Optimal Timing of Risk Adjustment Payments in Health Insurance*

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November 6, 2025

Abstract

We develop a theoretical framework to evaluate whether risk adjustment payments should be made ex-ante (relative to the realization of claims) to prevent adverse selection versus ex-post to prevent moral hazard. We apply our framework to data from Colombia where the government started ex-post compensations for HIV-AIDS in 2016. Using an event study design, we find that the policy improved quality of care for HIV-AIDS patients. Then, using a structural model of insurer demand, we confirm ex-post payments are optimal for HIV-AIDS and should be used for renal disease and cardiovascular disease. Certain cancers should be compensated ex-ante.

Keywords: Health insurance, Provider networks, Adverse selection, Competition.

JEL codes: I11, I13, I18, L13.

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1 Introduction

Risk adjustment is the most commonly used tool to combat adverse selection in health insurance markets with regulated competition (Newhouse, 1998, 1994). It consists of predicting the annual healthcare spending per beneficiary based on their health and sociodemographic characteristics. The spending prediction is then paid to insurers, typically at the beginning of an enrollment period, to encourage them to cover individuals of different health statuses. The consequences of failing to address adverse selection in insurance markets are potentially dire, ranging from inefficient insurance coverage (Einav and Finkelstein, 2011) to market unraveling (Kong et al., 2024). This has motivated research examining incentives created by risk adjustment mechanisms (e.g., Geruso and Layton, 2020; Lavetti and Simon, 2018; Carey, 2017; Brown et al., 2014) as well as research on how best to design these mechanisms to eliminate selection incentives (e.g., McGuire et al., 2021b; Zink and Rose, 2021; Layton et al., 2018).

However, adverse selection is not the only market failure present in insurance markets. Ex-post moral hazard (either from consumers or insurers) is also a concern. Conditional on enrollment, individuals with more generous insurance coverage tend to consume more healthcare services (Einav and Finkelstein, 2018) and insurers with ex-post riskier enrollee populations can engage more strongly in utilization management strategies (Gaines et al., 2020). Both of these market failures (adverse selection and moral hazard) can jeopardize a health system's fiscal sustainability and potentially harm patient health outcomes. Yet, the consequences of moral hazard for risk adjustment are poorly understood. In this paper, we provide a close examination of how risk-adjusted payments can be designed to address adverse selection and moral hazard.

We begin by developing a theoretical framework that allows us to derive the optimal risk adjustment policy in a competitive insurance market. We characterize the optimal policy in terms of the timing of payments relative to the realization of health claims. Under this characterization, there are two possible risk adjustment policies: ex-ante or ex-post (Van de Ven et al., 2003). The former addresses adverse selection while the latter

addresses moral hazard.[1] Among these two options, the optimal policy is the one that maximizes social surplus or approximates the outcomes of a regulator (similar to Glazer and McGuire, 2000).

According to our model, the policy space is fully characterized by the binary choice between ex-ante and ex-post payments. Both types of policies also coexist in practice across several countries. For example, Germany's Social Health Insurance System has an ex-ante risk adjustment mechanism that compensates insurers (known as sickness funds) for demographics and diagnoses, and introduced in 2021 a pool of funds to compensate ex-post for high-risk individuals using their current spending (McGuire et al., 2021a). The US Marketplaces also use an ex-post risk adjustment model that compensates health plans for demographics and diagnoses measured in the current enrollment period (McGuire et al., 2021a). However, despite ex-post payments being widespread, the economic rationale for them remains unclear. Our theoretical framework provides clarity on this issue.

In our theoretical model, insurers choose their generosity of coverage per consumer type. Coverage generosity is defined as the actuarial value and a consumer type is characterized by their health risk. In this environment, we approximate the regulator's optimal choice of actuarial value as the maximizer of insurers' profits when there are no selection or moral hazard distortions.[2] We show (empirically) that this benchmark is without loss of generality. Then, we solve the insurers' profit maximization problem when facing adverse selection and moral hazard. We show that the insurer chooses lower coverage than the regulator. Thus, the regulator must implement either an ex-ante or an ex-post risk adjustment policy to induce the insurer to choose a higher actuarial value.

We show that the regulator must follow a simple cutoff rule to implement the optimal policy. This cutoff rule specifies that if, for a consumer type, the demand elasticity with

[1] Depending on the specific design of ex-post payments, these can also be viewed as a combination of reinsurance and repayments. On the one hand, under reinsurance, health plans are compensated ex-post whenever a beneficiary's spending exceeds certain threshold. On the other hand, for plans that spend less on an individual than predicted by the ex-ante risk adjustment formula, repayments can help limit their gains (McGuire et al., 2020).

[2] By choosing this benchmark, our implicit assumption is that the regulator's optimal actuarial value must be implemented through competing private insurers and hence the regulator must guarantee the insurers are willing to participate. By choosing the actuarial value that maximizes insurers' profits in a world without distortions, the regulator can guarantee insurer participation.

respect to the actuarial value is less than the (normalized) difference in healthcare spending between the consumer type and the benchmark—meaning moral hazard incentives are stronger than adverse selection incentives—then the optimal risk adjustment policy makes payments ex-post. When the inequality is reversed, the optimal policy is an ex-ante payment.

We apply the results from our theoretical framework to data from the Colombian health insurance system. This system is useful for our application not only because of the conditions of insurer competition but also because we can exploit a risk adjustment policy change in January 2016 that introduced ex-post compensations for patients with HIV-AIDS. In Colombia, private insurers compete by designing their provider networks to offer one national health insurance plan. Premiums, cost-sharing, and benefits are all regulated and are the same across insurers. Differences in insurers' provider networks can therefore be mapped to differences in the actuarial value they offer to patients of different health status.

Insurers in Colombia are compensated with two forms of risk adjustment: an ex-ante payment that controls for the individual's sex, age, and municipality of residence, and an ex-post policy that controls for a few chronic diseases. The ex-post mechanism is known as the High-Cost Account (HCA) and consists of redistributing ex-ante compensations from insurers with relatively low prevalence of diseases to those with a relatively high prevalence in the current enrollment period (see Decree 2699 of 2007). The government started ex-post compensations for renal disease in 2007, HIV-AIDS in 2016, and several other diseases in 2019.

Our data consist of individual-level enrollment records and health claims from all consumers who pay payroll taxes and are covered by the contributory health system between 2013 and 2019. We have information on more than 24 million enrollees yearly. Using these data, we first show whether the ex-post compensation for HIV-AIDS improved the outcomes of these patients.

Using an event study design comparing patients with HIV-AIDS to patients with other chronic diseases ever considered under the HCA, we find that healthcare spending on HIV-AIDS patients nearly doubled relative to baseline. Vaccination rates for hepatitis A and

B, pneumococcus and other common comorbidities increased by 127% and utilization of antiretroviral therapy (ART) was nearly 7 percentage points higher among patients diagnosed with HIV-AIDS after the policy than among those diagnosed before the policy. These findings suggest that ex-post compensations improved quality of care for patients with HIV-AIDS (and perhaps that ex-post payments are the optimal policy for this disease).

To predict the optimal policy for different diseases, we estimate a structural model of insurer demand that allows us to obtain the cutoff rule from the theoretical model. We assume consumers choose an insurer to maximize their utility, which is a function of the actuarial value and unobserved insurer quality. We allow preferences for coverage generosity to be heterogeneous across diseases to capture differential sorting to insurers by health status. Because the actuarial value is endogenous as it is determined in equilibrium, we use a Hausman-style instrument to identify consumers' preference for coverage generosity.

Our findings show that all consumers prefer more generous coverage or a higher actuarial value. Individuals with breast cancer, cardiovascular disease, and diabetes have a stronger preference for the actuarial value than individuals with asthma and tuberculosis, presumably because they have more frequent contact with medical providers. Using these estimates, we compute the cutoff rule and find that, in line with our reduced-form estimates, an ex-post policy is indeed optimal for HIV-AIDS. Other diseases for which ex-post payments are optimal include renal disease, tuberculosis, and asthma, while different types of cancers, such as skin and breast cancer, should be compensated ex-ante. Comparing the average actuarial value between diseases predicted to be compensated ex-ante and ex-post shows that our cutoff rule equalizes coverage generosity across patients, in line with the regulator's goals.

Our results make a novel contribution to the risk adjustment literature by focusing on the interaction between adverse selection and moral hazard when designing risk-adjusted payments. Literature to date studies risk adjustment from the perspective of adverse selection (e.g., Layton et al., 2018; Layton, 2017), health plan design (e.g., Geruso et al., 2019; Carey, 2017), or algorithm design (e.g., Bergquist et al., 2018). Similar to ours, Zwart (2025) examines the implications of moral hazard for risk adjustment through a

theoretical lens. We provide not only a theoretical foundation for the timing of risk-adjusted payments, but also an empirical application exploiting rich policy variation in Colombia. Notably, we derive a simple cutoff rule that determines whether there is scope for ex-post compensations for a given disease and can be computed using data from any country with a managed care system.

By conditioning payments to current spending, our analysis of ex-post compensations is related to the concept of reinsurance, whereby health plans are compensated for enrollees that exceed certain spending thresholds in the current enrollment period. Reinsurance has gained recent momentum in the literature (in papers such as McGuire et al., 2021b; Jacobs et al., 2017; Zhu et al., 2013) and has been proposed as an effective tool for improving the fit of risk-adjusted payments to observed plan spending (e.g., McGuire et al., 2020).

Our study of ex-post compensations for HIV-AIDS in Colombia also contributes to the literature on performance pay models in healthcare (Miller and Barbiarz, 2013; Eijkenaar, 2012). The HCA mechanism for HIV-AIDS tied insurer compensations to quality metrics in the treatment of patients living with HIV-AIDS, such as viral load monitoring, early detection, and ART use. Our findings that these payments to insurers improved outcomes for patients with HIV-AIDS contributes to the growing evidence on performance pay being welfare-enhancing, which has mostly focused on provider payment (e.g., Gupta et al., 2023; Einav et al., 2022; Gupta, 2021; Mullen et al., 2010).

2 Theoretical Framework

We propose a model of a health insurance market in which premiums are fixed and insurers choose their generosity of coverage conditional on receiving risk-adjusted transfers from the regulator. The question we aim to address is whether these transfers should be paid ex-ante or ex-post relative to the realization of health claims, in order to approximate the outcomes of a regulator.

Define insurer j's generosity of coverage as its actuarial value a_j—the fraction of total healthcare costs that it covers for its beneficiaries. Suppose consumers are of type

$\theta \in 0, 1, ..., I \equiv \Theta$, with $\theta = 0$ denoting healthy individuals. Let R be the revenue per enrollee, c_θ the cost per enrollee with $c_0 < c_{\theta>0}$, $s_\theta(a_j)$ the insurer's market share with $s'_\theta(a_j) > 0 > s''_\theta(a_j)$ and $|s''_\theta(a_j)| < s'_\theta(a_j)$, N_θ the market size of type-θ consumers, and $p_\theta(a_j)$ the per capita transfer from the regulator, with $p_0(a_j) = 0$ and $p'_\theta(a_j) > 0 > p''_\theta(a_j)$. We express the policy as a function of the actuarial value, without loss of generality, since under ex-post transfers, the regulator can observe the coverage provided over the current enrollment period and adjust payments accordingly. Our simplifying assumption is that insurer demand depends only on the actuarial value, since this is the only contract feature observable to consumers at the time of initial enrollment. This assumption is not overly restrictive as different plan features, such as provider networks and cost-sharing, can be mapped to coverage generosity.

