The Impact of a National Formulary Expansion on Diabetics

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Abstract

This paper estimates the causal effect of the expansion of Colombia's national prescription drug formulary to include five new types of insulin on the healthcare utilization and costs of type I diabetics, and identifies the mechanism through which outpatient cost reductions are realized. We find that expanded coverage generates a 17% increase in the cost of insulin for type I diabetics. At the same time, annual outpatient care utilization falls by 1.9 claims. We devise tests to explore the relative importance of two mechanisms by which the expansion may have lowered non-drug healthcare utilization: spillovers from drug to non-drug spending and rationing of care. We find no evidence that the formulary expansion reduces the rate of complications from diabetes, and find substantial declines in non-drug costs even among the subset of diabetics with no scope for spillovers. We find large reductions in the utilization of discretionary care including diagnostic tests, but no such declines for the use of essential drugs, suggesting that rationing of care is the primary driver of observed cost savings.

Keywords: Healthcare rationing, prescription drug formulary, diabetes, insulin, health insurance.
JEL Codes: I100, I110, I130, I180.

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1 Introduction

Prescription drug formularies are an element of health insurance plan design that determine coverage and coinsurance rates for medications. Formularies are an important mechanism for healthcare cost containment that can increase the bargaining power of insurance companies in their negotiations with pharmaceutical manufacturers over the price of prescription drugs. The complexity of insurance plan design in settings such as the U.S. healthcare market and insurers' discretion over the elements of that design make it difficult to assess how changes in prescription drug coverage impact consumers. Evaluating changes in formulary design when such changes are endogenous choices of the insurer usually requires a structural approach, as well as information on all other plan characteristics. While expanded coverage might increase prescription drug costs, spillovers from drug to non-drug spending raise the possibility that adding drugs to a formulary might decrease healthcare costs overall. For instance, Tamblyn et al. (2001) show that the rate of adverse health outcomes and emergency room visits increase among poor and elderly individuals following an increase in cost sharing for essential prescription drugs. Understanding how formulary design impacts healthcare costs and utilization is of great concern to countries like Canada, Mexico, Japan, Colombia, and the U.S. where prescription drug spending comprises more than 10% of total healthcare costs (OECD, 2020). Also of keen interest is how insurers' ability to respond to exogenous changes in formulary design impacts enrollees.

In this paper, we examine the impact of an exogenous expansion of Colombia's national prescription drug formulary at the end of 2011. The national formulary in Colombia is designed by the government and determines the set of covered medications and their level of cost sharing for all insurers. The formulary is part of a wider benefits package that covers inpatient and outpatient care and which private health insurers are obliged to offer to all of their enrollees. An estimated 96.6% of Colombians are covered by the nation's universal healthcare system (OECD, 2015). The government regulates premiums and cost sharing, but service and drug prices are determined through bilateral bargaining between insurers and pharmaceutical companies. The government also regulates drug prices by setting price ceilings according to the degree of competition in each drug class. Before 2012, the formulary covered 673 medications. At the end of 2011, it was expanded to include 736 medications as part of a broader healthcare reform which unified the income-based insurance plans. We describe the Colombian healthcare system and this reform in more detail in section 2.

Regulation of cost sharing and coverage schedules in Colombia alleviates the endogeneity of formulary design and allows us to isolate the impact of the formulary's expansion. We are able to separate the effect of the formulary expansion from the effect of plans' unification by focusing on a particular type of drug and its users, namely, insulin and diabetics. The formulary expansion affected all enrollees to the healthcare system, but focusing on expanded coverage of insulin - which is taken exclusively by diabetics - allows us to build a control group from the non-diabetic population. Since there is no generic insulin,[1] our focus also allows us to

[1] Because insulins are biologically based rather than molecularly based, they are too complicated to replicate exactly. Insulins that are relatively close substitutes for one another are called biosimilars.

examine the impact of an increase in branded drug competition on healthcare utilization and costs. This is in contrast to the bulk of literature examining drug pricing and entry, which has focused on the effects of generic drug entry (Tenn and Wendling, 2014; Regan, 2008; Reiffen and Ward, 2005; Scott Morton, 2005). Diabetes is an increasingly prevalent chronic condition in many countries, especially the United States, where over 1 in 10 individuals had diabetes in 2018 and the total direct estimated costs of diagnosed diabetes increased from $188 billion in 2012 to $237 billion in 2017 (CDC, 2020). Research on how formulary design affects the costs associated with diabetes is therefore of particular interest to policymakers.

We use a difference-in-differences approach to identify the causal effect of the expanded coverage of insulin. The treatment group is comprised of individuals with type I diabetes and the control group is constructed by exactly matching diabetics to non-diabetics based on demographics, comorbidity profiles, and insurance carrier. Using granular claims data, we are able to analyze the impact of expanded insulin coverage on the utilization and cost of several types of healthcare. We find that annual consumption of insulin increased by 2 claims (28%) among type I diabetics as a result of expanded insulin coverage. Because we do not observe out-of-pocket insulin purchases, we cannot quantify how much of the observed increase in insulin consumption is attributable to moral hazard, and how much is the mechanical result of out-of-pocket payments becoming covered claims. Substitution toward newly covered, relatively more expensive insulins increases insulin costs by over half a million Colombian pesos or 17% of baseline total healthcare costs for type I diabetics. At the same time, outpatient care and non-insulin prescription drug utilization as well as hospitalization rates for type I diabetics all decline as a result of expanded coverage of insulin. We look for evidence of two mechanisms which might generate this increase in insulin and decline in non-drug spending: spillovers and rationing of care. The spillovers hypothesis posits that increased drug spending can result in lower non-drug costs as patients are matched to their optimal prescription and their health status is improved. Empirical evidence on spillovers include Lavetti and Simon (2018) who find that Medicare Advantage plans capitalize on spillovers once open enrollment has closed by lowering coinsurance rates for drugs that are associated with lower non-drug spending. Tamblyn et al. (2001) show that reductions in the utilization of essential drugs result in increased rates of adverse health events in elderly individuals and welfare recipients. In our setting, increased access to insulin, an essential drug for type I diabetics, has the potential to decrease the use of non-drug treatment of adverse health events among this population.

The rationing of care hypothesis posits that in the short run, insurers respond to increases in prescription coverage and costs by limiting the amount of discretionary care that newly more costly patients receive. In the long run, this rationing can result in lower enrollment from these more costly individuals, acting as a mechanism for selection.[2] The main contribution of this paper is providing evidence consistent with insurers engaging in rationing of care in response to changing selection incentives in a setting where they have no control over premiums or cost sharing. Risk selection through premium setting is well studied (Akerlof, 1970;

[2]If rationing care is a well-known phenomenon, we might worry about rationing generating disenrollment in the short run as well. The best way to account for that correlation would be to focus on the subsample of patients that are continuously enrolled. Unfortunately we have no data on enrollment spell lengths for our analysis period.

Handel et al., 2015; Hackmann et al., 2015). There is also an impressive literature examining how insurers alter plan design in response to regulatory changes and risk selection incentives in government coordinated health insurance markets. Andersen (2017) finds that in the United States, insurers respond to drug coverage requirements under the Affordable Care Act (ACA) by placing both marginal and inframarginal drugs on higher formulary tiers, or subjecting them to utilization management. Geruso et al. (2019) also find that insurers in the ACA Exchanges increase cost sharing and utilize non-price barriers, such as prior authorization for drugs, for patients who are predictably unprofitable conditional on risk adjustment. Whether insurers in tightly regulated health insurance markets like Colombia's are able to respond to changes in risk selection incentives is still an outstanding empirical question. We show that in a setting where plan design is heavily regulated and risk adjustment is coarse, selection is still possible through rationing of care. We devise tests to show that spillovers from drug to non-drug spending are unlikely to be the source of cost savings, and provide evidence that these cost reductions stem from the targeted rationing of discretionary outpatient healthcare.

Our paper is also related to the literature studying the effects of prescription drug coverage and insulin consumption on diabetics' healthcare utilization and costs. In recent work, Américo and Rocha (2020) evaluate the impact of a policy implemented in Brazil that made subsidized pharmaceutical drugs available at retail pharmacies, focusing on the spillover effects of the policy. They find that the increase in cost sharing for and availability of prescription drugs reduced the hospitalization rate of diabetics by 3.6 percent. This paper complements Américo and Rocha (2020) by examining how a different element of formulary design – the extensive margin decision of whether a drug is covered at all – impacts healthcare utilization by type I diabetics. In testing for rationing of care as a response to changing selection incentives, this paper is also related to the literature on rationing of healthcare, the vast majority of which is both theoretical and specific to the use of waiting time as a tool for engaging in general rather than targeted rationing (Cullis and Propper, 2000; Fabbri and Monfardini, 2009). We draw on insights from Ellis and McGuire (2007) and Frank et al. (2000) to examine how utilization of discretionary and non-discretionary types of healthcare decline for type I diabetics as a result of expanded insulin coverage. Consistent with the rationing hypothesis, we show that utilization of lab tests, which are a type of diagnostic and preventive care that is predictably used by type I diabetics, declines across the board.

