i,t}, \tag{7}$$

where $y_{it}$ represents the treatment gap for patient $i$, a measure of medication adherence. $\alpha_i$'s are patient fixed effects and $\gamma_{ym}$ are year/month dummies.[27] $RR_{c,t}$ is a variable which measures the adoption of the *Receta Resurtible* program at the clinic level as defined above. The $NonDiabetic_i$ variable indicates whether a patient is identified as non-diabetic, and is thus more likely to be eligible to receive automatic refill prescriptions.[28] The coefficient of interest are $\beta_1$ and $\beta_2$. If the *Receta Resurtible*

[26] I use whether a patient is non-diabetic since the eligibility criteria specify that stable patients should have no additional comorbidities. Additionally, an econometric analysis using probit regressions on patient characteristics before August 2013 for the subsample of patients for whom I have medical data, suggests that empirically non-diabetic patients are more likely to receive automatic refill prescriptions. Figure A.7 in the Appendix shows the distribution of predicted probabilities associated with the probit regression for diabetic and non-diabetic patients.

[27] Patients rarely change the clinic where they are treated in the data (less than 1% of patients). Therefore, it is not necessary to include clinic fixed effects as they are almost perfectly correlated with patient fixed effects.

[28] I am able to identify diabetic patients on therapeutic treatment by analyzing whether they have filled a prescription for any of the medication used to treat diabetes at IMSS clinics, according to their clinical guidelines. This is a subset of all diabetic individuals, as patients with less severe diabetes may not receive therapeutic treatment.

program is indeed improving medication adherence for those individuals that receive longer prescriptions, we would expect $\beta_2$ to be negative, as patients who are more likely to receive automatic refill prescriptions once their clinic starts issuing *Recetas Resurtibles* would exhibit a lower treatment gap which indicates improved compliance. Additionally, a negative and significant $\beta_1$ would suggest that positive spillovers for patients that remain on the monthly regime.

Finally, and in line with this last empirical strategy, I conduct an event study analysis. In particular, I analyze the impact of the different start dates of the *Receta Resurtible* program at the clinic level on patients' individual medication adherence. The equation I estimate is of the form:

$$y_{it} = \beta_0 + \sum_{s=-6}^{-1} \beta_s \mathbb{1}_{c[s=T+s]} + \sum_{s=1}^{6} \beta_s \mathbb{1}_{c[s=T+s]} + \beta_{pre} D_{pre} + \beta_{post} D_{post} + \alpha_i + \gamma_{ym} + \varepsilon_{it}, \quad (8)$$

where $y_{it}$ represents an individual measure of medication adherence (i.e., treatment gap), $\mathbb{1}_{c[s=T+s]}$ is an indicator function which takes a value equal to one when the observation occurs $s$ months before or after the month when the clinic adopted the *Receta Resurtible* program. $D_{pre}$ and $D_{post}$ are dummy variables which are equal to one if the observation occurs 6 months prior to or 6 months after the clinic's adoption of the program.[29] $\alpha_i$'s are patient fixed effects and $\gamma_{ym}$ are year/month dummies. If longer prescriptions have a positive effect on adherence, we would expect to see negative coefficients for the $\beta$'s corresponding to the months after the start of the program.

## 5.3 Do Patients Prefer Low Monitoring?

The *Receta Resurtible* policy has a unique policy design in which (i) although the frequency with which a patient must see a doctor to renew a prescription increased, we may observe patients every month in the data when they fill prescriptions at a pharmacy, and (ii) patients on the low frequency regime are exposed to high and low transaction costs of filling a prescription on a systematic basis (as they sometimes fill prescription after a doctor's appointment and sometimes directly at the pharmacy).

Exploiting this particular structure which can be analyzed in the data, I am able to test whether there is evidence that patients value the regime with low health monitoring (and low transaction costs). In order to do so, I use the empirical finding which suggests that—in addition to the well-defined eligibility criteria—physicians seem to be looking at patient's adherence once they go on the automatic-refill regime to determine whether

[29] With this specification, the base category is the actual month when the *Receta Resurtible* program begins at a clinic, and thus all $\beta$'s are stated in relation to a zero value for the starting month.

they may remain in this regime. Figure 4 shows the estimated coefficients from an event study regression, where the event is defined as the moment when a 90-day regime patient is reassigned back to the 30-day, high health monitoring regime. What we see in this graph is a very elevated treatment gap *before* the patient is expelled from the automatic-refill regime. A high treatment gap can arguably give a signal of poor self-management of the disease, which inclines physicians to transfer the patient back to the frequent monitoring scheme.

My first strategy uses the fact that patients who receive automatic refill prescriptions still have to fill their prescriptions on a monthly basis. However, as shown in Figure A.2 over a three month period, a patient fills one prescription at the time of his doctor's appointment, and then fills two prescriptions by simply going to the pharmacy. Having in mind that doctor's appointments have higher transaction costs (i.e., waiting time, time of the actual appointment, patient's presence necessary), we can think of patients who receive *Recetas Resurtibles* as having one costly prescription filling (when they visit their physician) and two non-costly prescription fillings (when only a pharmacy pick-up is required), over a three month period.

By exploiting this feature of the data, and looking at *costly* and *non-costly* visits separately, I may assess whether patients are only improving adherence due to lower transaction costs, or whether they also modify their behavior to stay on the low-frequency regime, which would be consistent with an improvement of medication adherence in those visits where costs are the same as before the policy.

My first empirical strategy to explore whether patients value being on the low-frequency regime is to estimate Equation 5 separately for *costly* and *non-costly* prescription fillings. If patients value remaining in the low-monitoring regime, we would expect a decrease in the treatment gap in both the non-costly and the costly visists for patients who have been assigned to the automatic-refill regime. However, if longer prescriptions are only improving adherence by lowering transaction costs, then we should only observe an effect on non-costly visits. In terms of the model, this would imply testing whether $\bar{a}_{i,2}^{RR} < \bar{a}_{i,0}^{RR}$, or not.

Furthermore, I can analyze how patients' adherence evolves as they have been on the low-frequency regime for a longer period of time. In particular, I can estimate the impact of the $n^{th}$ automatic-refill prescription on a patient's adherence, and see how the effect evolves over time. In this setting, the *costly* prescription fillings would be the third, sixth, ninth, and so on. I estimate an equation of the form:

$$y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n RR^{n^{th}} + \alpha_i + \gamma_{ym} + \varepsilon_{it}, \tag{9}$$

where $RR^{n^{th}}$ is a dummy variable for the $n^{th}$ automatic refill prescription received by patient $i$. If we assume that patients may establish a "good reputation" regarding the way in which they manage their disease, they might perceive a lower probability of being removed from the program if they are a bit late (i.e., the $\alpha$ could be decreasing as a patient has been on the program for longer). A diminishing effect of the policy on adherence would be consistent with patients modifying their behavior to remain on the low-frequency regime.

As an additional check in line with the previous empirical strategy, I may compare how patients' behavior regarding doctor's appointment scheduling differs between those receiving regular and automatic refill prescriptions. This strategy also takes into account the *costly* visit (when patients must attend a doctor's appointment). To do so, I construct a variable to capture the "appointment gap", measured as the number of days a patient delays his visit to the physician.[30] An improvement of the appointment gap for patients on automatic refill prescriptions is consistent with patients preferring the low-frequency regime, as it suggests improved adherence on those visits that are costly.

To analyze which patients appear to respond the most to the incentive of staying on the low monitoring regime, I present the results using an interaction term for clinic congestion, as measured by the number of appointments per doctor. This strategy allows me to assess whether patients with an arguably higher $\delta_i$ (as filling a prescription at a pharmacy as opposed to renewing it with the doctor represents a relatively higher decrease of transaction costs the more costly it is to attend a doctor's appointment) have a higher incentive to improve their adherence in order to stay on the 90-day regime—as predicted by the theoretical model.

## 5.4 Health Outcomes

To address the concern that patients' health may be negatively affected due to the *Receta Resurtible* program, I estimate Equation 5 using different clinical variables as dependent variable for the subset of patients for whom I have clinical data. In this specification, however, I must use a lagged $RR_{it}$ variable (which indicates whether the prescription in automatic refill), to assess the effect of the longer prescription on future health outcomes (not contemporaneous since by policy design only stable patients should get prescriptions covering 90 days of treatment). I use different health outcomes as the dependent variable, $y_{it}$. Among the health outcomes I consider are patients' blood pressure, heart rate, prevalence of ischemic heart disease, and body mass index.

As an additional check on whether issuing longer prescriptions may be detrimental

[30]Ideally, patients on the *Receta Resurtible* regime should attend a doctor's appointment every 90 days, and all other hypertensive patients should go very 30 days.

for individuals' health, I created variables which measure changes in the patients' pharmacological treatment between doctor's appointments. The hypothesis is that a change in the treatment prescribed to patients could indicate a worsening of the condition. If the *Receta Resurtible* is not having a negative effect on patients' health, then we would not expect a positive relationship between receiving an automatic refill prescription and a measure of changes in treatment. To measure changes in treatment, I created a dummy variable which indicates whether there was any change in the medications that are prescribed to a patient, and another which measures how many medications were changed. As these variables are constructed from prescription fillings, they can be calculated for all hypertensive patients, and not only for those in the subsample for which I have clinical records. Using these variables as dependent variables I estimate Equation 5.

# 6 Results

## 6.1 Patient-Level Results

Table 2 presents the results for different econometric specifications to explore the effect of prescription duration on medication adherence, as measured by the treatment gap. Regressions include patient and year-month fixed effects, and cluster standard errors at the clinic level. All coefficients are significant and negative, indicating that going from the regular 30-day regime to the low-frequency regime significantly reduces the treatment gap in 2.61 days. The magnitude of the coefficient indicates that the improvement in adherence is large, and of around 35%, with respect to the mean number of days patients were out of medication *before* the implementation of the program of 7.4 days.

Columns 3 through 5 use a dichotomous measure of adherence, where a patient is considered to be non-adherent if he was out of medication for a positive number of days, more than seven, fourteen, or thirty days respectively. Including measures of adherence in this way allows me to rule out the possibility that changes where negative treatment gaps become less negative—which are not giving us relevant information about adherence—are not driving the reduction in patients' treatment gap. In these regressions, a negative coefficient implies a reduction in the probability that a patient will be out of hypertensive medication for a given period of time. These results suggest that patients that receive longer prescriptions are less likely to be out of medication for different periods of time. All coefficients are statistically significant at a level of 1%.

I additionally examine heterogeneity in $\delta_i$ (using the notation of the model), where we would expect that patients in congested clinics experience a greater reduction in transaction costs by avoiding a doctor's visit. Table 3 shows that the effect of being on the automatic-refill regime is stronger for patients that are treated in congested clinics (using as a measure of congestion the number of appointments per doctor for each month). The negative sign on the coefficient from the interaction term (between being on the *Receta Resurtible* regime and a clinic's congestion) suggests that patients adherence improves relatively more in highly congested clinics. These results are consistent with a greater improvement in adherence for patients where transaction costs were reduced the most (i.e., high $\delta_i$).[31]

## 6.2 Clinics' Adoption of the *Receta Resurtible* Program

Table 4 shows the results corresponding to estimating Equation 6. Columns 1 and 2 use the share of automatic refill prescriptions issued at a clinic regressed on the mean and median treatment gap respectively. Both columns show a significant aggregate effect of prescription duration on aggregate medication adherence, and the magnitude of the coefficients is surprisingly similar to that of the individual level regressions, which suggests the results are robust. Columns 3 through 5 use the share of patients with treatment gaps which are positive, over a week, and over two weeks in a clinic as the dependent variable. My results show that the share of patients who are non-adherent according to these thresholds has been reduced due to the adoption of the *Receta Resurtible* program. Columns 6 through 8 use dummy variables to indicate whether the observation occurred after the clinic adopted the program as independent variables,[32] and also show a significant reduction in clinics' treatment gap in response to the adoption of the *Receta Resurtible* program.[33]

These results are consistent with a positive effect of increased prescription duration on patients' medication adherence. As Table 4 shows, the timing (and intensity) in which specific clinics adopt the *Receta Resurtible* policy appears to be causing a reduction in the aggregate treatment gap of the patients in these clinics.

[31] Table A.6 in the Appendix shows the results from estimating Equation 5 separately for patients from different clinics, classified according to their levels of congestion. As expected, we can see that the magnitude of the effects of the policy are larger the busier a clinic is. Both the decline in the treatment gap and in the probability that a patient will run out of medication is larger for patients in clinics with the highest number of appointments per doctor.

[32] The start dates are defined as follows: (A) the first month in which the share of automatic refill prescriptions is equal or greater than 5%; (B) the first month in which the share of automatic refill prescriptions is equal or greater than 3%; and (C) the month on which the number of automatic refill prescriptions increased the most with respect to the previous month.

[33] Figures A.8, A.9, and A.10 in the Appendix show event study graphs for the share of automatic refill prescriptions issued at the clinic level for each of the chosen start dates.

## 6.3 Do Patients Prefer Low Monitoring?

Table 5 presents evidence that patients value the reduction of health monitoring and are not merely reacting to a reduction in transaction costs. I find that patients on the low-frequency regime not only improve their adherence when they have low transaction costs, but also when they must renew a prescription with the doctor (a decrease in their treatment gap in $s = 2$ in the model). They appear to improve their behavior in order to increase the probability of remaining in this less costly regime (90-day). Column 1 presents the baseline estimate from the patient fixed effects model as reference. Columns 2 and 3 correspond to my first empirical strategy, and show the results of estimating Equation 5 on non-costly (pharmacy pick-up) and costly (doctor's appointment) observations differentially. Both coefficients are negative and statistically significant. This finding is evidence of patients valuing the low-cost regime, as patients on the *Receta Resurtible* program are not only responding to the reduced transaction costs of the intermediate prescription fillings (in terms of the theoretical model, it suggests that $\alpha \Delta U > 0$).

Column 4 and 5 of Table 5 correspond to my second empirical strategy and show the effect of receiving an automatic refill prescription on the attendance to doctor's appointments (column 5 only considers positive appointment gaps). The results are consistent with a reduction in the delay of doctor's appointments for patients on the automatic refill regime, which is consistent with the low-frequency regime further improving medication adherence by incentivizing patients to improve their adherence in order to remain on the regime with lower health monitoring, and not only through a reduction in transaction costs.

Patients in the most congested clinics are likely to benefit the most from going on the low-monitoring regime. Therefore, we would expect that the incentive to improve adherence in order to remain on this low-cost regime is greater for patients in these clinics. Table 6 shows that patients on highly congestion clinics indeed seem to value remaining on the 90-day regime, as the coefficient on the interaction term with clinic congestion is negative and statistically significant. We can see a large, negative effect of the policy on both costly and non-costly appointments, which is higher for high congestion clinics.