The goal of the regulator's transfers is to incentivize insurers to exert high effort in delivering care to their enrollees. Under our framework where effort is proxied by the generosity of coverage, this translates into encouraging insurers to select a high actuarial value. Our implicit assumption is that more generous coverage enhances consumer welfare, either through improved financial protection or better health outcomes.[3] The insurer cannot engage in first-degree discrimination of the actuarial value, because a consumer type is an individual's private information. Also, the insurer chooses its actuarial value before health claims are realized, so consumers make insurance choices observing this actuarial value. The insurer profit function without any regulation is:

$$\pi(a_j) = \sum_{\theta \in \Theta} (R - a_j c_\theta) s_\theta(a_j) N_\theta \geq 0$$

The first-order condition (FOC) of the private problem is given by:

$$FOC_\theta(a_j) = \pi'(a_j) = \sum_{\theta \in \Theta} [(R - a_j c_\theta) s'_\theta(a_j) - c_\theta s_\theta(a_j)] N_\theta \tag{1}$$

which implicitly defines the private optimum actuarial value a^{**}.

[3] There is substantial evidence in the literature suggesting higher coverage improves healthcare utilization (e.g., Aron-Dine et al., 2013) and lower coverage reduces utilization of high- and low-value care (e.g., Brot-Goldberg et al., 2017).

We approximate the social welfare function as insurer profits in a market without distortions or unobserved individual heterogeneity. The socially optimal uniform actuarial value is the argument a^* that maximizes the following profit function:

$$\pi_0(a_j) = \sum_{\theta \in \Theta} (R - a_j c_0) s_\theta(a_j) N_\theta$$

where, without loss of generality, we have assumed that all consumers are healthy to eliminate distortions. Generally we only require normalizing all consumers to the type for which the insurer will choose the highest actuarial value. This simplification is analytically convenient to determine how risk adjustment policies shift behavior relative to a benchmark without scope for behavior. As we will show later, the choice of social benchmark has no implications for our predictions of the optimal policy. The FOC of the social problem is:

$$FOC_0(a_j) \equiv \pi'(a_j) = \sum_{\theta \in \Theta} [(R - a_j c_0) s'_\theta(a_j) - c_0 s_\theta(a_j)] \tag{2}$$

Proposition 1. *Under these conditions, the socially optimal uniform actuarial value is higher than the privately optimal uniform actuarial value.*

Proof. We show that $FOC_0(a_j) > FOC_\theta(a_j)$. Taking the difference between the two FOCs yields:

$$\Delta FOC_\theta(a_j) \equiv FOC_0(a_j) - FOC_\theta(a_j) = \sum_{\theta \in \Theta} [-a_j(c_0 - c_\theta) s'_\theta(a_j) - (c_0 - c_\theta) s_\theta(a_j)]$$

Given that $c_0 < c_\theta$ and that the profit maximization problem is strictly concave by assumption, we obtain that $\Delta FOC(a_j) > 0$. Hence $a^* > a^{**}$. □

Proposition 1 shows that insurance coverage is underprovided in the private optimum. Thus, the regulator sets a risk adjustment policy $p_\theta(a_j)$ to minimize the difference between the social and the private optima. With regulation, the insurer's profit function is:

$$\pi(a_j) = \sum_{\theta \in \Theta} [(R - a_j c_\theta) s_\theta(a_j) + p_\theta(a_j)] N_\theta$$

and its FOC is:

$$FOC_\theta(a_j) = \pi'(a_j) = \sum_{\theta\in\Theta}[(R - a_j c_\theta)s'_\theta(a_j) - c_\theta s_\theta(a_j) + p'_\theta(a_j)]N_\theta \tag{3}$$

We now show that minimizing the difference between social and private optima is equivalent to choosing the policy that minimizes the difference between the social FOC in equation (2) and the private FOC in equation (3).

Proposition 2. *Let* $p^*_\theta = \arg\min a^* - a^{**}(p_\theta)$. *Then,* $p^*_\theta = \arg\min FOC_\theta(a_j) - FOC_0(a_j)$.

Proof. It suffices to show that $FOC_\theta(a_j) - FOC_0(a_j)$ is monotonic in a_j. For the insurer's problem we have:

$$-\Delta FOC'_\theta(a_j) \equiv FOC'_\theta(a_j) - FOC'_0(a_j) = \sum_{\theta\in\Theta}[-(c_\theta - c_0)a_j s''_\theta(a_j) - 2(c_\theta - c_0)s'_\theta(a_j) + p''_\theta(a_j)] < 0$$

since $a_j < 1$ and by assumption $s_\theta(a_j)'' < 0 < s'_\theta(a_j)$. □

Let $c_\Delta \equiv c_\theta - c_0$ and rewrite the difference between the private and social FOCs as:

$$-\Delta FOC_\theta(a_j) \equiv \pi'(a_j) - \pi'_0(a_j) = \underbrace{-\sum_{\theta\in\Theta} a_j c_\Delta s'_\theta(a_j)N_\theta}_{\text{adverse selection}} \underbrace{-\sum_{\theta\in\Theta} c_\Delta s_\theta(a_j)N_\theta}_{\text{moral hazard}} + \sum_{\theta\in\Theta} \underbrace{p'_\theta(a_j)N_\theta}_{\text{policy impact}} \tag{4}$$

The first term on the right-hand side of equation (4) reflects adverse selection: it measures how demand shifts in response to a change in coverage generosity, scaled by the fixed cost differential between each consumer type and the benchmark. The second term reflects ex-post moral hazard, capturing how costs rise with the consumer type while holding demand fixed. The third term reflects the role of the risk-adjustment policy, showing how it influences the choice of coverage generosity. Since insurance coverage is underprovided in the private optimum, and both the first and second terms in equation (4) are negative, any risk adjustment policy will improve outcomes—since $p'_\theta(a_j) > 0$ by assumption. We focus then on the binary choice between an ex-ante or an ex-post policy to deal with the consequences of adverse selection or moral hazard, respectively.

We characterize a consumer type-specific policy, as is standard in real-world risk adjustment. Holding total transfers fixed, define the ex-ante risk adjustment policy as one that reimburses insurers the average cost per consumer type, weighted by demand:

$$p_\theta^{\text{ante}}(a_j) = \overline{ac_\Delta} s_\theta(a_j)$$

We do not make any assumptions on how this average cost is calculated, so our framework is general enough to embed risk adjustment formulae with different predictive ratios. This policy eliminates adverse selection since:

$$\sum_{\theta\in\Theta} p_\theta^{\text{ante}\prime}(a_j)N_\theta = \sum_{\theta\in\Theta} \overline{ac_\Delta} s'_\theta(a_j)N_\theta = \sum_{\theta\in\Theta} a_j c_\Delta s'_\theta(a_j)N_\theta$$

where the last term equals the adverse selection term in equation (4).

Define the ex-post risk adjustment policy as one that reimburses insurers exactly their cost weighted by average demand:

$$p_\theta^{\text{post}}(a_j) = a_j c_\Delta \overline{s_\theta}.$$

The ex-post policy eliminates moral hazard since:

$$\sum_{\theta\in\Theta} p_\theta^{\text{post}\prime}(a_j)N_\theta = \sum_{\theta\in\Theta} c_\Delta \overline{s_\theta} N_\theta = \sum_{\theta\in\Theta} c_\Delta s'_\theta(a_j)N_\theta$$

where the last term reflects the impact of moral hazard in equation (4).

If $p_\theta^{\text{post}\prime}(a_j) > p_\theta^{\text{ante}\prime}(a_j)$, then the optimal policy is an ex-post reimbursement, because it maximizes $\sum_\theta p'_\theta(a_j)N_\theta$—the condition required to minimize the distance between the socially optimal and the privately optimal actuarial value. Thus, an ex-post policy is optimal if

$$\begin{aligned} p_\theta^{\text{post}\prime}(a_j) > p_\theta^{\text{ante}\prime}(a_j) &\Leftrightarrow c_\Delta \overline{s_\theta} > \overline{ac_\Delta} s'_\theta(a_j) \\ &\Leftrightarrow \frac{\overline{c_\Delta}}{c_\Delta}\,\epsilon < 1 \end{aligned} \tag{5}$$

where $\epsilon = s'_\theta(a_j)\frac{\bar{a}}{\bar{s}_\theta}$ is the demand elasticity with respect to the actuarial value. Equation (5), which we label the "cutoff rule," provides an empirically testable prediction that requires data on insurer market shares, actuarial values, and healthcare spending per consumer type, and can be applied to any healthcare system with managed care competition. Note also that the choice of social benchmark will likely have small impacts on our predictions because this benchmark affects both the numerator and the denominator of the cutoff rule.[4]

3 Institutional Background

We apply our theoretical model to the Colombian healthcare system to determine the set of diseases that should be compensated ex-ante versus ex-post. This system is ideal for our purpose not only because it allows us to estimate flexible insurer demand functions to recover the elasticities per diagnoses needed for the cutoff rule in equation (5), but also because it has policy variation that allows us to conduct model-free analyses.

3.1 The Colombian Healthcare System

The Colombian healthcare system was created in 1993 and is divided into a contributory scheme and a subsidized scheme. The first covers the half of the population in the country who pay payroll taxes and their families. The second is fully funded by the government and covers the remaining fraction of the population who have low incomes. The national health insurance system has near-universal coverage.

[4]We note that our model has several limitations. First, an implicit assumption throughout the model is that all consumers value generous coverage (to varying degrees depending on their health status) and thus that consumer surplus is increasing in coverage generosity. We do not explicitly model the consumers' utility function but solely capture their willingness-to-pay through insurer demand. This modelling choice stems from our focus on insurance markets in which premiums are either fixed or zero. Second, we consider only the binary choice of ex-ante versus ex-post policies, however regulators may use a combination of both types of payments. One way in which our model could be extended to consider these cases is by making predictions of the optimal policy conditional on R (the revenue per enrollee) being itself an ex-ante payment. Appendix 1 extends our model to this case. Third, we model insurers as being heterogeneous only in their actuarial value. In reality, insurers may differ in multiple dimensions which could make it difficult to determine which dimension matters for social surplus and how should we target the risk adjustment policy. As long as the dimensions of insurer heterogeneity can be mapped smoothly to the actuarial value our predictions hold.

Both private and public insurers within each scheme offer a single national health insurance plan to their enrollees. This plan features zero premiums, standardized cost-sharing rules indexed to enrollees' monthly income, and a uniform set of covered services determined by the government. While the benefit package and cost-sharing rules are fixed, insurers compete by forming provider networks and negotiating service prices with in-network providers. As a result, insurers differ in their generosity of coverage—or actuarial value—based on the prices they negotiate and the providers they include in their networks. Individuals are free to enroll with any insurer operating in their municipality of residence. Although there is no formal open enrollment period, individuals must remain with their chosen insurer for at least 12 (non-consecutive) months before they are allowed to switch insurers.