This paper both provides anecdotal evidence of the mechanisms by which rationing is achieved, and quantifies insurers' success at achieving rationing targeted at a perfectly observable, newly unprofitable set of enrollees. Quantifying the degree to which the formulary expansion increased access to essential drugs and reduced access to discretionary care among the population of type I diabetics provides valuable insights into the efficacy of health insurance market regulations and the welfare impacts of expanding prescription drug coverage.

2 Background

2.1 Colombia's universal health insurance system & formulary expansion

Colombia's universal health insurance system was established in 1993 with Law 100. All individuals are divided into one of the two regimes - the Contributory Regime (CR) and the Subsidized Regime (SR) - that make up the health insurance system. The CR covers individuals above a monthly income threshold. The 51% of the population eligible to join the CR contribute 12% of their monthly income to the system. The remaining 49% of the population below the income threshold are part of the SR. Before 2012, the national plan offered by the CR covered different services, procedures and medications than that offered by the SR. At the beginning of that year the plans' benefits were equalized. Individuals choose from amongst a set of private insurers with which to enroll and access the national plan. To deliver the services covered under the national plan, insurers contract with healthcare providers to create a network. Out-of-network claims are not covered. The sample of enrollees used in our analysis belong only to the CR.

The cost sharing rules in the CR are determined by the government and indexed to the enrollee's monthly income. For individuals earning less than two times the monthly minimum wage (MMW), the coinsurance rate is 11.5% of the price of the health claim, the copay is 11.7% of the daily minimum wage, and the maximum out-of-pocket expenditure in a year equals 57.5% of the MMW. For those whose monthly income is between 2 and 5 times the MMW, the coinsurance rate is 17.3% of the health claim price, the copay is 46.1% of the daily minimum wage, and the maximum out-of-pocket expenditure in a year equals 230% of the MMW. Finally, for enrollees whose income exceeds 5 times the MMW, the coinsurance rate equals 23%, the copay is 121.5% of the daily minimum wage, and the maximum out-of-pocket expenditure in a year is 460% of the MMW. There are no deductibles in the Colombian system, so copays and coinsurance rates always apply. These cost sharing percentages have remained fixed since the establishment of Colombia's healthcare system and their absolute levels only vary with changes in the minimum wage. Individuals are required to report their income monthly so that their plan can apply the appropriate cost sharing rules to them.

Insurers are not allowed to charge premiums through the national plan. Instead, they are reimbursed by the government every year with capitated payments that are risk adjusted for age, sex, and location. Transfers for year t are approximately calculated as the present value of the average healthcare cost of a given risk pool using the data of all claims reimbursed by insurers during year $t-2$. The capitated payments replace premiums, so that other than the monthly contribution to the CR, enrollment in the national insurance plan is free. The strict regulation of cost sharing and benefits means that insurers compete in terms of quality and provider networks (Giedion and Uribe, 2009). As in the US, insurers and providers bargain freely over the price of health services, devices, and medications. Private insurers are also allowed to offer complementary insurance plans, for which they can determine cost sharing rules and premiums. However, consumers can only access these complementary packages once they are enrolled in the national plan. The data used in this paper are the cross sections of health claims made by all enrollees to the CR through the national insurance

plan in 2011 and 2013.

At the end of 2011, the Colombian Ministry of Health implemented a reform that unified the contributory and subsidized systems' insurance plans and expanded the national prescription drug formulary by 63 drugs.[3] Most drug inclusions were for treatment of mental health conditions (all of which were previously uncovered), insulin, antibiotics, and chemotherapy. The wider benefits package was also expanded to cover complex procedures like open breast biopsy, laparoscopy ovary cystectomy, and colored doppler echocardiogram. Although there have been studies that measure the overall impact of the unification of the CR and SR (Riascos and Camelo, 2014), there is less work on the impact of the formulary expansion. The exogeneity of variables that in other countries would be chosen by the insurer allows us to isolate the impact of the fomulary expansion on healthcare costs and utilization. This is relevant not only for Colombia, where the formulary continues to be modified, but also for countries where the scope and role of national health insurance continues to be debated.

While many of the tools that insurers in other settings use to engage in risk selection are not available to insurers in the CR, there is still scope for insurers to target healthier enrollees through "illicit formularies," whereby insurers deny the provision of or payment for certain medical services or medicines. It is perhaps in part because of these illicit formularies that, since the establishment of its universal health system, Colombia has become the most litigious country in Latin America with respect to lawsuits concerning the refusal of treatments, exams, and pharmaceuticals by insurers. In 2013, 115,147 of such lawsuits were filed in Colombia (Lamprea and Garcia, 2016). We provide anecdotal and empirical evidence of the use of illicit formularies in section 6.

2.2 Diabetes & insulin

Insulin is a hormone produced by the pancreas that allows glucose from food to enter a person's cells and controls their blood sugar. A person has diabetes if they do not produce enough insulin or their body does not use insulin well. Type I diabetics produce no insulin, and must take insulin every day in order to stay alive. Type II diabetics produce some insulin, but less as the disease progresses. Type II diabetics can control their blood sugar with diet and exercise or oral medications such as metformin, but others will require insulin (FDA, 2020). In the short run, failure to control blood sugar can result in hypoglycemia. In the long run, uncontrolled blood sugar can result in kidney disease, heart disease, nerve damage, and several other adverse health outcomes (NIH, 2020).

Prior to its expansion in 2012, two types of insulin were covered by the Colombian formulary: regular and NPH.[4] Regular insulin is a type of bolus insulin. Bolus insulins are fast-acting, taking effect and wearing off more quickly. Bolus insulin is usually taken shortly before mealtimes to provide immediate blood sugar control. NPH belongs to the class of basal insulins, which are longer-lasting and provide blood sugar control

[3] Established in decree 029 of 2011.
[4] ATC codes A10AB01 and A10AC01, respectively.

throughout the day. These two types of insulin can be consumed together to better manage the disease. With the expansion of the formulary in 2012, the number of insulins covered increased from two to seven, providing more options for patients to exploit the complementarities between types of insulin. The five newly added insulins included three additional bolus insulins and two additional basal insulins.[5] The characteristics of these insulin types are summarized in table 1. Differentiation in the characteristics of insulin including onset time, peak time, and duration generate the potential for increased insulin coverage to allow diabetics to be better matched to an insulin regimen and generate spillovers. Note that the average price of newly added insulins is anywhere from 5 to 12 times the price of NPH or regular insulin in 2013. This means that even modest amounts of substitution towards the newly added insulins can generate large increases in costs.

Table 1: Types of insulin

Insulin type (brand name)	Onset	Peak	Duration	Avg. price 2011	Avg. price 2013
Bolus (preprandial or mealtime) insulins					
Rapid-acting insulin analogues					
• Insulin aspart (NovoRapid®)	9-20 min	1-1.5 hr	3-5 hr	—	79.2
• Faster-acting insulin aspart (Fiasp®)	4 min	0.5-1.5 hr	3-5 hr		
• Insulin glulisine (Apidra®)	10-15 min	1-1.5 hr	3.5-5 hr	—	86.2
• Insulin lispro (Humalog®)	10-15 min	1-2 hr	3-4.75 hr	—	81.6
Short-acting insulins					
• Insulin regular (Humulin®-R, Novolin®ge)	30 min	2-3 hr	6.5 hr	33.4	15.6
• Insulin regular (Entuzity®(U-500))	15 min	4-8 hr	17-24 hr		
Basal Insulins					
Intermediate-acting					
• Insulin NPH (Humulin®-N, Novolin®ge NPH)	1-3 hr	5-8 hr	Up to 18 hr	14.5	15.5
Long-lasting insulin					
• Insulin detemir (Lemevir®)	90 min	N/A	16-24 hr	—	146.3
• Insulin glargine U-100 (Lantus®)			24 hr	—	182.1
• Insulin glargine U-300 (Toujeo®)			> 30 hr		

Notes: Adapted from Canadian Journal of Diabetes, 2018-04-01, Volume 42, Pages S314-S314. Continuously covered insulins are regular and NPH. The rest of insulins in the table were added to the formulary by the end of 2011. Prices are in thousands of Colombian pesos.

3 Data

We use two samples of cross sectional health claims data from the CR from 2011 and 2013, which are one year pre- and post-policy respectively. For every enrollee, we observe basic demographic characteristics including sex, age, and municipality of residence. For every claim, we observe date of provision, service

[5] ATC codes A10AB05, A10AB06, A10AB04, A10AE05, and A10AE04.

provided, service price, contract under which the claim is reimbursed, insurer, provider, and associated ICD-10 diagnosis code. Since patients must remain enrolled with their choice of insurer for at least a year, we do not observe patients switching insurers during either cross-section of our data.

We obtain each enrollee's set of diagnoses by grouping ICD-10 codes according to Alfonso et al. (2013) into the following conditions: genetic anomalies, arthritis, arthrosis, asthma, autoimmune disease, cancer, cardiovascular disease, type I diabetes, long-term pulmonary disease, renal disease, HIV-AIDS, transplant, tuberculosis, and epilepsy. Note that because diagnoses are defined using claims, our definition does not include individuals who have a diagnosis but who do not file any claims associated with its treatment. We believe that there is limited scope for this type of measurement error for the aforementioned diagnoses, which are chronic conditions that require treatment. For other diagnoses, such as type II diabetes, which can be treated with or without the use of prescription drugs, measurement error of this type is likely. Age is categorized into the following groups used by the government for the risk adjustment formula: 19-44, 45-54, 55-59, 60-64, 65-69, 70-74, 75+. We do not observe each enrollee's monthly income, but rather an aggregate income measure that is collinear with combinations of sex, age group, and municipality, so we cannot separately identify the impact of differences in cost sharing across income groups on healthcare utilization. We collapse the claims level data to the patient-year level and build measures of utilization and cost by summing across each patient's claims within a year.

