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Subsidizing Access to Prescription Drugs and Health Outcomes: The Case of Diabetes*

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Abstract

This paper evaluates the health effects of a large-scale subsidizing program of prescription drugs introduced in Brazil, the *Aqui Tem Farmácia Popular* program (ATFP). We exploit features of the program to identify its effects on mortality and hospitalization rates by diabetes for individuals aged 40 years or more. We find weak evidence for a decline in mortality, but a robust reduction in hospitalization rates. According to our preferred specification, an additional ATFP pharmacy per 100,000 inhabitants is associated with a decrease in hospitalization rates by diabetes of 8.2, which corresponds to 3.6% of its baseline rate. Effects are larger for Type II diabetes in comparison to Type I, and among patients with relatively lower socioeconomic status. Overall, the results are consistent with insulin-dependent patients being relatively less responsive to subsidies because of higher immediate life-threatening risks; and with lower-SES individuals being more responsive because of liquidity constraints. These results support the view that the optimal design of health systems and cost-sharing mechanisms should take into account equity concerns, heterogeneous impacts by health condition, and their potential offsetting effects on the utilization of downstream health services.

Key Words: subsidies, prescription drugs, diabetes, hospital admissions, mortality.
JEL Codes: I10; I13; I18; H51.

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1 Introduction

Increased financial pressures on health systems have made countries cut subsidies and adopt a variety of approaches to contain costs. One of the most widespread and contentious strategy has been the introduction of patient cost-sharing, which is intended to increase patient costs, to induce more price sensitivity, and to potentially reduce moral hazard and system costs. In particular, many high-income countries have increased cost-sharing in health services in general, with the most substantial increases for prescription drugs – as observed in the UK, Germany, Japan, France, and the US (Zare and Anderson, 2013). However, while lower subsidies and greater out-of-pocket spending within cost-sharing schemes could help reduce the scope for moral hazard, it is also possible that patients could reduce necessary medications because of out-of-pocket costs. This is of particular concern for those facing immediate life-threatening risks as well as for low-income patients, who may be more responsive to out-of-pocket spending as they face liquidity constraints. If this is the case, higher patient costs may lead to worse health outcomes and to offsetting effects through increased use of downstream health services, disability and mortality. The optimal design of health systems therefore depends not only on whether strategies to contain direct costs are effective in achieving this goal, but also on the balance between subsidies *vs* out-of-pocket spending within systems, and its ultimate consequences on health outcomes and equity.

In this paper we evaluate the health effects of a large-scale subsidizing program of prescription drugs introduced in Brazil. In 2006 the federal government launched the *Aqui Tem Farmácia Popular* program (ATFP), a copayment system in partnership with private retail pharmacies.[1] In the ATFP system, the government establishes a reference price for the generic version of each listed medicine. Patients pay for the difference between the retail price and 90% of the reference price – generally resulting in substantially lower prices for the patient at the pharmacy counter. The program expanded fast. A decade later, it had already reached approximately half the total number of private retail pharmacies in Brazil, and nearly 20 million users.

More specifically, this paper evaluates the effects of ATFP on mortality and hospitalization by diabetes for individuals aged 40 years or more. We focus on diabetes for two main reasons. First, diabetes is considered a major global health threat (Zimmet et al., 2016; UN, 2007). Around 1 in 11 adults has diabetes in the world today (0.43 billion individuals), while 12% of global health expenditures are spent on the disease (IDF, 2017). Productivity losses and the financial burden of diabetes tend to escalate as the poor management of the

[1] *Aqui Tem Farmácia Popular* in Portuguese stands for "Here There is Popular Pharmacy".

disease can lead to serious complications in the long run, such as vision loss, kidney and heart failure, nerve problems, and amputations. Second, the needs for prescription drugs are different for distinct types of diabetes. ATFP provides a range of antidiabetic drugs, including insulin and oral hypoglycemics (metformin and glibenclamide). Daily use of insulin is vital for Type I patients, for whom cessation of use leads to death in a matter of weeks.[2] For Type II patients, the need for insulin is variable, not necessarily urgent, and depends on clinical conditions. The management of Type II diabetes often includes changes in lifestyle and the use of oral hypoglycemics, such as metformin. Although severe hyperglycemia is a cause of hospital admissions, life-threatening diabetic ketoacidosis is much less common for Type II patients. By looking at Type I *vs* Type II outcomes, we are therefore able to examine whether high- *vs* low-risk patients respond differently to variation in cost-sharing schemes.

Our empirical strategy is based on a municipality-by-year fixed effects model, and exploits two idiosyncratic features of the Brazilian context to associate variation in subsidized access to medicines, through the expansion of pharmacies accredited to ATFP across time and space, with variation in health outcomes. The first feature relates to the design of the Brazilian health system, in which both the public and the private sectors provide health services. The Unified Health System (SUS, for *Sistema Único de Saúde*) is committed to provide free, universal, integral, and equal health coverage; while the private sector provides services either funded by out-of-pocket spending or regulated private insurance.[3] Further, access to medicines within the public sector is largely constrained by rationing of pharmaceutical services, as availability in stock is often limited and intermittent, while private health insurance rarely covers prescription drugs. For most Brazilians, prescription drugs have been thus obtained through out-of-pocket payments at private pharmacies. In this situation, the ATFP roll-out corresponds to an expansion in subsidized access to prescription drugs, net of simultaneous changes in access to other health services as well as in other cost-sharing mechanisms aimed at controlling pharmacy use.

Second, we draw on institutional constraints required for pharmacy accreditation in the system to gain exogenous variation in the sequential process of expansion of ATFP pharmacies across municipalities. Although any private pharmacy is eligible to the program, in practice many fail to meet the official requirements needed even for their operation in the retail market. In particular, many pharmacies are unable to hire and retain a pharmacist

[2]Acute, life-threatening consequences of uncontrolled diabetes are hyperglycemia with the nonketotic hyperosmolar syndrome or ketoacidosis (American Diabetes Association, 2014; Kitabchi et al., 2009).

[3]By virtue of guaranteeing free universal coverage, SUS comes closer to the Canadian and British NHS models. Commitment to the provision of integral coverage means that coverage should include all types of health services, in particular access to pharmaceutical services.

on their payroll. While the lack of pharmacists has not represented a *de facto* constraint to pharmacies' operation, accreditation in ATFP strictly requires the pharmacy to continuously prove compliance with this requirement. A limited supply of pharmacists in the local labor market at the time of program introduction is then expected to constrain its expansion throughout the following years. We explore this feature in a IV approach, in which the instrumental variable is defined by the interaction between the supply of pharmacists across municipalities in the baseline year and a linear time trend. Thus, conditional on municipality and time fixed-effects, we expect the process of ATFP diffusion to be relatively slower in localities where the baseline supply of pharmacists was more limited. A series of falsification tests supports the validity of this identification strategy.

We use unique administrative records to build a yearly panel of municipality-level data. The Brazilian Ministry of Health (Datasus) provides individual-level data on the universe of all deaths in Brazil, and all hospital admissions through SUS. These data include main diagnosis, patients' municipality of residence and demographic characteristics, which are used to construct age-specific diabetes mortality and hospitalization rates, by diabetes type. In the specific case of hospital admissions, we observe patients' zip code of residence and hospitalization costs, which enables us to further examine heterogeneity by socioeconomic status and to estimate averted spending in terms of hospital admissions. The Brazilian Ministry of Health also provides data on the number of retail pharmacies accredited to the program in each municipality and year. In order to examine local labor market dynamics, we complement our data with information on the total number of private retail pharmacies as well as on the number and wages of pharmacists and other pharmacy workers from the *Registro Anual de Informacões Sociais* (RAIS), an administrative microdata set from the Ministry of Labor that contains the universe of formal workers and firms in Brazil.

We find weak evidence for a decline in mortality, but a robust reduction in hospitalization rates. According to our preferred IV specification, an additional ATFP pharmacy per 100,000 inhabitants is associated with a decrease in hospitalization rates by diabetes of 8.2, which corresponds to 3.6% of its baseline rate of 226 admissions per 100,000. Effects are larger for Type II diabetes in comparison to Type I, and among patients with relatively lower socioeconomic status. In particular, we observe that ATFP effects on the reduction of hospitalization by Type II diabetes are 33% greater in comparison to Type I when adjusted by the average hospitalization rate for each group. These results are consistent with insulin-dependent patients being relatively less responsive to subsidies because of higher immediate life-threatening risks, and with lower-SES individuals being more responsive because of liquidity constraints. More generally, the results suggest that high-risk patients are less responsive to variations in subsidies or out-of-pocket spending within cost-sharing

schemes as they face greater likelihood of experiencing adverse health outcomes because of non-adherence to treatment. Based on secondary data, we also observe that ATFP is associated with increased adherence to medication in general and, importantly, among those under poor management of the condition in particular. Counterfactual simulations indicate that ATFP averted approximately 242 thousand hospital admissions by diabetes during the period of analysis. This represents 16.7% of the total number of hospital admissions, and 12.7% of the hospitalization costs funded by SUS, considering counterfactual trends had the program been not implemented.

The existing literature has largely focused on the effects of variations in cost-sharing on health spending, while causal evidence on its effects on health outcomes has been sparse and mixed. Further, evidence has been overwhelmingly raised from US studies, which often explore specific contexts of multiple-payer managed care, and where variation in prescription drug cost-sharing is often bundled with variation in cost-sharing in other health services. For instance, Chandra et al. (2010) find that, among the elderly Medicare population in California, an increase in patient cost-sharing in both physician visits and prescription drugs decreased service utilization, but led to substantial offsetting effects in terms of increased hospitalization. On the other hand, the same authors find that, among low-income enrollees in the Massachusetts' Commonwealth Care program, an increase in cost-sharing reduced services utilization, but did not have any offset effects (Chandra et al., 2014).

We also observe mixed results in the few and specific contexts in which exogenous variation in either cost-sharing or health insurance coverage applied solely to prescription drugs. For instance, Gaynor et al. (2007) find that an increase in prescription drug cost-sharing, among the non-elderly enrolled in employer-provided health insurance, reduced pharmacy use, increased outpatient care spending, but did not affect hospitalization. Kaestner et al. (2019) find that obtaining prescription drug insurance through Medicare Part D was associated with a reduction in hospitalization, but not with a decline in mortality rates. Huh and Reif (2017) and Dunn and Shapiro (2019), on the other hand, employ different empirical strategies and find that the Medicare Part D roll-out was significantly associated with a decline in mortality rates among the eligible elderly. Puig-Junoy et al. (2016) find that an exemption from pharmaceutical copayment granted to retired individuals in Spain increased the consumption of prescription drugs, but did not have any offset effects in terms of reduced hospitalization. Consistent with that, evaluations of value-based insurance design schemes suggest positive but modest effects on medication adherence, and have not supported any clear consensus about impacts on overall spending and on clinical

outcomes (Farley, 2019; Agarwal et al., 2018; Tang et al., 2014; Lee et al., 2013).[4]

Overall, notwithstanding the efforts from previous studies, the understanding of the extent to which patient cost-sharing affects health outcomes remains unsettled. This may reflect the fact that the existing evidence comes from context-specific settings in developed countries, where variation in subsidies or out-of-pocket spending within cost-sharing schemes often applies to multiple health services at once, and where health care coverage is nearly universal. The consequences of variations in subsidies or out-of-pocket costs should depend on whether individuals are able to respond to prices so as to minimize adverse health outcomes. If this is the case, we should expect little variation, possibly coupled with mixed results, in health outcomes in contexts where liquidity constraints are relatively less binding and where individuals are often covered by, and could respond differently to distinct insurance schemes. This is consistent, for instance, with the lack of consensus regarding clinical benefits from value-based insurance design schemes. This is also consistent with Kaestner and Khan (2012), which shows that prior to Medicare Part D, the elderly without prescription drug insurance filled nearly as many prescriptions per year as elderly with prescription drug insurance.

This paper advances the existing literature by providing new evidence from a nationwide intervention within a unique empirical setting, in which variation in subsidies to prescription drugs comes net of simultaneous changes in access to other health services as well as in other cost-sharing mechanisms, where access to pharmaceuticals are mostly made through out-of-pocket expenses, and where liquidity constraints are relatively binding for most individuals. Causal evidence from developing countries is particularly mute and, differently from prior studies, mostly based on specific settings in the US, we thus provide evidence from a context where individuals are more vulnerable and substantially less insured on pharmaceutical services. By looking at outcomes for different types of diabetes, we are also able to examine whether patients facing distinct health risks respond differently to variation in subsidies within cost-sharing schemes. In that sense, our results are particularly informative to many countries across the world that are developing or revising health financing policies in an effort to improve health system performance, enhance access to essential medicines, and progress towards universal health coverage.