Instead of charging premiums, insurers receive per capita, risk-adjusted payments from the government at the start of each calendar year before health claims are realized (ex-ante), compensating for the enrollee's sex, age, and municipality of residence. Appendix 2 describes this ex-ante risk-adjusted transfer in detail. Because the formula is relatively coarse, insurers engage in risk selection against enrollees with chronic conditions that are not accounted for and are therefore predictably unprofitable. They do so by adjusting their actuarial value—or the underlying features that determine it, such as provider networks and service prices—to attract more profitable enrollees while deterring unprofitable ones.

3.2 Ex-Post Payment Mechanism for HIV-AIDS

To complement the coarse ex-ante risk adjustment formula, in 2007 the Colombian government created an additional mechanism to compensate insurers for their enrollees' health risk known as the High-Cost Account (HCA). The HCA initially compensated insurers for enrollees with end-stage renal disease, but introduced compensations for HIV-AIDS and hemophilia in 2016, and cancer in 2019 (breast, cervical, colon, stomach, prostate, leukemia, and non-Hodgkin lymphoma).[5] Unlike the ex-ante risk adjustment, the HCA is an ex-post mechanism designed to redistribute capitated payments from insurers with

[5] See Resolution 1912 of 2015, Ministry of Health and Social Protection.

a relatively low prevalence of diseases to those with a relatively high prevalence.

The theoretical rationale for this ex-post mechanism is that it allows the government to contract on insurers' actions after enrollment, thereby addressing the moral hazard problem in which insurers have incentives to provide inadequate care to less healthy enrollees. This stands in contrast to the ex-ante risk adjustment mechanism, which compensates insurers for consumers' private information about their health status prior to enrollment.

Specifically, the HCA for HIV-AIDS rewards insurers based on the health outcomes of their patients living with HIV-AIDS. Under this mechanism, all insurers—whether or not they cover such patients—contribute to a common pool of funds in proportion to their national market shares. Funds from this pool are then redistributed exclusively to insurers that meet specified quality standards in the treatment of HIV-AIDS patients. These quality standards include thresholds for the percentage of pregnant women screened for HIV-AIDS, percentage of people living with HIV-AIDS on ART with a recent adequate viral load, percentage of people with early detection of HIV-AIDS, among others. Appendix 3 provides a detailed description of the mechanism. Between November and December 2015, the government collected contributions for the common pool of funds, and in January 2016 redistributed the funds to qualifying insurers.[6]

4 Data

We use the introduction of HCA payments for HIV-AIDS to assess, in reduced form, the optimality of this ex-post risk adjustment mechanism relative to the ex-ante approach. Then, we estimate a more flexible structural model of insurer demand to predict, following our theoretical framework in Section 2, which diseases should the government compensate ex-ante versus ex-post.

To conduct these analyses, we have individual-level enrollment and health claims data for the nearly half of the population in the country covered by the contributory system between 2013 and 2019. The enrollment files are snapshots of enrollment in June of every year, reporting the individual's insurer, municipality of residence, sex, and age. We

[6] See Resolution 5036 of 2015, Ministry of Health and Social Protection.

assume that if an individual is enrolled with insurer A in June of year t and in June of year $t+1$, then this individual is enrolled with A every month in between.

The health claims data report all the healthcare services that an individual received every year and include information such as the insurer, provider, negotiated service price, procedure code, and diagnoses following the International Classification of Diseases (ICD). We determine each individual's comorbidities by mapping the ICD codes to the disease categories in Riascos et al. (2014). However, to identify HIV-AIDS diagnoses we use the ICD code set from World Health Organization (2014), which excludes certain HIV-related complications that may create false positives and are included in Riascos et al. (2014). To construct annual measures of healthcare utilization and spending, we sum over the number of claims and prices paid by insurers for healthcare services, respectively. We assign to each individual a unique disease based on the diagnosis that accounts for the highest share of the individual's healthcare cost. Appendix 4 describes our data cleaning process in detail.

For the reduced-form analysis, we restrict the data in several ways to accommodate the event study research design. We focus on the subsample of individuals who have any of the chronic diseases that have ever been targeted by the HCA: HIV-AIDS, renal disease, arthritis or arthrosis, breast cancer, cervical cancer, stomach cancer, lung cancer, non-Hodgkin lymphoma, prostate cancer, epilepsy, and autoimmune diseases. The treatment group are individuals with HIV-AIDS and the control group are those with any of the other diseases. This control group is relevant since patterns of utilization and spending make these diseases eligible for ex-post compensations under the government's scheme.

Among individuals with these chronic health conditions, we focus on those who were continuously enrolled with insurers in the contributory system between the first and last years we observe them in the enrollment data (i.e., who have no gaps in enrollment) and who never switched their insurer nor moved across municipalities. These restrictions prevent the causal effect of the HCA to be confounded by endogenous enrollment or location choices. For example, if relatively healthier HIV-AIDS patients switch to insurers with higher actuarial value in the pre-period, we might wrongly conclude that the HCA policy improves health among these patients. Our sample restrictions prevent these kinds

of confounding biases.

Finally, because the government applies several data quality filters to the health claims database, which may lead to the exclusion of certain insurers in specific years, we will conduct robustness checks imposing an additional restriction in which we include only insurers that appear in the claims data every year.

For the structural analysis, our sample consists of individuals with any chronic disease as well as those without diseases, restricting continuously enrolled consumers who did not move across municipalities. In contrast to the reduced-form analysis, we allow for insurer switching in this sample. For dimensionality reasons, we use a random sample of 2 million patients. This part of the analysis will cover the period from 2013 to 2015, prior to the introduction of HCA payments for HIV-AIDS, so that we can make out-of-sample predictions of the optimal policy for this and other diseases. Since our model follows a discrete choice random utility framework, we construct each individual's choice set of insurers from the enrollment data. Specifically, we include in a municipality's choice set only those insurers with an annual market share of at least 0.05%.

Table 1 presents summary statistics of our analysis samples from 2013 to 2015. Column (1) focuses on people with HIV-AIDS, column (2) considers individuals with any other chronic condition considered by the HCA, and column (3) summarizes the characteristics of patients we use to estimate our structural model.

We identify around 61 thousand individuals living with HIV-AIDS in Colombia following the WHO's definition.[7] Compared to patients with other diseases considered under the HCA, individuals with HIV-AIDS are predominantly young males. Their total healthcare spending and spending on outpatient services and prescription medications is nearly twice as high as for patients with other chronic conditions. Individuals with HIV-AIDS have an associated actuarial value of 92%. Around 8% of individuals with HIV-AIDS are under an ART regime.[8]

[7] This number is very close to official government reports for 2015 (Cuenta de Alto Costo, 2015) and other estimates in the literature (Montana et al., 2021). The official government records consider the total number of patients with HIV-AIDS both in the contributory and subsidized insurance schemes. Although we only have health claims data for individuals in the contributory scheme, we can closely match the government records as long as patients with HIV-AIDS are enrolled in the contributory scheme for at least one year.

[8] We later corroborate that differences between patients with HIV-AIDS and those with other diseases

In the sample for model estimation, the average age is 37.6 years, more than half of patients are female, and the average total healthcare spending is around 592 thousand pesos ($216 of 2015). These spending patterns correspond to an average out-of-pocket spending equal to 33 thousand pesos ($12 of 2015) and an average actuarial value of 89%.

TABLE 1: Summary Statistics

	HIV		Control Diseases		Structural Sample	
	Mean	SD	Mean	SD	Mean	SD
Male	0.541	(0.498)	0.327	(0.469)	0.468	(0.499)
Age	48.10	(17.70)	54.30	(16.80)	37.60	(20.70)
Income*	0.718	(1.190)	0.527	(1.011)	0.617	(1.215)
Total Healthcare Cost*	2.341	(16.60)	1.229	(5.635)	0.592	(3.085)
Out-Of-Pocket Spending*	0.072	(0.138)	0.060	(0.106)	0.033	(0.073)
Actuarial Value	0.920	(0.084)	0.896	(0.091)	0.892	(0.092)
Outpatient Spending*	1.634	(15.80)	0.775	(4.346)	0.345	(1.868)
Prescription Spending*	0.795	(15.60)	0.337	(4.204)	0.141	(1.798)
Inpatient Spending*	0.564	(4.138)	0.378	(2.974)	0.204	(1.951)
Vaccination Rates	0.021	(0.142)	0.017	(0.130)	0.013	(0.115)
Hepatitis Rates	0.006	(0.075)	0.001	(0.037)	0.001	(0.029)
ART Rate	0.079	(0.270)	0.001	(0.034)	0.001	(0.035)
Number of Patients	60,747		1,909,885		2,000,000	
Number of Insurers	11		11		13	

Note: Table reports summary statistics of the sample used in the reduced form analysis in the pre-policy period from 2013 to 2015. Column (1) reports the mean and standard deviation (in parentheses) of the characteristics of HIV-AIDS patients, column (2) describes patients with any other chronic condition as defined in Section 4, column (3) describes describes the sample for model estimation which includes 2 million randomly chosen individuals. (*) Measured in millions of pesos.

5 Reduced-Form Evidence

Our empirical analysis begins by quantifying the impact of introducing HCA payments for HIV-AIDS on the outcomes of patients living with the disease. We use an event study design to measure the causal effects of the policy. We compare outcome trends between individuals diagnosed with HIV-AIDS at any point during the sample period (treatment group), against those diagnosed with other diseases ever considered by the HCA (control group), before and after the introduction of HCA payments for HIV-AIDS. We take 2016

considered under the HCA correspond only to level differences in characteristics, since these do not translate into significant trend differences before the introduction of HCA payments for HIV-AIDS (see Appendix Figure 1).

as the year of the start of the policy because the policy was announced in 2015 but the first contributions to the common pool of funds were made in December 2015 and the distribution of funds was in January 2016. The regression of interest is:

$$y_{it} = \sum_{s \neq 2015} \beta_s \text{HIV}_i \mathbf{1}\{t = s\} + \eta_i + \gamma_{j(i)t} + \varepsilon_{it}$$

where y_{it} is an outcome of individual i in year t, HIV_i is an indicator of whether i has HIV-AIDS, η_i are individual fixed effects, and $\gamma_{j(i)t}$ are insurer-year fixed effects.

The dynamic treatment effects β_s are identified under the assumption that, absent HCA payments for HIV-AIDS, outcomes in the treatment group would have followed the same trend as the control group—an assumption we can partially assess through the statistical significance of pre-policy coefficients. Identification also requires that the policy generated no spillover effects on the control group, which is plausible given that the HCA conditioned payments to quality metrics in the treatment of patients with HIV-AIDS. Finally, we require that no other policies happen around the time of the introduction of HCA payments which can confound our treatment effects. We know only of the termination of a large insurer that happened in 2015, so we will provide robustness checks to this termination later on (see Serna (2025)). We cluster standard errors at the insurer level both because HCA compensations are made to insurers meeting certain quality thresholds and to account for correlation between patients of the same insurer.

There are several potential threats to identification. First, as noted above, we construct our treatment group by considering people who are diagnosed with HIV-AIDS at any point during the sample period. However, the policy could have changed insurer incentives to report enrollees with HIV-AIDS, a practice sometimes referred to as "upcoding." To account for the potential endogeneity of HIV-AIDS diagnosis, we will conduct a robustness check considering only individuals diagnosed before 2015.