We define treatment in a year as having been diagnosed with type I diabetes at any moment during that year and being at least 19 years old. We exclude type II diabetics from our analyses, as their decision to use medication to manage their diabetes determines whether we observe a diabetes diagnosis through their claims. In some cases, Type II diabetes can be managed with diet and exercise alone, without the use of any medication (CDC, 2021). The formulary expansion may have impacted this extensive margin decision of whether to use medication both by expanding the insulin choice set and through its impact on the price of insulin. This implies that treatment for type II diabetics is not exogenous conditional on observables, which is a requirement of the differences-in-differences approach we employ. We determine which patients are diabetic using the ICD-10 diagnoses that accompany their claims, so treated units who did not make a health claim are unobserved. We expect the number of unobserved treated individuals to be close to zero since type I diabetics can be expected to make at least one claim in a year associated with diabetes management.

We use exact matching to create a control group that is similar to the treatment group of type I diabetics in terms of comorbidities (with the exception of diabetes), sex, age, insurer, and municipality. This choice of control group implies that the effect being estimated is that of the element of the formulary expansion that is relevant only to type I diabetics, namely expanded coverage of insulins. Using exact matching to create the comparison group has three advantages. First, the comparison group will resemble the treatment group, and will therefore be expected to respond to shocks in a similar way. This is important, since both the treatment and control groups were subject to universal elements of the healthcare reform in the post-policy

period, including the plan unification. Second, by matching treated units in the pre-policy to those in the post-policy period and then matching treated units to controls separately for each year, we achieve common support on the distribution of the covariates across all four cells. This will keep us from making inferences about outcomes for treated individuals we don't observe in the data. Third, common support also allows us to relax the assumption that the effect of the policy is homogeneous across individuals.

Table 2: Balance table of type I diabetics and exactly-matched control units

	Control	Treated
Demographics		
Male (%)	43.08	43.18
Age, mean (sd)	62.99 (12.81)	63.02 (12.81)
Diagnoses (%)		
Arthrosis	2.28	2.32
Cardiovascular disease	73.61	73.43
Long term pulmonary disease	4.52	4.66
Renal disease	14.83	15.24
Insurer (%)		
A	1.78	1.79
B	7.75	7.74
C	1.81	1.81
D	4.18	4.18
E	5.66	5.61
F	9.78	9.75
G	1.73	1.74
H	12.60	12.62
I	12.69	12.73
J	7.08	7.05
K	0.04	0.04
L	0.00	0.00
M	0.31	0.31
Type of municipality (%)		
Metropolitan	73.47	73.05
Normal	26.35	26.75
Special	0.19	0.20
N	2,333,213	97,210

Notes: This table shows some summary statistics of treated and control units after $1 - to - n$ exact matching on age, sex, comorbidities, type of municipality, and insurer. Summary statistics for control units are weighted by the inverse number of controls matched to each diabetic.

We perform one-to-many matching of diabetics to non-diabetics. Table 2 presents summary statistics of the demographic characteristics and diagnoses of the treatment and control groups. Statistics for control

units are weighted by the inverse number of controls matched to each diabetic. 43% of our sample is male, and the average individual is 63 years old. The most common comorbidities are cardiovascular disease which is present in 73% of patients and renal disease which is present in 15% of patients. More than 12% of individuals are enrolled to each of insurers H and I. 73% of diabetics live in urban or metropolitan municipalities. The matched sample consists of 97,210 type I diabetics and 2,333,213 exactly matched controls.

Table 3: Utilization and cost for type I diabetics and exact match counterparts

	Control		Treated	
	2011	2013	2011	2013
Claims				
All claims	48.5 (46.9)	50.8 (50.1)	100.6 (71.3)	101.3 (75.6)
Outpatient claims	22.2 (27.2)	20.7 (25.9)	39.8 (41.2)	34.2 (37.7)
Inpatient claims	3.0 (11.1)	3.3 (11.4)	7.9 (21.0)	8.0 (20.5)
Prescription claims	23.4 (24.7)	26.8 (29.9)	52.9 (35.7)	59.0 (44.6)
Insulin claims	0.0 (0.4)	0.0 (0.4)	7.3 (4.9)	9.3 (5.9)
Procedure claims	10.8 (14.2)	10.8 (16.7)	20.8 (21.2)	18.1 (21.8)
Imaging claims	1.4 (2.4)	1.5 (2.5)	1.9 (3.2)	1.9 (3.2)
Lab claims	10.0 (16.1)	10.0 (15.6)	23.5 (28.7)	21.7 (26.5)
Office/consultation claims	7.3 (5.8)	7.1 (5.8)	10.6 (7.3)	10.4 (7.4)
Essential drugs claims	3.4 (5.5)	3.4 (6.1)	6.2 (7.2)	6.6 (8.3)
Costs (Million COP)				
All costs	1.80 (6.44)	1.68 (6.12)	3.44 (8.50)	3.84 (8.22)
Outpatient costs	0.92 (3.21)	0.77 (2.49)	1.50 (3.86)	1.38 (3.42)
Inpatient costs	0.67 (4.21)	0.59 (3.79)	1.37 (5.45)	1.26 (5.10)
Prescription costs	0.21 (1.80)	0.31 (2.68)	0.57 (1.96)	1.21 (2.72)
Insulin costs	0.00 (0.01)	0.00 (0.03)	0.14 (0.30)	0.64 (0.99)
Procedure costs	0.57 (2.60)	0.46 (1.97)	0.94 (3.09)	0.79 (2.77)
Imaging costs	0.12 (0.34)	0.12 (0.36)	0.18 (0.43)	0.19 (0.55)
Lab costs	0.12 (0.29)	0.13 (0.31)	0.30 (0.48)	0.30 (0.52)
Office/consultation costs	0.15 (0.23)	0.14 (0.25)	0.22 (0.21)	0.29 (0.51)
Essential drugs costs	0.04 (0.29)	0.05 (0.70)	0.09 (0.44)	0.11 (0.51)
Observations	1,065,674	1,267,539	41,911	55,299

Note: This table presents summary statistics of outcomes measures after 1-to-n exact matching on age, sex, comorbidites, type of municipality, and insurer. Summary statistics for control units are weighted by the inverse number of controls matched to each diabetic.

Table 3 summarizes healthcare utilization and costs respectively for each group in the pre- and post-policy periods. Outcomes for control units are weighted as they were in table 2. We define outpatient claims as those associated with a hospital length-of-stay (LOS) less than 1 day and inpatient claims as being associated with a LOS of at least 1 day. Our measure of insulin consumption is the number of insulin claims. Almost all of these claims are for a concentration of 100 UL/ml. As a sanity check, in table 3 we note that while the average diabetic has 7.3 insulin claims in the pre-policy and 9.3 in the post-policy period, non-diabetics have virtually no insulin claims before or after the formulary expansion. We see that diabetics have a significantly

higher number of claims for outpatient care, lab tests, and office visits than non-diabetics. Diabetics are also costlier than their matched counterparts both before and after the expansion as seen in the second panel of table 3. The detailed distribution of outcomes stratified by treatment status for the pre- and post-expansion periods can be found in appendix tables C1 and C2.

4 Methodology

To estimate the impact of the formulary expansion on outcomes for type I diabetics, we employ a differences-in-differences identification strategy and a generalized linear modeling approach, summarized by the estimating equation:

$$G(\mathbb{E}[y_{it}]) = \alpha + \tau D_i * P_t + \delta D_i + \gamma P_t + \mathbf{x}_i'\beta. \tag{1}$$

Here, y_{it} is the outcome for patient i in year t; D_i is an indicator variable for patient i being a type I diabetic; P_t is an indicator variable for year t following the formulary expansion; and $\mathbf{x}_i$ is a vector of demographic characteristics including sex, age group, comorbidity dummies, insurer dummies, and municipality dummies. The coefficient of interest is τ, which provides an estimate of the average treatment effect on the treated. G in equation 1 is the link function of the generalized linear model. For each of our outcomes, we specify a link function G and a distribution function F such that $y \sim F$. We assume that y follows a negative binomial distribution for specifications with counts of healthcare claims as outcomes and that y follows a gamma distribution for specifications using healthcare costs as outcomes.[6] Basu et al. (2004) show that the gamma regression model performs better than OLS on log transformed cost data. Alternatively, we could use a generalized beta distribution to choose nested distributions for each healthcare type as described in Jones et al. (2014), but we employ gamma regressions for clarity of exposition. For all specifications, we employ a log link function.