The effect of each of the automatic refill prescriptions on patients' adherence can be graphically seen in Figure 5, which plots the first twelve coefficients from estimating Equation 9. This figure shows the effect of receiving the $n^{th}$ automatic refill prescription. We can see that the effect is quite stable over time. Additionally, we can see that the coefficients for the third, sixth, ninth, and twelfth prescriptions (associated with the costly visits), are statistically different from zero, and are in fact statistically indistinguishable from their two anteceding coefficients, which suggests that patients are modifying their behavior for reasons besides the reduction in costs present in the non-costly pharmacy visits. The general trend of these coefficients is relatively flat, but is slightly increasing (suggesting a weaker effect the longer a patient has been in the program). When thinking of the incentives to improve adherence in order to remain on the low-cost regime, this could suggest that the incentives of behaving better weaken in time as a patient build a reputation of good-self management of his disease with his physician (and is thus less likely to be removed from the low-monitoring regime if his adherence "slips" on one occasion).

## 6.4 Spillovers

The richness of my data allows me to check whether this improvement of aggregate medication adherence at the clinic level is exclusively being driven by patients that are assigned on the low-frequency regime, or whether there are positive spillovers for patients not on the *Receta Resurtible* regime,as clinic congestion declines.

Table 7 shows that increases in the share of automatic-refill prescriptions for hypertensive patients issued at the clinic level imply a reduction in clinics' congestion. All the measures of clinics' implementation of the *Receta Resurtible* program are associated with a reduction of clinic congestion, as measured by the number of monthly appointments per doctor. This is evidence that the program was successful in reducing clinic congestion, and is a necessary condition for the policy having positive spillovers on patients that remained on the general, high-frequency regime.

Table 8 estimates a version of Equation 5 separately for stable and non-stable patients in order to decompose the effect of a clinic's adoption of the low-frequency program. It uses measures that indicate a clinic's adoption of *Receta Resurtible* as the independent variable, and the individual's treatment gap as the dependent variable (including patient and time fixed effects as well). The results show that the improvement in medication adherence is present both for eligible patients (direct effect) but also from non-eligible patients (spillover)—taking non-eligible patients to be those that never received a 90-day prescription over the period I study. These results suggest that as clinic congestion was reduced, non-stable patients also improved adherence as transaction costs of renewing prescriptions decreased for all patients. The magnitude of the spillover effect is at most half that of the direct effect of patients that went on the low-frequency regime.

Table 9 shows the results from estimating Equation 7. It presents further evidence of the direct and spillover effects of the low-frequency regime on patients' adherence. It shows the differential effect of the *Receta Resurtible* program on non-diabetic and diabetic patients—as hypertensive patients that are diabetic patients are in theory not eligible for the low-frequency regime. A negative coefficient in the interaction terms suggests that once a clinic adopts the *Receta Resurtible* program, individuals that are more likely to receive automatic refill prescriptions (i.e., non-diabetics) are indeed improving the adherence differentially more than other patients.

Column 1 of Table 9 shows the baseline estimate using patient-level variation in prescription duration, which was presented in Table 2. Column 2 uses the share of patients at a clinic who receive automatic refill prescriptions (calculated excluding the individual herself) as a measure of $RR_{ct}$, the clinic's adoption of the program. The significant negative coefficient suggests an improvement of medication adherence from reducing health monitoring (the treatment gap or number of days a patient is out of medication was reduced). Columns 3 and 4 present the same estimates only considering diabetic patients—arguably not stable, and hence not likely recipients of automatic-refill prescriptions. Again, these coefficients are negative and significant, suggesting the presence of spillovers.

Columns 5 and 6 of Table 9 add interaction terms for non-diabetic and male patients. The negative significant coefficient on the interaction with "non-diabetic" is consistent with the hypothesis that these patients—who are more likely to receive automatic refill prescriptions—improved their medication adherence more than diabetic patients, and is evidence of a causal link of prescription duration on medication adherence.

Figure 6 shows an event study graph corresponding to estimating Equation 8, using the month when automatic refill prescriptions increased the most as the date of the event. This graph shows positive coefficients for the months prior to the clinic's adoption of the *Receta Resurtible* policy and negative coefficients afterwards. This evidence is consistent with a reduction in patients' treatment gap after longer prescriptions begin to be issued.[34]

## 6.5 Health Outcomes

Table 10 presents the results from estimating Equation 5 using health outcomes for the patients for which I have clinical data. Column 1 shows the effect of longer prescriptions on the treatment gap for this sample of patients. Even though the sample is significantly smaller (around 700 patients, given I only consider persistent patients) than the full sample, I find an improvement in adherence for patients receiving automatic refill prescriptions. Columns 2 through 7 show that patients' hypertension remains controlled in spite of visiting the doctor less frequently. Patients' health outcomes are stable and show no sign of a decline in health, which would be an important concern when reducing health monitoring. In particular, I find no effect on patients'

[34]Figures A.11 and A.12 in the Appendix use alternative start dates.

blood pressure, heart rate, prevalence of ischemic heart disease, or body mass index.[35] This suggests that patients on the low-monitoring regime remain with their condition under control.

Table 11 present the results from using a measure of the changes in the patients' pharmacological treatment between doctor's appointments as dependent variable. My estimates suggest that patients who receive longer prescriptions are no more likely to get a change in their prescribed therapeutical treatment than those who receive 30-day prescriptions, as can be seen in Column 1. Column 2 shows a slight increase in the total number of hypertensive medications changed, but the magnitude of this effect is negligible (around 0.3%). These findings, along with the results from the regressions on health outcomes, present evidence which suggests that patients' health remains stable even after reducing the frequency in which they meet with a physician.

## 6.6 Robustness

The results of the following robustness checks are presented in the tables in the Appendix. Table A.5 shows the effects of the policy on different subgroups of the population. We can see that the relative size of the effect of receiving an automatic refill prescription is larger for (i) male patients, and (ii) employed individuals as opposed to beneficiaries. Additionally, we can see that the effect for retired individuals is in fact larger than that of non-retired individuals (which include workers currently affiliated to IMSS and their families), which yields suggestive evidence that larger transportation cost for older (retired) individuals possibly outweighs the larger opportunity cost of time of employed individuals. Individuals classified as old and middle aged have higher coefficients than young individuals, a result which is consistent with higher transaction costs associated to costly transportation for the elderly. However, most of these differences are not statistically different from zero. The coefficients range from -2.39 to -2.76.

Table A.7 shows some additional specifications from estimating Equation 5 for the treatment gap. Column 1 presents the baseline regression as reference. Column 2 presents estimates for a median regression, and the magnitude of the coefficient is consistent with that of the baseline specification.

As discused above, the main assumption for the patient fixed effects model to be correctly specified is that there are no omitted time-varying patient-specific characteristics which are correlated with receiving an automatic refill prescription. This assumption

[35] I have argued that better medication adherence is associated to better health outcomes, in particular for chronic diseases. However, as the *Receta Resurtible* program has only been operating since August 2013, we cannot at this point evaluate the positive impact of issuing automatic refill prescriptions on long term health outcomes, such as strokes, heart attacks, and ultimately deaths.

is arguably more likely to hold for patients that started on the 90-day regime closer to the beginning of the program (i.e., since the program is new, patients have not had a chance to modify their behavior in response to the program). Column 3 shows the estimates of only considering patients that got their first automatic-refill prescription before November 2013. The magnitude and significance of the coefficient is consistent with the baseline estimate.

Column 4 only considers observations before September 1, 2014. Since I am only looking at persistent users, this allows me to control for the effect of right censoring at the end of my database. I can therefore exclude the year/month fixed effects (although I include month fixed effects to control for any seasonal variation). Columns 5 and 6 consider patients besides persistent users. Column 5 presents the results from estimating the baseline patient fixed effects model considering all patients that are not considered dropouts (i.e., patients that never had a gap between prescriptions greater than 180 days). The coefficient on receiving an automatic refill prescription continues to be significant although its magnitude decreases. Column 6 includes all the patients in my data. It is still significant and has the expected sign.

The results for some additional robustness checks are presented for the baseline specification which uses the fixed effects model to assess the effect of prescription duration on patients' medication adherence are presented in Table A.8. Column 1 and 2 limit the observations to those visits when the treatment gap was positive and when it was not smaller than -10, respectively.[36] Column 3 controls for whether the patients could not receive his medication from the pharmacy due to it being out of stock, while column 4 controls for the number of different medications filled by the patient. The magnitude and significance of the estimates do not differ much across the different specifications.

## 6.7 Do Patients Really Prefer Low-Monitoring? Alternative Stories

I interpret the improvement in adherence on "costly" visits—where transaction costs are unchanged—as evidence of patients' increasing their adherence in order to be able to remain on the low-frequency regime. However, there are other alternative explanations which could account for this finding, and that could explain why there seems to be more than just an effect driven by a reduction of transaction costs.

One possible hypothesis is habit formation, which has been a promising road to

[36] These specifications ignore negative treatment gaps which may be due to a patient returning to the pharmacy a few days later after filling due to medication shortage, for example. Other thresholds were chosen and results do not differ significantly.

promote healthy habits.[37] If there exists habit formation in medication adherence, improvements in adherence could be persistent, so once patients improve their adherence on the pharmacy "non-costly" visits they could form a habit that makes them improve in the "costly" visits as well. However, the fact that the effect of being in the program is not reenforced over time (as can be seen in Figure 5) and the patterns of adherence once stable patients who go on the automatic-refill regime are reassigned to the general monthly regime (Figure 4), present evidence against this hypothesis. The same is true for a hypothesis with learning (where persistence in adherence comes from patients learning to adhere better, for example).

Another potential explanation for the persistent effect could be that antihypertensive medications are an experience good (such as in Dupas (2013)). However, the lack of an effect on patients' short term health outcomes (Table 10) and the increasing effect for congested clinics, also present some evidence against this hypothesis. Other alternative explanations are that being assigned to the low-frequency regime conveys some sort of health-information or "gold-star" effect that change the costs or benefits of adhering as perceived by the patient. But again, the differential effect by clinics' congestion does not support these hypothesis.

# 7 Conclusions

A large scale policy to better allocate scarce resources in the public healthcare sector in Mexico reduced the frequency of monitoring for stable hypertensive patients. This policy has been able to not only maintain patients' hypertension under control, but has additionally—and unintentionally—improved patients' medication adherence, an effect which could have considerable implications in the long term, both for health outcomes and for healthcare expenditures. Additionally, patients seem to prefer a low monitoring regime and the reduced transaction costs associated with, and appear to be further modifying their behavior to keep these benefits.

Using a rich longitudinal data set, I am able to exploit the offset of a nationwide policy which allows physicians to issue longer prescriptions to stable patients to analyze the effects of prescription duration on patient behavior and explore the mechanism through which it may be affected. My results show that receiving an automatic refill prescription reduces the treatment gap in 2.6 days, a reduction of 35% with respect to the treatment gap prevailing in the population before the offset of the program. A meta-analysis of studies of interventions to improve medication adherence revealed an

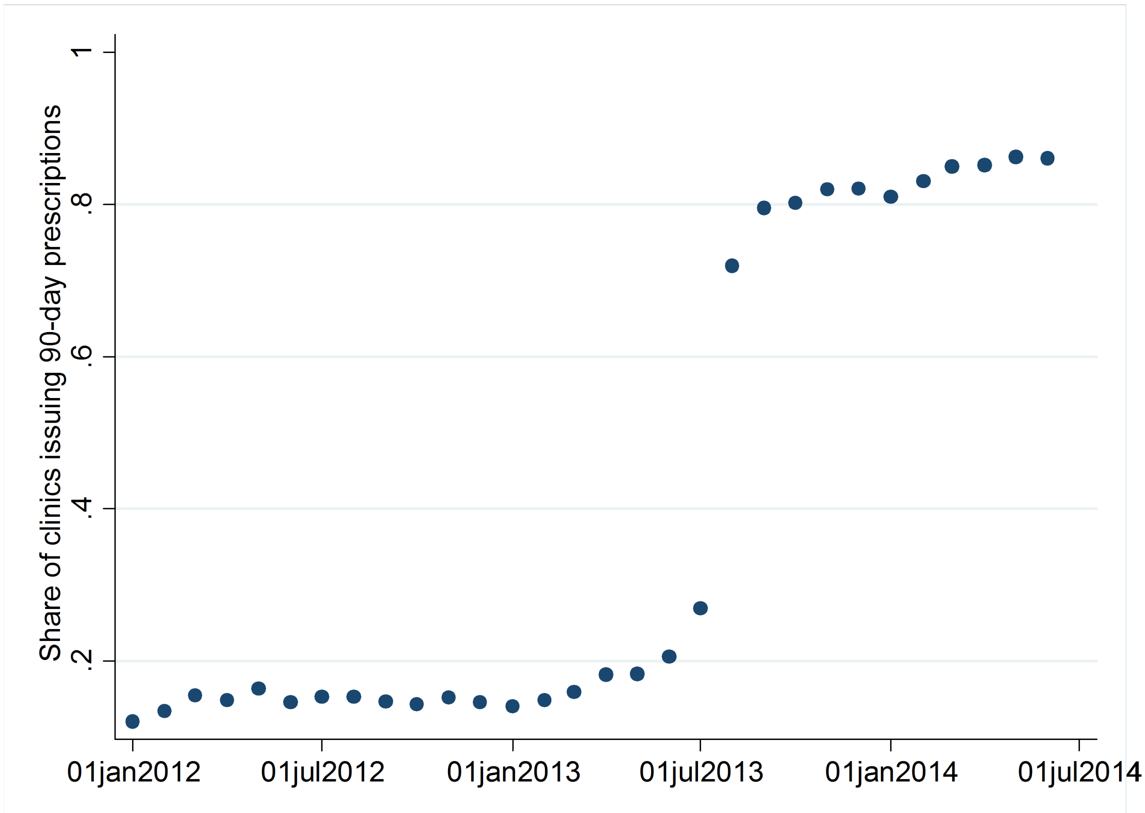
[37] Charness and Gneezy (2009) and Bhattacharya, Garber and Goldhaber-Fiebert (2015) both explore how to promote habit formation in exercise, the first using monetary incentives, and the second using *nudges*. Agüero and Beleche (2014) finds that exposure to the 2009 H1N1 influenza outbreak in Mexico led to important improvements in hand washing practices.

increase in compliance of between 4 and 11% (Peterson, Takiya and Finley (2003)), which suggests that the effect of the *Receta Resurtible* is not negligible. Subgroup analysis—for different levels of clinic congestion—suggests that patients appear to be improving adherence due to lower transaction costs, as those with high opportunity cost or facing higher transaction costs associated to attending doctor's appointments present a larger effect of the policy on their adherence-related behavior.

I find that patients that go on the *Receta Resurtible* program value being on this low monitoring regime, and improve their adherence to retain this benefits. This is reflected from the fact that patients' adherence is improving not only when they fill their prescriptions directly at a pharmacy, but also when they must renew their prescription by attending a doctor's appointment (and thus no reduction in transaction costs is present).