Second, although the policy mainly acted as an ex-post mechanism by conditioning payments to care quality standards for existing enrollees with HIV-AIDS, insurers could have responded to the policy by either discouraging enrollment from patients with the disease if they expected not to get reimbursed or to encourage their enrollment if they

expected to get reimbursed and the reimbursement exceeded the marginal cost of treating these patients. These kinds of risk selection incentives can affect the composition of our sample, hence we will explore whether screening incentives are salient in our setting later on.[9]

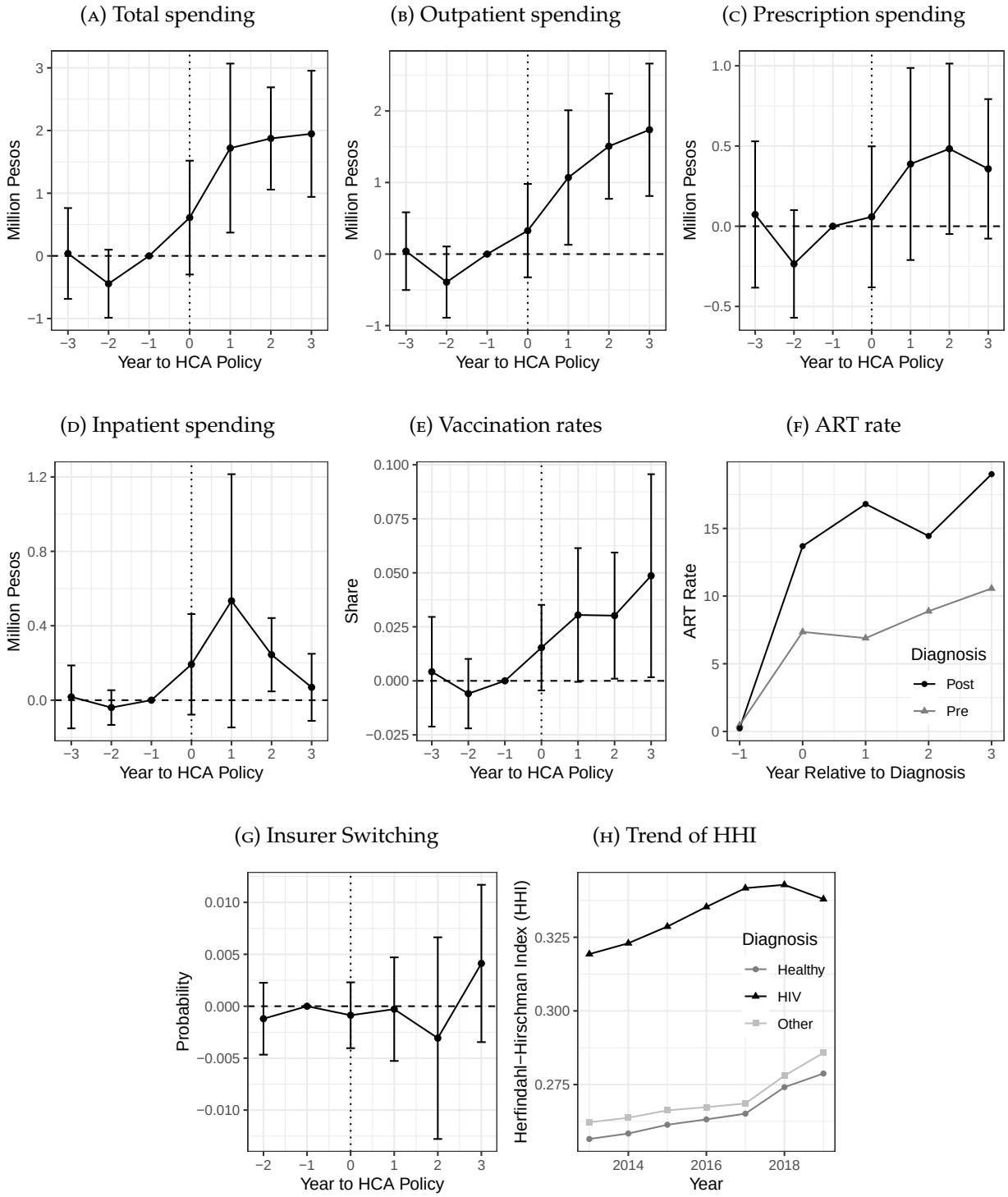
5.1 Results

Figure 1, Panels A to D present results using healthcare spending as an outcome. Panel A shows that the HCA mechanism for HIV-AIDS increased total healthcare spending on these patients by about 2 million pesos the year after the policy. This effect represents a 92% increase over baseline on average. Panels B and C show that increases in total spending are mainly driven by increases in outpatient and prescription spending, something we would expect if insurers are improving the treatment of patients with HIV-AIDS by providing more routine outpatient care and adequately filling ART prescriptions. Panel D shows no effects on inpatient healthcare spending.

To provide more direct evidence of the impact of the policy on quality of care, we focus on healthcare utilization outcomes that are particularly relevant for the management and/or treatment of HIV-AIDS. These include whether the patient is vaccinated for hepatitis A and B, pneumococcus, flu, or tuberculosis, and whether they claim ART. Figure 1, Panel E shows that vaccination rates increased substantially among HIV-AIDS patients one year after the policy, corresponding to a 127% increase over baseline. In Panel F we compare the fraction of HIV-AIDS patients who make any ART claim conditional on whether they are diagnosed before or after the policy as an interrupted time series (since only HIV-AIDS patients take these drugs). We find that ART use among individuals diagnosed after policy is higher and grew faster over the sample period compared to those diagnosed before the policy. Together these findings indicate that quality of care for people living with HIV-AIDS improved thanks to the ex-post compensations.

[9] Recall that to construct our sample we focus on individuals who are continuously enrolled between the first and last years we observe them in the enrollment records. For example, an individual can be continuously enrolled between 2013 and 2016 or between 2015 and 2019. However, risk selection incentives could make it more likely for one of these types of patients to appear in the enrollment records, potentially biasing our estimates.

FIGURE 1: Impact of HCA on Healthcare Spending, Quality of Care, and Selection Incentives



Note: Panels A-E present event study coefficients and 95% confidence intervals comparing patients diagnosed with HIV-AIDS in any year against patients with other diseases ever considered under the HCA. The sample is restricted to patients who do not switch their insurer nor move across municipalities during the sample period. Panel F presents the fraction of HIV-AIDS patients using ART conditional on whether they are diagnosed before (in gray) or after (in black) the policy. Panel G presents event study results using as outcome an indicator for whether the patient switched their insurer. The estimation sample in Panel G uses patients with HIV-AIDS and other diseases ever considered under HCA who did not move across municipalities. Panel H presents the average HHI across markets conditional on patients with HIV-AIDS, other diseases considered under the HCA, and no diseases (healthy).

5.2 Robustness Checks

We conduct several robustness checks to our results in this section. In Appendix Figure 2 we show event study results using total healthcare spending as outcome variable and relaxing our sample restrictions. First, we include year fixed effects rather than insurer-year fixed effects. Second, we allow for a one-year anticipation to the policy, since the Ministry of Health's regulation was published in May 2015. Third, we consider individuals as having HIV-AIDS based on the ICD code list from Riascos et al. (2014). Fourth, we consider patients as having HIV-AIDS if they received diagnoses consistent with this disease in at least two (non-consecutive) years. Fifth, we enforce that individuals make at least one claim every year. Sixth, we exclude HIV-AIDS patients who are diagnosed after the policy. Seventh, we exclude patients with cancer from the control group, since this disease was considered under the HCA in the last year of our sample. Eighth, we exclude individuals living in municipalities where a large insurer was terminated in 2015. Ninth, we relax the restriction requiring that individuals do not switch their insurer. Tenth, we keep only insurers that appear in the claims data every year. In all these exercises, our main results remain unchanged.

5.3 Screening

In our model in Section 2, the insurer chooses the same generosity of coverage for all consumer types. This means that if the HCA policy for HIV-AIDS increases an insurer's generosity for patients with the disease, it will also increase for other types of patients, potentially changing the composition of consumers that enroll with each insurer in equilibrium. For example, if the reimbursement from the HCA is lower than marginal cost of HIV-AIDS patients, then the insurer can respond to the policy by directly avoiding patients with HIV-AIDS or choosing to enroll relatively healthier consumers. This type of screening would result either in new HIV-AIDS patients disproportionately switching to the subsidized system or switching to other insurers within the contributory system. Increased switching, in turn, could lead to higher insurer market concentration among

people living with HIV-AIDS.[10]

To examine these screening incentives, first we relax our sample restriction requiring that individuals do not switch between insurers (or between insurance schemes) and estimate our event study specification using as outcome variable an indicator for whether the individual switched their insurer in year t relative to $t-1$. Figure 1, Panel G presents the results. We find that switching rates among patients with HIV-AIDS did not change after the policy. The lack of evidence that insurers respond to screening incentives is further supported by Panel H, which reports the average insurer Herfindahl-Hirschman Index (HHI) among patients with HIV-AIDS, patients with other health conditions covered by the HCA, and patients without diagnoses. The results show no meaningful changes in insurer market concentration across any of these groups after the policy.

6 Structural Model

In this section, we propose and estimate a structural model of insurer demand that allows us to recover the cutoff rule in equation (5) determining the optimal reimbursement policy per disease. We assume consumers indexed by i who are of type θ and live in market m in year t, choose an insurer j to maximize their indirect utility function:

$$u_{ijmt} = \alpha_\theta AV_{\theta(i)mjt} + \xi_{jm} + \phi_{\theta(i)j} + \gamma_{jt} + \varepsilon_{ijt}$$

Consumer types are given by a combination of sex, age group (19-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65-69, 70-74, ≥75), and diagnosis (breast cancer, cervical cancer, stomach cancer, lymphatic cancer, prostate cancer, lung cancer, other cancers, diabetes, cardiovascular disease, pulmonary disease, renal disease, arthritis, HIV-AIDS, other diseases, and no diseases).[11] In the utility function, $AV_{\theta(i)mjt}$ is the actuarial value

[10] Because Colombia has an insurance mandate, all HIV-AIDS patients must be enrolled. Insurers that are more sophisticated in screening these patients after the HCA will have lower market shares compared to the pre-period and compared to insurers that are less sophisticated in screening. Hence, we can expect greater market concentration among patients with HIV-AIDS if insurers actively engage in screening.

[11] We choose the diagnoses that have ever been targeted by the HCA. For consumers with multiple diseases, we assign the diagnosis that accounts for the higher fraction of the individual's health care cost per year.

that insurer j chooses for consumer type θ in market m in year t, ξ_{jt} is an insurer-market fixed effect with markets being defined as municipalities, $\phi_{\theta(i)j}$ is an insurer-diagnosis fixed effect, γ_{jt} is an insurer-year fixed effect, and ε_{ijt} is a shock to preferences assumed to be distributed T1EV.

We obtain the actuarial value from our data using consumer's total healthcare spending and the cost-sharing rules that apply to them given their income level.[12] The fixed effects ξ_{jm} account for observed and unobserved insurer characteristics that vary across markets but not across individuals, such as the breadth of their provider networks (e.g., as in Serna, 2024). $\phi_{\theta(i)j}$ captures observed and unobserved insurer characteristics that vary across consumer types but not across markets, which would apply if some insurers are more specialized in the treatment of a particular disease. Finally, γ_{jt} captures any systematic trends in insurer market shares that are common across markets.