We use as outcomes six categories of healthcare claims and costs: all insulin, continuously covered insulin, outpatient, inpatient, prescriptions, and total. In the case of inpatient outcomes, which are zero for 75% of patient-years, we model y as the outcome of a two-part process. First, we model the probability that a patient is admitted to the hospital. Then, conditional on admission, we model either the number of inpatient claims made during the hospital stay or inpatient costs. We assume y follows a Bernoulli distribution in the first part of the model,[7] followed by a truncated negative binomial distribution in the second part of the model for inpatient claims, and a truncated gamma distribution in the second part of the model for inpatient costs. Insulin utilization and costs are subtracted from total and prescription utilization and costs respectively so that any declines from spillovers or rationing are not muted by increases in insulin consumption.

[6] For all specifications with counts of claims as the outcome, we provide an estimate of the log-transformed overdispersion parameter, $\ln\alpha$. Likelihood ratio tests that α equals zero strongly reject the Poisson model in favor of the negative binomial across all specifications.

[7] In the two-part model for inpatient claims, we employ a logit link rather than log link in the first stage.

Our identifying assumptions are that the formulary expansion affected all insurance companies and enrollees so there is no selection into the policy, and that our definition of treatment as being type I diabetic is exogenous conditional on all other comorbidities and demographics. Because we use one-to-many matching, we weight our regressions using the weighting scheme described in Iacus et al. (2011b).

In the case of insulin, we note that outcomes for the control group of non-diabetics are mechanically zero across both periods. So, we estimate the effects on insulin outcomes using an interrupted-time-series identification strategy, estimating the following equation on the subsample of type I diabetics:

$$G(\mathbb{E}[y_{it}]) = \alpha + \tau P_t + \mathbf{x}_i'\beta. \tag{2}$$

Here, we assume total insulin utilization follows a truncated negative binomial distribution, truncated at zero, since for type I diabetics insulin consumption is strictly positive.

In equation (2), τ represents the average treatment effect on the treated. This effect is causal because the formulary expansion is exogenously determined and because, to our knowledge, there were no other interventions in the health system during this period. Additionally, because we implement exact matching of type I diabetics across the pre- and post-policy periods, our results are not biased by changes in type I diabetics' enrollment patterns across time. While exact matching across years controls for changes in enrollment, our results might still be biased if insurers' networks are changing over time in a way that affects their ability to provide care to diabetics. In appendix table C3, we show that the average number of reimbursed providers across municipalities does not change between 2011 and 2013 for the vast majority of insurers. It is therefore unlikely that insurers' ability to provide diabetes care through their network over time biases our estimate of expanded insulin coverage.

We provide evidence of parallel trends in pre-treatment outcomes for treated and control units in appendix A. We see no pre-trend in total claims, outpatient claims, or prescription claims. There are no statistically significant differences in the total costs of type I diabetics and control units in the 9 months preceding the expansion. There is an uptake in inpatient admissions in the quarter prior to the formulary expansion, but no trend prior to this. We do not present the event study estimates as our main results as many of the kinds of healthcare we consider are not received on a quarterly basis, and measuring them so frequently results in an overwhelming number of zeros. We therefore proceed by implementing the differences-in-differences framework laid out above.

5 Results

In table 4, we present the results of equations (1) and (2) using as dependent variable the annual utilization for various types of drug and non-drug healthcare utilization. Results are presented as average marginal effects. We turn first to the effect of expanded insulin coverage on insulin consumption by type I diabetics, the relevant outcomes for which are given in columns 1 and 2. These specifications are estimated on the

subsample of type I diabetics, since for control units this outcome is by definition zero in both periods. Note that because our measure of insulin utilization is constructed using claims, our outcome does not capture out-of-pocket purchases of insulins not covered by the national formulary. If type I diabetics consumed uncovered insulins in the pre-policy period, then after the formulary expansion, these out-of-pocket purchases would become claims and generate an increase in insulin utilization as a result of the policy, even though insulin consumption patterns would not have changed. Column 1 shows that type I diabetics made 2 (28%) more insulin claims per year with the expansion. Column 2 shows that consumption of regular insulin and insulin NPH declined by 2 claims (27%). The positive impact of expanded insulin coverage on insulin consumption and the substitution it generated away from continuously covered insulins toward the newly covered insulins suggests that it was potentially welfare enhancing for diabetics who were newly able to consume a more optimal insulin regimen. These results are also consistent with the story of spillovers from drug to non-drug spending, which we explore further in section 6.

Table 4: Impact of expanded insulin coverage on healthcare utilization

	(1)	(2)	(3)	(4)	(5)		(6)
	All insulin	Continuously covered insulin	All (net insulin)	Outpatient	Inpatient		Prescriptions (net insulin)
Diabetic × policy			-2.82***	-1.91***	-0.04***	0.81***	-1.30***
			(0.26)	(0.11)	(0.00)	(0.15)	(0.18)
Diabetic			34.77***	12.91***	0.13***	5.04***	20.34***
			(0.20)	(0.08)	(0.00)	(0.11)	(0.14)
Policy	2.04***	-2.04***	0.90***	-2.26***	0.00***	-0.64***	2.65***
	(0.04)	(0.03)	(0.05)	(0.02)	(0.00)	(0.04)	(0.04)
Model	Zero-truncated negative binomial	Negative binomial	Negative binomial	Negative binomial	Logit	Negative binomial	Negative binomial
lnα	-1.11***	-0.37***	-0.59***	-0.59***		-0.22***	0.04***
	(0.01)	(0.01)	(0.00)	(0.00)		(0.00)	(0.00)
Observations	97210	97210	2430423	2430423	2430423		2430423

Notes: Cells contain average marginal effects (standard errors). Equation (2) estimated on sample of type I diabetics in columns 1 and 2. Equation (1) estimated on sample of type I diabetics and their exactly matched controls in columns 3-6. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In column 3, we see that expanded insulin coverage decreased total non-insulin healthcare utilization by type I diabetics by 2.8 claims. This decline in overall utilization is driven by reductions in outpatient and non-insulin prescription drug utilization as well as a fall in hospitalization rates. Outpatient utilization by type I diabetics declined by 1.9 claims, while non-insulin prescription drug utilization fell by 1.3 claims. The estimates of the two part model for inpatient utilization show that the hospitalization rate for type I

diabetics decreased by 3.6 percentage points from a baseline rate of 24.9 as a result of the expanded coverage of insulin. Conditional on a hospitalization, inpatient utilization increased by 0.8 claims. These changes in the rate of hospitalizations and the number inpatient claims incurred conditional on admission together imply an overall decline in inpatient care utilization.

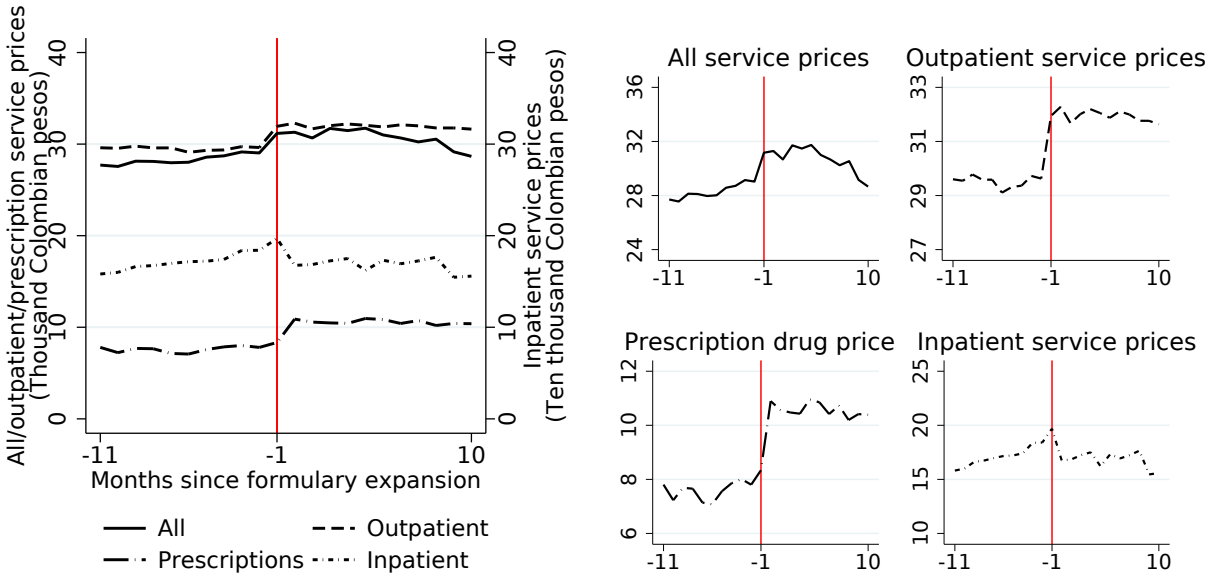
Table 5: Impact of expanded insulin coverage on healthcare costs

	(1)	(2)	(3)	(4)	(5)		(6)
	All insulin	Continuously covered insulin	All (net insulin)	Outpatient	Inpatient		Prescriptions (net insulin)
Diabetic × policy			0.04	0.05***	-0.04***	0.37***	-0.06***
			(0.03)	(0.01)	(0.00)	(0.10)	(0.01)
Diabetic			1.22***	0.45***	0.13***	0.84***	0.25***
			(0.03)	(0.01)	(0.00)	(0.07)	(0.01)
Policy	0.58***	-0.06***	-0.14***	-0.14***	0.00***	-0.22***	0.12***
	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.03)	(0.01)
Model	Gamma	Gamma	Gamma	Gamma	Logit	Gamma	Gamma
Observations	97210	97210	2430423	2430423	2430423		2430423