The remainder of this paper is organized as follows. Section 2 describes the institutional

[4]For evidence specifically related to diabetes, for instance, se Nair et al. (2010) and Musich et al. (2015). Value-based insurance design (VBID), which is commonly found in the US context, aims at calibrating cost-sharing schemes in order to increase adherence to effective treatments and simultaneously contain health costs. In these schemes, access to high-value services, such as access to medication for chronic conditions, should have lower cost-sharing requirements while low-value services should face higher cost-sharing.

setting. Section 3 presents the data, while section 4 describes our empirical strategy. Section 5 presents the main results and robustness checks. In Section 6 we assess equity by examining whether ATFP utilization and its effects on health outcomes vary with socioeconomic status and by health condition. In Section 7 we explore secondary data to investigate heterogeneity by adherence to treatment and to discuss whether ATFP has helped improve the management of the condition. In Section 8 we present estimates on averted costs, and further discuss the implications of our results. Section 9 concludes.

2 Institutional Context

2.1 Access to Health Care and Medicines in Brazil

The Brazilian Unified Health System (SUS) is constitutionally committed to provide universal, integral, and equal health coverage, including free-of-charge access to medicines. In particular, medicines listed in the National List of Essential Drugs (RENAME) should be continuously available at public health facilities.[5,6] In reality, however, access to medicines within SUS is constrained by rationing of pharmaceutical services, as availability in stock is often limited and intermittent (Santos and Nitrini, 2004; Naves and Silver, 2005; Brasil, 2005a).[7] According to a nationwide survey carried out in the early 2000s, only 22% of those households who had recently needed medicines obtained them free-of-charge from public sources. This figure was no higher than 38% among the poorest ones. The vast majority had to resort to the private retail market of pharmacies (Brasil, 2005a).

Given the limited access within SUS, and the fact that private health insurance rarely covers prescription drugs, for most Brazilians medicines have been thus obtained through out-of-pocket payments at private pharmacies. This represents a heavy financial burden for the poor and for the chronically-ill who make continuous use of medications. Out-of-pocket spending with medicines have accounted for about 80% of total spending on health among the poorest households (Menezes et al., 2007), while the elderly have spent, on average,

[5]RENAME is an extensive list of medicines officially defined as essential, which includes, among many others, medicines for hypertension and diabetes.

[6]Public health facilities are widespread across the country. A recent nationwide survey revealed that in Brazil about 63% of households are located within 1km from a public primary health care unit. This figure is just about 10 percentage points lower than the share of households located within 1km from any private pharmacy (Brasil, 2005a).

[7]Public health studies from different contexts indicate that about 40-50% of the medicines prescribed in public primary health care facilities have not been available in stock (Naves and Silver, 2005; Santos and Nitrini, 2004). Also, even when readily available, supplies might soon run out-of-stock (Brasil, 2005a). Naves and Silver (2005), for instance, observed that interruption of hypertension or diabetes medicine supplies was frequent in public health facilities of Brasília, the federal capital of Brazil.

nearly 50% of the minimum wage with monthly medications (Lima et al., 2007). In particular, the monthly costs with medications to treat diabetes, if purchased in private pharmacies, could reach about 4 days of work in terms of the minimum wage (Pinto et al., 2010; Brasil, 2005a).[8] This means that diabetes treatment has been unaffordable and hardly accessible for a substantial part of the population, potentially resulting in either non-adherence or intermittent use of drugs that should be continuously taken (WHO, 2012).

The federal government has acknowledged that SUS has been unable to grant continuous access to essential medicines, in particular for the urban poor and for the lower-middle classes – populations that usually lack the financial resources to purchase medicines and are barely covered by public primary healthcare programs (Brasil, 2005b). In order to overcome these limitations, in 2004 the federal government launched the *Farmácia Popular* program. In its initial phase, called *Programa Farmácia Popular do Brasil* (FPB, Brazilian Popular Pharmacy Programme), the government created a small number of state-owned retail pharmacies to dispense selected medicines at low fixed prices. FBP was targeted at large urban centers. The ratio of FPB pharmacies per capita, however, remained rather limited. In 2006, the program entered into its second phase, called *Aqui Tem Farmácia Popular* (ATFP, Here There is Popular Pharmacy), when it was rapidly expanded through a co-payment system in partnership with private retail pharmacies.

2.2 Aqui Tem Farmácia Popular

In the ATFP, participating private pharmacies dispense listed medicines through a co-payment system. The government establishes a reference price (RP) for the generic version of each medicine. When the pharmacy retail price is equal to or higher than the RP, the government reimburses the pharmacies 90% of the RP; when it is lower, the government reimburses 90% of the retail price. Patients pay for the difference between the retail price and 90% of the reference price.

Patients must hold a medical prescription and must sign for the purchase. Medicines can be dispensed only monthly and directly to the user. Pharmacies must keep a record of medical prescriptions and users' identification. The initial list of medicines covered by ATFP included anti-diabetics, anti-hypertensives, and contraceptive pills. In 2010 it was expanded to also include medicines for asthma, dyslipidemia, rhinitis, glaucoma, Parkinson disease, osteoporosis, and influenza H1N1 (see Appendix Table B.1 for a list of medicines covered

[8] More precisely, in 2012, the official minimum wage in Brazil, calculated on a daily basis, was R$20.73. The average monthly cost of diabetes medication was estimated in R$83. This cost, therefore, roughly corresponded to 4 days of work for a salaried worker that earns the minimum wage.

by ATFP). In 2011, anti-diabetic and anti-hypertensive drugs listed in ATFP became fully subsidized and available for free.

The number of participating pharmacies rapidly increased, from 2,955 in 2006 up to 34,625 in 2015, corresponding to about half the total number of private retail pharmacies in Brazil. The number of municipalities with at least one participating pharmacy increased from 594 in 2006 (about 11% of the total number of municipalities) to 4,445 in 2015 (80%). Figure 1 presents these trends.

ATFP users represent a substantial share of the total number of Brazilians diagnosed with diabetes (7.5 million out of 12.5 million).[9] Indeed, according to a recent nationwide survey (PNS, 2013), 56% of the individuals older than 40, who had recently taken medications for diabetes, had obtained at least some of them through the program. Data on retail prices and quantities are not systematically available for medications, but case studies, qualitative information and aggregate series on sales indicate that the use of anti-diabetic medication increased with ATFP. According to WHO (2012), data from IMS Health Brazil on quantities indicate that retail sales of insulin derivatives not covered by ATFP have remained stable, while there has been a substantial increase in the sales of insulin derivatives listed in ATFP (WHO, 2012). This indicates that overall demand for ATFP-listed medicines has increased, likely reflecting higher adherence to treatment. Also, although each retailer is free to set its own sale price, and despite the increase in sales, the available evidence suggests that users of antidiabetic medications have paid about 90% less within ATFP in comparison to retail prices (Pinto et al., 2010).

2.3 Accreditation of Pharmacies to the ATFP Program

There are approximately 75,000 private retail pharmacies in Brazil. The retail market is mostly composed of independent pharmacies (90%), with the five main chains representing only a small fraction of the total number of pharmacies (2.8%) (Bertoldi et al., 2012). In principle, accreditation to the ATFP program requires the pharmacy to meet the same official requirements needed for the opening and operation of retail pharmacies in general. These requirements include the submission of (i) state-issued documents attesting compliance with sanitary conditions for operation, as well as with labor and fiscal regulations; and (ii) a document attesting the presence of a technically responsible pharmacist in place – or, more precisely, the pharmacist's Certificate of Technical Responsibility (CRT), issued by the Regional Pharmacy Council. The documentation must be submitted to Caixa

[9] Source: DAF/SCTIE, Ministry of Health, accessed online on http://sage.saude.gov.br/; and IDF (2017) for the total number of Brazilians diagnosed with diabetes.

Econômica Federal (CEF), the official public bank responsible for the accreditation and the reimbursement systems. Accreditation must be renewed every year based on the submission of updated documentation.

Although any private pharmacy is eligible to the program, in practice many fail to meet the official requirements needed even for their operation in the retail market. In particular, many pharmacies are unable to hold a technically responsible pharmacist in place. According to Law 5,991 of December 1973, retail pharmacies must have a certified pharmacist always available in place to provide assistance to patients. Since pharmacists are required to complete a bachelor's degree to gain their CRT, in many places the supply of pharmacists is limited while their salaries are relatively high. Although penalties should apply in case of non-compliance, both local auditing capacity and enforcement are rather limited. Further, pharmacy owners can also exploit gray areas of the legislation to overcome sanctions.[10] In consequence, pharmacies are often staffed with non-certified pharmacy technicians, or just pharmacy clerks. According to a recent census of the pharmacy sector, nearly a third of the private retail pharmacies had not a technically responsible pharmacist available in place at the time of the survey, while many failed to have any pharmacist, at anytime (ICTQ, 2014). Thus, the lack of certified pharmacists has not represented a *de facto* constraint to pharmacies' operation in the retail market.

Accreditation in the ATFP program, on the other hand, strictly requires the pharmacy to identify the responsible pharmacist on the submission form, and to submit her CRT jointly with her employment contract. Because ATFP is a federal program, it is subject to tighter enforcement as audits can be directly carried out by federal agencies. Also importantly, in case of any wrongs regarding the accreditation process or the pharmacy participation in the program, the pharmacists are legally liable and could be also subject to penalties. Thus, although any private pharmacy is eligible to ATFP, the actual expansion of the number of participating pharmacies in a given locality should vary with the availability of pharmacists in that locality. We further discuss sources of variation in pharmacy participation in ATFP on Section 4, which presents our empirical strategy.

[10] According to Article 5 of Law 5,991/1973, if the pharmacy owner proves not to be able to hire a pharmacist – e.g., because of a shortage of pharmacists in the locality – then she may be authorized to register another employee as a substitute. However, this substitute should also be certified by the Regional Pharmacy Council, which usually resists to grant certification for non-pharmacists. In fact, there are as few as about 200 cases of non-pharmacists whom were granted certification after legal action (information from G1, accessed online on http://g1.globo.com/, October 10, 2013).

3 Data

3.1 ATFP and Health Outcomes

Our analysis is based on a yearly panel of data at the municipality level for the 2000-2012 period. Data related to the implementation of the ATFP are obtained from the Brazilian Ministry of Health (Department of Basic Attention, MS/DAB), and provide the number of retail pharmacies accredited to the program in each municipality and year. We complement this information with municipality data on the total number of private retail pharmacies as well as on the number and wages of pharmacists, pharmacy clerks and other pharmacy workers from the *Registro Anual de Informacões Sociais* (RAIS), an administrative microdata set from the Ministry of Labor that contains the universe of formal workers and firms in Brazil.

Data on mortality and hospital admissions are available from the Brazilian Ministry of Health (MS/Datasus). We obtain mortality microdata from the Brazilian National System of Mortality Records (Datasus/SIM). SIM gathers information on every death officially registered in Brazil, and contains information on the deceased's age, gender, and municipality of residence, as well as the diagnostic codes, which are identified according to the International Classification of Diseases, 10th Revision (ICD-10). We obtain hospitalization microdata from the National System of Information on Hospitalizations (Datasus/SIH), which contains administrative information at the hospital admission level. The data are managed by the Health Care Agency (SAS/Ministry of Health) with support of local and regional public health agencies, which receive information about hospitalizations from public and private hospitals through standardized inpatient forms. The dataset includes all hospital admissions funded by SUS. It provides information on cause of hospitalization (ICD-10), duration of stay, final outcome (discharge or death), socioeconomic characteristics of the patient (municipality and zipcode of residence, gender, and age) and costs in BRL. Both microdata sets include patients' municipality of residence and exact date of the event (year of death or hospital admission). The date of the death/hospitalization and the code of the municipality of residence are used to collapse the microdata into a municipality-by-year data set and to match with data from other sources.

We select all diabetes deaths and hospital admissions of individuals aged 40 or older. These microdata are collapsed into an yearly panel of data at the municipality of residence level.[11]

[11] Although we do have microdata on hospital admissions and deaths, our empirical approach relies on a municipality-by-year panel of data. The aggregation is justified by two reasons. First, our key regressor and its respective instrumental variable are measured at the municipality-by-year level. Second, we do not observe diabetes patients that have not been hospitalized or died. We thus need to resort to hospital admissions

Annual data on municipality population by age are obtained from projections estimated and provided by MS/Datasus. These data allow us to convert number of deaths and hospital admissions of individuals aged 40 or older into mortality and hospitalization rates for the same population group, respectively. Diabetes mortality and hospitalization rates for individuals aged 40 or older at the municipality-by-year level are then merged with ATFP and RAIS variables.[12]

3.2 Auxiliary Data

We make use of two other pieces of municipality data that are auxiliary to our analysis. First, we obtain from Ipeadata the annual GDP and the area size in km^2 of each municipality. These data enable us to construct, respectively, the municipality GDP per capita and the municipality population density. Second, we collect indicators of healthcare provision. Information on hospital infrastructure (number of hospitals and hospital beds per 100,000 individuals) is obtained from the Ministry of Health. We also collect data from the Ministry of Health on the coverage of the *Programa Saúde da Família* (PSF) and of the *Programa Agentes Comunitários da Saúde* (PACS), the most relevant public primary healthcare programs in Brazil. In particular, PSF is now widespread in the country. It was designed to focus on prevention and provision of basic health care, to handle coordination of public health campaigns and actions, and to function as the first point of contact between citizens and public health provision.