The parameter of interest is α_θ, which measures consumer's preferences for coverage generosity and factor into the calculation of demand elasticities with respect to the actuarial value. One worry with the identification of this parameter is the classic simultaneity bias in demand models: insurers with higher demand may find it profitable to offer more generous plans, but also more generous plans attract higher demand. Another potential endogeneity concern stems from omitted variable bias: the actuarial value may be correlated with insurers' claim denial patterns among certain consumer types, which could vary across markets and is not captured by the fixed effects.

To address these endogeneity concerns we use a Hausman-style instrument for the actuarial value. The instrument for insurer j's actuarial value in market m is that same insurer's average actuarial value in other markets besides m. This instrument is relevant because insurers' choice of coverage generosity is correlated across markets (as seen in Appendix Figure 4), and satisfies the exclusion restriction because it is highly likely that demand shocks are orthogonal across markets.

[12] Cost-sharing rules are indexed to the enrollee's monthly income as follows. For individuals earning less than 2 times the monthly minimum wage (MMW) the coinsurance rate equals 11.5%, the copay equals 11.7% of the daily minimum wage (DMW), and the maximum out-of-pocket amount in a year is 57.5% times the MMW. For those with incomes between 2 and 5 times the MMW, the coinsurance rate is 17.3%, the copay is 46.1% of the DMW, and the maximum out-of-pocket amount is 230% times the MMW. Finally, for people with incomes above 5 times the MMW, the coinsurance rate equals 23%, the copay is 121.5% of the DMW, and the maximum out-of-pocket amount is 460% times the MMW.

Integrating out the idiosyncratic preference shock yields the following expression for insurer demand among type-θ consumers:

$$s_{\theta jmt} = \frac{\exp(\alpha_\theta AV_{\theta(i)mjt} + \xi_{jm} + \phi_{\theta(i)j} + \gamma_{jt})}{\sum_{g \in J_{mt}} \exp(\alpha_\theta AV_{\theta(i)mgt} + \xi_{jm} + \phi_{\theta(i)g} + \gamma_{gt})}$$

where J_{mt} is the set of insurers that operate in market m in year t. Note that there is no outside option of uninsurance, since enrollment is mandatory in Colombia.

6.1 Estimation Results

Table 2 shows results of the insurer demand model using two specifications. In column (1) we include insurer-year, insurer-market, and insurer-diagnosis fixed effects. In column (2) we include insurer-market-year and insurer-diagnosis fixed effects. Our preferred specification is in column (1), which strikes a balance between accounting for endogenous unobserved insurer quality while not absorbing most of the variation in the actuarial value—although our results are largely robust across the two specifications. In both specifications we use data from 2013 to 2015, before the introduction of HCA payments for HIV-AIDS.

First of all, we find that our instrument for the actuarial value is strong as seen by the first-stage F-statistic reported at the bottom of the table. First-stage results in Appendix Table 5 show that the instrument is positively correlated with the actuarial value as expected. Then, in the second stage, our preferred specification shows that on average all consumers have a strong preference for a higher actuarial value. A 1 percentage point increase in the actuarial value raises insurer demand by 1.2%, suggesting demand is on average elastic with respect to this variable.

We find that the preference for coverage generosity is heterogeneous across patients and, in general, higher for those with chronic diseases compared to those without diagnoses (labelled "healthy"). For example, patients with breast cancer, diabetes, prostate cancer (included in male genital cancer), and autoimmune diseases have much stronger preferences for the actuarial value compared to individuals with cardiovascular disease, asthma, and tuberculosis. Appendix Table 6 summarizes our estimates of the demand

elasticity with respect to the actuarial value for each disease.[13] We find that this elasticity is greater than 1 among patients with breast cancer, autoimmune diseases, COPD, and skin cancer.

TABLE 2: Insurer Demand

	(1)	(2)
Actuarial Value	1.196 (0.079)	0.830 (0.073)
Actuarial Value × Diagnosis		
Healthy	ref (ref)	ref (ref)
Arthritis	0.412 (0.402)	0.647 (0.332)
Asthma	-3.006 (0.392)	-1.925 (0.280)
Autoimmune Disease	1.831 (0.644)	1.479 (0.461)
Breast Cancer	1.451 (0.302)	1.058 (0.233)
Cardiovascular Disease	-0.079 (0.180)	0.283 (0.151)
Cervical Cancer In Situ	-2.773 (0.128)	-1.818 (0.115)
Diabetes	0.402 (0.256)	-0.112 (0.206)
Epilepsy	-1.513 (0.539)	-1.361 (0.443)
Genetic Disorders	-0.799 (0.203)	-1.000 (0.159)
HIV-AIDS	0.021 (0.553)	-0.434 (0.408)
Hypertension	0.609 (0.127)	0.419 (0.113)
Renal Disease	-3.618 (0.447)	-3.076 (0.333)
COPD	0.809 (0.324)	1.050 (0.282)
Male Genital Cancer	0.158 (0.518)	0.610 (0.399)
Osteoarthritis	0.716 (0.263)	0.869 (0.220)
Other	1.122 (0.459)	0.972 (0.355)
Other Cancers	0.571 (0.348)	0.753 (0.270)
Skin Cancer	3.923 (0.756)	3.332 (0.582)
Tuberculosis	-1.552 (0.673)	-1.371 (0.491)
Insurer-Year FE	Yes	No
Insurer-Market FE	Yes	No
Insurer-Diagnosis FE	Yes	Yes
Insurer-Market-Year FE	No	Yes
First-stage F-stat	6494.3	12099.9
Number of patients	5982957	5982670
Pseudo-R^2	0.166	0.166

Note: Table presents a conditional logit model of insurer choice estimated by maximum likelihood on a random sample of 2 million patients. Column (1) includes insurer-year, insurer-market, and insurer-diagnosis fixed effects. Column (2) includes insurer-market-year and insurer-diagnosis fixed effects. In both specifications, we use a Hausman-style instrument for the actuarial value, namely, the insurer's average actuarial value in other markets excluding the focal market. The table reports the first-stage F-statistics. Estimation uses data from 2013 to 2015. Robust standard errors are reported in parenthesis.

[13] Calculated as $\frac{\partial s_{\theta jmt}}{\partial AV_{\theta jt}} \frac{AV_{\theta jt}}{s_{\theta jmt}}$ and averaged across individuals.

7 Ex-Ante Vs. Ex-Post Risk Adjustment

Using our demand model estimates, we compute the cutoff rule in equation (5) summarizing the conditions under which an ex-post policy can implement the regulator's solution relative to an ex-ante policy. Figure 2 presents the results; values below one correspond to diseases for which ex-post reimbursement is optimal, while values above one correspond to those where ex-ante payments are optimal. To calculate this cutoff rule, we use as benchmark c_0 the healthcare spending by individuals without diagnoses and later test the robustness of our results to this choice.

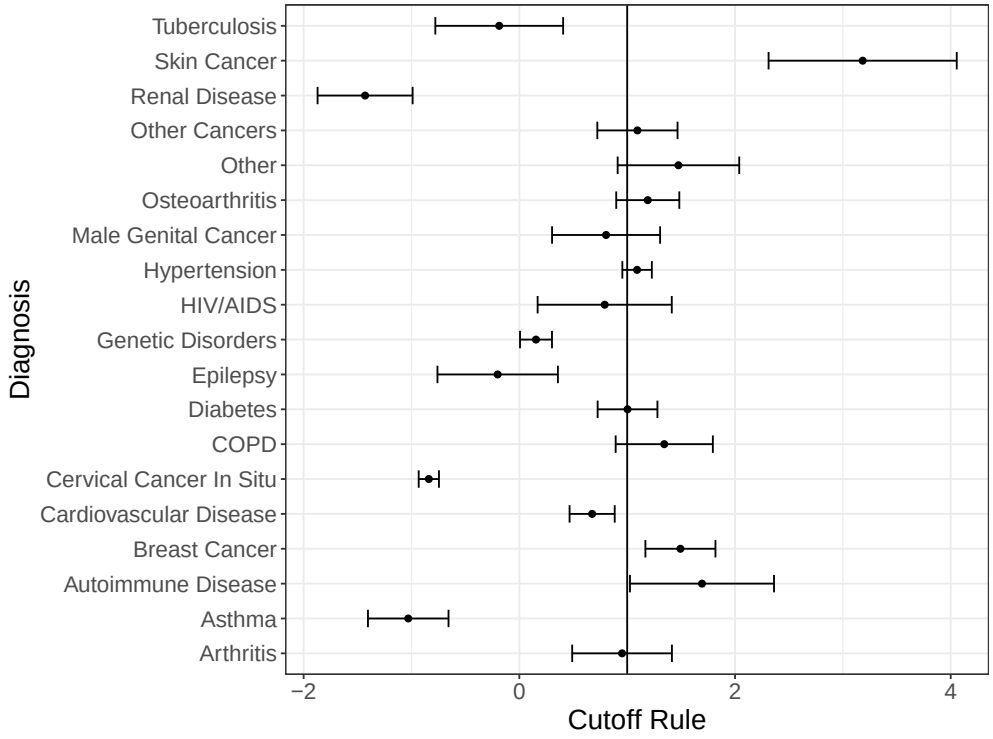
Our results corroborate the reduced-form findings suggesting ex-post payments improved quality of care for patients with HIV-AIDS. The point estimate for this disease is less than one indicating ex-post compensations are optimal, although the 95% confidence interval includes the threshold. Other diseases for which we predict an ex-post policy is optimal include: tuberculosis, prostate cancer, renal disease, genetic disorders, epilepsy, cervical cancer, cardiovascular disease, and asthma. Diseases we predict should be compensated in the ex-ante risk adjustment formula include: skin cancer, osteoarthritis, COPD, hypertension, diabetes, breast cancer, and autoimmune diseases.

Appendix Table 8 pools individuals with the health conditions predicted to be compensated ex-ante versus ex-post and summarizes their characteristics. In general, diseases that should be compensated ex-ante are more prevalent among younger patients, males, and those with lower healthcare spending compared to diseases that should be compensated ex-post. For example, the age difference between diseases with ex-post compensations and those with ex-ante compensations is 11 years and the difference in healthcare spending is 200 thousand pesos ($73 of 2015).

Importantly, the split of diseases by optimal timing of the risk-adjusted compensation generates the same average actuarial value across the two groups, equal to 90%, suggesting the cutoff rule equalizes coverage generosity across patients with chronic diseases—one of the goals of the regulator. We also find that insurer N, known to have a high concentration of individuals with chronic diseases, is overrepresented among the group of patients for

whom ex-post compensations are optimal.[14]

FIGURE 2: Cutoff Rule



Note: Figure shows the cutoff rule from equation (5) for each diagnosis listed in the vertical axis and their 95% confidence intervals. Confidence intervals are obtained through 100 bootstrap resamples of patients.

In Appendix Table 7 we test the robustness of the cutoff rule to choosing a different benchmark for healthcare spending. Column (1) reproduces our main results and column (2) uses as benchmark the average healthcare spending in our sample rather than the spending among patient without diagnoses. We find that our conclusions about the set of diseases that should be compensated ex-ante versus ex-post remain unchanged.