Notes: Cells contain average marginal effects (standard errors). Equation (2) estimated on sample of type I diabetics in columns 1 and 2. Equation (1) estimated on sample of type I diabetics and their exactly matched controls in columns 3-6. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 presents the results of equations (1) and (2) using costs for the same healthcare categories considered in table 4. Column 1 shows that the total cost of insulin consumption among type I diabetics increased by 0.58 million COP, a more than threefold increase relative to baseline insulin costs. There is no statistically significant effect of expanded insulin coverage on overall costs net of insulin. While expanded coverage of insulin decreased outpatient utilization, it increased outpatient costs. We plot the trends in average service prices in figure 1 to clarify how changes in utilization and service prices are separately affected by the expansion. We see that outpatient service prices increased with the formulary expansion, offsetting the reduction in costs generated from decreased utilization. Because the government's risk adjustment formula controls for only sex, age category, and type of municipality, all of which are covariates in our regressions, the estimated increase in insulin costs directly translates into changes in insurers' profits from coverage of type I diabetics, potentially altering baseline risk selection incentives. In the following section, we look for evidence that insurers respond to these changes in selection incentives by rationing discretionary care for type I diabetics and test competing hypotheses.

Figure 1: Average service price time trends for broad healthcare types



Notes: These figures show the trend in weighted average service prices for each type of healthcare category. Weights are computed using 2011 utilization. In particular, for healthcare type $x \in \{\text{All, Outpatient, Prescriptions, Inpatient}\}$ and period $y \in \{2011, 2013\}$, the average service price of healthcare type x in month m of year t is $AverageServicePrice_{xtm} = \sum_{s \in x} \frac{Claims_{st=2011}}{Claims_{xt=2011}} \times \frac{Cost_{stm}}{Claims_{stm}}$.

6 Mechanisms

In this section, we test for spillovers from drug to non-drug spending and provide evidence of insurers' rationing of discretionary healthcare provided to type I diabetics. Our tests will examine how proxies for the health status of diabetics and utilization of both discretionary and non-discretionary types of healthcare change with the increased availability of insulin. A theoretical framework of how drug availability impacts the relative effects of spillovers and rationing in the insurers' profit function can be found in appendix B.

6.1 Testing for spillovers

Spillovers from drug to non-drug spending are generated when patients with specific diagnoses take up a drug that has the potential to prevent serious adverse health events. Because some of the diabetics in our sample change their choice of insulin following the expansion of insulin coverage, as seen in table 4, there is the potential for such spillovers. Our first test uses the subsample of diabetics to estimate equation (2) using logistic regression. We use as outcome variables indicators for being diagnosed with a complication associated with type I diabetes. We use only the subsample of treated units in these specifications as these diagnoses only apply to type I diabetics by definition and so will mechanically be zero for all non-treated units. The effect of the expanded coverage of insulin on complications from type I diabetes estimated by equation (2)

is therefore identified using time series variation in the rate of such diagnoses and can be interpreted as causal for the same reasons laid out in section 4. We estimate the effect of expanded coverage on the rates of kidney complications; neurological complications; circulatory complications; other specified complications including diabetic arthropathy, skin complications, oral complications, hypoglycemia, and hyperglycemia; and unspecified complications due to diabetes.[8]

The results of estimating these specifications are presented in table 6. Results are presented as average marginal effects times 100. The rates of all complications from diabetes rise as a result of the formulary expansion. We do not employ a balanced panel, so these results are not a mechanical byproduct of the accumulation of chronic conditions over time. Assuming that the rate of complications from diabetes is reflective of the patient's underlying health status, these results in general suggest that health status does not improve with the formulary expansion and constitute evidence against spillovers being the primary mechanism generating the reduction in non-drug care and costs observed in section 5.

Table 6: Impact of formulary expansion on rate of complications from diabetes

	(1) Kidney complications	(2) Neurological complications	(3) Circulatory complications	(4) Other specified complications	(5) Unspecified complications
Policy	1.49***	1.29***	0.64***	0.72**	1.88***
	(0.18)	(0.13)	(0.13)	(0.22)	(0.24)
Model	Logistic	Logistic	Logistic	Logistic	Logistic
Pseudo R^2	0.09	0.05	0.06	0.03	0.04
Observations	96753	96091	96557	96902	97022

Notes: Cells contain average marginal effects*100 (standard errors). Logistic regression estimation of equation (2) with binary indicator for diagnosis as dependent variable, on the sample of type I diabetics. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We perform another test for spillover effects which leverages the fact that diabetics who only ever consume continuously covered insulins have no scope for more optimal matching to a newly covered insulin and thus no scope for a subsequently improved health status. We construct a subsample of our data which includes only diabetics whose choice of insulin does not change as a result of the policy. If this subsample experiences declines in healthcare utilization and costs at least as large as those estimated for the full sample, then we will interpret this as evidence against the spillovers hypothesis. We create a sample of type I diabetics that have zero consumption of newly added insulins and for whom the amount of regular and NPH insulin consumed did not change. We use coarsened exact matching (CEM) as in Iacus et al. (2011a) to match diabetics in 2011 and diabetics in 2013 based on demographics, diagnoses, and their level of regular and NPH insulin claims, and estimate equation (2) using the resulting subsample. We also weight our regressions according to the weighting scheme outlined in Iacus et al. (2011a). 58% of all type I diabetics satisfied the sample

[8]ICD10 codes used to create these indicators are E10.2, E10.4, E10.5, E10.6, and E10.8 respectively. Rates of ketoacidosis and ophthalmic complications are not sufficient for estimation.

selection criteria of having no change in insulin consumption and having an exact match counterpart. This test does not make use of control units, and exploits time-series variation in utilization by type I diabetics. Appendix table C4 shows the characteristics of type I diabetics stratified by whether they are matched by CEM. Type I diabetics whose insulin consumption does not change and who are matched by CEM have similar demographic profiles as those who are not matched, but have lower rates of all comorbidities and are more likely to live in more rural areas.

Table 7: Impact of expanded insulin coverage on healthcare utilization for subsample of type I diabetics with no change in insulin consumption

	(1)	(2)	(3)	(4)		(5)
	Insulin	All (net insulin)	Outpatient	Inpatient		Prescriptions (net insulin)
Policy	0.05	-9.27***	-10.17***	-0.07***	2.06***	1.45***
	(0.05)	(0.63)	(0.28)	(0.00)	(0.49)	(0.34)
Model	Zero-truncated negative binomial	Negative binomial	Negative binomial	Logit	Negative binomial	Negative binomial
lnα	-1.41***	-1.24***	-0.99***	-0.26***		-0.94***
	(0.01)	(0.01)	(0.01)	(0.01)		(0.01)
Observations	56537	56537	56537	56536		56537

Notes: Cells contain average marginal effects (standard errors). Equation (2) estimated on the sample of type I diabetics who have zero consumption of newly added insulins and similar consumption of continuously covered insulins before and after the formulary expansion. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results for our second spillovers test are presented in table 7. The estimates for the policy coefficient τ capture the causal effect of the formulary expansion as a whole on utilization for this subsample of type I diabetics. As a sanity check of our matching strategy, we note that there is no statistically or economically significant change in insulin consumption as seen in column 1. We use our estimates from tables 4 and 7 to compute the average marginal effects of the formulary expansion on utilization for all type I diabetics and for the subsample of type I diabetics with no change in insulin consumption. These marginal effects are presented in table 8. With the exception of insulin consumption, the effect of the formulary expansion on healthcare utilization in each of the samples are all of the same sign. The formulary expansion's effect on type I diabetics whose insulin consumption does not change is in fact greater than for those whose insulin consumption does change.

Given that changing one's insulin prescription requires an appointment with a primary care physician, it is likely that diabetics who do not alter their insulin consumption in response to the formulary expansion have less contact with the healthcare system overall compared to their counterparts who consume the newly covered insulins. Selection of this kind could explain the lower rates of comorbidities among matched diabetics observed in appendix table C4. While we might expect a lower baseline level of non-drug utilization for this

subsample, its limited scope for spillovers indicates that we would also expect a decline in non-drug utilization smaller in magnitude than the one estimated for the full sample. Instead, we find that the reduction in non-drug healthcare utilization for this subsample is larger than that estimated for the full analysis sample. We now turn to exploring a second mechanism - namely, rationing of care - that might explain the change in drug and non-drug consumption patterns that we observe as result of the formulary expansion.

Table 8: Impact of formulary expansion on healthcare utilization of all type I diabetics and those with no change in insulin consumption

	(1) Insulin	(2) All (net insulin)	(3) Outpatient	(4) Hospitalizations	(5) Prescriptions (net insulin)
All type I diabetics	1.99 (1.92, 2.06)	-3.53 (-4.36, -2.71)	-7.05 (-7.46, -6.64)	-0.04 (-0.05, -0.04)	2.71 (2.18, 3.25)
Type I diabetics with no change in insulin consumption	0.05 (-0.04, 0.14)	-9.27 (-10.5,-8.04)	-10.17 (-10.72, -9.62)	-0.07 -(0.08, -0.07)	1.45 (0.78, 2.12)

Notes: Cells contain average marginal effects (95% confidence intervals). Marginal effects of formulary expansion on type I diabetics computed using the estimates in tables 4 and 7 respectively.