3.3 Descriptive Statistics

Our final panel of data contains 5,507 municipalities over the 13 years throughout the 2000-2012 period, which allows a window of six years of data before and after the introduction of ATFP.[13] Table 1 presents some descriptive statistics for municipalities over the years of 2000-2005, the baseline period prior to ATFP introduction. Panel A presents diabetes mortality and hospitalization rates for individuals aged 40 or older (per 100,000). Diabetes is defined within E10-E14 ICD10 codes. We record as diabetes Type I the cases classified as E10 (insulin-dependent), while the remaining cases are grouped as diabetes Type II and

and deaths as outcome variables measured at a given local-time dimension.

[12]Given that we rely on administrative microdata on mortality and hospitalization for diabetes as well as on projected population size by age at the municipality-year level, outcome variables become noisier as cells become smaller. Moreover, we unfortunately do not observe comorbidities, illness severity or any other relevant markers of health status in the data. For these reasons, we compute mortality and hospitalization indicators for the population of individuals aged 40 or older without further risk adjustments within the population group considered in the analysis.

[13]The sample size of 5,507 corresponds to the total number of municipalities in Brazil according to the 2000 Census.

are computed from E11-E14 ICD10 codes (non-insulin-dependent and other types).[14] As expected, Table 1 shows that mortality rates are larger for Type II diabetes, which reflects higher prevalence. In fact, there are nearly 12.5 million Brazilians diagnosed with diabetes (IDF, 2017), approximately 90% to 95% of whom with Type II diabetes (Sociedade Brasileira de Diabetes, 2017). Hospitalization rates are much higher than their mortality counterparts. Together, average annual hospital admissions for Type I and Type II diabetes reach 226 cases per 100,000 inhabitants.

Panel B presents baseline descriptive statistics for municipality socioeconomic conditions and healthcare provision, used as control variables in our empirical analysis. We highlight that access to primary care reaches a substantial share of the population, as shown by PSF (average of 49%) and PACS coverage (23%). We also observe that the average number of private pharmacies per 100,000 inhabitants reaches 61. Panel C presents descriptive statistics of variables that are used to construct our IV (number of pharmacists per 1,000 inhabitants in 2006) as well as to construct auxiliary indicators, used in falsification tests. This latter panel also presents the average number of ATFP-accredited pharmacies, our key variable of interest. We further discuss pharmacy network and pharmacy workers in the next section.

4 Empirical Model

4.1 Empirical Strategy

Our goal is to examine the extent to which the introduction of ATFP is associated with changes in health outcomes. In order to do so, we explore variation in the sequential process of expansion of ATFP pharmacies across municipalities. More specifically, the following equation provides our conceptual setup:

$$H_{it} = \alpha_i + \phi_t + \beta_1 ATFP_{it} + \beta_2 Pharmacies_{it} + Controls'_{it}\beta_3 + \epsilon_{it} \quad (1)$$

Where H_{it} is a health outcome in municipality i and year t. Our main variable of interest is $ATFP_{it}$, the number of private retail pharmacies accredited to ATFP per 100,000 inhabitants. The term $Pharmacies_{it}$ indicates the total number of private retail pharmacies per 100,000 inhabitants, and should absorb the confounding effects of the number of private

[14] We follow American Diabetes Association (2014) to group Type II diabetes together with other cases of diabetes mellitus as insulin is generally not required for survival among these patients.

retail pharmacies in general. The term α_i represents municipality fixed effects, which absorb initial conditions and persistent municipality characteristics, such as climate and the epidemiological context. The term ϕ_t represents year fixed effects to control for common time trends, such as macroeconomic conditions, the political cycle and common healthcare policies. The term $Controls_{it}$ includes a series of controls for the influence of other determinants of health and healthcare. First, it includes demand-side determinants of health such as municipality economic conditions (the logarithm of the GDP per capita and of the population density, defined by the number of inhabitants per km^2) and the age composition of the municipality population (the share of inhabitants within each 5-year age bracket, from 5-9 up to 80 years or older). Further, it also includes controls for the provision of healthcare, such as the number of hospitals and hospital beds per 100,000 inhabitants, and the population coverage of PSF and PACS.

Our parameter of interest is β_1. Should the number of ATFP pharmacies per capita be random, β_1 would report the effects on health of an additional pharmacy accredited to the ATFP co-payment system. However, pharmacy selection into ATFP is expected to be endogenous and should correlate with several latent determinants of health. Although we consider a series of controls in equation (1), β_1 can be biased by the influence of non-observable confounding trends. In particular, we do not directly observe trends in health status nor in the demand for healthcare. If pharmacy selection into ATFP responds to a non-observable deterioration in population health, for instance, we should expect attenuation bias in our estimates because of reverse causality.[15]

We thus complement the analysis with a IV strategy that exploits our empirical setting to generate exogenous variation in ATFP diffusion. We draw on the fact that the program expansion has relied on the availability of pharmacists in the local labor market. As mentioned in Section 2.2, while the limited supply of pharmacists has not represented a *de facto* constraint to pharmacies' operation, accreditation in ATFP strictly requires the pharmacy to submit a pharmacist's CRT jointly with her employment contract. The limited supply of pharmacists in the locality at the time of the program introduction is then expected to constrain its expansion throughout the following years. We explore this feature in the following first-stage equation:

[15]This is consistent with Appendix Figure B.1, which plots the roll-out of ATFP by marking the year in which the first pharmacy was accredited to the program in each municipality. Notwithstanding the fact that the program has reached very diverse regions of the country, except for the most sparsely inhabited areas, such as the Brazilian Amazon, in the Northern region, we do observe a prevalence of early adopters in the Southern and Southeastern regions, where both the share of the elderly in the total population and the income per capita are relatively higher.

$$ATFP_{it} = \alpha_i' + \phi_t' + \gamma_1 Pharmacists_{i,06} * T_t + \gamma_2 Pharmacies_{it} + Controls_{it}'\gamma_3 + v_{it} \quad (2)$$

where $Pharmacists_{i,06}$ indicates the number of pharmacists per 1,000 inhabitants in municipality i and year 2006, when ATFP is launched. We interact this baseline supply of pharmacists in the local labor market with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. Conditional on the same set of fixed-effects and controls of equation (1), we expect the process of ATFP diffusion to be relatively slower in localities where the baseline supply of pharmacists is more restricted. In particular, municipality fixed-effects should absorb the confounding effects of the cross-sectional variation in the per capita number of pharmacists at the baseline, $Pharmacists_{i,06}$.

The exclusion restriction is valid if, conditional on fixed-effects and control variables, the instrumental variable ($Pharmacists_{i,06} * T_t$) is uncorrelated with any other latent determinant of population health. Although not directly testable, we put this assumption under strain by performing a series of falsification exercises. We present first-stage results and further discuss the validity of our IV approach in the next section.[16]

4.2 First-Stage Results

Table 2 presents first-stage results and falsification tests. All specifications follow equation (2). We weight all regressions by municipality population size and estimate standard errors clustered at the municipality level, to allow for serial correlation within municipalities. The first column of Table 2 reports our first-stage results. We observe a positive and robust coefficient for the interaction term $Pharmacists_{i,06} * T_t$, with a Partial-F of 197.8. This indicates that the availability of pharmacists in the locality at the time of the ATFP introduction is a strong predictor of its expansion over time, conditional upon municipality and year fixed-effects as well as on our full set of controls.

In columns 2-4 of Table 2 we test whether ATFP responds to alternative predictors in falsi-

[16] Although our IV approach has been specifically designed to our context, the reduced-form is analogous to first-difference specifications in which the definition of the treatment actually relies on a potential of treatment intensity indicator that varies in the cross-section, either at the baseline year or fixed over time. Some examples from different contexts include Bleakley (2007), Dinkelman (2011) and Bustos et al. (2016). In a first-difference approach, with two periods of time, the effects of a cross-sectional feature included in the right-hand side of the model reflect the specific-time trend effects of this feature. In our context, we exploit more variation in a fixed-effects model over many years. Conditional on year and municipality fixed-effects and controls, the instrument is expected to exogenously assign municipalities into treatment given the assumption that a cross-sectional feature exogenously determines differential dynamics in the roll-out of that treatment.

fication tests. In column 2 we follow equation (2), but replace the number of pharmacists by the number of pharmacy clerks and other pharmacy workers per 1,000 inhabitants as our variable of interest. We find a weak and non-robust association between ATFP diffusion and pharmacy clerks and other pharmacy workers at the baseline. This helps reassure that the results from column 1 reflect a specific institutional constraint to the program expansion, irrespective of a more general dynamics of employment in the local pharmacy retail market. More generally, however, the number of pharmacists at the baseline might be simply reflecting the confounding influence of a high-profile local labor market and the presence of other college-degree workers in general. In columns 3 and 4 we examine whether ATFP responds to the number of lawyers and college-degree management workers per 1,000 inhabitants, as also recorded by RAIS data at the municipality level for 2006 – being law and business & administration the majors that enroll the largest shares of undergraduate students in Brazil (Censo da Educação Superior, 2015). We find again weak and statistically insignificant coefficients. Column 5 reports a specification that simultaneously includes all these variables. We still observe a robust coefficient for the term $Pharmacists_{i,06} * T_t$, with a large Partial-F. The coefficient for other pharmacy workers is negative and statistically significant, but rather small in magnitude (Partial-F of 3.99), while the remaining coefficients are again non-significant.

Figure 2 complements this analysis and further test whether the results from columns 1-5 are picking any idiosyncratic non-linearities instead of the actual influence of the baseline supply of pharmacists on ATFP diffusion. We follow again equation (2), but now estimate coefficients of interaction terms between $Pharmacists_{i,06}$ and year dummies for the entire period. Panel A plots the results. We observe an increasing influence of the number of pharmacists per capita in the baseline year on the expansion of ATFP pharmacies. Point estimates roughly double in each three-year interval, beginning with 4.8 (SD 0.50) in 2006 and increasing up to 22.4 (SD 1.61) in 2012. Indeed, availability of pharmacists, which may be considered inelastic in the short-term, should become relatively tighter as the program expands. Panel B plots analogous results for other pharmacy workers. Although both baseline variables have similar descriptive statistics (see Table 1), the influence of the number of other pharmacy workers on ATFP expansion is limited and converges to zero. We observe a similar pattern for the cases of lawyers and college-degree management personnel.[17]

Appendix Table B.3 provides additional results. We first examine how pharmacists' wages

[17]We also tested for pre-trends in other relevant economic and health indicators, such as municipality-by-year average wages (built on RAIS administrative microdata, for all occupations), total health care spending (built on annual municipality expenditures, officially collected by FINBRA/Ministry of Economy), total mortality (Datasus/SIM) and total hospitalizations (Datasus/SIH). Overall, we do not observe systematic pre-trends in any of these alternative outcome variables. Results are available upon request.

respond to the availability of pharmacists in the locality at the time of ATFP introduction. In column 1 we follow equation (2), but replace the diffusion of ATFP pharmacies as dependent variable by the logarithm of the yearly average wage of pharmacists in the locality. We observe that wages increase relatively less in places with a larger supply of pharmacists at the baseline. On the following three columns, we do not find any statistically significant association for the cases of pharmacy workers, lawyers and college-degree management personnel. In the remainder column, we rely on the same reduced-form specification to examine migration of pharmacists. We use RAIS microdata to follow individuals in the data and to compute the annual number of pharmacists that moved from/to each municipality in each point in time. More specifically, we compute the net migration of pharmacists, i.e., the difference between the number of exits and entries per year (mean 0.63, SD 6.51). We do not find any statistically significant association between migration of pharmacists and our instrument. The findings from Table B.3 suggest that the local supply of pharmacists remain relatively unaltered. They also suggest a context in which labour does not adjust rapidly and where mobility is not flexible enough to change the local supply of workers, at least during the time frame of our analysis. These results, which are consistent with the observed patterns from Table 2 and Figure 2, help reassure the view that the ATFP diffusion was restricted by a specific institutional constraint, irrespective of any more general dynamics of the local labor market.

5 Main Results

In this section we report ATFP effects on mortality and hospitalization rates, and present the main robustness checks. We complement the analysis in Section 6, in which we test for heterogeneous effects by socioeconomic status and by diabetes type; and in Section 8, in which we present estimates of averted costs and provide further discussion.