Finally, Appendix Figure 3 explores the heterogeneity of the cutoff rule to markets with above and below median insurer HHI (based on the total number of enrollees in the market). For most diseases we find that higher market concentration is correlated with lower cutoff rules, suggesting ex-post payments are more often optimal in these types

[14] Although the Colombian government has long debated adding diagnoses as risk factors in the ex-ante risk adjustment formula, anecdotal evidence suggests one of the reasons they have not done so is that Insurer N has a high concentration of patients with chronic diseases and may either end up overcompensated or undercompensated depending on the fit of the formula.

of markets compared to ex-ante payments. One potential explanation for this is that if market concentration reflects true market power, it is possible that in concentrated markets insurers operate along the inelastic portion of the demand curve, reducing our cutoff rule in equation (5).

8 Conclusions

The interaction between risk adjustment and other market failures in insurance markets, such as moral hazard, is poorly understood. In this paper, we study when should risk adjusted payments be made to insurers relative to the realization of health claims to address adverse selection and moral hazard. We develop a theoretical framework in which the regulator chooses a disease-specific ex-ante or ex-post risk adjusted payment to induce the insurer to choose a higher actuarial value for patients with the disease. We show that the optimal policy follows a simple cutoff rule establishing that if the demand elasticity with respect to the actuarial value is lower than the healthcare cost difference between patients with the disease and a benchmark, the regulator should make risk adjusted payments ex-post.

We apply our theoretical framework to the health insurance market of Colombia, finding that ex-post payments are optimal for HIV-AIDS, tuberculosis, renal disease, genetic disorders, etc., while diseases such as skin cancer, chronic obstructive pulmonary disorder, and breast cancer should be included in the ex-ante formula. Our findings imply that combinations of ex-ante and ex-post payments may be desirable in healthcare systems and that recent policy initiatives in Germany, Colombia, and the United States establishing these types of payments may improve healthcare delivery and quality of care for patients with severe health conditions.

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Appendix 1 Existing Ex-Ante Risk Adjustment

In this appendix, we show that our theoretical results are robust to scenarios in which there exists an ex-ante risk adjustment policy before the regulator chooses whether to implement additional ex-ante compensations or ex-post compensations. We show that as long as the existing ex-ante payment does not over-compensate, our results carry through.

To characterize an existing ex-ante risk adjustment, we allow the revenue per enrollee to be type-specific, i.e., $R_i = R_{\theta(i)}$. The insurer's profit becomes:

$$\pi(a_j) = \sum_{\theta \in \Theta} (R_\theta - a_j c_\theta) s_\theta(a_j) N_\theta \geq 0,$$

with the corresponding FOC:

$$FOC_\theta(a_j) = \pi'(a_j) = \sum_{\theta \in \Theta} [(R_\theta - a_j c_\theta) s'_\theta(a_j) - c_\theta s_\theta(a_j)] N_\theta$$

Similarly, the regulator's objective function with healthy beneficiaries as benchmark is:

$$\pi_0(a_j) = \sum_{\theta \in \Theta} (R_0 - a_j c_0) s_\theta(a_j) N_\theta,$$

with corresponding FOC given by:

$$FOC_0(a_j) \equiv \pi'(a_j) = \sum_{\theta \in \Theta} [(R_0 - a_j c_0) s'_\theta(a_j) - c_0 s_\theta(a_j)].$$

The difference between the two FOCs is:

$$\begin{aligned} &\Delta FOC_\theta(a_j) \equiv FOC_0(a_j) - FOC_\theta(a_j) \\ &= \sum_{\theta \in \Theta} [-a_j(c_0 - c_\theta - (R_0 - R_\theta)) s'_\theta(a_j) - (c_0 - c_\theta - (R_0 - R_\theta)) s_\theta(a_j)]. \end{aligned}$$

Note that as long as the existing ex-ante payment does not over-compensate, $c_0 - R_0 < c_\theta - R_\theta$, and Propositions 1 and 2 would continue to hold.

For the cutoff rule, the cost differential in the model from the main text would be replaced with an adjusted cost differential. Let $\tilde{c}_\Delta \equiv c_\theta - c_0 - (R_\theta - R_0)$ and rewrite the difference between the private and social FOCs as:

$$-\Delta FOC_\theta(a_j) \equiv \pi'(a_j) - \pi_0'(a_j) = \underbrace{-\sum_{\theta\in\Theta} a_j \tilde{c}_\Delta s_\theta'(a_j) N_\theta}_{\text{adverse selection}} \underbrace{-\sum_{\theta\in\Theta} \tilde{c}_\Delta s_\theta(a_j) N_\theta}_{\text{moral hazard}} + \sum_{\theta\in\Theta} \underbrace{p_\theta'(a_j) N_\theta}_{\text{policy impact}}$$

Define the two policies analogously as:

$$\tilde{p}_\theta^{\text{ante}}(a_j) = \overline{a\tilde{c}_\Delta} s_\theta(a_j)$$

$$\tilde{p}_\theta^{\text{post}}(a_j) = a_j \tilde{c}_\Delta \overline{s_\theta}.$$

Thus, a similar cutoff rule is obtained

$$p_\theta^{\text{post}\prime}(a_j) > p_\theta^{\text{ante}\prime}(a_j) \Leftrightarrow \frac{\overline{\tilde{c}_\Delta}}{\tilde{c}_\Delta} \epsilon < 1.$$

Appendix 2 Ex-ante Risk Adjustment Formula

For year t, the base (unadjusted) capitated transfer is calculated using claims data from year $t-2$. The per-enrollee transfer equals the population's average annualized healthcare cost, scaled by a risk-adjustment factor that varies by sex, age group, and municipality. Average costs are annualized by multiplying by 360 and dividing by the number of enrollee-days. Appendix Table 1 reports the national unadjusted transfer, while Appendix Table 2 presents the risk-adjustment multipliers. See MinSalud, 2015.

Appendix Table 1: Base Capitated Transfer for the Contributory System During 2015

Department/city		Transfer
National (pesos)		629,975
Market multiplier a_m	Armenia, Barrancabermeja, Barranquilla, Bello, Bogotá, Bucaramanga, Buenaventura, Cali, Cartagena, Cúcuta, Floridablanca, Ibagué, Itagüí, Manizales, Medellín, Montería, Neiva, Palmira, Pasto, Pereira, Popayán, Riohacha, Santa Marta, Sincelejo, Soacha, Soledad, Tuluá, Valledupar, Villavicencio	$\times$ 1.0986
	San Andrés, Providencia, Santa Catalina	$\times$ 1.379

Note: Table reports national base risk-adjusted transfer and risk adjustment multipliers for each market.

Appendix Table 2: Risk Adjustment Factors in the Contributory System during 2011

Age group	Sex	Multiplier
Less than 1	—	2.9679
1-4	—	0.9530
5-14	—	0.3329
15-18	M	0.3173
15-18	F	0.5014
19-44	M	0.5646
19-44	F	1.0475
45-49	—	1.0361
50-54	—	1.3215
55-59	—	1.6154
60-64	—	2.0790
65-69	—	2.5861
70-74	—	3.1033
More than 74	—	3.8997

Note: Table reports government risk-adjustment multipliers by sex and age group.

Appendix 3 High Cost Account for HIV-AIDS

The HCA for HIV-AIDS mandated that all insurers, regardless of whether they cover patients with the disease, contribute to a pool of funds in proportion to the national market share. Funds from the pool would then be redistributed to insurers that met certain quality metrics in the treatment of HIV-AIDS patients.

To determine the size of the common pool of funds, let D_{aj} be the number of patients with HIV-AIDS in age group a enrolled with insurer j and N_{aj} the total number of enrollees in age group a enrolled with j. The prevalence of HIV-AIDS for insurer j is $\rho_{aj} = 100,000 \cdot \frac{D_{aj}}{N_{aj}}$, and the total prevalence in the population is $\rho_a = 100,000 \cdot \frac{\sum_j D_{aj}}{\sum_j N_{aj}}$. Define the differential prevalence of HIV-AIDS at insurer j as $f_{aj} = (\rho_{aj} - \rho_a) \cdot N_{aj}/100,000$ and the total differential prevalence for insurer j as $f_j = \sum_a f_{aj}$. Finally, let $\overline{c}$ be the per capita amount necessary to treat HIV-AIDS patients. Then, the size of the common pool of funds is $CF = \sum_j \mathbf{1}\{f_j > 0\} f_j \cdot \overline{c}$, and each insurer must contribute $b = CF \cdot \frac{N_j}{\sum_j N_j}$ where $N_j = \sum_a N_{aj}$.

Insurers that receive payments from this mechanism are the ones that meet certain quality indicator thresholds set by the government. Let I_k^* be the threshold for the k-th quality indicator and I_{kj} insurer j's measure of this quality indicator. Define the population-weighted compliance with the indicator as $q_{kj} = \mathbf{1}\{I_{kj} > I_k^*\}(I_{kj} - I_k^*)N_j$ and the probability of compliance as $p_{kj} = \frac{q_{kj}}{\sum_j q_{kj}}$. Then, insurer j receives a payment equal to $Y = \sum_k w_k \cdot p_{kj} \cdot FC$ where w_k is the weight of the k-th quality indicator.

Quality indicators considered by the Ministry of Health for the HIV-AIDS mechanism include: percentage of pregnant women screened for HIV-AIDS, percentage of people living with HIV-AIDS on ART with a recent adequate viral load, percentage of people with early detection of HIV-AIDS, and HIV-AIDS prevalence. For more details, see https://www.minsalud.gov.co/sites/rid/Lists/BibliotecaDigital/RIDE/DE/DIJ/resolucion-1912-de-2015.pdf.

Appendix 4 Data Cleaning

Appendix Table 3 presents the steps in our detail cleaning process for the reduced-form estimation sample and the structural estimation sample. The table also reports the number of patients that remain after imposing each sample restriction. Appendix Table 4 lists the ICD-10 codes we use to identify patients with different diseases in both samples.

Appendix Table 3: Sample Criteria

Sample Criteria	Number of patients
DID sample	
(1) Ever enrolled from 2013 to 2019	32,186,092
(2) Continuously enrolled from 2013 to 2019	8,264,491
(3) Never changed market nor insurer	5,291,484
(4) Diagnosed with HIV or control diseases	1,970,632
Structural sample	
(1) Ever enrolled from 2013 to 2015	24,727,487
(2) Continuously enrolled from 2013 to 2015	14,230,562
(3) Never changed market	13,161,913
(4) 2 million random sample	2,000,000

Note: Table reports sample criteria and associated number of patients.