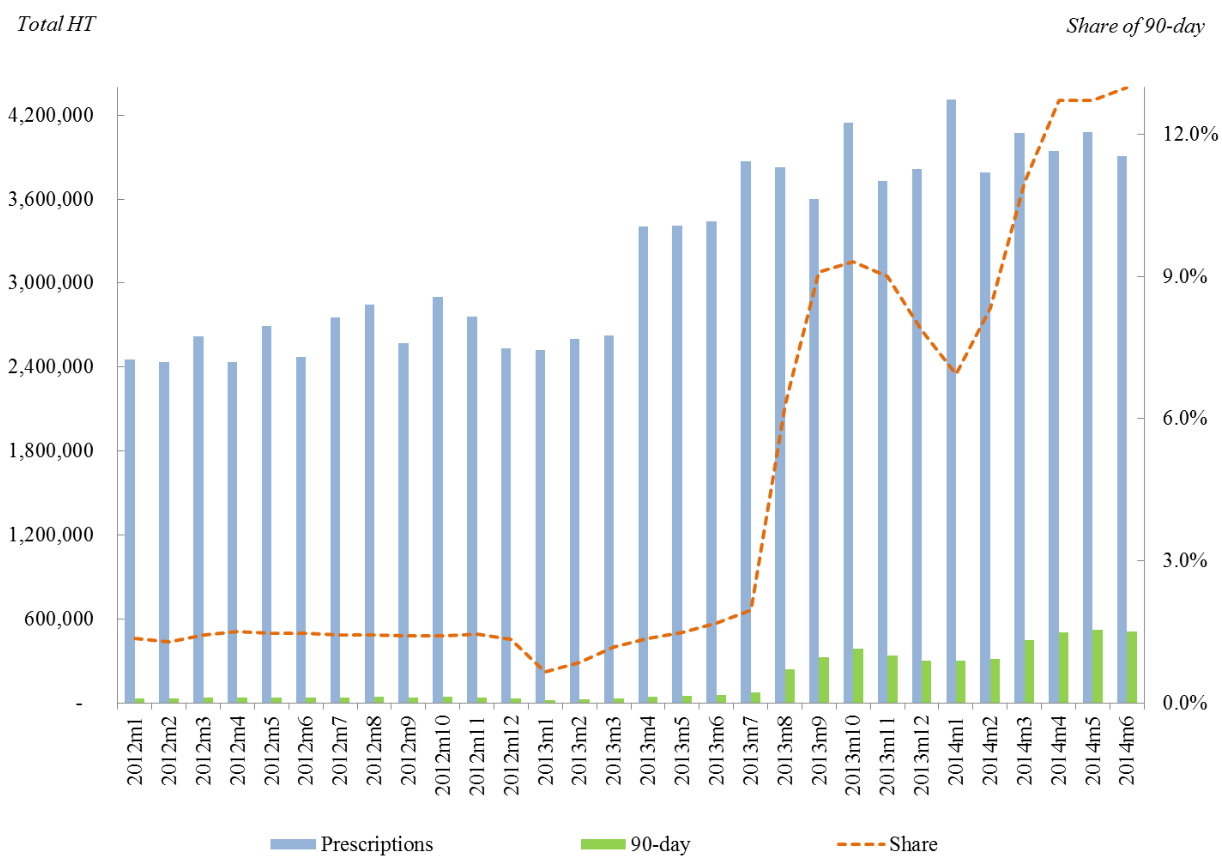
# 8 Figures and Tables

Figure 1: Clinics issuing automatic refill prescriptions



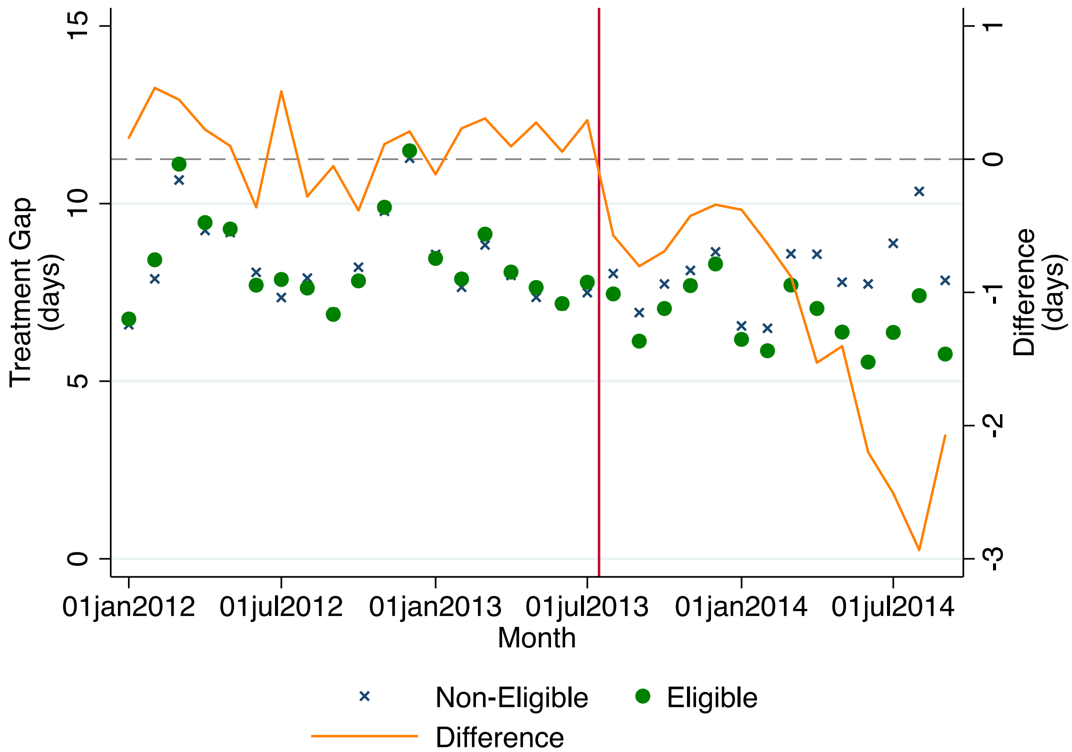

Notes: The graph displays the share of clinics issuing automatic-refill prescriptions from all the IMSS clinics treating hypertensive patients. Calculated using IMSS administrative data for prescription fillings.

Figure 2: Prescriptions issued by IMSS



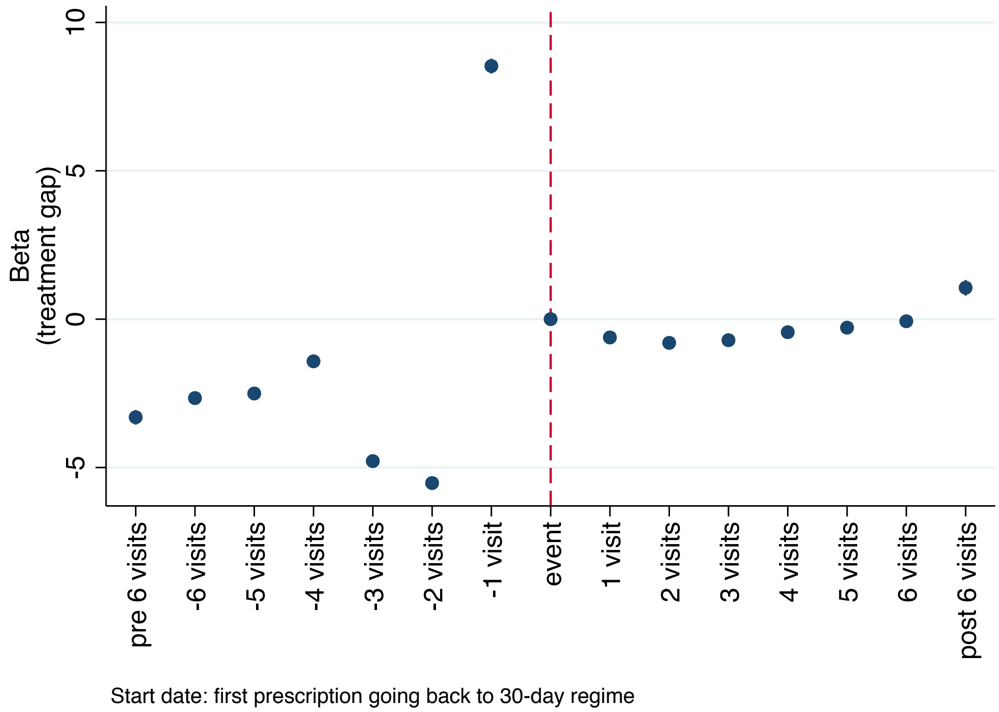

Notes: Blue and green bars are plotted on the left axis and correspond to the total number of hypertensive prescriptions issued per month. The green (short) bars are automatic refill prescriptions. The line—plotted on the right axis—indicates the share of HT prescriptions that are automatic-refill.

Figure 3: Mean Treatment Gap by Type of Patient



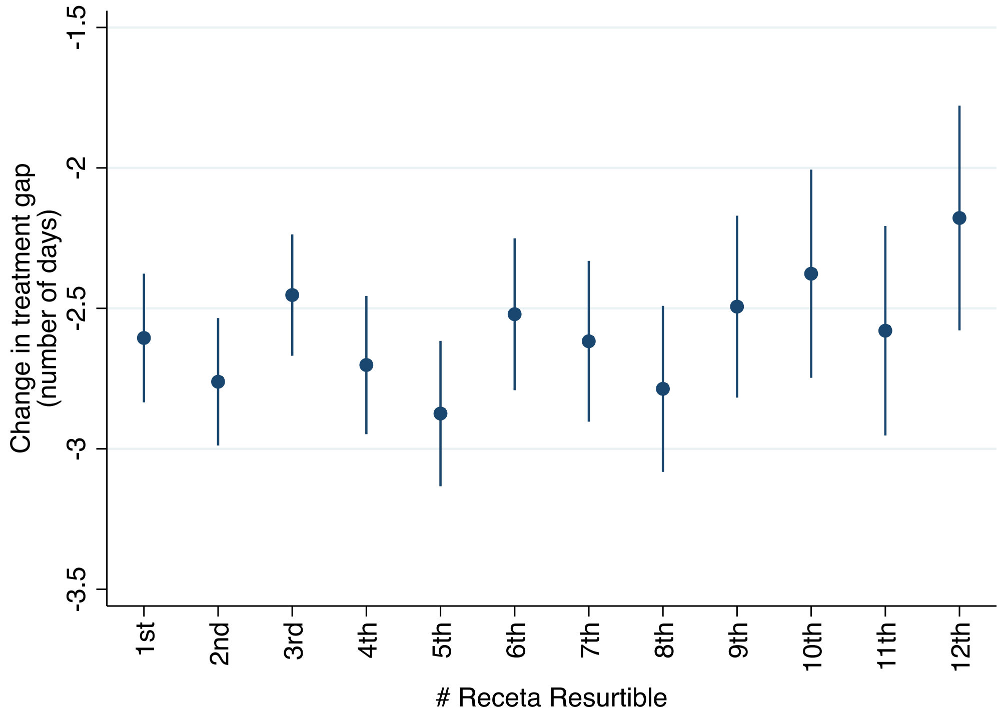

Notes: Markers show the monthly mean treatment gap for eligible and non-eligible patients (left axis). The solid line shows the difference in treatment gaps for eligible and non-eligible individuals. Eligible patients are defined as those who received at least 1 automatic-refill prescription during the period covered by the data. Non-eligible patients are those that never received one.

Figure 4: Event study graph: Event is date when patient is removed from 90-day regime



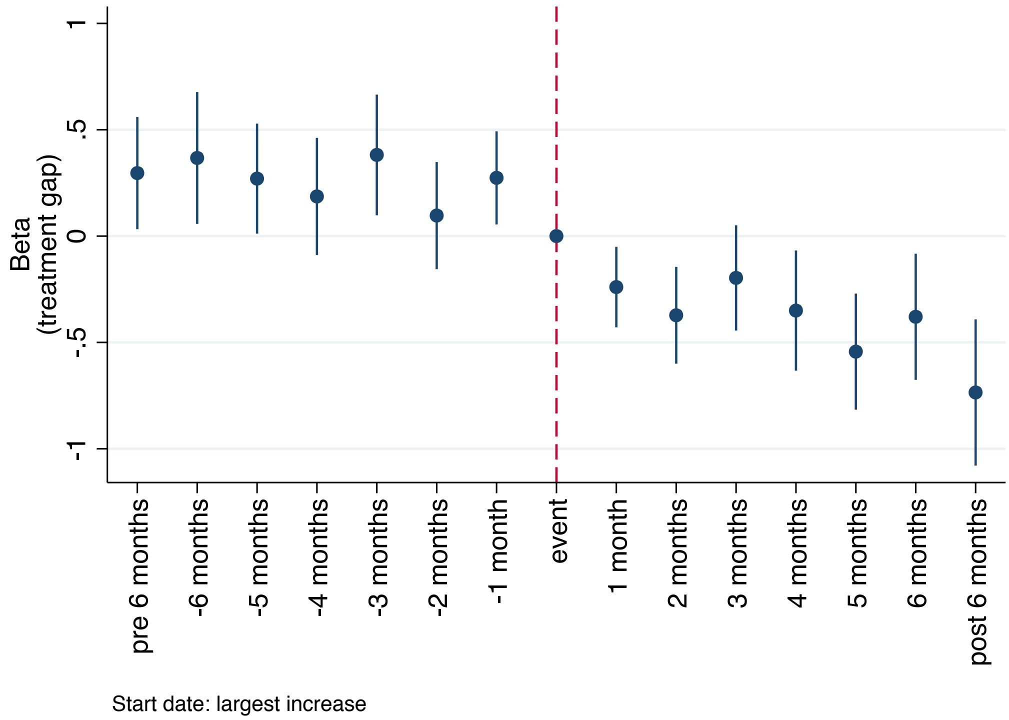

Notes: Event study graph that uses the treatment gap as the dependent variable. The model is estimated at the individual level, where $T = 0$ corresponds to the visit when a patient on the automatic-refill regime gets reassigned to the regular 30-day regime. Coefficients greater than zero indicate a larger treatment gap that that experienced at the time of the event (which has a coefficient of zero at the vertical dashed red line). Patient and time fixed effects are included. Only persistent patients are considered.

Figure 5: Effect of the $n^{th}$ automatic refill prescription. Regression coefficients




Notes: The graph displays the coefficients of of receiving the $n^{th}$ automatic-refill prescription, using the treatment gap as the dependent variable. The model is estimated at the individual level. Coefficients show the effect of the $n^{th}$ automatic-refill prescription on the treatment gap (measured in days). Only persistent patients are considered.