6.2 Evidence of rationing

By making type I diabetics relatively more expensive than other enrollees with similar comorbidity profiles, the formulary expansion incentivized insurers to selectively avoid enrollment from type I diabetics by decreasing the quality of care offered to them. One way to do this is through rationing. Insurers in Colombia can ration care by limiting the provider network or provider choices made available to their enrollees, by requiring authorization for provision of certain services or procedures, or by steering physicians away from recommending certain treatments. Anecdotal evidence in local newspapers and magazines shows that healthcare rationing is a prevailing strategy used by insurers to contain costs. In 2014, *Semana* magazine conducted an investigation that revealed some of the most popular cost containment mechanisms used by insurers: notifying doctors periodically about the expenditures they generate, putting caps on per-patient spending, and denying requests by primary care physicians to refer patients to a specialist or provide expensive diagnostic services. Their investigation noted,

> "Although primary care physicians already have limited access to expensive diagnostic services like CT scans or MRIs, insurers also restrict the use of basic clinical services. In this email, the insurance company states that physicians need to start filing a formulary every time they request a Thyroid Stimulating Hormone (TSH) test for their patients. After evaluating every request, the insurer will notify physicians they believe are overprescribing this lab test."

In 2009, *El Colombiano* magazine published,

> "In a study conducted by the National University of Colombia, findings show that out of 458 people who visited their healthcare provider, 17% were denied a medical evaluation. Of those who were evaluated by the doctor, 24.9% were denied laboratory tests and 45% were denied other types of treatment including medications, surgeries, and medical equipment."

Our test for rationing of care is premised on the assumption that insurers will ration discretionary diagnostic services rather than essential healthcare. We construct three measures of discretionary healthcare services - claims for imaging, lab tests, and office visits - as well as a measure of utilization of essential drugs as defined in Tamblyn et al. (2001). The authors define essential drugs as those that "prevent deterioration in health or prolong life and would not likely be prescribed in the absence of a definitive diagnosis." Examples of essential drugs include insulin, inhaled steroids, and beta blockers. We do not include in our measure of essential drug utilization drug classes that were expanded as part of the policy. The full list of essential drugs as well as those that are included in our measure can be found in table C6 in the appendix. We employ the same differences-in-differences empirical specification as in equation (1) to estimate the impact of the formulary on diagnostic outpatient care and essential drug use.

Table 9: Impact of expanded insulin coverage on outpatient & essential drug utilization

	(1)	(2)	(3)	(4)
	Imaging	Labs	Office vists/ consultations	Essential drugs
Diabetic × policy	-0.09***	-0.94***	0.11**	0.28***
	(0.07)	(0.08)	(0.03)	(0.04)
Diabetic	0.45***	9.43***	2.68***	2.77***
	(0.01)	(0.06)	(0.03)	(0.03)
Policy	0.05***	-0.09***	-0.18***	-0.40***
	(0.00)	(0.02)	(0.01)	(0.01)
Model	Negative binomial	Negative binomial	Negative binomial	Negative binomial
$\ln\alpha$	0.32***	0.27***	-0.99***	1.09***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	2430423	2430423	2430423	2430423

Notes: Cells contain average marginal effects (standard errors). Equation (1) estimated on the sample of type-I diabetics and their exactly matched controls. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of estimating these specifications are presented in table 9. Lab tests see the largest decline in annual utilization as a result of the expanded coverage of insulins, falling by 0.9 claims. Both imaging and office visits see statistically but not economically significant effects on utilization. Essential drug utilization increases by 0.3 claims as a result of the expansion. That essential drug utilization rises while use of lab tests falls is consistent with a story of rationing of care in which insurers under-provide healthcare that is diagnostic and preventive in nature, but do not ration drugs which are necessary to avoid adverse health outcomes.

Table 10: Impact of expanded coverage of insulin on utilization of labs and office visits

	(1) Blood sugar labs	(2) Cholesterol labs	(3) Tryglicerides labs	(4) Creatinine labs	(5) A1C tests
Diabetic × policy	-0.26***	-0.08***	-0.05***	-0.09***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Diabetic	1.75***	1.01***	0.81***	0.87***	0.54***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Policy	0.06***	-0.05***	-0.02***	-0.03***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Model	Negative binomial	Negative binomial	Negative binomial	Negative binomial	Negative binomial
lnα	-0.52***	-0.28***	-0.21***	-0.60***	-0.24***
	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	2430423	2430423	2430423	2430423	2430423

Notes: Cells contain average marginal effects (standard errors). Equation (1) estimated on the sample of type-I diabetics and their exactly matched controls. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Having presented evidence that reductions in non-drug spending stem primarily from reductions in discretionary services and in particular from lab tests, we now zoom in and examine which types lab tests are subject to rationing. We decompose lab tests into blood sugar, cholesterol, triglycerides, and creatinine lab tests, which together comprise more than two-thirds of all lab tests. The difference-in-difference coefficients displayed in table 10 show significant reductions in all types of laboratory tests. The largest effect is observed for blood sugar lab tests, which fall by 0.26 claims for type I diabetics. The results presented in tables 9 and 10 also hold for the subsample of diabetics who exhibit no change in insulin consumption as seen in appendix tables C7 and C8.

The rationing of routine lab tests like those included in table 10 is consistent with weakened adherence to guidelines for diabetes management, which recommend lab testing at regular intervals. For example, the U.S. Department of Health and Human Services and the Centers for Disease Control both recommend annual cholesterol and kidney disease testing for diabetics, blood glucose testing every 3 months, and biannual A1C tests (CDC, 2019; National Institute of Diabetes and Digestive and Kidney Diseases, 2016). That these types of lab tests are a routine part of diabetes management is reflected in the fact that type I diabetics in 2011 received over twice as many lab tests as their exactly matched counterparts, a greater differential than any other type of outpatient care. In figure 2, we present effect of the expanded coverage of insulin on the share of type I diabetics that are up to date with lab testing. We see that expanded coverage has a small negative effect on the share of type I diabetics that are up to date with blood sugar, cholesterol, and A1C

testing. Ellis and McGuire (2007) also find that lab tests are a relatively predictable type of healthcare and that they are at higher risk of underprovision by insurers. Rationing of these lab tests reduces costs in the short run. In the long run, it may disincentivize the enrollment of diabetics and delay the diagnosis and treatment of comorbidities.

Figure 2: Predicted utilization of common laboratory tests by diabetics for years before and after formulary expansion

Notes: Plotted are the 95% confidence intervals of the marginal effects of the formulary expansion. Marginal effects are computed using estimates from specifications of equation (1) using binary indicators for being up to date with lab testing as outcome variables. Patients are up to date with cholesterol and kidney disease testing if they receive at least one lab test annually, blood glucose testing if they receive at least four tests annually, and A1C testing if they receive at least two tests annually.

7 Conclusion

In this paper, we measure the impact of expanded insulin coverage on type I diabetics in Colombia. We find that the expansion raises the relative cost of providing health insurance to type I diabetics by increasing the utilization of relatively more expensive types of insulin. Insurers respond to this decreased profitability of type I diabetics mostly by rationing discretionary outpatient care, including lab tests. This targeted rationing in part offsets the more than tripling of insulin costs. The ability to ration care to an identifiable subset of enrollees allows insurers in this market to respond to changes in selection incentives despite having no control over premiums, coinsurance rates, or co-pays. Our results are generalizable to other health systems where public health insurance is provided by private plans whose reimbursements are risk adjusted. This includes the ACA Marketplaces, Medicare Advantage, and Medicare Part D in the U.S. Despite the fact

that the risk adjustment schemes in these systems take into account diagnostic and clinical information that makes them more robust than the scheme employed in the Colombian system, there is still evidence of adverse selection in these settings (Juhnke et al., 2016; Newhouse et al., 2013; Montz et al., 2016). Our results indicate that limiting insurers' ability to risk select through premiums and plan design does not keep them from responding to changing selection incentives. Carriers instead respond by rationing the amount of care provided to less profitable enrollees, reducing quality and encouraging disenrollment.

We focus on how the expansion of insulin coverage affects the profitability and quality of care received by type I diabetics. We do so because the exclusivity of insulin to diabetics facilitates identification of the causal effect of expanded insulin coverage on healthcare utilization and costs. Our findings, however, are not exclusive to Diabetics and insulin. If insurers can use prediction methods to identify patients who are likely to become less profitable conditional on risk adjustment, we show that they can ration care according to these predictions.

There are several limitations to our study. While our granular claims data allows us to identify the narrow types of discretionary care that insurers ration, our short time frame does not allow us to observe any effects of the policy that may take longer to manifest, such as changes in enrollment patterns and health status. While our focus on type I diabetics has some advantages, we cannot construct a control group for outcomes that are specific to this group. The results presented here suggest that insurers respond to changes in selection incentives with the tools available to them, no matter how unrefined they may be, and that careful consideration must be given to policy changes altering the profitability of identifiable groups of enrollees.