5.1 Diabetes Mortality and Hospital Admissions

Tables 3 and 4 present ATFP effects on diabetes mortality and hospitalization rates, respectively. In both tables, we split the results into three panels. Panel A presents OLS regressions, based on equation (1), while Panel B reports analogous results for our 2SLS specification. Panel C reports the results of reduced-form specifications, in which outcomes are regressed on our instrument ($Pharmacists_{i,06} * T_t$), conditional on controls. Throughout the three panels, the first column reports the results of specifications that include only municipality fixed-effects, year fixed-effects, and socioeconomic controls. In the second column

we add controls for the presence of health services and health infrastructure. In the remainder column, we add the number of private pharmacies per capita in order to control for the supply of pharmacies in the municipality. We weight all regressions by municipality population size and estimate standard errors clustered at the municipality level, to allow for serial correlation within municipalities.

Panel A of Table 3 reports positive but insignificant OLS estimates. We observe that coefficients flip to negative in the 2SLS specifications of Panel B. Although stable across columns, point estimates are statistically significant only at 10%. A similar pattern is observed in Panel C across reduced-form estimates. Overall, the comparison of OLS and 2SLS results suggests attenuation bias in OLS specifications. This is expected should pharmacy selection into ATFP respond to a non-observable deterioration in population health. According to the 2SLS coefficient of column 3, an additional ATFP pharmacy per 100,000 inhabitants is associated with a decrease of 0.625 in the annual municipality number of deaths by diabetes per 100,000 individuals. This represents approximately 1% of the average baseline rate of 62 deaths by diabetes per 100,000 individuals aged 40 years or more (see Table 1).

Table 4 reports ATFP effects on hospital admissions. We find larger and robust coefficients across all specifications. Point estimates range from about -1.0 in OLS regressions to approximately -8.0 in 2SLS specifications, being remarkably stable across columns. The 2SLS point estimate of column 3 indicates that an additional ATFP pharmacy per 100,000 inhabitants is associated with a decrease in hospitalization rates by diabetes of 8.217, which corresponds to 3.6% of its baseline rate of 226 admissions per 100,000. This indicates that ATFP impacts on hospital admissions are more than threefold the effects estimated for mortality rates. These results suggest weaker subsidy effects in cases where patient conditions are more critical, and are consistent with insulin-dependent patients being relatively less responsive to subsidies, and to variation in prices, because of higher immediate life-threatening risks. We provide further discussion on this in Section 6, in which we test for heterogeneous effects by SES and diabetes type.

5.2 Robustness Checks

Our main identifying assumption is that, conditional on municipality fixed-effects as well as on year fixed-effects and controls, differences in the number of pharmacists per capita in 2006 across municipalities should be related to trends in diabetes mortality and hospitalization rates only through effects on the number of ATFP pharmacies. In other words, conditional on fixed-effects and controls, the dynamic effects of baseline pharmacists should not affect outcome variables through any other alternative channel but through ATFP.

In this section we present two sets of robustness checks. In order to provide further support to the exclusion restriction, we first test for the required parallel trends assumption. More precisely, while the exclusion restriction is not directly testable, we assume that the dynamic effects of baseline pharmacists on outcome variables for the period before the launch of ATFP should be unsystematic – otherwise they would flag concerns related to potential non-observable confounder trends correlated with the dynamic effects of baseline pharmacists. We rely on a reduced-form event study specification similar to what is shown in Figure 2. More specifically, we follow again equation (2), but now estimate the effects on health outcomes of interaction terms between $Pharmacists_{i,06}$ and year dummies for the entire period. Figure 3 presents the results. The upper figure plots the results for mortality rates, while the bottom figure reports the results for hospital admissions. Consistent with Table 3, in the upper plot we observe irrelevant mortality effects in the post-ATFP period. This is despite a modest but still negative pre-trend in the dependent variable. Oppositely, in the bottom figure we find a remarkably stable and statistically insignificant pre-trend in hospital admissions, followed by a well-marked downward trend in the post-ATFP period.

Next, we examine whether our estimated effects of ATFP on mortality and hospitalization rates hold when conditioned on the potentially confounding influence of municipality specific trends. In order to do so, we add to our 2SLS specification interaction terms between a linear time trend (which varies across years) and baseline municipality characteristics (which vary across municipalities, for the year 2000). Appendix Table **??** presents the results. The first four columns report the effects of ATFP on mortality rates, while the remaining columns present the results for hospitalization rates. Columns 1 and 5 replicate the results from our 2SLS specifications of Tables 3 and 4, respectively. In the specification of columns 2 and 6 we add an interaction term between a linear time trend and the municipality share of individuals aged 40 years or older in the baseline year 2000. Analogously, in columns 3 and 7 the interaction term considers the number of hospital beds per capita, while in columns 4 and 8 we consider the PSF coverage. The specifications of Table **??**, therefore, test for the potentially confounding influence of municipality specific trends from initial conditions of relevant demand-side and supply-side determinants of health.

Overall, results remain qualitatively unchanged. In the first four columns we now observe some insignificant coefficients for mortality rates. In particular, the point estimate drops nearly twofold (in module) when conditioned on specific trends in the population share of individuals aged 40 or older. In the four remainder columns, and despite the rather demanding specifications, we observe remarkably stable and robust coefficients for hospitalization rates.

Together with Tables 3 and 4, Figure 3 and Appendix Table **??** report a generally consistent set of results. We find weak evidence for a decline in mortality, and negative and statistically significant impacts on hospital admissions. This latter result is not driven by pre-trends in health outcomes, and holds when conditioned on the confounding influence of municipality specific trends from baseline demand-side and supply-side determinants of health.

6 Heterogeneity by Diabetes Type and by SES

6.1 Heterogeneity by Diabetes Type

According to American Diabetes Association (2014, p.S81), "diabetes is a group of metabolic diseases characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both. The chronic hyperglycemia of diabetes is associated with long-term damage, dysfunction, and failure of different organs, especially the eyes, kidneys, nerves, heart, and blood vessels". The vast majority of cases of diabetes fall into two categories Type I and Type II diabetes. Importantly, the needs for prescription drugs are often different for distinct types. On the one hand, daily use of insulin is vital for Type I patients, for whom cessation of use leads to death in a matter of weeks – life-threatening, acute consequences of uncontrolled diabetes are hyperglycemia with the nonketotic hyperosmolar syndrome or ketoacidosis, which is relatively more common (American Diabetes Association, 2014; Kitabchi et al., 2009). For Type II patients, the need for insulin is often not required nor necessarily urgent. The management of Type II diabetes often includes changes in lifestyle (diet and exercises are capable of lowering blood sugar within hours or days) and the use of oral hypoglycemics (such as metformin).[18] Although severe hyperglycemia is a cause of hospital admissions, life-threatening diabetic ketoacidosis is much less common for Type II patients.

By looking at Type I *vs* Type II outcomes, we are therefore able to examine whether high- *vs* low-risk patients respond differently to variation in subsidies within cost-sharing schemes. On the one hand, high-risk patients may be less responsive to variations in out-of-pocket spending as they face enhanced likelihood of experiencing adverse health outcomes because of non-adherence to treatment. On the other hand, however, liquidity constraints tend to be relatively tighter for those patients because of greater cumulative financial burden related to comorbidities and other healthcare needs. If this is the case, and in particular for lower-SES individuals, high-risk patients might decrease adherence to treatment. Al-

[18] For a synopsis of the pharmacologic therapy for Type II diabetes, see Chamberlain et al. (2017).

though scarce, the existing evidence from context-specific case studies and correlational analysis suggests that price sensitivity is lower for high-risk patients (Wang et al., 2011; Remler and Atherly, 2003).

In order to examine whether distinct patients respond differently to variation in subsidies, we compute both mortality and hospitalization rates for Type I and Type II diabetes separately. We then run our most complete specifications, as reported in column 3 of Tables 3 and 4, to test how outcomes by diabetes type respond to ATFP. Table 7 presents the results. We find larger effects for both mortality and hospitalization rates for Type II diabetes. In particular, we see that ATFP is significantly associated with a decline in hospital admissions for both types. However, while OLS coefficients are similar, in column 2 we observe that the 2SLS point estimate is significantly larger for Type II diabetes – nearly threefold the magnitude observed for Type I diabetes. Relying on Wald tests, we do not reject the null hypothesis that the coefficients are the same for mortality, but we do reject for hospitalization (at 1%). Also, ATFP effects on hospital admissions by Type II diabetes are 33% greater in comparison to Type I when considered the average hospitalization rate for each group (-1.93/65 $\sim$ -2.9% for Type I *vs* -6.28/161 $\sim$ -3.9% for Type II). Overall, these results are consistent with insulin-dependent patients being relatively less responsive to subsidies because of higher immediate life-threatening risks.

6.2 Heterogeneity by SES

Patients are allowed access to medications within ATFP once they hold a medical prescription, irrespectively of their socioeconomic status, age or health condition. Given that antidiabetic drugs are now available free-of-charge at accredited pharmacies, ATFP mimics SUS in the sense that it has granted equal access to listed medications for all prescription holders. However, although the poor have in general resorted to SUS in order to access health services, while the non-poor have generally used the private system, there is no evidence on whether this pattern also holds within the particular case of ATFP. In practice, better-off individuals could benefit relatively more from ATFP have they had better access to accredited pharmacies as well as to information regarding their own health status, medication needs, and eligibility to the program. This would make ATFP a regressive co-payment system, potentially escalating the gap between the poor and the non-poor in terms of access to resources and health outcomes.[19] In this section we examine whether both ATFP utilization and its effects on health outcomes vary with socioeconomic status.

[19]The Brazilian tax system is not far from neutral as it largely relies on indirect taxation (OECD, 2009). Thus, given that the ATFP's sources of financing are not particularly progressive, the program becomes relatively more regressive as the participation of the better-off in pharmaceutical spending increases.

We start by exploring the microdata from the National Health Survey (*Pesquisa Nacional de Saúde*, PNS), a nationwide survey carried out in 2013 by IBGE and the Brazilian Ministry of Health. The PNS contains household and individual socioeconomic information as well as a series of questions related to health conditions, lifestyle, access to (and utilization of) health and pharmaceutical services, and so forth. In particular, the PNS contains questions on ATFP utilization. By the year of the survey, the program had already completed most of its expansion, both across and within municipalities. As mentioned in Section 2.2, according to PNS data, 56% of the individuals older than 40 who had recently taken medications for diabetes, had obtained at least some of them through the program.

We now use PNS data to test whether ATFP utilization varies with socioeconomic status. Table 5 reports two sets of OLS regressions based on the sub-sample of individuals aged 40 years old or more. All specifications include state fixed-effects.[20] In the first two columns we further restrict the sample to those individuals who had been recently prescribed any medication, and regress on socioeconomic variables an indicator of whether the individual obtained any of the prescribed drugs through ATFP. The specification in the first column includes demographic variables (dummies for gender, race, urban, and age in completed years) and dummies for levels of schooling. We observe that ATFP utilization monotonically decreases with education, being individuals with college degree 13.4 percentage points less likely to use ATFP than those with no schooling (the omitted category). In column 2 we observe that part of the negative association between schooling and ATFP utilization is absorbed by dummies indicating PSF and private insurance coverage. The overall pattern indicates that ATFP utilization correlates with lower socioeconomic status. In the third column we restrict the sample to those who had recently taken antidiabetic drugs, and regress on the same set of variables included in column 2 an indicator of whether the individual had obtained any of those drugs through ATFP. We observe again a negative correlation between ATFP utilization and socioeconomic status.

Having shown that ATFP utilization by the chronically-ill is relatively higher among the poor, we next examine whether and how the program's effects on health outcomes vary by socioeconomic status. We focus on hospital admissions, for which we have the patients' zip codes of residence. We first use GIS to match zip codes to census tracts and their respective average income, obtained from the 2000 Census.[21] This enables us to associate each zip code with a dummy indicating whether it is located in a poor *vs* a non-poor census tract,

[20] We do not observe municipality identifiers in the PNS data.

[21] The data at the census tract level are geocoded and publicly provided by IBGE. More specifically, our average income variable refers to the average income of the heads of the households located in the census tract. The year of 2000 is the first of our period of analysis.

i.e., respectively, below *vs* above the median average income. Next, we count the number of hospital admissions of patients aged 40 years old or more from zip codes located in poor census tracts by diabetes, municipality and year. We analogously repeat the counting for admissions of patients from non-poor zip codes. The final variables are then merged with our main panel of data at the municipality-by-year level.