Figure 6: Effect of clinics' adoption of the *Receta Resurtible* program on patients' treatment gap




Notes: The event study uses the treatment gap as the dependent variable. The equation is estimated at the individual level, where $T = 0$ corresponds to the month when the patient's clinic is considered to have adopted the *Receta Resurtible* program—indicated by the month when the share of automatic-refill prescriptions increased the most. Coefficients greater than zero indicate a larger treatment gap that that experienced at the time of the event (which has a coefficient of zero at the vertical dashed red line). Patient and time fixed effects are included. Only persistent patients are considered—both eligible and non-eligible.

Table 1: Patient characteristics by type of prescription filled. August, 2013

| | Total *N=2,118,444* | | 30-day *N=1,981,903* | | 90-day *N=136,541* | | Difference | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | |
| Year of birth | 1949.9 | 12.5 | 1949.9 | 12.5 | 1950.7 | 12.1 | 0.785 | *** |
| Male | 0.368 | 0.482 | 0.368 | 0.482 | 0.375 | 0.484 | 0.007 | *** |
| Retired | 0.482 | 0.500 | 0.483 | 0.500 | 0.466 | 0.499 | -0.017 | *** |
| Personal insurance | 0.021 | 0.144 | 0.021 | 0.144 | 0.021 | 0.143 | 0.000 | |
| Total number of meds | 6.813 | 3.196 | 6.866 | 3.206 | 6.034 | 2.936 | -0.832 | *** |
| Total number of HT meds | 1.811 | 1.003 | 1.811 | 1.006 | 1.806 | 0.961 | -0.005 | * |
| Persistent patient | 0.401 | 0.490 | 0.401 | 0.490 | 0.401 | 0.490 | 0.000 | |
| Dropout | 0.065 | 0.247 | 0.067 | 0.249 | 0.045 | 0.207 | -0.022 | *** |
| Ever on 90-day regime | 0.189 | 0.391 | 0.133 | 0.339 | 1.000 | 0.000 | 0.867 | *** |
| Medication unavailability | 0.015 | 0.115 | 0.015 | 0.115 | 0.013 | 0.109 | -0.002 | *** |
| Chlorthalidone | 0.119 | 0.324 | 0.117 | 0.322 | 0.149 | 0.356 | 0.032 | *** |
| Captopril | 0.160 | 0.367 | 0.158 | 0.365 | 0.183 | 0.387 | 0.025 | *** |
| Enalapril | 0.336 | 0.472 | 0.334 | 0.472 | 0.368 | 0.482 | 0.035 | *** |
| Hydrochlorothiazide | 0.164 | 0.370 | 0.163 | 0.369 | 0.181 | 0.385 | 0.018 | *** |
| Metoprolol | 0.248 | 0.432 | 0.247 | 0.431 | 0.260 | 0.438 | 0.013 | *** |

Notes: Summary statistics calculated for all patients that are considered persistent (ie, never had a gap between prescriptions of over 90-days). Patients were considered eligible if they received at least one 90-day (RR) prescription during the time covered by the data. The pre- and post- time periods refer to the whole interval before/after receiving a RR for ”eligible” patients, and for ”non-eligible” patients the period before/after the mean date in which eligible patients got their first RR (October 23, 2013).

Table 2: Effect of automatic refill prescriptions on medication adherence

| | (1)<br>Treat. Gap | (2)<br>Positive T.G. | (3)<br>$\geq$ 7 days | (4)<br>$\geq$ 14 days | (5)<br>$\geq$ 30 days |
|---|---|---|---|---|---|
| Receta Resurtible | -2.61*** | -0.21*** | -0.13*** | -0.05*** | -0.02*** |
| | (0.117) | (0.005) | (0.006) | (0.003) | (0.002) |
| Mean dept. var. | 5.04 | 0.67 | 0.21 | 0.13 | 0.08 |
| No. patients | 1,192,797 | 1,192,797 | 1,192,797 | 1,192,797 | 1,192,797 |
| N: patient - purch. | 21,385,388 | 21,385,388 | 21,385,388 | 21,385,388 | 21,385,388 |
| R-squared | 0.16 | 0.18 | 0.20 | 0.14 | 0.10 |
| Patient F.E. | yes | yes | yes | yes | yes |
| Month - Year F.E. | yes | yes | yes | yes | yes |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication, or a dummy variable indicating whether the patient's treatment gap was $\geq X$ days. The independent variable of interest is whether the prescription was automatic refill. No additional covariates were used. Regressions for persistent patients, i.e., those whose maximum gap between two prescriptions was never over 90 days. Standard errors in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table 3: Effect of automatic refill prescriptions on medication adherence controlling for clinic congestion

| | (1)<br>Treat. Gap | (2)<br>Positive T.G. | (3)<br>$\geq$ 7 days | (4)<br>$\geq$ 14 days | (5)<br>$\geq$ 30 days |
|---|---|---|---|---|---|
| Receta Resurtible | -2.597*** | -0.211*** | -0.130*** | -0.048*** | -0.024*** |
| | (0.119) | (0.005) | (0.006) | (0.003) | (0.002) |
| $\times$ Congestion | -0.171** | -0.019*** | 0.003 | 0.003* | 0.001 |
| | (0.082) | (0.004) | (0.004) | (0.002) | (0.001) |
| Congestion | 0.216*** | 0.018*** | -0.007*** | -0.008*** | -0.005*** |
| | (0.061) | (0.002) | (0.001) | (0.001) | (0.001) |
| Mean dept. var. | 5.04 | 0.67 | 0.21 | 0.13 | 0.08 |
| No. patients | 1,192,771 | 1,192,771 | 1,192,771 | 1,192,771 | 1,192,771 |
| N: patient - purch. | 21,347,151 | 21,347,151 | 21,347,151 | 21,347,151 | 21,347,151 |
| R-squared | 0.16 | 0.18 | 0.20 | 0.14 | 0.10 |

Notes: The dependent variable is the treatment gap or a dummy variable indicating whether the patient's treatment gap was $\geq x$ days. Regressions control for clinic congestion, which is calculated from the (normalized) number of appointments per doctor per month, and include an interaction term between this variable and whether the patient is on the automatic-refill regime. Regressions for persistent patients, i.e., those whose maximum gap between two prescriptions was never over 90 days. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$

Table 4: Effect of automatic refill prescriptions on treatment gap at the clinic level

| | (1) Mean T.G. | (2) Median T.G. | (3) Share > 0 | (4) Share > 7 | (5) Share > 14 | (6) Mean T.G. | (7) Mean T.G. | (8) Mean T.G. |
|---|---|---|---|---|---|---|---|---|
| Share Receta | -2.191*** | -2.896*** | -0.173*** | -0.103*** | -0.0515*** | | | |
| Resurtible | (0.470) | (0.565) | (0.0158) | (0.0135) | (0.0122) | | | |
| Post Start-Date A | | | | | | -0.408*** | | |
| | | | | | | (0.129) | | |
| Post Start-Date B | | | | | | | -0.446*** | |
| | | | | | | | (0.141) | |
| Post Start-Date C | | | | | | | | -0.542*** |
| | | | | | | | | (0.140) |
| Mean dept. var. | 4.574 | 2.017 | 0.614 | 0.215 | 0.148 | 4.574 | 4.574 | 4.574 |
| No. clinics | 1351 | 1351 | 1351 | 1351 | 1351 | 1351 | 1351 | 1351 |
| N: clinic - month | 43445 | 43445 | 43550 | 43550 | 43550 | 43445 | 43445 | 43445 |
| R-squared | 0.540 | 0.484 | 0.660 | 0.412 | 0.298 | 0.540 | 0.540 | 0.540 |

Notes: The dependent variable is the treatment gap at the clinic level. The share variables refer to the number of patients in a clinic/month that presented which were positive ($> 0$), of over a week ($> 7$), or of over two weeks ($> 14$). Only persistent patients are considered for calculating the aggregate measures of adherence. Persistent patients are those whose maximum gap between two prescriptions was never over 90 days. All regressions include clinic and month/year fixed effects. Start dates are specified as follows: (A) the first month in which the share of automatic refill prescriptions is equal or greater than 5%; (B) the first month in which the share of automatic refill prescriptions is equal or greater than 3%; and (C) the month on which the share of automatic refill prescriptions increased the most with respect to the previous month. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table 5: Patients improve adherence to remain on the low-monitoring regime

| | Baseline | S1: Type of refill | | S2: App't gap | |
|---|---|---|---|---|---|
| | (1) | (2) Non-Costly | (3) Costly | (4) All | (5) $\geq 0$ |
| Receta Resurtible | -2.61*** | -2.69*** | -2.98*** | -8.96*** | -3.62*** |
| | (0.12) | (0.13) | (0.13) | (0.17) | (0.14) |
| Mean dept. var. | 5.04 | 5.11 | 5.20 | 6.22 | 8.74 |
| No. patients | 1,192,797 | 1,192,797 | 1,186,739 | 1,186,820 | 1,161,100 |
| N: patient - purch. | 21,385,388 | 20,959,496 | 20,207,430 | 19,712,161 | 16,041,102 |
| R-squared | 0.16 | 0.17 | 0.17 | 0.10 | 0.10 |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. The independent variable of interest is whether the prescription was automatic refill. Patient fixed effects are included. No additional covariates were used. Only considers persistent patients (i.e., those whose maximum gap between two prescriptions was never over 90 days). Non-costly refers to prescriptions that can automatically be filled at an IMSS pharmacy; costly refers to prescriptions that are filled after a doctor's appointment. The appointment gap refers to the number of days a patient delays his visit to the physician. Standard errors clustered at the clinic level in parentheses.
$^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$

Table 6: Patients improve adherence to remain on the low-monitoring regime more in highly congested clinics

| | Baseline | S1: Type of refill | | S2: App't gap | |
|---|---|---|---|---|---|
| | (1) | (2) Non-Costly | (3) Costly | (4) All | (5) $\geq 0$ |
| Receta Resurtible | -2.60*** | -2.68*** | -2.96*** | -8.98*** | -3.72*** |
| | (0.12) | (0.13) | (0.13) | (0.17) | (0.15) |
| $\times$ Congestion | -0.17** | -0.14 | -0.25*** | 0.42 | 0.66** |
| | (0.08) | (0.09) | (0.09) | (0.26) | (0.33) |
| Congestion | 0.22*** | 0.22*** | 0.23*** | -0.46 | -1.25* |
| | (0.06) | (0.06) | (0.06) | (0.56) | (0.75) |
| Mean dept. var. | 5.04 | 5.11 | 5.20 | 6.22 | 8.74 |
| No. patients | 1,192,771 | 1,192,771 | 1,186,712 | 1,186,806 | 1,161,085 |
| N: patient - purch. | 21,347,151 | 20,921,515 | 20,169,845 | 19,675,362 | 16,008,905 |
| R-squared | 0.16 | 0.17 | 0.17 | 0.10 | 0.10 |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. The independent variable of interest is whether the prescription was automatic refill. Patient fixed effects are included. Clinic congestion is calculated from the (normalized) number of appointments per doctor per month. Only considers persistent patients (i.e., those whose maximum gap between two prescriptions was never over 90 days). Non-costly refers to prescriptions that can automatically be filled at an IMSS pharmacy; costly refers to prescriptions that are filled after a doctor's appointment. The appointment gap refers to the number of days a patient delays his visit to the physician. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table 7: Effect of reducing health monitoring on clinic congestion

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Share R.R. | -133.70*** | | | |
| | (14.22) | | | |
| Post Start-Date A | | -10.89*** | | |
| | | (1.69) | | |
| Post Start-Date B | | | -10.65*** | |
| | | | (1.71) | |
| Post Start-Date C | | | | -8.15*** |
| | | | | (1.52) |
| Mean dept. var. | 199 | 199 | 199 | 199 |
| No. clinics | 1,369 | 1,369 | 1,369 | 1,369 |
| N: clinic-month | 45,290 | 45,290 | 45,290 | 45,290 |
| R-squared | 0.70 | 0.69 | 0.69 | 0.69 |

Notes: The dependent variable is the average number of appointments per doctor at the clinic level. Regressions include clinic and month/year fixed effects. Start dates are specified as follows: (A) the first month in which the share of automatic refill prescriptions is equal or greater than 5%; (B) the first month in which the share of automatic refill prescriptions is equal or greater than 3%; and (C) the month on which the share of automatic refill prescriptions increased the most with respect to the previous month. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table 8: Spillovers in Medication Adherence for Non-Stable Patients

| | Eligible | | | Non-Eligible | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post Start-Date A | -0.60*** | | | -0.36*** | | |
| | (0.178) | | | (0.123) | | |
| Post Start-Date B | | -0.52** | | | -0.36*** | |
| | | (0.206) | | | (0.128) | |
| Post Start-Date C | | | -0.78*** | | | -0.36*** |
| | | | (0.114) | | | (0.113) |
| Mean dept. var. | 4.89 | 4.89 | 4.89 | 5.11 | 5.11 | 5.11 |
| No. patients | 329,200 | 329,200 | 329,200 | 863,597 | 863,597 | 863,597 |
| N: patient - purch. | 6,864,922 | 6,864,922 | 6,864,922 | 14,520,466 | 14,520,466 | 14,520,466 |
| R-squared | 0.14 | 0.14 | 0.14 | 0.17 | 0.17 | 0.17 |

Notes: The dependent variable is the patient's treatment gap. Only persistent patients are considered. Eligible patients are those that received at least one automatic-refill prescription during the period covered by the data, and Non-Eligible patients are those that never received one. Start dates are specified as follows: (A) the first month in which the share of automatic refill prescriptions is equal or greater than 5%; (B) the first month in which the share of automatic refill prescriptions is equal or greater than 3%; and (C) the month on which the share of automatic refill prescriptions increased the most with respect to the previous month. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table 9: Effect of automatic refill prescriptions on treatment gap by diabetes status

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Receta Resurtible | -2.61*** | | -2.48*** | | | |
| | (0.117) | | (0.115) | | | |
| Clinic Share RR (-i) | | -2.17*** | | -1.58** | -1.84*** | -1.83*** |
| | | (0.658) | | (0.668) | (0.655) | (0.653) |
| × non-diabetic | | | | | -0.60*** | -0.63*** |
| | | | | | (0.170) | (0.187) |
| × male | | | | | | -0.03 |
| | | | | | | (0.148) |
| × non-diabetic | | | | | | 0.07 |
| × male | | | | | | (0.197) |
| Mean dept. var. | 5.04 | 5.04 | 4.93 | 4.93 | 5.04 | 5.04 |
| No. patients | 1,192,797 | 1,192,796 | 545,012 | 545,012 | 1,192,796 | 1,192,796 |
| N: patient - purch. | 21,385,388 | 21,385,344 | 10,270,553 | 10,270,534 | 21,385,344 | 21,385,344 |
| R-squared | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 |
| Sample | all | all | diab. | diab. | all | all |