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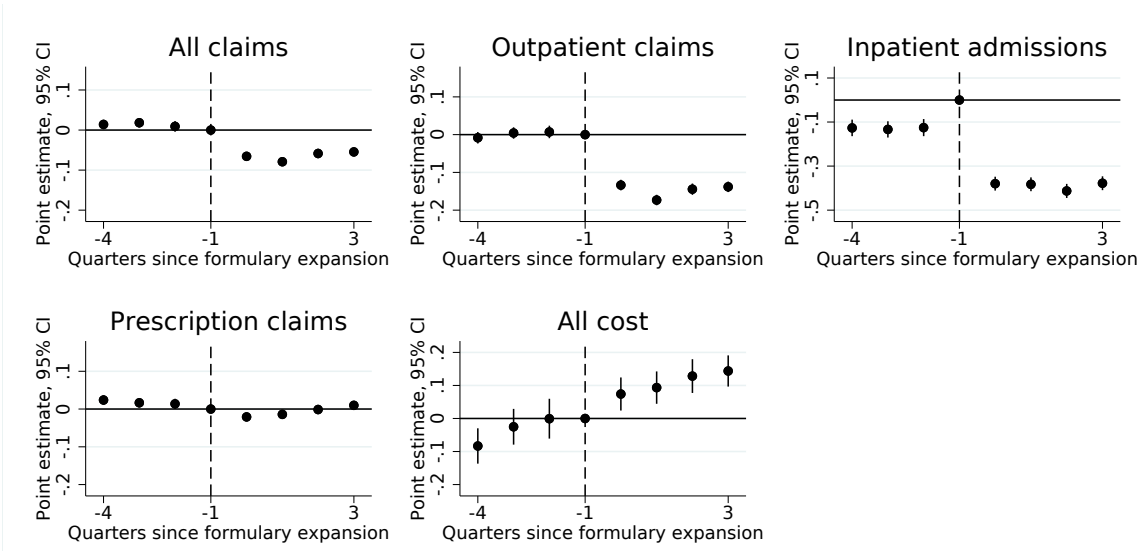
Appendix A Parallel trends

We test the parallel trends assumption of the differences-in-differences methodology presented in section 4 by conducting an event study for our primary outcomes: total claims, total cost, outpatient claims, prescription claims, and inpatient admissions. Let τ_{it} be the number of quarters since enrollee i was treated by the expanded coverage insulins, and let τ_{it} be normalized to -1 for control units. We estimate

$$G(\mathbb{E}[y_{it}]) = \alpha + \beta_{\tau_{it}} + \delta D_i + \eta_t + \mathbf{x}_i'\beta \tag{3}$$

where y_{it} is the outcome for patient i in year t; D_i is an indicator variable for patient i being a type I diabetic; η_t are month-year fixed effects; and $\mathbf{x}_i$ is a vector of demographic characteristics including sex, age group, comorbidity dummies, insurer dummies, and type of municipality dummies. As in the main analyses, we assume that y follows a negative binomial distribution for the total claims, outpatient claims, and prescription claims specifications; follows a Bernoulli distribution for the inpatient admission specification; and follows a gamma distribution for the total cost specification. We employ a log link throughout except in the case of inpatient admissions for which we employ a logit link. We plot the $\hat{\beta}_\tau$s in figure 3 below.

Figure 3: Plot of quarters-since-expansion fixed effects from event study regressions



Notes: Negative binomial regressions estimated for all claims, outpatient claims, and prescriptions claims specifications. Logistic regression estimated for inpatient admission specification. Gamma regression estimated for all costs specification. All specifications control for age group, sex, municipality, comorbidities, and insurance carrier. All and prescription claims include insulin utilization. Dashed vertical line at period before formulary expansion. Solid horizontal line at zero.

Appendix B Theoretical framework

Let a denote a measure of availability of prescription drugs, d the probability of rationing, TC^D drug-related costs, TC^M non-drug costs, R per patient reimbursement, and Q total demand. An insurer's profits are given by:

$$\pi(a,d) = (R - TC^D(a,d) - TC^M(a,d))Q(a,d) \tag{4}$$

Assume $\frac{\partial Q}{\partial a} > 0$, $\frac{\partial Q}{\partial d} < 0$, $\frac{\partial TC^D}{\partial a} > 0$, $\frac{\partial TC^D}{\partial d} < 0$, $\frac{\partial TC^M}{\partial d} < 0$, so that demand for an insurance carrier is increasing in the availability of drugs and decreasing in the probability of rationing. Both types of costs are also decreasing in the probability of rationing. If there are spillovers from drug to non-drug spending then $\frac{\partial TC^M}{\partial a} < 0$, otherwise the partial derivative is non-negative. For simplicity assume $\frac{\partial^2 TC^D}{\partial a \partial d} = \frac{\partial^2 TC^M}{\partial a \partial d} = 0$. The availability of drugs is exogenous and determined by the government, while the probability of rationing is a choice variable to the insurer. The insurer's problem is to maximize profits choosing d, the FOC given by:

$$\partial\pi/\partial d = (R - TC^D(a,d) - TC^M(a,d))\partial Q/\partial d - (\partial TC^D/\partial d + \partial TC^M/\partial d)Q = 0 \tag{5}$$

We check whether the profit function is supermodular in (a,d) by taking the derivative of the FOC with respect to a as seen in the equation below:

$$\begin{aligned}\partial^2\pi/\partial a\partial d = (R - TC^D(a,d) - TC^M(a,d))\partial^2 Q/\partial a\partial d - (\partial TC^D/\partial a + \partial TC^M/\partial a)\partial Q/\partial d \\ - (\partial TC^D/\partial d + \partial TC^M/\partial d)\partial Q/\partial a\end{aligned} \tag{6}$$

If there are no spillovers from drug to non-drug spending, $\partial TC^M/\partial a \geq 0$ and π is supermodular in (a,d). In this case, exogenous increases in the availability of drugs, as the one generated by the formulary expansion, increases the probability of rationing. In the polar case where spillovers are present and large in magnitude, π is submodular in (a,d). Intuitively, if spillovers are large then insurers need not engage in rationing to achieve cost savings following an increase in the availability of drugs. For moderate levels of spillovers from drug to non-drug spending, there is scope for a positive relation between a and d.

Appendix C Appendix tables

Table C1: Distribution of utilization outcomes for type I diabetics and exact match counterparts

	Diabetics							Exactly-matched non-diabetics						
	p1	p25	p50	p75	p99	Mean	S.d.	p1	p25	p50	p75	p99	Mean	S.d.
2011														
All claims	13	58	87	125	346	100.6	71.3	1	18	38	65	212	48.5	46.9
Outpatient claims	3	20	32	48	171	39.8	41.2	1	9	17	28	104	22.2	27.2
Inpatient claims	0	0	0	5	104	7.9	21.0	0	0	0	0	55	3.0	11.1
Prescription claims	1	28	47	71	161	52.9	35.7	0	4	16	35	105	23.4	24.7
Insulin claims	1	4	6	10	22	7.3	4.9	0	0	0	0	0	0.0	0.4
Procedure claims	0	8	16	27	89	20.8	21.2	0	2	7	14	62	10.8	14.2
Imaging claims	0	0	1	2	14	1.9	3.2	0	0	1	2	10	1.4	2.4
Lab claims	0	9	17	29	121	23.5	28.7	0	1	7	12	67	10.0	16.1
Office/consultation claims	0	6	9	14	33	10.6	7.3	0	3	6	10	27	7.3	5.8
Essential drugs claims	0	0	4	10	31	6.2	7.2	0	0	1	5	24	3.4	5.5
Observations	41,911							1,065,674						
2013														
All claims	11	57	88	127	362	101.3	75.6	1	18	40	69	213	50.8	50.1
Outpatient claims	1	17	27	42	152	34.2	37.7	0	9	16	26	93	20.7	25.9
Inpatient claims	0	0	0	3	100	8.0	20.5	0	0	0	0	56	3.3	11.4
Prescription claims	3	29	52	80	185	59.0	44.6	0	5	17	41	120	26.8	29.9
Insulin claims	1	5	9	13	24	9.3	5.9	0	0	0	0	0	0.0	0.4
Procedure claims	0	7	14	24	79	18.1	21.8	0	2	7	14	58	10.8	16.7
Imaging claims	0	0	1	2	14	1.9	3.2	0	0	1	2	11	1.5	2.5
Lab claims	0	9	16	27	110	21.7	26.5	0	2	7	13	63	10.0	15.6
Office/consultation claims	0	5	9	14	35	10.4	7.4	0	3	6	9	27	7.1	5.8
Essential drugs claims	0	0	4	10	33	6.6	8.3	0	0	0	5	27	3.4	6.1
Observations	55,299							1,267,539						

Note: This table presents summary statistics of utilization outcomes after 1-to-n exact matching on age, sex, comorbidites, type of municipality, and insurer. Summary statistics for control units are weighted by the inverse number of controls matched to each diabetic.