We follow our benchmark specifications, as reported in column 3 of Tables 3 and 4, to estimate ATFP effects on the logarithm of the number of hospital admissions of patients from poor *vs* non-poor zip codes.[22] Table 6 presents the results. The upper panel reports the ATFP effects on the number of hospital admissions of patients from poor zip codes, while the bottom panel shows the analogous estimates for non-poor ones. The comparison of the point estimates from our 2SLS specification indicates that ATFP effects are significantly larger for patients from lower socioeconomic status, confirmed by a Wald test at 1%, which is consistent with our findings on ATFP utilization from Table 5. Despite the fact that access to listed medications is equal for all prescription holders, irrespective of socioeconomic status, the overall evidence supports the view that, in practice, diabetic patients from relatively lower SES have benefited the most from ATFP.

7 Adherence to Treatment and Medication

As mentioned in Section 2.2, the existing qualitative evidence indicates that the use of antidiabetic medication increased with ATFP, likely reflecting higher adherence to treatment. In particular, the program may be improving adherence among those that intermittently follow prescriptions in general, but also bringing in patients that usually do not take medications and are not managing the condition. In this section, we use PNS data to bear on these conjectures and further discuss the different mechanisms at play.

We first select the sample of all diabetic individuals aged 40 years or more from PNS (2013), and compute three sets of variables: (i) dummies that indicate whether either oral hypoglycemics (mean 77%) or insulin (mean 17%) were recently taken; (ii) a dummy for whether the individual had obtained this medication through ATFP (mean 56%); and (iii) a proxy indicator for poor management of the condition – more specifically, we define a dummy for those that responded not having regularly visited a physician or healthcare service for diabetes under the claim that he/she believed not to be necessary (mean 22%). We then run an OLS model in which indicators for medication use, as a proxy for adherence, are regressed

[22] We are unable to build hospitalization rates by zip codes because we do not observe the respective population at risk at this level of geographical aggregation.

against purchase through ATFP, poor management of the condition, and their interaction, conditional upon the same set of socioeconomic variables included in the specifications of Table 5.[23]

Table 8 reports the results. In the first two columns the dependent variable is a dummy for oral hypoglycemics, while the remaining two columns display results for insulin. In the first column we observe that use of oral hypoglycemics is positively correlated with purchase at ATFP and, as expected, negatively associated with the proxy for poor management of diabetes. Interestingly, in the second column we find that the interaction between ATFP and poor management mitigates the latter. The remaining two columns report the same pattern for insulin, although the interaction term is now statistically insignificant. While PNS (2013) does not allow us to identify Type I *vs* Type II patients, the overall picture indicates that Type II patients are relatively more responsive to ATFP; and the picture is consistent with insulin-dependent patients being relatively less responsive to the program. Importantly, Table 8 indicates that ATFP is associated with greater use of medication in general; and it is associated with greater use of medication among those under poor management of the condition in particular. Overall, the results suggest a positive association between ATFP and adherence to medication.

8 Averted Hospital Admissions and Costs

In this section we use counterfactual simulations to estimate ATFP effects in terms of total number of averted hospital admissions by diabetes and their respective costs over the period of analysis.[24]

We depart from our baseline 2SLS specification, which delivers a predicted hospitalization rate $\widehat{H}_{it}$ for each municipality and year. Given the estimated parameters, we are able to recalculate each $\widehat{H}_{it}$ under the alternative condition $ATFP_{it} = 0, \forall(i,t)$. We then multiply these rates by the population at risk in each municipality and year (individuals aged 40 years old or more) to estimate the respective number of hospital admissions by diabetes. This calculation delivers the predicted number of admissions had ATFP been not imple-

[23]Regarding the dummies computed for medication use, we rely on questions Q03401 and Q03402 of the PNS (2013) questionnaire, which ask "in the past two weeks, because of diabetes, did you take oral hypoglycemics?"; "did you take insulin?". We have defined dummies equal to 1 for those who answered yes for each respective medication. These indicators are proxies for medication adherence. Unfortunately, we are not able to use validated measures of adherence that are typically used in the literature, as those recommended by the National Quality Forum (NQF), such as the proportion of days covered methods (for instance, as in Muench et al., 2019).

[24]In this section, we focus only on hospital admissions since the estimated ATFP effects on mortality rates are either statistically weak or null.

mented. Finally, we sum up hospital admissions across all municipalities and all years to estimate the total number of admissions by diabetes had ATFP been not implemented.

Column 1 of Table 9 shows the observed number of diabetes hospital admissions for the 2000 through 2012 period. In column 2, we present the counterfactual trend for the hypothetical scenario described above. As seen in column 1, the number of observed admissions totaled 1,205,507. We estimate that, had ATFP been not implemented, this number would have equaled 1,447,659. This indicates that ATFP averted approximately 242 thousand admissions, which represent 16.7% of the total number of hospital admissions predicted in the counterfactual scenario.

Hospitals determine procedures and services provided to SUS patients, and charge the Ministry of Health according to fixed official fees. SIH is the administrative hospitalization dataset that informs the costs in R$ for each hospital admission within SUS. We collapse admissions' costs by year and patients' municipality of residence in order to build an annual measure of diabetes hospitalization costs per capita. We follow exactly the same counterfactual exercise described above to estimate ATFP effects in terms of averted costs.

Column 3 of Table 9 shows the observed hospitalization costs for diabetes for the 2000 through 2012 period, while column 4 reports the counterfactual trend had ATFP been not implemented. The simulation indicates that ATFP averted R$114.5 million on hospital admissions for diabetes.[25] In other words, the Ministry of Health would have transferred an additional R$114.5 million to hospitals had ATFP been not implemented. This amount of funds nevertheless corresponds exclusively to fees reimbursed by the federal government and transferred to hospitals. It is important to emphasize that federal reimbursement fees within SUS are undervalued not only for international standards, but also in comparison to market prices in the domestic private sector (Couttolenc and La Forgia, 2009). Based on the SUS reimbursement schedule of 2012, the average inpatient cost per admission for diabetes reimbursed by the federal government was as low as R$631, or about US$315.[26] State and municipal governments often add funds on top of federal transfers to match variable costs, and additionally cover the remaining fixed costs. Indeed, the estimated averted hospitalization costs for diabetes represents 12.7% of the costs had ATFP been not implemented. The amount of averted costs is thus substantial in relative terms.

In order to compute a more accurate picture of total averted costs, we proceed as follows. First, we estimate the total amount of reimbursements made by the federal government to hospitals in 2012 (R$11.6 billion) and total spending with hospitals within SUS in the same

[25] All values in R$ 2012.

[26] Based on the official exchange rate of US$1 = R$2.04, as of December 31st, 2012.

year according to the System of Health Accounts (R$61 billion).[27] Federal reimbursements thus corresponded to 19% of the total hospital costs, and the difference between reimbursements and total costs corresponded to R$49.4 billion. Second, we estimate the share of total federal reimbursements in 2012 due to hospitalization for diabetes (0.52%). Applying this factor to the difference between total federal reimbursements and total hospital spending in 2012 leads to R$258.8 million. We interpret this latter figure as the amount of resources needed to cover the remainder costs of hospital admissions for diabetes in 2012, which roughly corresponded to four times the total amount of federal reimbursements for diabetes in 2012 (R$60 million). Summing up that annual figure over the 2006 throughout 2012 years, and applying a conservative flat rate of 12.7% of averted costs, as estimated in Table 8 for reimbursements, leads to R$230 million. Together with averted federal reimbursements (R$114.5 million) we find total averted costs related to hospital admissions for diabetes of R$344.5 million over the 2006 throughout 2012 period.

Throughout the 2006-2012 period, the ATFP system transferred approximately R$607 million to accredited pharmacies on reimbursements for antidiabetic drugs.[28] Averted hospitalization costs alone thus corresponded to 19% of this value. In order to put these figures into perspective, according to American Diabetes Association (2018), in the US in 2017, hospital inpatient care corresponded to about 30% of the direct medical cost attributed to diabetes, and to 21% of the total financial burden of the disease, which includes both medical costs and labor market productivity losses. This suggests that each dollar spent on inpatient care reflects a total financial burden of about 5 dollars. If we multiply by 5 the predicted hospitalization costs had ATFP been not implemented, and take 12.7% of this total, we find that ATFP averted a total financial burden of R$1.7 billion. Overall these results indicate that the benefit accrued from ATFP outpaces its costs.[29]

[27] See Ministério da Saúde e Fiocruz (2018).

[28] It is important to mention that antidiabetic drugs are currently free-of-charge for patients, means that pharmacies are paid the program's reference prices, and are thus not able to mark-up retail prices. In this sense, ATFP transfers are supposed to be entirely channeled towards patients.

[29] It is important to mention that the incidence of comorbidities would add another layer of complexity to our calculations and was not considered here. On the one hand, diabetic patients with other chronic conditions, and access to other medications covered by ATFP, could be less likely to incur in hospitalizations for these other conditions. On the other hand, the same applies for patients with comorbidities that might incur in less hospitalizations for other chronic conditions because ATFP helped improve the management of diabetes. Unfortunately, we are not able to look at comorbidities and further disentangle the cross-treatment of ATFP over conditions.

9 Conclusions and Policy Implications

This paper evaluates the health effects of a large-scale subsidizing program of prescription drugs introduced in Brazil, the *Aqui Tem Farmácia Popular* program (ATFP). We exploit features of the program to identify its effects on mortality and hospitalization rates by diabetes for individuals aged 40 years or more. In our empirical setting, variation in subsidies comes net of simultaneous changes in access to other health services as well as in other cost-sharing mechanisms; also, access to pharmaceuticals are mostly made through out-of-pocket spending, and liquidity constraints are relatively binding for most individuals. Differently from prior studies, overwhelmingly raised from context-specific settings in the US, we thus provide estimates of health effects of variation in subsidies within a cost-sharing scheme in a context where individuals are more vulnerable and substantially less insured on pharmaceutical services.

We find weak evidence for a decline in mortality, but a robust reduction in hospitalization rates. Effects are larger for Type II diabetes in comparison to Type I, and among patients with relatively lower socioeconomic status. These results are consistent with insulin-dependent patients being relatively less responsive to subsidies because of higher immediate life-threatening risks, and with lower-SES individuals being more responsive because of liquidity constraints.

We highlight at least two relevant policy implications based on the overall results of this paper. First, the results support the view that the choice on the balance between subsidies and out-of-pocket spending within cost-sharing strategies might have relevant impacts on health outcomes and equity, particularly in a context where patients are more vulnerable. In this situation, the optimal design of health systems and cost-sharing policies should take into account their potential offsetting effects on the utilization of downstream health services and health outcomes. This is informative to many countries across the world that are developing or revising health financing policies in an effort to improve health system performance, enhance access to essential medicines, and progress towards universal health coverage. In particular, to the best of our knowledge, this paper provides the first empirical evidence on prescription drug cost-sharing effects from a developing country. Our estimates are thus particularly informative to countries where the delivery of health services and the access to essential medicines are still challenging policy issues.

Regarding a second key policy implication, while never before have there been so many resources for medicines worldwide (PAHO, 2011), and so many countries expanding universal health coverage (Rodin and de Ferranti, 2012), there still exists an enormous gap

between what countries achieve and what they could potentially achieve with the same resources (WHO, 2010). Particularly in developing countries, the lack of access to essential medicines often reflects the lack of state capacity to provide public goods and services in general. Despite all donor or government sponsored programs devoted to improving access to medicines in low and middle-income countries, for instance, median availability of selected generic drugs in public health facilities is no higher than 37% and 46%, respectively (WHO, 2017). While improving public service delivery is one of the biggest policy challenges worldwide (Besley and Ghatak, 2007), the delivery of pharmaceutical services is particularly difficult. The management of medicines supply requires a series of complex steps, such as the selection of drugs according to local needs, procurement, storage, distribution, and dispensing. The magnitude of inefficiencies, waste and diversion over the entire supply cycle can be substantial in developing countries, where government failures are widespread (MSH, 2012). The identification of efficient ways of delivering essential medicines has become a center piece of policymaking in health care. In this regard, we document the implementation and the outcomes of a program built in partnership with the private retail sector to enhance access to antidiabetic drugs. Our results indicate that the ATFP program has overcome logistical challenges for the delivering of pharmaceutical services in a cost-efficient way.