Notes: The dependent variable is the treatment gap. Only persistent patients are considered in the regressions. Persistent patients are those whose maximum gap between two prescriptions was never over 90 days. All regressions include clinic and month/year fixed effects. The *Receta Resurtible* variable indicates whether the prescription received by a patient is automatic refill. Clinic share-i is the share of prescriptions at the clinic level which are automatic refill, calculated excluding the patient himself. Start dates are specified as follows: (A) the first month in which the share of automatic refill prescriptions is equal or greater than 5%; (B) the first month in which the share of automatic refill prescriptions is equal or greater than 3%; and (C) the month on which the share of automatic refill prescriptions increased the most with respect to the previous month. Non-diabetic patients are those that didi not fill prescriptions for any of the medications for treating diabetes in IMSS clinical guidelines. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table 10: Effect of automatic refill prescriptions on health outcomes

| | (1) T.G. | (2) Systolic BP | (3) Diastolic BP | (4) IHD | (5) HT index | (6) Critical | (7) BMI |
|---|---|---|---|---|---|---|---|
| Receta Resurtible | -3.055*** | | | | | | |
| | (0.396) | | | | | | |
| Receta Resurtible | | 0.713 | 0.137 | 0.00670 | 0.0269 | 0.00917 | 0.0744 |
| (in prev. app't) | | (0.462) | (0.299) | (0.00577) | (0.0439) | (0.00852) | (0.0531) |
| Mean dept. var. | 5.132 | 124.7 | 77.42 | 0.0163 | 2.067 | 0.0399 | 30.63 |
| No. patients | 692 | 698 | 698 | 698 | 695 | 698 | 696 |
| N: patient - purch. | 14,756 | 14,350 | 143,86 | 15,004 | 9,320 | 15,004 | 13,862 |
| R-squared | 0.146 | 0.305 | 0.297 | 0.594 | 0.369 | 0.332 | 0.932 |

Notes: The dependent variable is indicated on each column. IHD stands for Ischemic Heart Disease. HT index consists of five categories of hypertension, depending on systolic and diastolic readings (Mayo Clinic). Critical is a dummy variable equal to 1 for severe hypertension (systolic BP above 160 mmHg or diastolic BP above 100). BMI represents the Body Mass Index. Only persistent patients are considered in each of the specifications. Persistent patients are those whose maximum gap between two prescriptions was never over 90 days. All regressions include patient and month/year fixed effects. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table 11: Effect of automatic refill prescriptions on therapeutic treatment

| | (1) Change of any HT med. | (2) Total HT meds. changed |
|---|---|---|
| Receta Resurtible | 0.0005 | 0.0022*** |
| (lagged) | (0.0004) | (0.0006) |
| Mean dept. var. | 0.20 | 0.28 |
| No. patients | 1,146,297 | 1,190,281 |
| N: patient - purch. | 18,772,000 | 19,827,469 |
| R-squared | 0.21 | 0.21 |

Notes: The dependent variable in the first column is a dummy indicating whether there was any change in the medications that are prescribed to a patient. In the second column, the deponent variable measures how many medications were changed since the last appointment. Receta Resurtible indicates whether the prescription was automatic refill. Patient fixed effects are included. No additional covariates were used. Only considers persistent patients (i.e., those whose maximum gap between two prescriptions was never over 90 days). Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

# References


Abel, Andrew B. 1990. "Asset prices under habit formation and catching up with the Joneses." *The American Economic Review* pp. 38–42.

Acton, Jan Paul. 1975. "Nonmonetary factors in the demand for medical services: some empirical evidence." *The Journal of Political Economy* 83(3):595.

Agüero, Jorge and Trinidad Beleche. 2014. "Did the swine flu save lives? Evidence from Mexico.".

Ariely, Dan and Klaus Wertenbroch. 2002. "Procrastination, deadlines, and performance: Self-control by precommitment." *Psychological science* 13(3):219–224.

Atella, Vincenzo, Franco Peracchi, Domenico Depalo and Claudio Rossetti. 2006. "Drug compliance, co-payment and health outcomes: evidence from a panel of Italian patients." *Health economics* 15(9):875–892.

Baicker, Katherine, Sendhil Mullainathan and Joshua Schwartzstein. 2012. Behavioral hazard in health insurance. Technical report National Bureau of Economic Research.

Balkrishnan, Rajesh, Rukmini Rajagopalan, Fabian T Camacho, Sally A Huston, Frederick T Murray and Roger T Anderson. 2003. "Predictors of medication adherence and associated health care costs in an older population with type 2 diabetes mellitus: a longitudinal cohort study." *Clinical therapeutics* 25(11):2958–2971.

Batal, Holly A, Mori J Krantz, Rita A Dale, Phillip S Mehler and John F Steiner. 2007. "Impact of prescription size on statin adherence and cholesterol levels." *BMC health services research* 7(1):175.

Becker, Gary S. 1992. "Habits, addictions, and traditions." *Kyklos* 45(3):327–345.

Becker, Gary S and Kevin M Murphy. 1988. "A theory of rational addiction." *The Journal of Political Economy* pp. 675–700.

Bhattacharya, Jay, Alan M Garber and Jeremy D Goldhaber-Fiebert. 2015. Nudges in Exercise Commitment Contracts: A Randomized Trial. Technical report National Bureau of Economic Research.

Carroll, Christopher D, Jody Overland and David N Weil. 2000. "Saving and growth with habit formation." *American Economic Review* pp. 341–355.

Case, Anne, Angela Fertig and Christina Paxson. 2005. "The lasting impact of childhood health and circumstance." *Journal of health economics* 24(2):365–389.

Case, Anne, Ingrid Le Roux and Alicia Menendez. 2004. "Medical compliance and income-health gradients." *American Economic Review* pp. 331–335.

Chaloupka, Frank J and Kenneth E Warner. 2000. "The economics of smoking." *Handbook of health economics* 1:1539–1627.

Charness, Gary and Uri Gneezy. 2009. "Incentives to exercise." *Econometrica* 77(3):909–931.

Cisneros, Noé Sánchez. 2006. "Adherencia terapéutica en hipertensión arterial sistémica." *Revista mexicana de enfermería cardiológica* 14(3):98–101.

Cutler, David M and Adriana Lleras-Muney. 2010. "Understanding differences in health behaviors by education." *Journal of health economics* 29(1):1–28.

Cutler, David M. and Edward Glaeser. 2005. "What Explains Differences in Smoking, Drinking, and Other Health-Related Behaviors?" *American Economic Review* 95(2):238–242.

Cutler, David M, Genia Long, Ernst R Berndt, Jimmy Royer, Andrée-Anne Fournier, Alicia Sasser and Pierre Cremieux. 2007. "The value of antihypertensive drugs: a perspective on medical innovation." *Health affairs* 26(1):97–110.

DellaVigna, Stefano and Ulrike Malmendier. 2006. "Paying not to go to the gym." *The American Economic Review* pp. 694–719.

Dupas, Pascaline. 2013. "Short-Run Subsidies and Long-Run Adoption of New Health Products: Experimental Evidence from Kenya." *Econometrica* .

Elliott, Rachel A, Judith A Shinogle, Pamela Peele, Monali Bhosle and Dyfrig A Hughes. 2008. "Understanding medication compliance and persistence from an economics perspective." *Value in Health* 11(4):600–610.

Fischer, Michael A, Margaret R Stedman, Joyce Lii, Christine Vogeli, William H Shrank, M Alan Brookhart and Joel S Weissman. 2010. "Primary medication non-adherence: analysis of 195,930 electronic prescriptions." *Journal of general internal medicine* 25(4):284–290.

Flynn, Sarah J, Jessica M Ameling, Felicia Hill-Briggs, Jennifer L Wolff, Lee R Bone, David M Levine, Debra l Roter, LaPricia Lewis-Boyer, Annette R Fisher, Leon Purnell et al. 2013. "Facilitators and barriers to hypertension self-management in urban African Americans: perspectives of patients and family members." *Patient preference and adherence* 7:741.

George, Johnson and Stephen J Shalansky. 2007. "Predictors of refill non-adherence in patients with heart failure." *British journal of clinical pharmacology* 63(4):488–493.

Gneezy, Uri, Stephan Meier and Pedro Rey-Biel. 2011. "When and why incentives (don't) work to modify behavior." *The Journal of Economic Perspectives* pp. 191–209.

Goldman, Dana and James P Smith. 2011. "The increasing value of education to health." *Social science & medicine* 72(10):1728–1737.

Goldman, Dana P and Darius Lakdawalla. 2005. "A theory of health disparities and medical technology." *Contributions to Economic Analysis & Policy* .

Goldman, Dana P and James P Smith. 2002. "Can patient self-management help explain the SES health gradient?" *Proceedings of the National Academy of Sciences* 99(16):10929–10934.

Grossman, Michael. 1972. "On the concept of health capital and the demand for health." *The Journal of Political Economy* 80(2):223.

Gruber, Jonathan and Botond Koszegi. 2000. Is addiction" rational"? Theory and evidence. Technical report National bureau of economic research.

Guéguen, Nicolas, Sebastien Meineri and Virginie Charles-Sire. 2010. "Improving medication adherence by using practitioner nonverbal techniques: a field experiment on the effect of touch." *Journal of behavioral medicine* 33(6):466–473.

Guthmann, Richard, Nancy Davis, Matthew Brown and Jose Elizondo. 2005. "Visit frequency and hypertension." *The Journal of Clinical Hypertension* 7(6):327–332.

Gwadry-Sridhar, F. H., E. Manias, L. Lal, M. Salas, D. A. Hughes, A. Ratzki-Leewing and M. Grubisic. 2013. "Impact of interventions on medication adherence and blood pressure control in patients with essential hypertension: a systematic review by the ISPOR medication adherence and persistence special interest group." *Value Health* 16(5):863–871.

Haushofer, Johannes. 2014. "The Cost of Keeping Track.".

Hayen, Andrew, Katy Bell, Paul Glasziou, Bruce Neal and Les Irwig. 2010. "Monitoring adherence to medication by measuring change in blood pressure." *Hypertension* 56(4):612–616.

Haynes, R Brian, Elizabeth Ackloo, Navdeep Sahota, Heather Pauline McDonald and Xiaomei Yao. 2008. "Interventions for enhancing medication adherence." *Cochrane database syst Rev* 2(2).

Herttua, Kimmo, Adam G Tabák, Pekka Martikainen, Jussi Vahtera and Mika Kivimäki. 2013. "Adherence to antihypertensive therapy prior to the first presentation of stroke in hypertensive adults: population-based study." *European heart journal* 34(38):2933–2939.

Ho, P Michael, Chris L Bryson and John S Rumsfeld. 2009. "Medication adherence its importance in cardiovascular outcomes." *Circulation* 119(23):3028–3035.

Jimmy, Beena and Jimmy Jose. 2011. "Patient medication adherence: measures in daily practice." *Oman medical journal* 26(3):155.

Kalichman, Seth C and David Rompa. 2000. "Functional health literacy is associated with health status and health-related knowledge in people living with HIV-AIDS." *Journal of acquired immune deficiency syndromes (1999)* 25(4):337–344.

Kalichman, Seth C, Sheryl Catz and Bineetha Ramachandran. 1999. "Barriers to HIV/AIDS treatment and treatment adherence among African-American adults with disadvantaged education." *Journal of the National Medical Association* 91(8):439.

Kenkel, Donald S. 1991. "Health behavior, health knowledge, and schooling." *Journal of Political Economy* pp. 287–305.

Khonsari, Sahar, Pathmawathi Subramanian, Karuthan Chinna, Lydia A Latif, Lee W Ling and Omid Gholami. 2014. "Effect of a reminder system using an automated short message service on medication adherence following acute coronary syndrome." *European Journal of Cardiovascular Nursing* p. 1474515114521910.

Kimmel, Stephen E, Andrea B Troxel, George Loewenstein, Colleen M Brensinger, Jane Jaskowiak, Jalpa A Doshi, Mitchell Laskin and Kevin Volpp. 2012. "Randomized trial of lottery-based incentives to improve warfarin adherence." *American heart journal* 164(2):268–274.

Kripalani, Sunil, Xiaomei Yao and R Brian Haynes. 2007. "Interventions to enhance medication adherence in chronic medical conditions: a systematic review." *Archives of internal medicine* 167(6):540–549.

Laba, Tracey-Lea, Jo-anne Brien and Stephen Jan. 2012. "Understanding rational non-adherence to medications. A discrete choice experiment in a community sample in Australia." *BMC family practice* 13(1):61.

Lee, Jeannie K, Karen A Grace and Allen J Taylor. 2006. "Effect of a pharmacy care program on medication adherence and persistence, blood pressure, and low-density lipoprotein cholesterol: a randomized controlled trial." *Jama* 296(21):2563–2571.

Ljungqvist, Lars and Thomas J Sargent. 2004. *Recursive macroeconomic theory.* MIT press.

Loewenstein, George, Troyen Brennan and Kevin G Volpp. 2007. "Asymmetric paternalism to improve health behaviors." *Jama* 298(20):2415–2417.

Maitra, Sudeshna. 2010. "Can patient self-management explain the health gradient? Goldman and Smith's "Can patient self-management help explain the SES health gradient?"(2002) revisited." *Social science & medicine* 70(6):802–812.

Mejía-Rodríguez, Oliva, Ramón Paniagua-Sierra, María del Refugio Valencia-Ortiz, Javier Ruiz-García, Benigno Figueroa-Núñez and Valentín Roa-Sánchez. 2009. "Factores relacionados con el descontrol de la presión arterial." *salud pública de méxico* 51(4):291–297.

Morisky, Donald E, David M Levine, Lawrence W Green, Sam Shapiro, R Patterson Russell and Craig R Smith. 1983. "Five-year blood pressure control and mortality following health education for hypertensive patients." *American Journal of Public Health* 73(2):153–162.

Nosé, Michela, Corrado Barbui, Richard Gray and Michele Tansella. 2003. "Clinical interventions for treatment non-adherence in psychosis: meta-analysis." *The British Journal of Psychiatry* 183(3):197–206.

O'Donoghue, Ted and Matthew Rabin. 1999. "Doing it now or later." *American Economic Review* pp. 103–124.

Peterson, Andrew M, Liza Takiya and Rebecca Finley. 2003. "Meta-analysis of trials of interventions to improve medication adherence." *American Journal of Health-System Pharmacy* 60(7):657–665.

Piette, John D, Morris Weinberger and Stephen J McPhee. 2000. "The effect of automated calls with telephone nurse follow-up on patient-centered outcomes of diabetes care: a randomized, controlled trial." *Medical care* 38(2):218–230.

Roebuck, M Christopher, Joshua N Liberman, Marin Gemmill-Toyama and Troyen A Brennan. 2011. "Medication adherence leads to lower health care use and costs despite increased drug spending." *Health affairs* 30(1):91–99.

Rosenzweig, Mark R and T Paul Schultz. 1989. "Schooling, information and nonmarket productivity: contraceptive use and its effectiveness." *International Economic Review* 30(2):457–77.