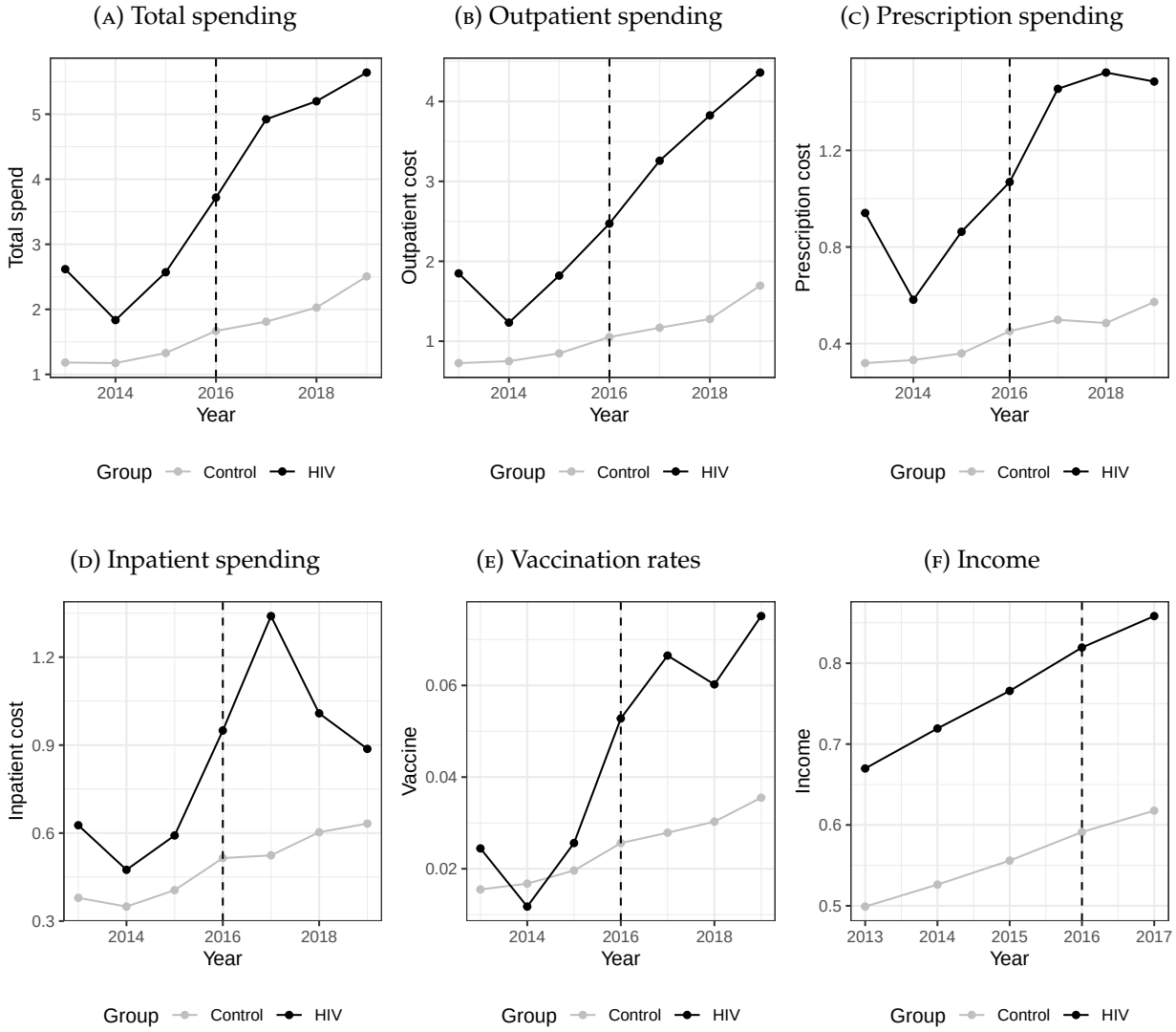
Appendix Table 4: ICD Code for Diagnosis

Diagnosis	ICD
Arthritis	M00, M01, M02, M03, M05, M06, M07, M08, M09, M10, M11, M12, M13, M14
Asthma	J45, J46, Y55, Z82
Autoimmune Disease	E06, E31, G36, G37, L93, M30, M31, M32, M33, M34, M35, M36
Breast Cancer	C50, D05, D48, N63, Z12, Z80, Z85
COPD	J41, J42, J43, J44, J84, J96, J98, R06, R09, R94, Y50, Y51, Y55, Z72, Z87
Cardiovascular Disease	G46, I05, I07, I08, I20, I21, I22, I23, I24, I25, I26, I27, I28, I30, I31, I32, I33, I34, I35, I36, I37, I38, I39, I40, I41, I42, I43, I44, I45, I46, I47, I48, I49, I50, I51, I52, I60, I61, I62, I63, I64, I65, I66, I67, I68, I69, I70, I71, I72, I73, I74, I77, I78, I79, R00, R01, R02, R03, R04, R07, R09
Cervical Cancer In Situ	D06, N87, N88, Z12
Diabetes	E10, E11, E12, E13, E14, E15, G59, G63, G99, H28, H36, M14, N08, T38, Y42, Z13, Z83
Epilepsy	G40, G41, R56, T42, Y46, Z82
Genetic Disorders	O28, O35, Q00, Q01, Q02, Q03, Q04, Q05, Q06, Q07, Q10, Q11, Q12, Q13, Q14, Q15, Q16, Q17, Q18, Q20, Q21, Q22, Q23, Q24, Q25, Q26, Q27, Q28, Q30, Q31, Q32, Q33, Q34, Q35, Q36, Q37, Q38, Q39, Q40, Q41, Q42, Q43, Q44, Q45, Q50, Q51, Q52, Q53, Q54, Q55, Q56, Q60, Q61, Q62, Q63, Q64, Q65, Q66, Q67, Q68, Q69, Q70, Q71, Q72, Q73, Q74, Q75, Q76, Q77, Q78, Q79, Q80, Q81, Q82, Q83, Q84, Q85, Q86, Q87, Q89, Q90, Q91, Q92, Q93, Q95, Q96, Q97, Q98, Q99
HIV/AIDS (Alvaro)	A07, A81, B00, B01, B02, B20, B21, B22, B23, B24, B25, B37, B38, B39, B45, B58, C46, Z21
HIV/AIDS (WHO)	B20, B21, B22, B23, B24, Z21
Hypertension	I10, I11, I12, I13, I15, I27, I67
Male Genital Cancer	C60, C61, C62, C63, C64, C65, C66, D07, D40, Z12
Osteoarthritis	M15, M16, M17, M18, M19
Other	C15, C16, C17, C18, C19, C20, C21, C22, C23, C24, C25, C26, C32, C33, C34, C37, C38, C39, C51, C52, C53, C54, C55, C56, C57, C58, C77, C78, C79, C81, C82, C83, C84, C85, C88, C90, C91, C92, C93, C94, C95, C96, C97, D02, D07, D38, D39, D46, D47, N16, N89, N90, T86, Y83, Z08, Z09, Z12, Z40, Z41, Z51, Z54, Z80, Z85, Z94
Other Cancers	C00, C01, C02, C03, C04, C05, C06, C07, C08, C09, C10, C11, C12, C13, C14, C30, C31, C32, C38, C39, C40, C41, C45, C47, C48, C49, C67, C68, C69, C70, C71, C72, C73, C74, C75, C76, C78, C79, C80, D00, D01, D03, D04, D05, D09, D18, D22, D37, D38, D39, D40, D41, D42, D43, D44, D48, G13, Z03, Z12, Z80, Z85, Z86
Renal Disease	N00, N01, N02, N03, N04, N05, N06, N07, N08, N10, N11, N12, N13, N14, N15, N16, N17, N18, N19, N25, N26, N27, N28, N29
Skin Cancer	C43, C44
Tuberculosis	A15, A16, A17, A18, A19, B90, J65, M01, N74, Z03, Z11, Z20, Z23

Note: Table reports the ICD code used to identify diagnoses. Only the first 3 digits of the codes are reported for brevity.

Appendix 5 Additional Results

Appendix Figure 1: Outcome Trends between HIV and Control Patients



Note: Figure presents outcome trends comparing patients diagnosed with HIV-AIDS at any point during the sample period (in black) against patients with other diseases ever considered under the HCA (in gray). The sample is restricted to patients who do not switch their insurer nor move across municipalities during the sample period. We do not have income data for 2018 and 2019.

Appendix Table 5: First Stage of Insurer Demand

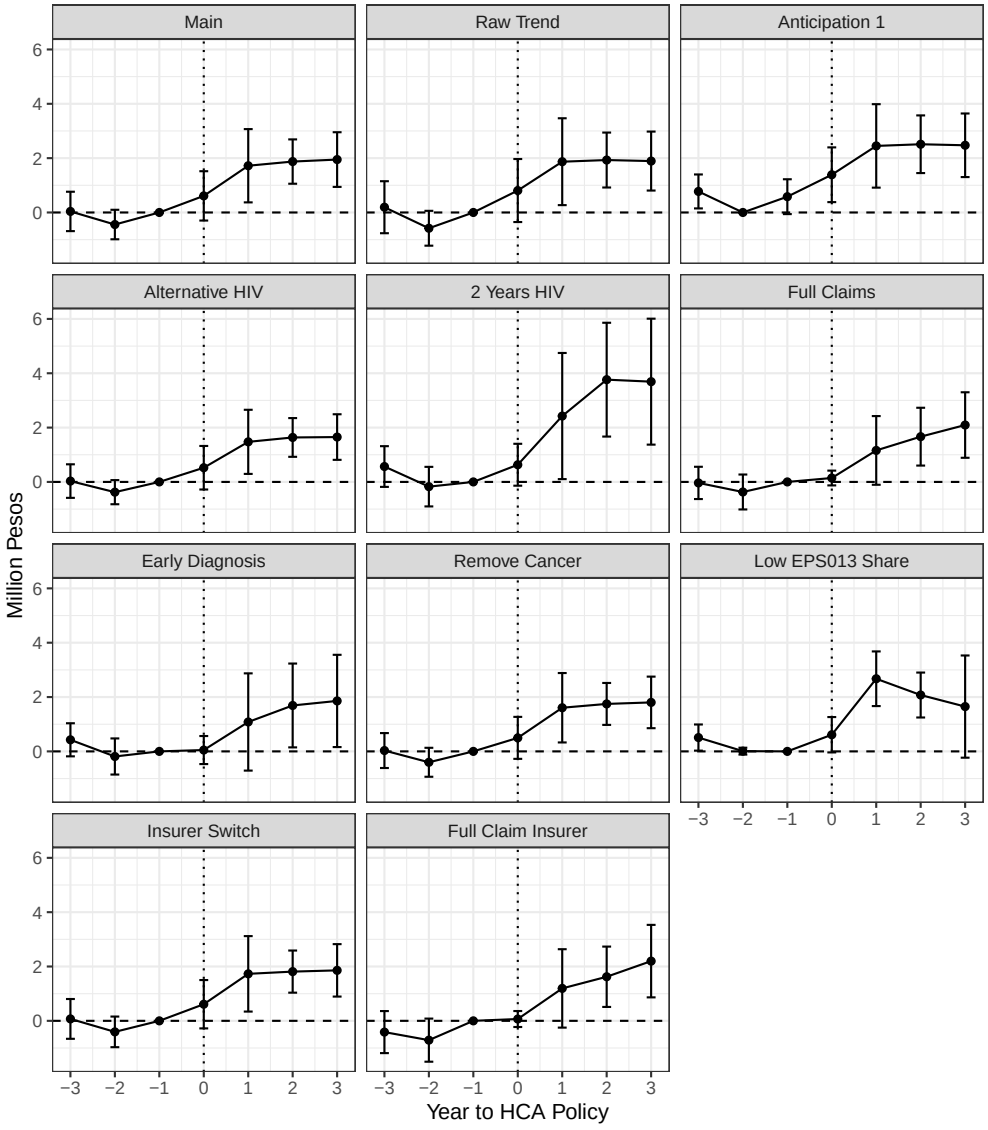
	(1)	(2)
Hausman IV	0.650 (0.095)	0.660 (0.078)
Insurer-Year FE	Yes	No
Insurer-Market FE	Yes	No
Insurer-Diagnosis FE	Yes	Yes
Insurer-Market-Year FE	No	Yes
F-statistic	6494.3	12099.9
Number of patients	5982957	5982670

Note: Table presents first-stage demand results regressing the actuarial value per insurer, market, and consumer type on the instrument. The instrument the insurer's average actuarial value across all other markets in which it operates excluding the focal market. Column (1) includes insurer-year, insurer-market, and insurer-diagnosis fixed effects. Column (2) includes insurer-diagnosis and insurer-market-year fixed effects. Table reports the F-statistic associated with the instrument. Robust standard errors in parenthesis.