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Tables and Figures

A Main Results

Table 1: Diabetes Mortality and Hospitalization Baseline Rates (at the Municipality-Year Level, per 100,000 Individuals Aged 40+) and Controls

	Obs (Mun*Years)	Mean	SD	Min	Max
		Panel A - Diabetes			
Mortality Rate	33,042	62	64	0	840
Type I	33,042	2	12	0	383
Type II	33,042	59	62	0	840
Hospitalization Rate	33,042	226	233	0	8,747
Type I	33,042	65	126	0	3,795
Type II	33,042	161	204	0	8,206
		Panel B - Controls			
Ln GDP per capita	33,042	9	1	7	13
Hospitals per capita (per 100,000)	33,042	6	8	0	92
Hospital Beds per capita (per 100,000)	33,042	217	272	0	5,339
Ln Pop Density	33,042	3	1	-2	9
PSF Coverage (in %)	33,042	49	40	0	100
PACS Coverage (in %)	33,042	23	31	0	100
Private Pharmacies per capita (per 100,000)	33,042	61	39	0	483
		Panel C - IV and ATFP			
Panel C.1: Inputs for IV (RAIS Data, 2006)					
Pharmacists	5,507	0.20	0.24	0.00	3.47
Other pharmacy workers	5,507	0.17	0.27	0.00	4.25
Lawyers	5,507	0.14	0.25	0.00	4.33
Managers	5,507	0.15	0.41	0.00	15.77
Panel C.2: ATFP per 100,000, 2006-2012	38,549	6.72	13.09	0.00	136.38

Notes: Diabetes mortality and hospitalization rates per 100,000 individuals aged 40 years or more and controls, computed for the period prior to the implementation of ATFP (pooled from 2000 to 2005), calculated at the municipality-year level. Data originally from: SIM/Datasus, SIH/Datasus, Ipeadata and RAIS/MTE. Panel C reports descriptive statistics for our instrumental variable and variable of interest. Panel C.1 presents the number of pharmacists, other pharmacy workers, lawyers and managers per 1,000 inhabitants in 2006. Data originally from 2006 RAIS. Panel C.2 presents the number of ATFP per 100,000 inhabitants, average over 2006-2012. Data originally from SAGE/MS. All cells report calculations at the municipality-year level.

Table 2: First-Stage Results and Falsification Tests

	Dep. Var.: ATFP per 100,000 Inhabitants				
	(1)	(2)	(3)	(4)	(5)
T_t * Pharmacists	2.924				3.420
	(0.208)***				(0.228)***
T_t * Other pharmacy workers		0.311			-0.389
		(0.206)			(0.195)**
T_t * Lawyers			-0.011		-0.173
			(0.189)		(0.189)
T_t * Managers				-0.029	-0.055
				(0.077)	(0.079)
KP F-Stat	197.8	2.275	0.003	0.143	225.7
Observations	71,591	71,591	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507	5,507	5,507
R^2	0.611	0.583	0.582	0.582	0.615
Year and Municipality FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table reports first-stage results and falsification tests. Dependent variable in all columns: ATFP per 100,000 inhabitants. In column (1), the variable of interest is the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. In columns (2)-(4) the variables of interest are, respectively, the number of pharmacy clerks, lawyers and managers per 1,000 inhabitants in 2006 interacted with T_t. All regressions include municipality and year fixed effects as well as the following additional controls (not shown in the table): the logarithm of GDP per capita, population density and the share of population by each 5-year bracket, health infrastructure (hospital beds, hospitals), health services (PSF and PACS coverage in %), and the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Effects of ATFP on Diabetes Mortality
(per 100,000 Individuals aged 40+)

	Diabetes Mortality Rates		
	(1)	(2)	(3)
	Panel A - OLS		
ATFP	0.040	0.050	0.038
	(0.058)	(0.056)	(0.056)
	Panel B - 2SLS		
ATFP	-0.753	-0.580	-0.625
	(0.362)**	(0.346)*	(0.354)*
	Panel C - Reduced Form		
Instrument	-2.251	-1.736	-1.827
	(1.039)**	(1.006)*	(1.003)*
Observations	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507
Year and Municipality FE	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes
Health services & infra.	No	Yes	Yes
Private pharmacies	No	No	Yes

Notes: Panels A and B report the effects of ATFP on diabetes mortality rates, respectively for OLS and 2SLS models. In the 2SLS specification, the instrument is defined by the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. Panel C reports reduced-form coefficients. The dependent variable in all columns is the mortality rate per 100,000 individuals aged 40 years or more by diabetes. All regressions include municipality and year fixed effects as well as socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket). Specifications in columns 2 and 3 control for hospitals per capita, hospital beds per capita, PSF and PACS coverage (in %). Specification in column 3 also includes the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Effects of ATFP on Diabetes Hospitalization Rates (per 100,000 Individuals aged 40+)

	Diabetes Hospitalization Rates		
	(1)	(2)	(3)
	Panel A - OLS		
ATFP	-1.032	-0.953	-1.025
	(0.277)***	(0.276)***	(0.269)***
	Panel B - 2SLS		
ATFP	-8.252	-7.849	-8.217
	(1.518)***	(1.474)***	(1.526)***
	Panel C - Reduced Form		
Instrument	-24.681	-23.498	-24.026
	(4.182)***	(4.063)***	(4.050)***
Observations	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507
Year and Municipality FE	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes
Health services & infra.	No	Yes	Yes
Private pharmacies	No	No	Yes

Notes: Panels A and B report the effects of ATFP on diabetes hospitalization rates, respectively for OLS and 2SLS models. In the 2SLS specification, the instrument is defined by the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. Panel C reports reduced-form coefficients. The dependent variable in all columns is the mortality rate per 100,000 individuals aged 40 years or more by diabetes. All regressions include municipality and year fixed effects as well as socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket). Specifications in columns 2 and 3 control for hospitals per capita, hospital beds per capita, PSF and PACS coverage (in %). Specification in column 3 also includes the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: ATFP Effects by Diabetes Type

	Effects by Diabetes Type		
	OLS	2SLS	RF
Panel A - Type I Diabetes (Insulin-Dependent)			
Mortality	0.022	0.019	0.057
	(0.009)**	(0.056)	(0.165)
Hospitalization	-0.498	-1.931	-5.645
	(0.157)***	(0.774)**	(2.285)**
Panel B - Type II Diabetes (Non Insulin-Dependent)			
Mortality	0.016	-0.644	-1.884
	(0.055)	(0.334)*	(0.944)**
Hospitalization	-0.528	-6.286	-18.381
	(0.226)**	(1.487)***	(3.989)***
Observations	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507

Notes: Each cell presents the results (point estimate and standard error) from a different regression. The first two columns show coefficients from OLS and 2SLS specifications, respectively, while the third column reports reduced-form estimates. Mortality/Hospitalization rows refer to estimates for effects on mortality and hospitalization rates, respectively. In the upper panel, outcomes are computed for type 1 diabetes only. The bottom panel refers to outcomes for type II diabetes. All regressions include municipality and year fixed effects, socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket), controls for the presence of hospitals, hospital beds per capita, PSF and PACS coverage (in %), and the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Determinants of ATFP Use, Individuals Aged 40+

	Medicines Purchased at ATFP		Diabetes Drugs Purchased at ATFP
	(1)	(2)	(3)
Male	0.001	0.001	-0.040
	(0.010)	(0.010)	(0.020)**
Age	0.001	0.001	-0.003
	(0.000)***	(0.000)***	(0.001)***
Non-White	0.004	-0.002	0.038
	(0.010)	(0.011)	(0.021)*
Urban	0.007	0.019	0.022
	(0.014)	(0.014)	(0.028)
Education - Primary (incomp)	0.001	0.006	0.032
	(0.015)	(0.015)	(0.027)
Education - Primary (comp)	-0.003	0.010	-0.043
	(0.018)	(0.018)	(0.032)
Education - Secondary (incomp)	-0.045	-0.024	-0.089
	(0.027)*	(0.027)	(0.058)
Education - Secondary (comp)	-0.053	-0.018	-0.137
	(0.017)***	(0.018)	(0.035)***
Education - College (incomp)	-0.063	-0.015	-0.177
	(0.030)**	(0.031)	(0.066)***
Education - College (comp)	-0.134	-0.074	-0.190
	(0.018)***	(0.019)***	(0.040)***
Covered by PSF		0.038	0.090
		(0.010)***	(0.020)***
Health Insurance		-0.077	-0.219
		(0.012)***	(0.023)***
Sample	**If Recently Prescribed**	**If Recently Prescribed**	**If Diabetes Drugs Taken**
Observations	8,749	8,749	2,579
Dep. Var. Mean	0.261	0.261	0.560

Notes: This table reports the determinants of ATFP use. In the first two columns, the dependent variable is a dummy that indicates whether medicines were purchased through ATFP. In columns 3 we restrict the sample to those who had recently taken anti-diabetics drugs. For columns (1)-(3) the independent variables are dummies indicating gender, age, race, urban and level of schooling. For columns (2)-(3), we also include dummies indicating coverage of PSF and private health insurance. All regressions include state fixed effects. Data from PNS (2013). Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: ATFP Effects on Hospitalization by SES
Poor Zipcodes *vs* Non-Poor Zipcodes

	Diabetes Hospitalization Rates		
	OLS	2SLS	RF
Poor Zipcodes	-0.003	-0.061	-0.177
	(0.004)	(0.019)***	(0.056)***
Non-Poor Zipcodes	0.001	-0.028	-0.081
	(0.002)	(0.012)**	(0.035)**
Observations	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507

Notes: Each cell presents the results (point estimate and standard error) from a different regression. In all specifications the dependent variable is the hyperbolic sine-transformation of the number of hospital admissions for diabetes. The first two columns show coefficients from OLS and 2SLS specifications, respectively, while the third column reports reduced-form estimates. Poor/non-poor zipcodes refer to zipcodes with average income below/above the median household income per capita. All regressions include municipality and year fixed effects, socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket), controls for the presence of hospitals, hospital beds per capita, PSF and PACS coverage (in %), and the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Determinants of Adherence to Medication Use for Diabetes: Diabetic Individuals, Aged 40+ (PNS 2013)

	Oral Hypoglycemics Taken		Insulin Taken	
	(1)	(2)	(3)	(4)
Anti-Diabetics Purchased at ATFP	0.312	0.267	0.159	0.164
	(0.014)***	(0.015)***	(0.014)***	(0.015)***
Adherence: Not Important	-0.209	-0.292	-0.081	-0.071
	(0.019)***	(0.025)***	(0.014)***	(0.014)***
Purchased at ATFP * Not Important		0.265		-0.032
		(0.033)***		(0.034)
Male	-0.017	-0.012	0.028	0.027
	(0.014)	(0.014)	(0.014)**	(0.014)**
Age	0.003	0.003	0.002	0.002
	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Non-White	-0.014	-0.013	0.022	0.021
	(0.015)	(0.014)	(0.014)	(0.014)
Urban	0.008	0.005	0.033	0.034
	(0.019)	(0.019)	(0.018)*	(0.018)*
Education - Primary (incomp)	-0.009	-0.010	0.030	0.030
	(0.018)	(0.018)	(0.019)	(0.019)
Education - Primary (comp)	0.018	0.017	0.010	0.010
	(0.022)	(0.022)	(0.022)	(0.022)
Education - Secondary (incomp)	0.052	0.047	-0.037	-0.037
	(0.035)	(0.034)	(0.034)	(0.034)
Education - Secondary (comp)	0.045	0.038	-0.012	-0.011
	(0.025)*	(0.025)	(0.023)	(0.023)
Education - College (incomp)	0.115	0.116	-0.000	-0.000
	(0.052)**	(0.052)**	(0.049)	(0.049)
Education - College (comp)	0.093	0.087	0.006	0.007
	(0.030)***	(0.030)***	(0.029)	(0.029)
Covered by PSF	-0.026	-0.026	-0.011	-0.011
	(0.014)*	(0.014)*	(0.014)	(0.014)
Health Insurance	0.066	0.061	0.056	0.057
	(0.017)***	(0.017)***	(0.016)***	(0.016)***
Observations	3,321	3,321	3,321	3,321

Notes: This table reports the determinants of anti-diabetics use for diabetic patients. In the first two columns, the dependent variable is a dummy that indicates whether oral hypoglycemics were taken in the past two weeks, while in the remaining two columns the outcome variable indicates whether insulin was taken in the past two weeks. All columns include an independent dummy variable indicating whether any anti-diabetic was purchased at ATFP; and an independent dummy indicating that the patient's reason not tot attend regular clinic visits to monitor diabetes is that it is not important. Columns 2 and 4 included interaction terms. For all columns controls include dummies indicating gender, age, race, urban and level of schooling, PSF coverage and private health insurance. All regressions include state fixed effects. Data from PNS (2013). Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

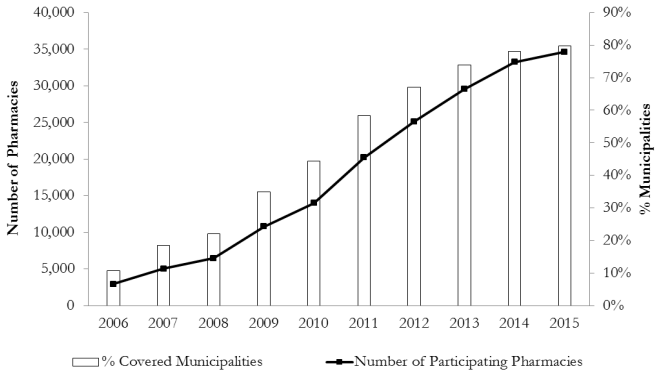
Table 9: Counterfactual Simulations: Diabetes Hospitalization and Hospitalization Costs (in R$1,000 of 2012)