Rozen, Kareen. 2010. "Foundations of intrinsic habit formation." *Econometrica* 78(4):1341–1373.

Smith, David H, Judith M Kramer, Nancy Perrin, Richard Platt, Douglas W Roblin, Kimberly Lane, Michael Goodman, Winnie W Nelson, Xiuhai Yang and Stephen B Soumerai. 2008. "A randomized trial of direct-to-patient communication to enhance adherence to $\beta$-blocker therapy following myocardial infarction." *Archives of internal medicine* 168(5):477–483.

Smith, James P. 1999. "Healthy bodies and thick wallets: the dual relation between health and economic status." *The journal of economic perspectives: a journal of the American Economic Association* 13(2):144.

Sokol, Michael C, Kimberly A McGuigan, Robert R Verbrugge and Robert S Epstein. 2005. "Impact of medication adherence on hospitalization risk and healthcare cost." *Medical care* 43(6):521–530.

Steiner, John F and Allan V Prochazka. 1997. "The assessment of refill compliance using pharmacy records: methods, validity, and applications." *Journal of clinical epidemiology* 50(1):105–116.

Steiner, John F, Laurence J Robbins, Stephen C Roth and William S Hammond. 1993. "The effect of prescription size on acquisition of maintenance medications." *Journal of general internal medicine* 8(6):306–310.

Tarozzi, Alessandro, Aprajit Mahajan, Joanne Yoong and Brian Blackburn. 2009. "Commitment mechanisms and compliance with health-protecting behavior: preliminary evidence from Orissa (India)." *American Economic Review* 99(2).

Uhlig, Katrin, Ethan M Balk, Kamal Patel, Stanley Ip, Georgios D Kitsios, Ndidiamaka O Obadan, Shana M Haynes, Mihaela Stefan, Madhumathi Rao, Lina Kong Win Chang et al. 2012. "Self-measured blood pressure monitoring: comparative effectiveness.".

Van Wijk, Boris LG, Olaf H Klungel, Eibert R Heerdink and Anthonius de Boer. 2006. "Refill persistence with chronic medication assessed from a pharmacy database was influenced by method of calculation." *Journal of clinical epidemiology* 59(1):11–17.

Villarreal-Ríos, Enrique, Alvaro Mathew-Quiroz, María Eugenia Garza-Elizondo, Georgina Núñez-Rocha, Ana María Salinas-Martínez and Martha Gallegos-Handal. 2002. "Costo de la atención de la hipertensión arterial y su impacto en el presupuesto destinado a la salud en México." *salud pública de méxico* 44(1):7–13.

Viswanathan, Meera, Carol E. Golin, Christine D. Jones, Mahima Ashok, Susan J. Blalock, Roberta C.M. Wines, Emmanuel J.L. Coker-Schwimmer, David L. Rosen, Priyanka Sista and Kathleen N. Lohr. 2012. "Interventions to Improve Adherence to Self-administered Medications for Chronic Diseases in the United StatesA Systematic Review." *Annals of Internal Medicine* 157(11):785–795.

Volpp, Kevin G, George Loewenstein, Andrea B Troxel, Jalpa Doshi, Maureen Price, Mitchell Laskin and Stephen E Kimmel. 2008. "A test of financial incentives to improve warfarin adherence." *BMC Health Services Research* 8(1):272.

WHO. 2003. "Adherence to long-term therapies: evidence for action.".

Zullig, Leah L, Eric D Peterson and Hayden B Bosworth. 2013. "Ingredients of Successful Interventions to Improve Medication Adherence." *JAMA* 310(24):2611–2612.

# A Appendix Figures

Figure A.1: Getting a prescription before *Receta Resurtible*

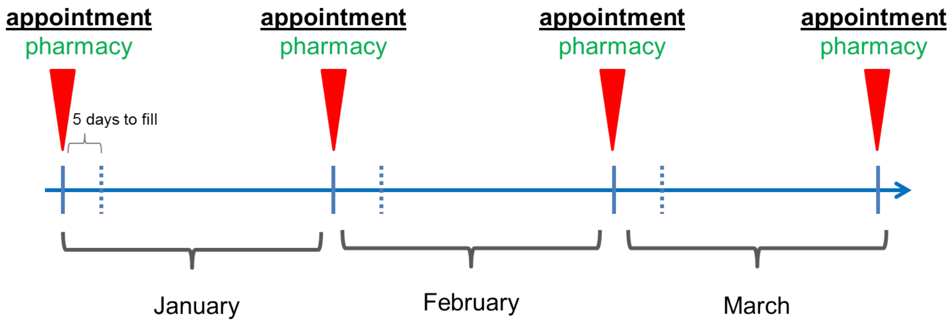



Figure A.2: Getting a prescription after *Receta Resurtible*

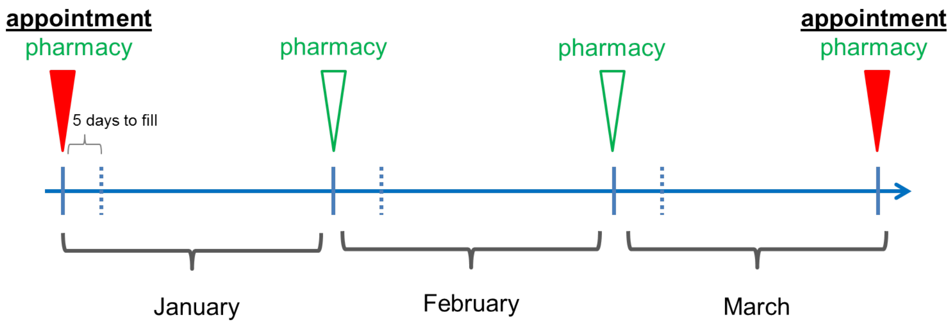


Figure A.3: Clinics issuing automatic refill prescriptions on January 2012

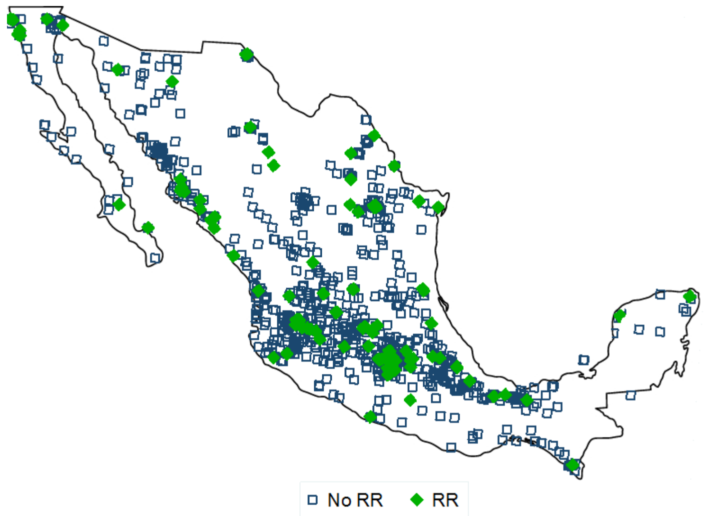



Figure A.4: Clinics issuing automatic refill prescriptions on March 2014

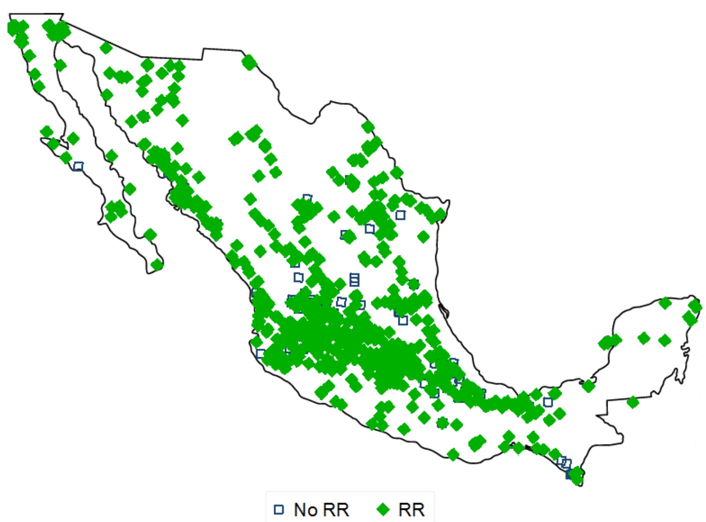
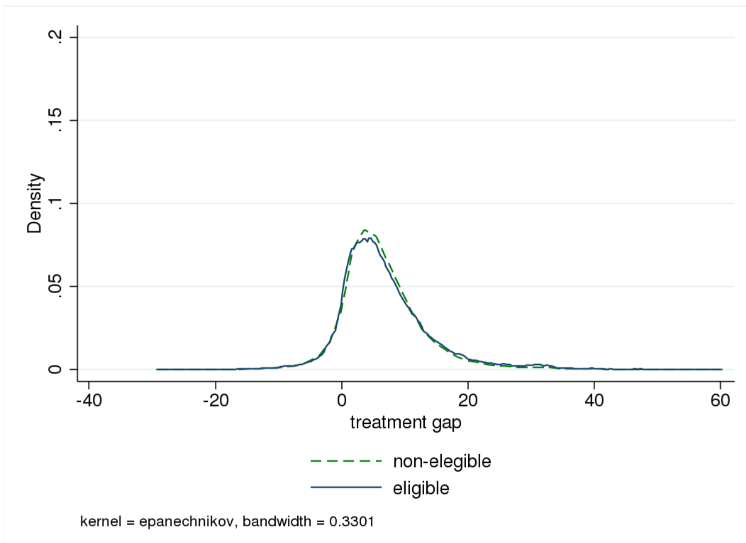
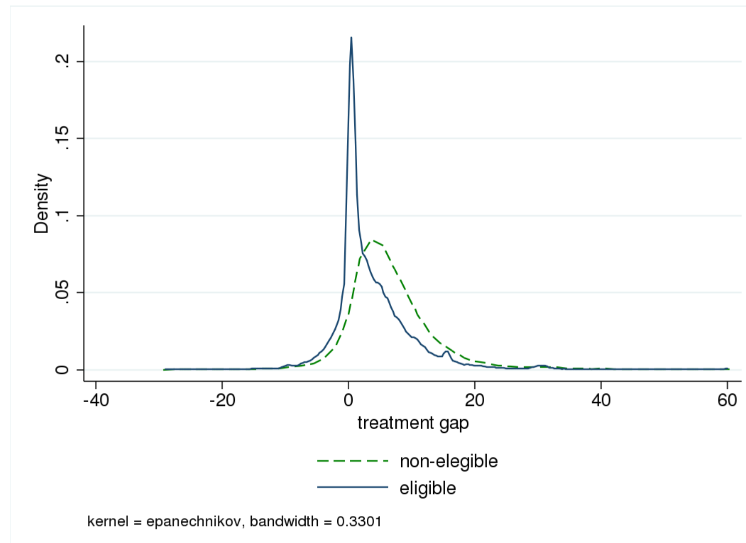


Figure A.5: Distribution of treatment gap for eligible and non-eligible patients before the implementation of the policy

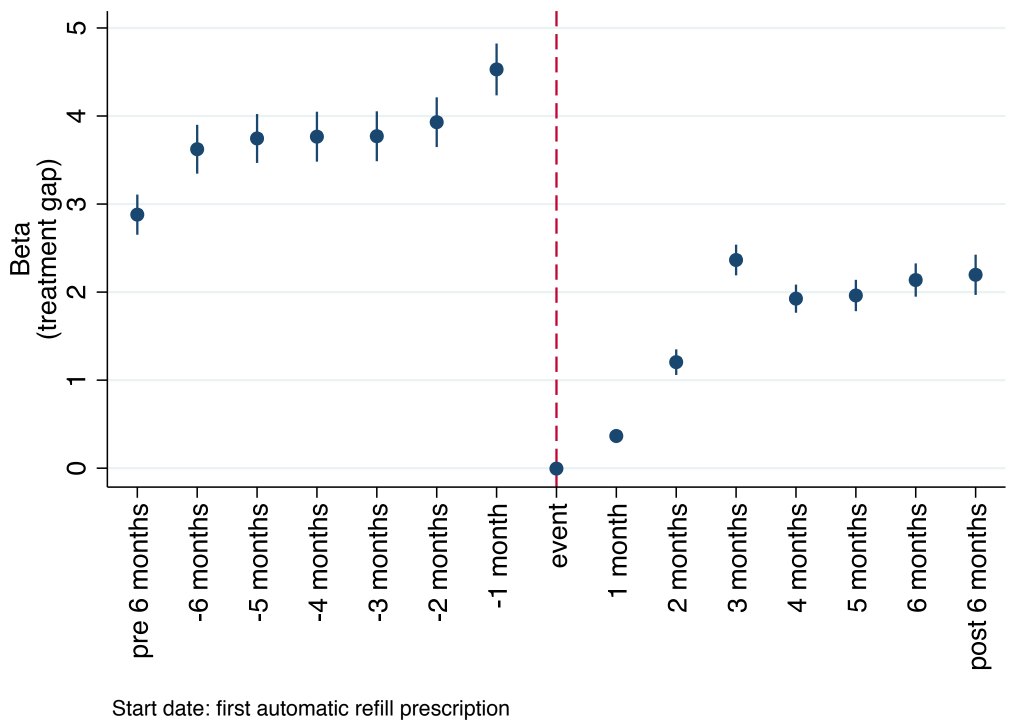



(a) Before




(b) After

Figure A.6: Event study graph. Effect of patient's first automatic refill prescription on the treatment gap




Notes: The graph displays the coefficients of estimating Equation 8 using the treatment gap as the dependent variable. The equation is estimated at the individual level, where $T = 0$ corresponds to the visit when the patient receives his first automatic-refill prescription. Coefficients greater than zero indicate a larger treatment gap that that experienced at the time of the event (which has a coefficient of zero at the vertical dashed red line). Patient and time fixed effects are included. Only persistent patients are considered.