Table C2: Distribution of cost outcomes for type I diabetics and exact match counterparts

	Diabetics							Exactly-matched non-diabetics						
	p1	p25	p50	p75	p99	Mean	S.d.	p1	p25	p50	p75	p99	Mean	S.d.
2011														
All costs	0.12	0.55	1.01	2.48	39.79	3.44	8.50	0.02	0.20	0.40	0.96	27.85	1.80	6.44
Outpatient costs	0.05	0.34	0.61	1.21	23.82	1.50	3.86	0.01	0.16	0.32	0.68	14.01	0.92	3.21
Inpatient costs	0.00	0.00	0.00	0.33	23.86	1.37	5.45	0.00	0.00	0.00	0.00	14.92	0.67	4.21
Prescription costs	0.02	0.11	0.19	0.37	7.27	0.57	1.96	0.00	0.01	0.02	0.07	3.33	0.21	1.80
Insulin costs	0.01	0.04	0.08	0.14	1.51	0.14	0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Procedure costs	0.00	0.12	0.27	0.65	20.49	0.94	3.09	0.00	0.04	0.13	0.35	9.06	0.57	2.60
Imaging costs	0.00	0.00	0.03	0.16	2.10	0.18	0.43	0.00	0.00	0.02	0.11	1.45	0.12	0.34
Lab costs	0.00	0.09	0.17	0.33	2.36	0.30	0.48	0.00	0.01	0.06	0.13	1.12	0.12	0.29
Office/consultation costs	0.00	0.10	0.17	0.28	0.85	0.22	0.21	0.00	0.06	0.11	0.19	0.67	0.15	0.23
Essential drugs cost	0.00	0.01	0.01	0.03	1.51	0.09	0.44	0.00	0.00	0.00	0.01	0.66	0.04	0.29
Observations	41,911							1,065,674						
2013														
All costs	0.12	0.65	1.57	3.55	40.05	3.84	8.22	0.01	0.18	0.40	0.99	26.73	1.68	6.12
Outpatient costs	0.01	0.27	0.54	1.17	21.11	1.38	3.42	0.00	0.14	0.30	0.66	8.60	0.77	2.49
Inpatient costs	0.00	0.00	0.00	0.31	23.17	1.26	5.10	0.00	0.00	0.00	0.00	12.84	0.59	3.79
Prescription costs	0.02	0.16	0.40	1.50	9.69	1.21	2.72	0.00	0.01	0.03	0.08	5.18	0.31	2.68
Insulin costs	0.01	0.06	0.16	0.87	4.40	0.64	0.99	0.00	0.00	0.00	0.00	0.00	0.00	0.03
Procedure costs	0.00	0.10	0.24	0.53	16.16	0.79	2.77	0.00	0.04	0.13	0.35	5.31	0.46	1.97
Imaging costs	0.00	0.00	0.03	0.16	2.34	0.19	0.55	0.00	0.00	0.02	0.11	1.56	0.12	0.36
Lab costs	0.00	0.09	0.17	0.32	2.52	0.30	0.52	0.00	0.02	0.06	0.14	1.18	0.13	0.31
Office/consultation costs	0.00	0.08	0.16	0.28	2.97	0.29	0.51	0.00	0.04	0.09	0.18	0.81	0.14	0.25
Essential drugs cost	0.00	0.00	0.02	0.05	1.93	0.11	0.51	0.00	0.00	0.00	0.02	0.86	0.05	0.70
Observations	55,299							1,267,539						

Note: This table presents summary statistics of utilization outcomes after 1-to-n exact matching on age, sex, comorbidites, type of municipality, and insurer. Summary statistics for control units are weighted by the inverse number of controls matched to each diabetic.

Table C3: Balance table of insurer's network size across markets

Insurer	2011	2013	p-value
A	117 (145)	88.0 (119)	0.37
B	145 (144)	221 (165)	0.10
C	40 (38)	17 (15)	<0.01
D	74 (74)	41 (60)	0.10
E	7 (14)	20 (36)	0.12
F	188 (191)	215 (187)	0.76
G	11 (13)	16 (39)	0.82
H	140 (42)	54 (16)	<0.01
I	375 (268)	365 (237)	0.91
J	143 (222)	134 (231)	0.82
K	56 (106)	66 (109)	0.82
L	18 (30)	7 (11)	0.03
M	158 (108)	132 (89)	0.34

Notes: Cells contain the average and standard deviation in parenthesis of the number of unique reimbursed providers for each insurer in the pre- and post-policy periods. P-values for comparison of network sizes across periods are computed using Wilcoxon rank-sum test for continuous variables and Pearson's chi-squared test for categorical and binary variables.

Table C4: Balance table of type I diabetics by whether they are matched in CEM

	Not matched by CEM	Matched by CEM	p-value
Demographics			
Male (%)	43.11	43.22	0.74
Age, mean (sd)	62.72 (13.10)	63.23 (12.59)	<0.001
Diagnoses (%)			
Arthrosis	3.74	1.29	<0.001
Cardiovascular disease	73.85	73.13	0.012
Long term pulmonary disease	6.50	3.33	<0.001
Renal disease	19.26	12.34	<0.001
Insurer (%)			<0.001
A	2.13	1.54	
B	8.66	7.08	
C	4.24	0.07	
D	4.58	3.89	
E	5.63	5.59	
F	8.95	10.33	
G	0.94	2.31	
H	5.79	17.54	
I	14.99	11.11	
J	6.05	7.78	
K	0.03	0.04	
L	0.01	0.00	
M	0.35	0.29	
Type of municipality (%)			<0.001
Metropolitan	67.20	77.25	
Normal	32.47	22.64	
Special	0.33	0.11	
N	40,673	56,537	

Notes: This table shows some descriptive summary statistics of type I diabetics who are and are not matched by conditional exact matching (CEM). Type 1 diabetics who are matched ahve no change in the level or composition of insulin composition across years. p-values for comparison of matched and unmatched type I diabetics are computed using Wilcoxon rank-sum test for continuous variables and Pearson's chi-squared test for categorical and binary variables.

Table C5: Impact of expanded insulin coverage on healthcare costs for subsample of type I diabetics with no change in insulin consumption

	(1) All insulin	(2) All (net insulin)	(3) Outpatient	(4) Inpatient		(5) Prescriptions (net insulin)
Policy	-0.03***	-1.01***	-0.38***	-0.08***	-0.42**	-0.08***
	(0.00)	(0.08)	(0.02)	(0.00)	(0.14)	(0.02)
Model	Gamma	Gamma	Gamma	Logit	Gamma	Gamma
Observations	56537	56537	56537	56456		56537

Notes: Cells contain average marginal effects (standard errors). Equation (2) estimated on the sample of type I diabetics who have zero consumption of newly added insulins and similar consumption of continuously covered insulins before and after the formulary expansion. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C6: List of essential drugs

Essential drug	Included in measure?
Insulin	No
Anticoagulants	No
Angiotensin-converting enzyme inhibitors	Yes
Lipid-reducing medication	No
Antihypertensives	Yes
Furosemide	Yes
β-blockers	No
Antiarrhythmics	Yes
Asprin	Yes
Antiviral medication	Yes
Thyroid medication	Yes
Neuroleptics	Yes
Antidepressants	No
Anticonvulsants	No
Antiparkinsonian drugs	No
Prednisone	Yes
β-agonists	Yes
Inhaled steroids	Yes
Chloroquines	Yes
Primaquines	Yes
Cyclosporine	Yes

Notes: Essential drugs as defined in Tamblyn et al. (2001) and whether each is included in measure used in table 9 column 5. We exclude drugs on the basis of being part of a drug class that was expanded as part of the formulary expansion.

Table C7: Impact of expanded insulin coverage on outpatient & essential drug utilization for subsample of type I diabetics with no change in insulin consumption

	(1) Imaging	(2) Labs	(3) Office vists/ consultations	(4) Essential drugs
Policy	-0.33***	-4.23***	-0.52***	-0.33***
	(0.03)	(0.23)	(0.07)	(0.08)
Model	Negative binomial	Negative binomial	Negative binomial	Negative binomial
lnα	0.28***	-0.41***	-1.35***	0.44***
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	56537	56537	56537	56537

Notes: Cells contain average marginal effects (standard errors). Equation (2) estimated on the sample of type I diabetics who have zero consumption of newly added insulins and similar consumption of continuously covered insulins before and after the formulary expansion. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C8: Impact of expanded coverage of insulin on utilization of labs and office visits for subsample of type I diabetics with no change in insulin consumption

	(1) Blood sugar labs	(2) Cholesterol labs	(3) Tryglicerides labs	(4) Creatinine labs	(5) A1C tests
Policy	-0.85***	-0.41***	-0.36***	-0.34***	-0.07***
	(0.05)	(0.03)	(0.03)	(0.02)	(0.01)
Model	Negative binomial	Negative binomial	Negative binomial	Negative binomial	Negative binomial
lnα	-0.56***	-0.66 ***	-0.54***	-1.03***	-16.23***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.17)
Observations	56537	56537	56537	56537	56537

Notes: Cells contain average marginal effects (standard errors). Equation (2) estimated on the sample of type I diabetics who have zero consumption of newly added insulins and similar consumption of continuously covered insulins before and after the formulary expansion. All models control for sex, age, comorbidities, municipality, and insurance carrier. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$