Year	Hospital Admissions		Hospitalization Costs	
	Observed	Predicted	Observed	Predicted
2000	91,874	91,874	69,005	69,005
2001	95,586	95,586	67,848	67,848
2002	87,805	87,805	52,725	52,725
2003	84,017	84,017	49,154	49,154
2004	83,655	83,655	52,241	52,241
2005	84,676	84,676	50,947	50,947
2006	84,278	90,982	47,036	50,209
2007	82,173	96,302	47,050	53,736
2008	93,957	112,621	61,881	70,713
2009	102,894	133,628	74,290	88,833
2010	108,885	150,054	77,470	96,950
2011	109,450	167,868	73,970	101,611
2012	96,257	168,591	60,775	95,001
Total, 2006-2012	1,205,507	1,447,659	784,392	898,971
Averted, 2006-2012		242,152		114,580
Averted, 2006-2012 (in % of predicted)		16.7%		12.7%

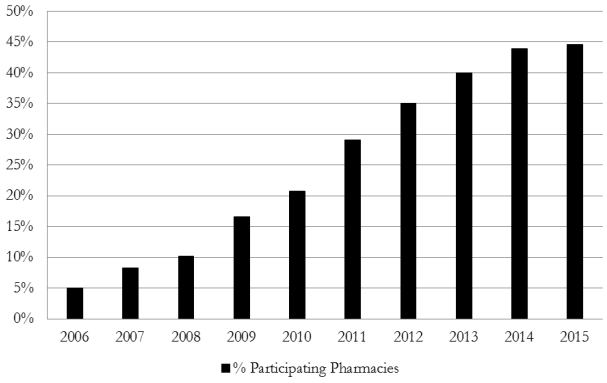
Notes: Counterfactual simulations as described in Section 8. Column 1 shows the observed hospitalization for diabetes from 2000 to 2012. In column 2, we present the counterfactual trend for the hypothetical scenario had ATFP been not implemented. The remainder two columns report the analogous results for diabetes hospitalization costs.

Figure 1: ATFP Expansion, 2006-2015

(a) Total Number of ATFP Pharmacies and Municipality Coverage



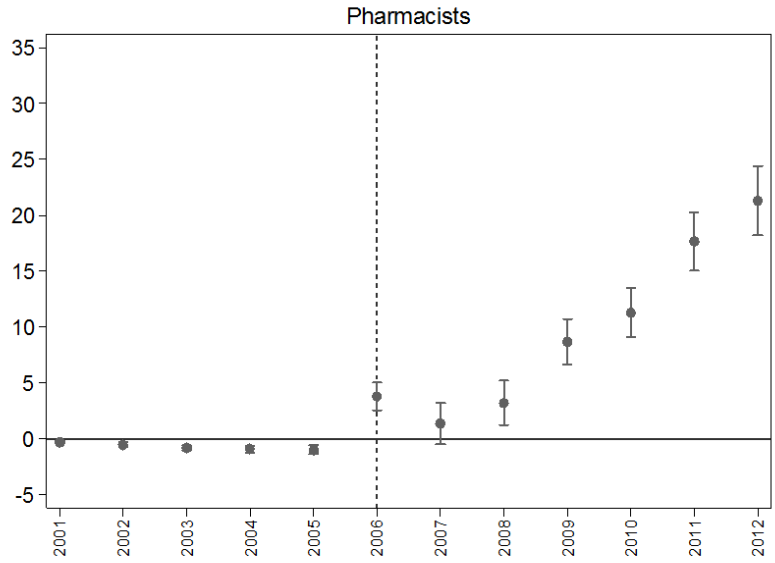
(b) Share of Private Pharmacies Accredited to ATFP



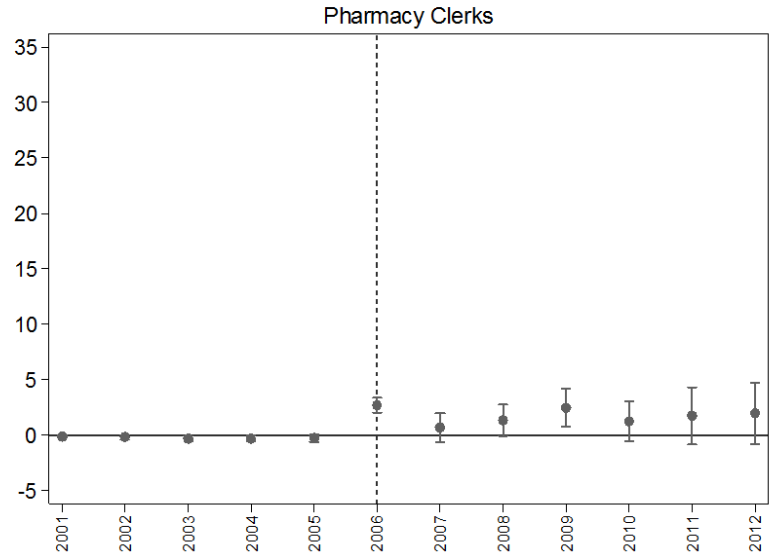
Source: Data on ATFP pharmacies from the Ministry of Health (SAGE/MS), available on http://189.28.128.178/sage/. Total number of pharmacies from RAIS.

Figure 2: First-Stage Results in a Flexible, Non-Linear Specification: How the Annual Expansion of ATFP Responds to the Supply of Pharmacists

(a) Pharmacists in the Baseline Year and the Expansion of ATFP



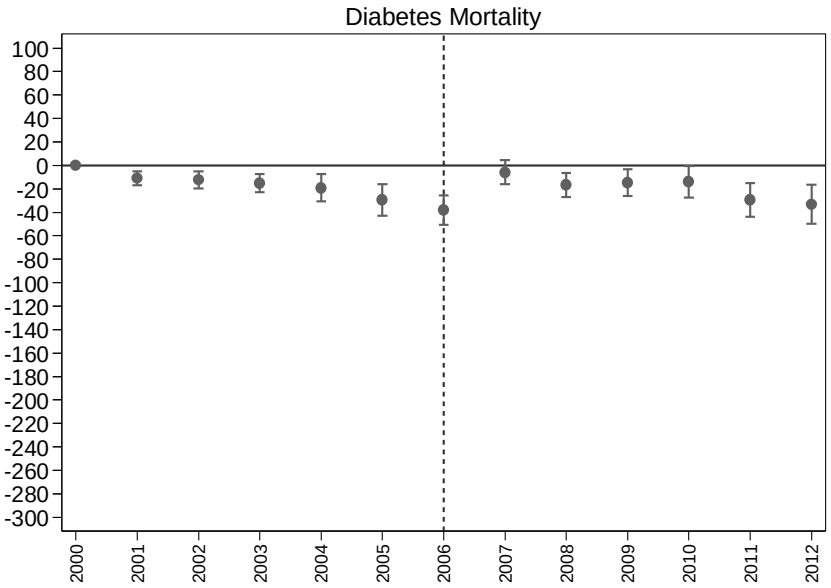
(b) Other Pharmacy Workers in the Baseline Year and the Expansion of ATFP



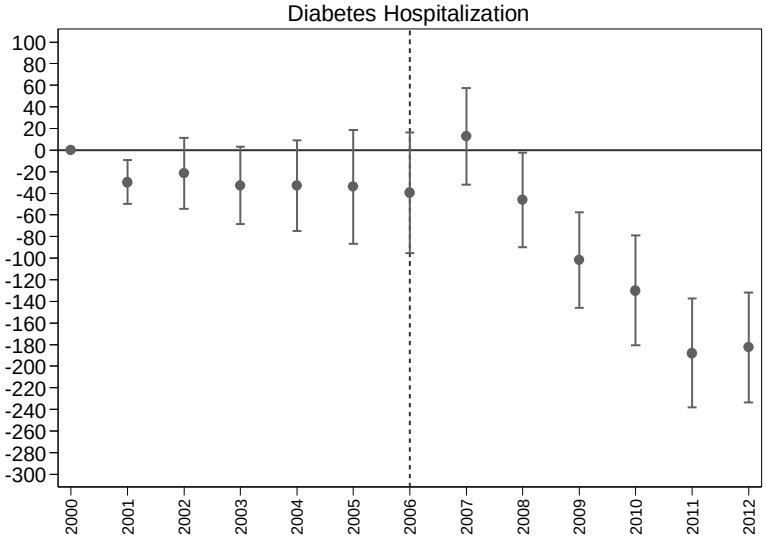
Notes: We follow equation (2), but now estimate coefficients of interaction terms between $Pharmacists_{i,06}$ (Panel A) or $PharmacyWorkers_{i,06}$ (Panel B) with year dummies for each year over the entire period.

Figure 3: Pre-Trends in a Flexible, Non-Linear Specification: How Diabetes Outcomes Respond to the Supply of Pharmacists

(a) Pharmacists in the Baseline Year and Diabetes Mortality



(b) Pharmacists in the Baseline Year and Diabetes Hospitalization



Notes: We follow equation (2), but now estimate coefficients of interaction terms between $Pharmacists_{i,06}$ with year dummies for each year over the entire period. Outcome variables are diabetes mortality (upper figure) and hospitalization (bottom figure) rates.

B Appendix Tables and Figures

Table B.1: List of Medicines Covered by ATFP, with Reference Prices, Government Reimbursement and Year of Inclusion in the Program

Indication	Active Principle and Composition	Reference Price* in R$	Government Maximum Copayment in R$	First Year
Contraception	Medroxyprogesterone Acetate 150 mg	12.36	11.12	2007
Contraception	Ethinylestradiol 0,03 mg + Levonorgestrel 0,15 mg	4.19	3.77	2007
Contraception	Norethisterone 0,35 mg	4.96	4.46	2007
Contraception	Estradiol Valerate 5 mg + Norethisterone Enanthate 50 mg	11.31	10.17	2007
Asthma	Ipratropium Bromide 0,02 mg	0.06	0.05	2010
Asthma	Ipratropium Bromide 0,25 mg	0.27	0.24	2010
Asthma	Beclometasone Dipropionate 200 mcg	0.25	0.23	2010
Asthma	Beclometasone Dipropionate 250 mcg	0.15	0.14	2010
Asthma	Beclometasone Dipropionate 50 mcg	0.13	0.12	2010
Asthma	Salbutamol 100 mcg	0.10	0.09	2010
Asthma	Salbutamol 5 mg	0.88	0.79	2010
Diabetes	Metformin 500 mg	0.13	0.13	2006
Diabetes	Metformin 500 mg - Prolonged Release	0.18	0.18	2006
Diabetes	Metformin 850 mg	0.16	0.16	2006
Diabetes	Glibenclamide 5 mg	0.12	0.12	2006
Diabetes	Human Insulin 100 IU/ml	26.55	26.55	2006
Diabetes	Regular Insulin 100 IU/ml	26.55	26.55	2006
Dyslipidemia	Simvastatin 10 mg	0.26	0.23	2010
Dyslipidemia	Simvastatin 20 mg	0.51	0.46	2010
Dyslipidemia	Simvastatin 40 mg	0.99	0.89	2010
Glaucoma	Timolol 2,5 mg	0.40	0.36	2010
Glaucoma	Timolol 5 mg	0.96	0.86	2010
Hypertension	Atenolol 25 mg	0.19	0.19	2006
Hypertension	Captopril 25 mg	0.28	0.28	2006
Hypertension	Propranolol 40 mg	0.08	0.08	2006
Hypertension	Hydrochlorothiazide 25 mg	0.08	0.08	2006
Hypertension	Losatan Potassium 50 mg	0.32	0.32	2006
Hypertension	Enalapril Maleate 10 mg	0.39	0.39	2006
Osteoporosis	Alendronate Sodium 70 mg	3.74	3.37	2010
Parkinson's disease	Carbidopa 25 mg + Levodopa 250 mg	0.64	0.58	2010
Parkinson's disease	Benserazide 25 mg + Levodopa 100 mg	1.17	1.05	2010
Rhinitis	Budesonide 50 mcg	0.13	0.12	2010

* Reference price by pill, ampoule or dose.

Notes: This list include all medicines covered by ATFP. Information from SAGE, MS: http://sage.saude.gov.br/ and Ministério da Saúde: http://portalms.saude.gov.br/assistencia-farmaceutica/programa-farmacia-popular.