Figure A.7: Distribution of predicted probabilities of ever receiving an automatic refill prescription by diabetes status

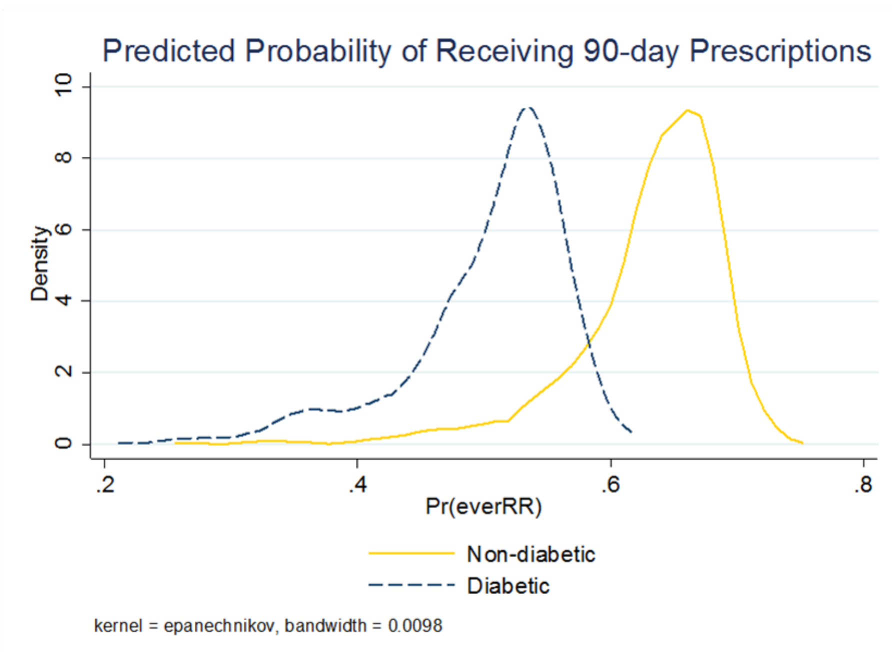
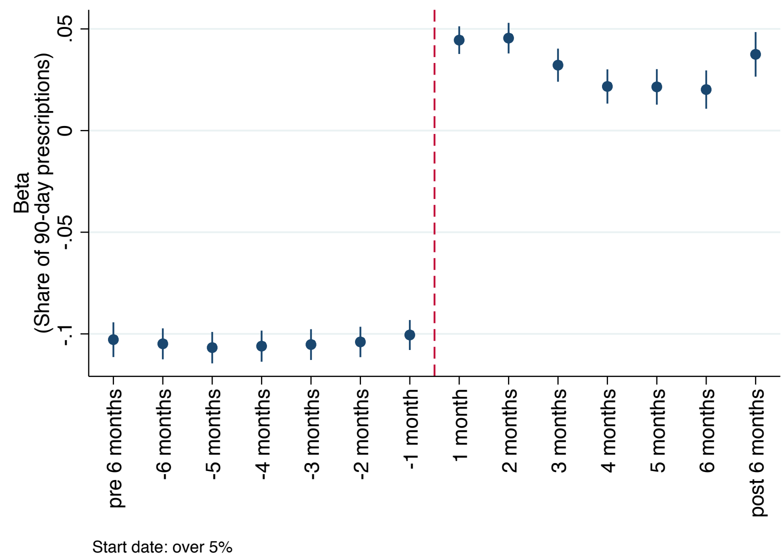
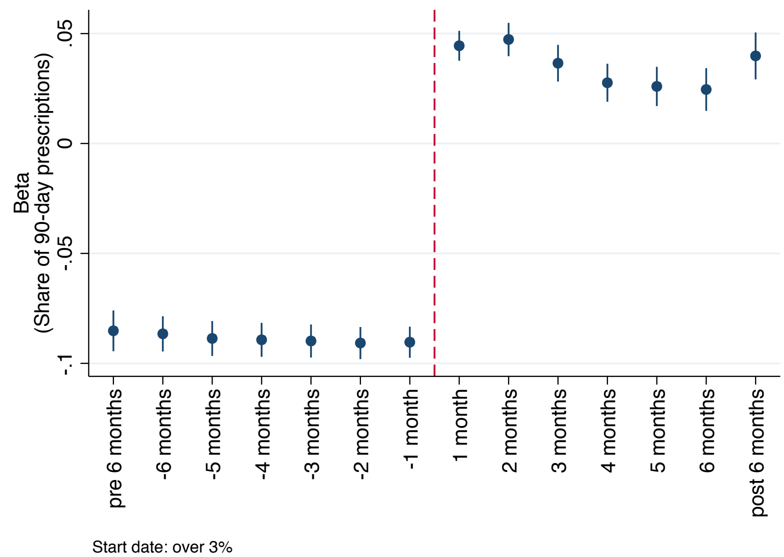


Figure A.8: Event study graph. Share of automatic refill prescriptions issued at the clinic level. Start date is first month when more than 5% of prescriptions are automatic refill



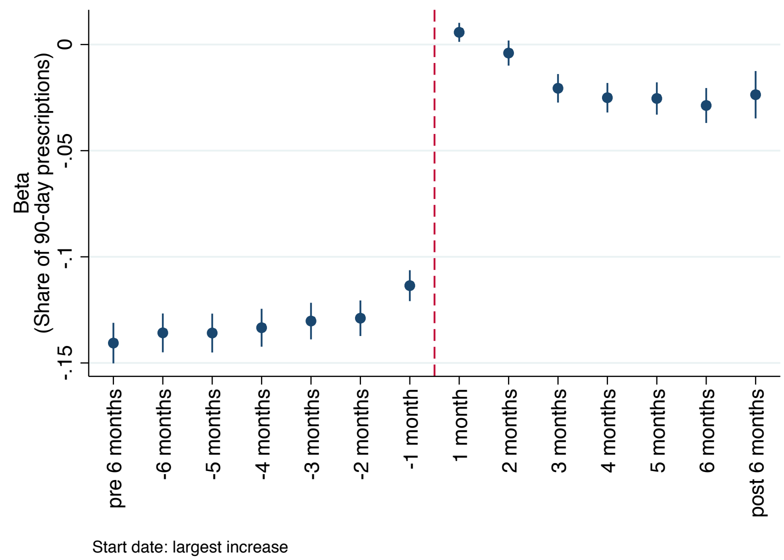

Notes: The graph displays the coefficients of estimating Equation 8 using the treatment gap as the dependent variable. The equation is estimated at the individual level, where $T = 0$ corresponds to the month when the patient's clinic is considered to have adopted the *Receta Resurtible* program—indicated by the first month when the share of automatic-refill prescriptions was greater or equal to 5%. Coefficients greater than zero indicate a larger treatment gap that that experienced at the time of the event (which has a coefficient of zero at the vertical dashed red line). Patient and time fixed effects are included. Only persistent patients are considered.

Figure A.9: Event study graph. Share of automatic refill prescriptions issued at the clinic level. Start date is first month when more than 3% of prescriptions are automatic refill




Notes: The graph displays the coefficients of estimating Equation 8 using the treatment gap as the dependent variable. The equation is estimated at the individual level, where $T = 0$ corresponds to the month when the patient's clinic is considered to have adopted the *Receta Resurtible* program—indicated by the first month when the share of automatic-refill prescriptions was greater or equal to 3%. Coefficients greater than zero indicate a larger treatment gap that that experienced at the time of the event (which has a coefficient of zero at the vertical dashed red line). Patient and time fixed effects are included. Only persistent patients are considered.

Figure A.10: Event study graph. Share of automatic refill prescriptions issued at the clinic level.




Notes: The graph displays the coefficients of estimating Equation 8 using the treatment gap as the dependent variable. The equation is estimated at the individual level, where $T = 0$ corresponds to the the month when number of automatic refill prescriptions most increased. Coefficients greater than zero indicate a larger treatment gap that that experienced at the time of the event (which has a coefficient of zero at the vertical dashed red line). Patient and time fixed effects are included.

Figure A.11: Event study graph. Effect of clinics' adoption of the *Receta Resurtible* program. Start date is first month when more than 5% of prescriptions are automatic refill

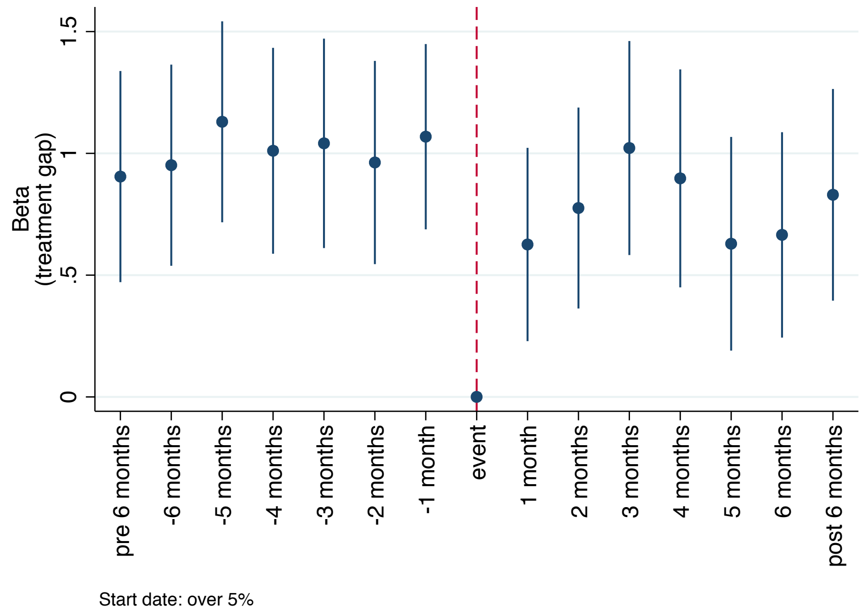
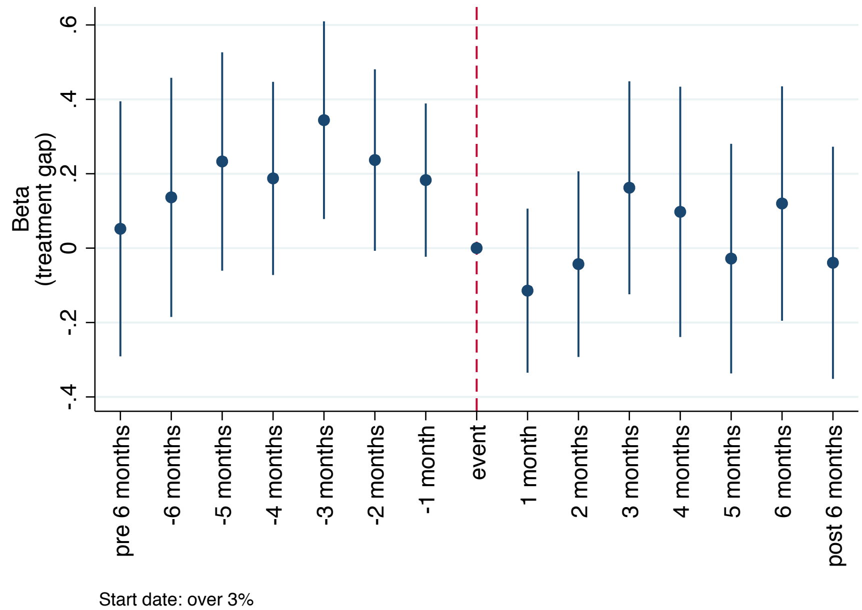


Figure A.12: Event study graph. Effect of clinics' adoption of the *Receta Resurtible* program. Start date is first month when more than 3% of prescriptions are automatic refill



# B Appendix Tables

Table A.1: Hypertensive patients receiving automatic refill prescriptions, August 2013

| | | |
|---|---|---|
| Total patients | 5,247,305 | 100% |
| 90-day | 177,980 | 3% |
| Take HT med | 138,589 | 78% |
| No HT med | 39,391 | 22% |
| 30-day | 5,069,325 | 97% |
| Take HT med | 2,049,798 | 40% |
| No HT med | 3,019,527 | 60% |

| | | |
|---|---|---|
| Total patients | 5,247,305 | 100% |
| Take any HT med | 2,188,387 | 42% |
| 30-day | 2,049,798 | 94% |
| 90-day | 138,589 | 6% |
| No HT meds | 3,058,918 | 58% |

Table A.2: Top prescribed medications at IMSS pharmacies, August 2013. All products

| | Medication | Description | Freq. | Per-cent | Cum. |
|---|---|---|---|---|---|
| | Paracetamol | Mild analgesic | 1,796,762 | 6.71 | 6.71 |
| | B-Complex | Vitamin B | 1,174,215 | 4.39 | 11.1 |
| | Metformin | Type-2 Diabetes | 1,129,200 | 4.22 | 15.32 |
| | Rantidine | Heartburn, stomach ulcers | 1,015,868 | 3.8 | 19.12 |
| | Diclofenac | Anti-inflammatory (osteoarthritis) | 983,507 | 3.67 | 22.79 |
| | Acetylsalicylic Acid | Aspirin | 944,627 | 3.53 | 26.32 |
| * | Enalapril | Angiotensin-converting enzyme (ACE) inhibitor. HT | 751,191 | 2.81 | 29.13 |
| | Pravastatin | High colesterol | 751,112 | 2.81 | 31.93 |
| | Bezafibrate | Hyperlipidaemia, lowers LDL and trigycerides | 714,619 | 2.67 | 34.6 |
| * | Losartan | HT and kidney disease in people with diabetes. Angiotensin receptor blocker (ARB). | 692,198 | 2.59 | 37.19 |
| | Glibenclamide | Type-2 Diabetes | 621,821 | 2.32 | 39.51 |
| * | Metoprolol | Beta-blocker. High BP and angina | 549,604 | 2.05 | 41.57 |
| | Pantoprozole | Gastroesophageal reflux disease and acid in the stomach | 519,335 | 1.94 | 43.51 |
| | Miconazole | Infections caused by fungus (ie, Athlete's foot) | 458,942 | 1.71 | 45.22 |
| | Folic Acid | Vitamin B9 | 424,149 | 1.58 | 46.81 |

Note: * Indicates the medication is prescribed to treat hypertensive patients

Table A.3: Top prescribed medications at IMSS pharmacies, August 2013. Hypertensive medications

| | Medication | Description | Freq. | Percent | Cum. |
|---|---|---|---|---|---|
| * | Enalapril | Angiotensin-converting enzyme (ACE) inhibitor. HT | 751,191 | 18.94 | 18.94 |
| * | Losartan | HT and kidney disease in people with diabetes. Angiotensin receptor blocker (ARB). | 692,198 | 17.45 | 36.4 |
| * | Metoprolol | Beta-blocker. High BP and angina | 549,604 | 13.86 | 50.25 |
| * | Hydrochlorothiazide | Diuretic. Treats water retention (edema) and HT | 367,028 | 9.25 | 59.51 |
| * | Captopril | HT and kidney disease in people with diabetes. Angiotensin-converting enzyme (ACE) inhibitor | 360,493 | 9.09 | 68.6 |
| | Chlorthalidone | Diuretic. Treats water retention (edema) and HT | 265,119 | 6.69 | 75.29 |
| | Furosemide | Diuretic. Treats water retention (edema) and HT | 220,510 | 5.56 | 80.85 |
| | Nifedipine | Calcium channel blocker | 188,769 | 4.76 | 85.61 |
| | Amlodipine | Calcium channel blocker | 159,457 | 4.02 | 89.63 |
| | Nifedipine | Calcium channel blocker | 76,353 | 1.93 | 91.55 |
| | Verapamil | Calcium channel blocker. HT, angina, and arrhythmia | 70,775 | 1.78 | 93.34 |
| | Spironolactone | Diuretic. Treats HT, water retention (edema), and low potassium | 70,723 | 1.78 | 95.12 |
| | Propranolol | Beta blocker. May also treat migraine | 63,116 | 1.59 | 96.71 |
| | Prazosin | Alpha blocker | 47,062 | 1.19 | 97.9 |
| | Telmisartan | Angiotensin receptor blocker (ARB) | 29,125 | 0.73 | 98.63 |

Note: *Indicates the medication is among the 15 most prescribed medications at IMSS pharmacies

Table A.4: Effect of issuing automatic refill prescriptions on clinics' patient composition

| | (1) Total HT | (2) Diabetic | (3) HT meds | (4) Male | (5) Age | (6) Retired |
|---|---|---|---|---|---|---|
| Share Receta Resurtible | 0.00936* | 0.00633 | 0.151*** | -0.00379 | 0.664*** | 0.0123 |
| | (0.00483) | (0.00918) | (0.0255) | (0.00946) | (0.246) | (0.00924) |
| Mean dept. var. | 0.483 | 0.471 | 1.725 | 0.392 | 64.27 | 0.544 |
| No. clinics | 1351 | 1351 | 1351 | 1351 | 1351 | 1351 |
| N: clinic - month | 43546 | 43550 | 43550 | 43550 | 43550 | 43550 |
| R-squared | 0.919 | 0.621 | 0.530 | 0.505 | 0.709 | 0.771 |

Notes: The dependent variable is indicated on each column. Total HT refers to the total share of hypertensive patients treated in a clinic; Diabetic refers to the share of hypertensive patients that are diabetic; HT Medication refers to the average number of HT medications prescribed to hypertensive patients. All regressions include clinic and month/year fixed effects. Standard errors at the clinic level in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A.5: Effect of automatic refill prescriptions on treatment gap on different subgroups of the population

| | (1) All | (2) Female | (3) Male | (4) Worker | (5) Dependent | (6) Retired | (7) Young | (8) Middle Aged | (9) Old |
|---|---|---|---|---|---|---|---|---|---|
| Receta Resurtible | -2.61*** | -2.52*** | -2.77*** | -2.55*** | -2.43*** | -2.75*** | -2.40*** | -2.70*** | -2.65*** |
| | (0.117) | (0.120) | (0.115) | (0.123) | (0.119) | (0.122) | (0.126) | (0.116) | (0.128) |
| Mean dept. var. | 5.04 | 5.14 | 4.89 | 5.21 | 5.11 | 4.96 | 5.34 | 5.00 | 4.91 |
| No. patients | 1,192,797 | 728,825 | 463,972 | 249,619 | 359,561 | 583,703 | 320,702 | 597,802 | 274,293 |
| N: patient - purch. | 21,385,388 | 13,256,773 | 8,128,615 | 3,536,408 | 5,964,965 | 11,884,359 | 4,249,800 | 10,934,304 | 6,201,284 |
| R-squared | 0.16 | 0.16 | 0.17 | 0.18 | 0.17 | 0.16 | 0.19 | 0.16 | 0.15 |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. Only persistent patients are considered in each of the specifications. Persistent patients are those whose maximum gap between two prescriptions was never over 90 days. All regressions include patient and month/year fixed effects. Dependents include parents, spouse, or children of the insured worker. Old patients are those born in 1941 or earlier, middle aged patients are those born between 1941 and 1958, and young patients are those born after 1958. These cutoffs correspond to percentiles 25 and 75 of the patients in the sample. Standard errors clustered at the clinic level in parentheses.
$^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table A.6: Effect of automatic refill prescriptions on medication adherence by clinic congestion

| | Low | | Medium | | High | |
|---|---|---|---|---|---|---|
| | (1) Treat. Gap | (2) Positive T.G. | (3) Treat. Gap | (4) Positive T.G. | (5) Treat. Gap | (6) Positive T.G. |
| Receta Resurtible | -0.493* | -0.0844*** | -2.276*** | -0.188*** | -2.997*** | -0.238*** |
| | (0.291) | (0.0141) | (0.135) | (0.00540) | (0.180) | (0.00659) |
| Mean dept. var. | 2.293 | 0.520 | 4.961 | 0.649 | 5.216 | 0.691 |
| No. patients | 84,060 | 84,060 | 547,740 | 547,740 | 627,567 | 627,567 |
| N: patient - purch. | 473,105 | 473,105 | 9,136,642 | 9,136,642 | 11,775,580 | 11,775,580 |
| R-squared | 0.366 | 0.301 | 0.166 | 0.177 | 0.164 | 0.185 |

Notes: The dependent variable is the treatment gap or a dummy variable indicating whether the patient's treatment gap was $\geq 0$ days. No additional covariates were used. Regressions for persistent patients, i.e., those whose maximum gap between two prescriptions was never over 90 days. Clinics were classified by congestion as measured by average monthly appointments per doctor, where "low" corresponds to the bottom 25th percentile (48 appointments per doctor per month) and "high" corresponds to the top 75th percentile (103 appointments per doctor per month). Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table A.7: Effect of automatic refill prescriptions on treatment gap. Various specifications

| | (1) Treat. Gap | (2) Treat. Gap | (3) Treat. Gap | (4) Treat. Gap | (5) Treat. Gap | (6) Treat. Gap |
|---|---|---|---|---|---|---|
| Receta Resurtible | -2.61*** | -2.00*** | -2.71*** | -3.60*** | -1.62*** | -1.46*** |
| | (0.117) | (0.005) | (0.150) | (0.129) | (0.201) | (0.207) |
| Mean dept. var. | 5.04 | 5.04 | 4.68 | 5.32 | 15.84 | 16.93 |
| No. patients | 1,192,797 | | 96,139 | 1,102,152 | 3,449,008 | 4,976,828 |
| N: patient - purch. | 21,385,388 | 21,385,388 | 2,584,472 | 19,622,469 | 57,326,411 | 66,949,231 |
| R-squared | 0.16 | | 0.13 | 0.15 | 0.28 | 0.31 |
| Sample | persistent | persistent | all | persistent | no drop-outs | all |
| Patient F.E. | yes | no | yes | yes | yes | yes |
| Time - Year F.E. | yes | yes | yes | monthly | yes | yes |
| Clustered Std. Err. | clinic | no | clinic | clinic | clinic | clinic |
| Comments | baseline | median reg. | RR by nov'13 | until 09.2014 | | |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. The independent variable of interest is whether the prescription was automatic refill. No additional covariates were used. Persistent patients are those whose maximum gap between two prescriptions was never over 90 days. Patients are considered dropouts if the gap between two prescriptions is ever greater than 180 days. Standard errors in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table A.8: Effect of automatic refill prescriptions on treatment gap. Various specifications

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Receta Resurtible | -3.137*** | -3.382*** | -2.613*** | -2.624*** |
| | (0.121) | (0.121) | (0.117) | (0.118) |
| Mean dept. var. | 6.449 | 8.564 | 5.042 | 5.042 |
| No. patients | 1183560 | 1165883 | 1192742 | 1192742 |
| N: patient - purch. | 20273557 | 16440905 | 21385327 | 21385327 |
| R-squared | 0.160 | 0.171 | 0.179 | 0.166 |
| Comments | TG $\geq$ -10 | TG $\geq$ 0 | X: out of stock | X: no. meds |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. The independent variable of interest is whether the prescription was automatic refill. Regressions in the first two columns only consider observations where the treatment gap is larger than -10 and 0, while the last two regressions include as controls whether the patient could not refill his prescription in the pharmacy at some point (shortage) or by the total number of medications prescribed by the physician. Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Table A.9: Effects on non-costly fillings in high congestion clinics

| | Baseline | Type of refill | | App't gap | | Into v. Out of | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) Non-Costly | (3) Costly | (4) All | (5) $\geq 0$ | (6) In | (7) Out |
| Receta Resurtible | -2.997*** | -3.069*** | -3.368*** | -8.785*** | -3.894*** | -2.774*** | -2.099*** |
| | (0.180) | (0.193) | (0.205) | (0.256) | (0.218) | (0.194) | (0.150) |
| Mean dept. var. | 5.216 | 5.285 | 5.384 | 6.338 | 8.534 | 5.225 | 3.344 |
| No. patients | 627,567 | 627,567 | 625,064 | 625,023 | 614,062 | 754,472 | 224,241 |
| N: patient - purch. | 11,775,580 | 11,543,578 | 11,146,150 | 10,877,539 | 9,049,942 | 11,728,942 | 1,529,580 |
| R-squared | 0.164 | 0.166 | 0.170 | 0.112 | 0.109 | 0.177 | 0.246 |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. The independent variable of interest is whether the prescription was automatic refill. Patient fixed effects are included. No additional covariates were used. Only considers persistent patients (i.e., those whose maximum gap between two prescriptions was never over 90 days). Non-costly refers to prescriptions that can automatically be filled at an IMSS pharmacy; costly refers to prescriptions that are filled after a doctor's appointment. The appointment gap refers to the number of days a patient delays his visit to the physician. Only patients assigned to clinics with in the highest 75th percentile with respect to clinic congestion as measured by appointments per doctor are considered (103 appointments per doctor per month). Standard errors clustered at the clinic level in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$

Table A.10: Effects on non-costly fillings in medium congestion clinics

| | Baseline | Type of refill | | App't gap | | Into v. Outof | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) Non-Costly | (3) Costly | (4) All | (5) $\geq 0$ | (6) In | (7) Out |
| Receta Resurtible | -2.276*** | -2.368*** | -2.624*** | -9.095*** | -3.261*** | -2.072*** | -1.606*** |
| | (0.135) | (0.146) | (0.140) | (0.228) | (0.191) | (0.144) | (0.163) |
| Mean dept. var. | 4.961 | 5.023 | 5.115 | 6.222 | 8.958 | 4.970 | 3.148 |
| No. patients | 547740 | 547740 | 544490 | 544370 | 528999 | 651033 | 194432 |
| N: patient - purch. | 9136642 | 8950983 | 8613206 | 8399406 | 6711827 | 9094981 | 1226400 |
| R-squared | 0.166 | 0.167 | 0.172 | 0.0968 | 0.0995 | 0.178 | 0.251 |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. The independent variable of interest is whether the prescription was automatic refill. Patient fixed effects are included. No additional covariates were used. Only considers persistent patients (i.e., those whose maximum gap between two prescriptions was never over 90 days). Non-costly refers to prescriptions that can automatically be filled at an IMSS pharmacy; costly refers to prescriptions that are filled after a doctor's appointment. The appointment gap refers to the number of days a patient delays his visit to the physician. Only patients assigned to clinics between the 25th and 75th percentile with respect to clinic congestion as measured by appointments per doctor are considered (between 48 and 103 appointments per doctor per month). Standard errors clustered at the clinic level in parentheses.
$^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$

Table A.11: Effects on non-costly fillings in low congestion clinics

| | Baseline | Type of refill | | App't gap | | Into v. Outof | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) Non-Costly | (3) Costly | (4) All | (5) $\geq 0$ | (6) In | (7) Out |
| Receta Resurtible | -0.493* | -0.614** | -0.832** | -10.43*** | -2.446*** | -0.297 | -0.409 |
| | (0.291) | (0.309) | (0.380) | (0.533) | (0.441) | (0.314) | (0.416) |
| Mean dept. var. | 2.293 | 2.299 | 2.273 | 3.263 | 10.20 | 2.286 | 2.067 |
| No. patients | 84060 | 84060 | 83735 | 82946 | 49776 | 89608 | 13040 |
| N: patient - purch. | 473105 | 464874 | 448055 | 435197 | 279325 | 470789 | 59148 |
| R-squared | 0.366 | 0.370 | 0.378 | 0.326 | 0.247 | 0.377 | 0.362 |

Notes: The dependent variable is the treatment gap, which is defined as the number of days a patient was out of medication. The independent variable of interest is whether the prescription was automatic refill. Patient fixed effects are included. No additional covariates were used. Only considers persistent patients (i.e., those whose maximum gap between two prescriptions was never over 90 days). Non-costly refers to prescriptions that can automatically be filled at an IMSS pharmacy; costly refers to prescriptions that are filled after a doctor's appointment. The appointment gap refers to the number of days a patient delays his visit to the physician. Only patients assigned to clinics in the lowest 25th percentile with respect to clinic congestion as measured by appointments per doctor are considered (48 appointments per doctor per month). Standard errors clustered at the clinic level in parentheses. ${}^{*}p < 0.1, {}^{**}p < 0.05, {}^{***}p < 0.01$

# C Modeling Doctor's Decision to Assign Patients to High or Low Frequency Regime

I model the doctor's decision to reflect the trade-off which is inherent to the frequency of doctor's appointments: higher frequency may have health benefits as the physician may closely monitor the patient's disease, but also increases the costs of treatment for the patient.

In this extension of the model the second stage is modified, as doctors will evaluate patients on the automatic-refill regime in stage $s = 2$, and may allow patients to remain in this regime or reassign them to the general regime, by choosing $k \in \{RR, g\}$ respectively. Doctors will consider the potential health benefits of higher monitoring, and the treatment costs of each regime imposed on the patient. The health benefits associated with frequent monitoring will depend on the doctor's assessment of the patient's past adherence and severity of the illness. In particular, a doctor maximizes:

$$\max_{k \in \{RR, g\}} \quad H^k(a_{k,2}, q_{k,2}) - c^k \tag{10}$$

where $H^k(\cdot)$ is the assessed health benefit of monitoring, which depends on the patient's past treatment gap $\bar{a}_{RR,2}$ and the severity of his illness, $q_{RR,2}$. We will assume that $H_a > 0$ (adherent patients with lower $a^*_{RR,2}$ will benefit less from increased monitoring as they give a signal of being "responsible" in the self-management of their disease), and $H_q > 0$ (sicker patients benefit more from frequent doctor's appointments). Additionally, $H^{RR}(a, q) \leq H^g(a, q)$ and $H_a^{RR}(a, q) \leq H_a^g(a, q)$ for every $a$ and $q$. Finally, I assume $H^{RR}(0, q) - H^g(0, q) < c^g - c^{RR}$, and $H^k(\cdot)$ to be strictly monotone and continuous.

A doctor will keep a patient on the $k = RR$ regime—thus allowing him to retain the benefits of a lower treatment cost—if and only if:

$$H^{RR}(a_{RR,s-1}, q_{s-1}) - c^{RR} \geq H^g(a_{RR,s-1}, q_{s-1}) - c^g, \tag{11}$$

which may be rewritten as:

$$c^g - c^{RR} \geq H^g(a_{RR,s-1}, q_{s-1}) - H^{RR}(a_{RR,s-1}, q_{s-1}). \tag{12}$$

which implies that doctors will only allow patients to stay on the automatic-refill regime if the reduction in costs it implies is larger than the health costs it imposes.

Given this equation, there must exist some $\bar{A}$ such that Equation 12 holds with equality. For any $a < \bar{A}$, the doctor will optimally reassign the patient to the automatic-refill regime, whereas he will assign the patient back to the general regime if $a > \bar{A}$.