Table B.2: Additional Reduced-Form Results: Supply of Pharmacists Wages and Net Migration

	Average Wage (ln)				Net
	Pharmacists	Other Pharma.	Lawyers	Managers	Migration
	(1)	(2)	(3)	(4)	(5)
T_t * Pharmacists	-0.041	-0.000	-0.005	0.015	-1.316
	(0.007)***	(0.007)	(0.011)	(0.012)	(3.053)
Observations	45,302	35,315	37,638	30,192	66,084
R^2	0.314	0.398	0.022	0.019	0.126
Number of Municipalities	4,802	4,271	4,393	4,222	5,507
Year and Municipality FE	Yes	Yes	Yes	Yes	Yes
Partial F-Stat	36.170	0.003	0.178	1.541	0.186

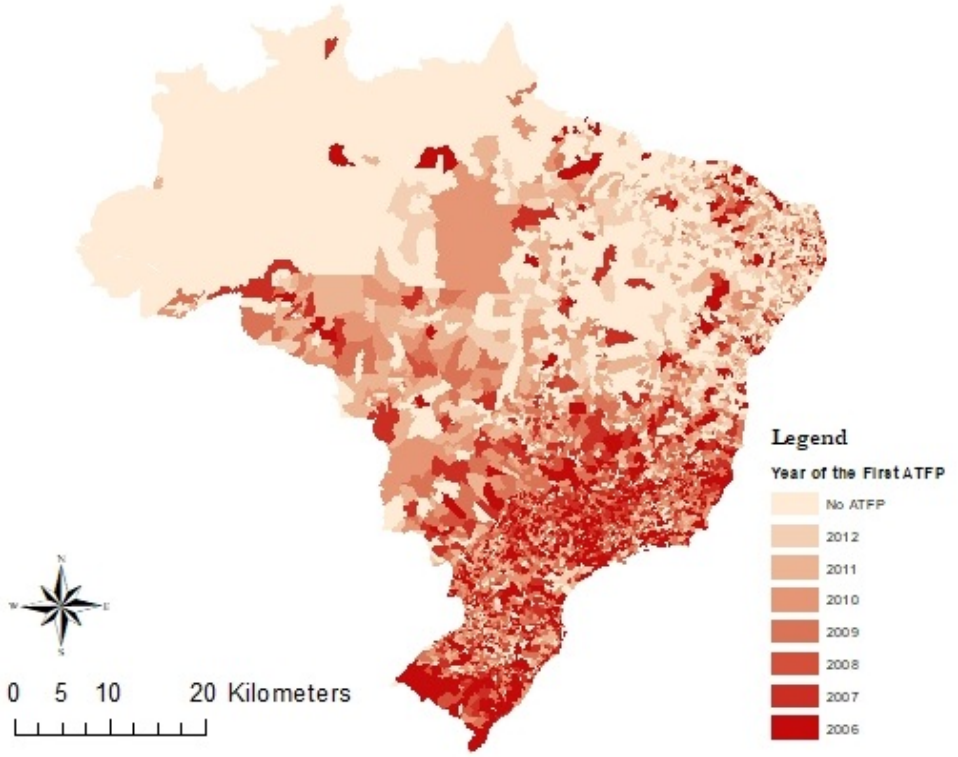
Notes: This table reports how pharmacists' wages respond to the supply of pharmacists in the locality at the time of ATFP introduction as well as net migration. Dependent variables, in the first four columns: average wage in natural logarithm for, respectively, pharmacists, pharmacy clerks, lawyers and managers. Dependent variable in the remainder column is net migration of pharmacists, the difference between the number of exits and entries per year (mean 0.63, SD 6.51) The variable of interest is the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. All regressions include municipality and year fixed effects, socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket), controls for the presence of hospitals, hospital beds per capita, PSF and PACS coverage (in %), and the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table B.3: Effects of ATFP on Mortality and Hospitalization Rates by Diabetes 2SLS Results Conditional on Municipality Specific Trends

	Diabetes Mortality Rate				Diabetes Hospitalization Rate			
Linear trends on:	None	Share Pop 40yo+	Hospital Beds	PSF Coverage	None	Share Pop 40yo+	Hospital Beds	PSF Coverage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ATFP	-0.625	-0.357	-0.598	-0.611	-8.217	-7.938	-8.697	-8.196
	(0.354)*	(0.413)	(0.366)	(0.356)*	(1.526)***	(1.911)***	(1.626)***	(1.519)***

Notes: Each cell reports 2SLS effects of ATFP on mortality (columns 1-4) or hospitalization rates (5-8) by diabetes. Columns 1 and 5 replicate results from 2SLS specifications of Tables 3 and 4, respectively. Specifications of the remainder columns add municipality-specific linear trends according to the variables listed at the top of each column (linear trends refer to an interaction term between a linear time trend and the variable listed at the top of each column and recorded for the year 2000 for each municipality). The variable of interest is the number of pharmacies accredited to ATFP per 100,000 inhabitants. All regressions include municipality and year fixed effects, socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket), controls for the presence of hospitals, hospital beds per capita, PSF and PACS coverage (in %), and the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure B.1: ATFP Roll-Out: 2006-2012



Notes: the map plots the roll-out of ATFP by marking the year in which the first pharmacy was accredited to the program in each municipality.

C Appendix Tables: Reporting Outputs on Health Controls

Table C.1: 2SLS Effects of ATFP on Diabetes Mortality
(per 100,000 Individuals aged 40+)

	Diabetes Mortality Rates		
	(1)	(2)	(3)
ATFP	-0.753	-0.580	-0.625
	(0.362)**	(0.346)*	(0.354)*
Hospitals		-0.715	-0.726
		(0.142)***	(0.141)***
Hospital Beds		-0.005	-0.005
		(0.005)	(0.005)
PSF Coverage		0.014	0.013
		(0.021)	(0.021)
PACS Coverage		-0.166	-0.166
		(0.021)***	(0.021)***
Pharmacies			0.068
			(0.022)***
Observations	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507
Year and Municipality FE	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes
Health services & infra.	No	Yes	Yes
Private pharmacies	No	No	Yes

Notes: The table reports the effects of ATFP on diabetes mortality rates for the 2SLS model. The instrument is defined by the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. The dependent variable in all columns is the mortality rate per 100,000 individuals aged 40 years or more by diabetes. All regressions include municipality and year fixed effects as well as socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket). Specifications in columns 2 and 3 control for hospitals per capita, hospital beds per capita, PSF and PACS coverage (in %). Specification in column 3 also includes the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.2: 2SLS Effects of ATFP on Diabetes Hospitalization (per 100,000 Individuals aged 40+)

	Diabetes Hospitalization Rates		
	(1)	(2)	(3)
ATFP	-8.252	-7.849	-8.217
	(1.518)***	(1.474)***	(1.526)***
Hospitals		-1.211	-1.302
		(0.613)**	(0.603)**
Hospital Beds		0.058	0.058
		(0.022)***	(0.022)***
PSF Coverage		0.095	0.085
		(0.111)	(0.113)
PACS Coverage		-0.369	-0.369
		(0.107)***	(0.107)***
Pharmacies			0.556
			(0.099)***
Observations	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507
Year and Municipality FE	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes
Health services & infra.	No	Yes	Yes
Private pharmacies	No	No	Yes

Notes: The table reports the effects of ATFP on diabetes hospitalization rates for the 2SLS model. The instrument is defined by the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. The dependent variable in all columns is thehospitalization rate per 100,000 individuals aged 40 years or more by diabetes. All regressions include municipality and year fixed effects as well as socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket). Specifications in columns 2 and 3 control for hospitals per capita, hospital beds per capita, PSF and PACS coverage (in %). Specification in column 3 also includes the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.3: 2SLS Effects of ATFP on Mortality Rates by Diabetes Type

	Type I			Type II		
	(1)	(2)	(3)	(4)	(5)	(6)
ATFP	0.011	0.021	0.019	-0.763	-0.601	-0.644
	(0.055)	(0.054)	(0.056)	(0.341)**	(0.327)*	(0.334)*
Hospitals		-0.034	-0.035		-0.680	-0.691
		(0.021)*	(0.021)*		(0.140)***	(0.139)***
Hospital Beds		0.001	0.001		-0.006	-0.006
		(0.000)	(0.000)		(0.005)	(0.005)
PSF Coverage		0.000	0.000		0.014	0.012
		(0.003)	(0.003)		(0.021)	(0.021)
PACS Coverage		-0.011	-0.011		-0.155	-0.155
		(0.003)***	(0.003)***		(0.021)***	(0.021)***
Pharmacies			0.002			0.066
			(0.004)			(0.022)***
Observations	71,591	71,591	71,591	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507	5,507	5,507	5,507
Year and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes	Yes	Yes	Yes
Health services & infra.	No	Yes	Yes	No	Yes	Yes
Private pharmacies	No	No	Yes	No	No	Yes

Notes: The table reports the effects of ATFP on mortality rates by diabetes type, for the 2SLS model. The instrument is defined by the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. The dependent variable in all columns is the mortality rate per 100,000 individuals aged 40 years or more by diabetes type. All regressions include municipality and year fixed effects as well as socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket). Specifications in columns 2 and 5, 3 and 6 control for hospitals per capita, hospital beds per capita, PSF and PACS coverage (in %). Specification in columns 3 and 6 also includes the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.4: 2SLS Effects of ATFP on Hospitalization Rates by Diabetes Type

	Type I			Type II		
	(1)	(2)	(3)	(4)	(5)	(6)
ATFP	-2.053	-1.803	-1.931	-6.199	-6.046	-6.286
	(0.766)***	(0.757)**	(0.774)**	(1.455)***	(1.447)***	(1.487)***
Hospitals		-1.159	-1.191		-0.052	-0.111
		(0.385)***	(0.385)***		(0.581)	(0.576)
Hospital Beds		0.033	0.032		0.025	0.025
		(0.014)**	(0.014)**		(0.025)	(0.025)
PSF Coverage		0.113	0.109		-0.017	-0.024
		(0.053)**	(0.053)**		(0.094)	(0.096)
PACS Coverage		-0.130	-0.130		-0.239	-0.239
		(0.055)**	(0.055)**		(0.096)**	(0.096)**
Pharmacies			0.193			0.363
			(0.057)***			(0.089)***
Observations	71,591	71,591	71,591	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507	5,507	5,507	5,507
Year and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes	Yes	Yes	Yes
Health services & infra.	No	Yes	Yes	No	Yes	Yes
Private pharmacies	No	No	Yes	No	No	Yes

Notes: The table reports the effects of ATFP on hospitalization rates by diabetes type, for the 2SLS model. The instrument is defined by the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. The dependent variable in all columns is the hospitalization rate per 100,000 individuals aged 40 years or more by diabetes type. All regressions include municipality and year fixed effects as well as socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket). Specifications in columns 2 and 5, 3 and 6 control for hospitals per capita, hospital beds per capita, PSF and PACS coverage (in %). Specification in columns 3 and 6 also includes the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.5: 2SLS Effects of ATFP on Hospitalization Rates by SES
Poor Zipcodes *vs* Non-Poor Zipcodes

	Poor			Non-Poor		
	(1)	(2)	(3)	(4)	(5)	(6)
ATFP	-0.062	-0.059	-0.061	-0.029	-0.027	-0.028
	(0.020)***	(0.019)***	(0.019)***	(0.012)**	(0.012)**	(0.012)**
Hospitals		-0.008	-0.009		-0.002	-0.002
		(0.006)	(0.006)		(0.005)	(0.005)
Hospital Beds		-0.000	-0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
PSF Coverage		0.001	0.001		0.000	0.000
		(0.001)	(0.001)		(0.001)	(0.001)
PACS Coverage		-0.003	-0.003		-0.003	-0.003
		(0.001)***	(0.001)***		(0.001)***	(0.001)***
Pharmacies			0.003			0.001
			(0.001)***			(0.001)*
Observations	71,591	71,591	71,591	71,591	71,591	71,591
Number of Municipalities	5,507	5,507	5,507	5,507	5,507	5,507
Year and Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomics	Yes	Yes	Yes	Yes	Yes	Yes
Health services & infra.	No	Yes	Yes	No	Yes	Yes
Private pharmacies	No	No	Yes	No	No	Yes

Notes: The table reports the effects of ATFP on hospitalization rates by diabetes type, for the 2SLS model. The instrument is defined by the number of pharmacists per 1,000 inhabitants in 2006 interacted with a function T_t that assumes $T_t = 0$ if $t < 2006$ and $T_t = (t - 2005)$ if $t \geq 2006$. In all specifications the dependent variable is the hyperbolic sine-transformation of the number of hospital admissions for diabetes. Poor/non-poor zipcodes refer to zipcodes with average income below/above the median household income per capita. All regressions include municipality and year fixed effects as well as socioeconomic controls (the logarithm of GDP per capita, population density and the share of population within each 5-year age bracket). Specifications in columns 2 and 5, 3 and 6 control for hospitals per capita, hospital beds per capita, PSF and PACS coverage (in %). Specification in columns 3 and 6 also includes the number of private pharmacies per capita. Robust standard errors allowing for clustering at the municipality level in parentheses; regressions weighted by population. * significant at 10%; ** significant at 5%; *** significant at 1%.