Appendix Table 6: Demand Elasticity with respect to Actuarial Value

Group	Elasticity	Age	Male Share	Income	Number of Patients
All Sample	0.89	37.57	0.47	617425.2	2000000
Diagnosed	0.55	44.90	0.37	494378.5	925796
Healthy	1.36	31.24	0.56	723472.2	1074204
Genetic Disorders	0.15	29.10	0.40	443110.8	113268
Arthritis	0.96	46.19	0.33	611272.8	24481
Osteoarthritis	1.18	55.52	0.31	493427.7	40196
Asthma	-1.00	20.44	0.49	287849.6	35668
Autoimmune Disease	1.74	43.49	0.20	674540.9	8849
Cervical Cancer In Situ	-0.84	39.21	0.00	603522.2	115467
Male Genital Cancer	0.81	56.73	0.99	720689.7	9759
Breast Cancer	1.53	44.56	0.04	578556.1	42218
Skin Cancer	3.11	48.71	0.48	507718.5	6387
Other Cancers	1.08	41.81	0.39	614007.2	24158
Diabetes	0.98	55.61	0.48	436486.2	52581
Hypertension	1.09	56.65	0.41	436511.6	224614
Cardiovascular Disease	0.68	41.93	0.52	547710.5	138112
COPD	1.27	53.14	0.48	396046.2	29445
Other	1.44	47.09	0.30	567496.7	14349
Renal Disease	-1.37	50.35	0.50	377741.0	18085
HIV/AIDS	0.74	35.41	0.66	748857.0	5774
Epilepsy	-0.19	30.68	0.52	367108.8	16336
Tuberculosis	-0.19	35.86	0.48	602976.1	6049

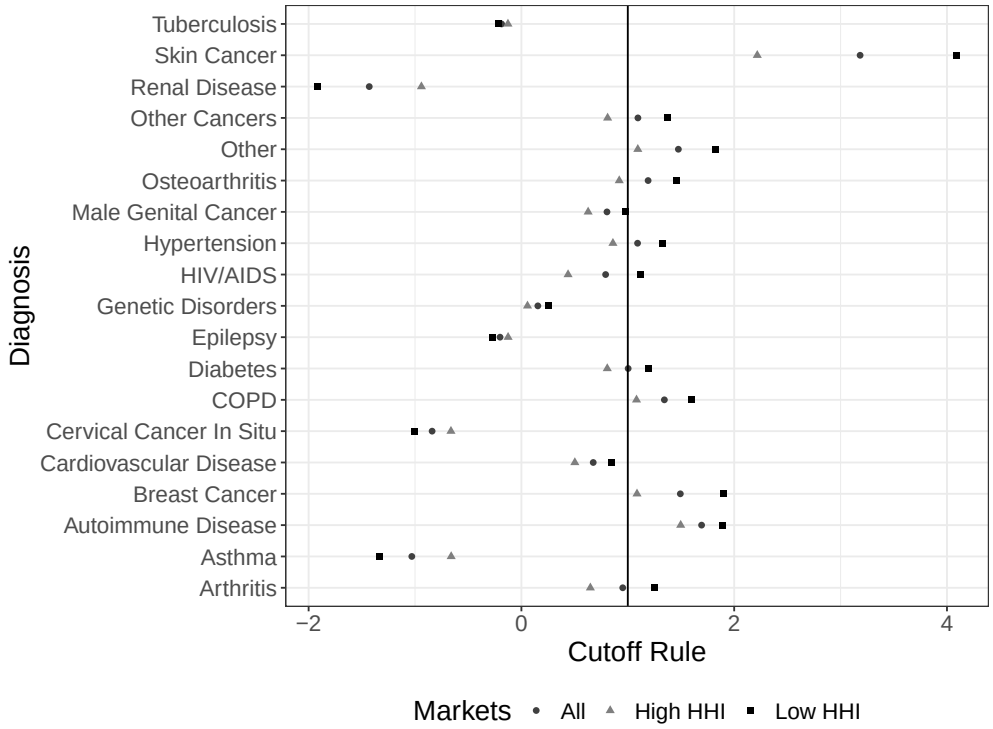
Note: Table reports the estimated average demand elasticity with respect to the actuarial value by diagnosis group and additional summary characteristics for each diagnosis. Income is measured in pesos. The last column reports the corresponding sample size in the full sample.



Appendix Figure 2: Robustness Checks on Sample Contruction

Note: Figure reports the robustness of estimates of the HCA's impact on healthcare spending (Figure 1) to alternative sample definitions. "Main" refers to our main results, "Raw Trend" includes a time trend instead of insurer-specific time trends, "Anticipation 1" uses 2014 as the baseline year to allow for short-term anticipatory effects, "Alternative HIV" utilizes the definition of HIV patients with ICD code set from Riascos et al. (2014), "Full Claims" requires that individuals make at least one claim every year, "Early Diagnosis" restricts HIV patients to be diagnosed before 2015, "Remove Cancer" excludes cancer as control chronic disease, "Low EPS013 Share" excludes municipalities where insurer EPS013 had over 25% market share before its termination in 2014, "Insurer Switch" relaxes the criteria requiring patients to stay in the same insurer, and "Full Claim Insurer" requires that insurers are observed every year in the claims data.

Appendix Figure 3: Heterogeneity of Cutoff Rule by Market Concentration



Note: Figure reports the point estimate of the cutoff rule in equation (5) by diagnosis and separately for markets with below- (in squares) and above-median (in triangles) insurer HHI in the number of enrollees. Figure also reports the point estimate of our main result in circles.

Appendix Table 7: Robustness of Cutoff Rule to Benchmark

	(1)	(2)
Arthritis	0.953 (0.272)	0.943 (0.269)
Asthma	-1.030 (0.221)	-0.893 (0.192)
Autoimmune Disease	1.694 (0.362)	1.681 (0.359)
Breast Cancer	1.494 (0.167)	1.484 (0.166)
Cardiovascular Disease	0.675 (0.111)	0.676 (0.111)
Cervical Cancer In Situ	-0.839 (0.051)	-0.899 (0.055)
Diabetes	1.003 (0.122)	0.965 (0.118)
Epilepsy	-0.201 (0.251)	-0.207 (0.259)
Genetic Disorders	0.155 (0.060)	0.246 (0.095)
HIV/AIDS	0.791 (0.337)	0.806 (0.343)
Hypertension	1.092 (0.071)	-0.059 (0.004)
Kidney Disease	-1.430 (0.229)	-1.425 (0.228)
Lung Disease	1.344 (0.240)	1.349 (0.241)
Male Genital Cancer	0.804 (0.233)	0.775 (0.224)
Osteoarthritis	1.191 (0.151)	1.102 (0.139)
Other	1.475 (0.308)	1.477 (0.309)
Other Cancers	1.095 (0.173)	1.114 (0.176)
Skin Cancer	3.183 (0.456)	3.295 (0.472)
Tuberculosis	-0.186 (0.348)	-0.286 (0.534)
Benchmark	Healthy	Average

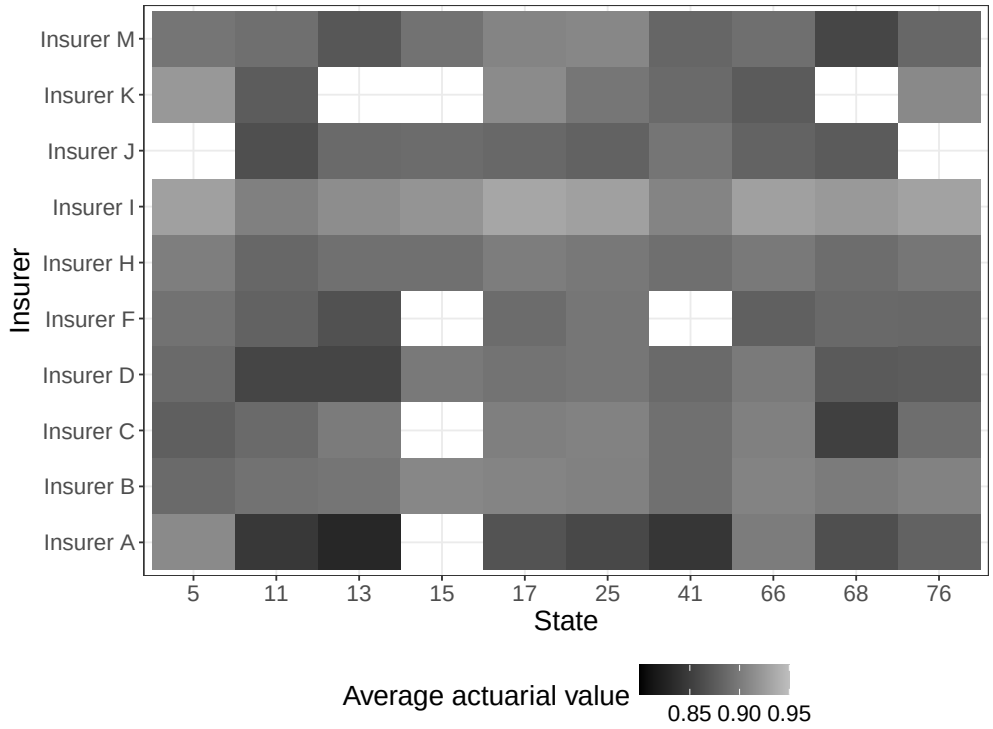
Note: Table reports the point estimate and robust standard error in parenthesis of the cutoff rule in equation (5) using different benchmarks for c_0. Column (1) is our main result using as benchmark the healthcare spending among healthy consumers. Column (2) uses as benchmark the average healthcare spending in our sample. Standard errors in parenthesis are based on 100 bootstrap resamples of patients.

Appendix Table 8: Summary Statistics of Diseases for Ex-ante and Ex-post Compensations

	Ex-ante	Ex-post
Age	38.656	49.587
Male	0.484	0.334
Total Spending	1.587	1.762
Insurer HHI	0.313	0.266
Actuarial Value	0.901	0.904
Insurer I	29.614	17.884
Insurer N	14.697	22.623
Insurer J	12.445	14.660
Insurer B	8.826	13.077
Insurer G	7.587	9.258
Insurer K	7.484	6.218
Insurer E	6.885	5.450
Insurer C	5.363	3.679
Insurer M	2.803	1.562
Insurer H	1.660	1.290
Insurer K	1.486	2.430
Insurer D	0.832	1.336
Insurer A	0.319	0.532
Number of Diagnoses	10	9
Number of Patients	3179229	2912701

Note: Table presents the mean of each characteristic conditional on diseases we predict should be compensated for ex-ante and ex-post based on our theoretical model. These means are calculated over the period 2013-2015.

Appendix Figure 4: Insurer Actuarial Value across Markets



Note: Figure presents the average actuarial value per insurer (in the row) and state (in the column) using the sample for structural model estimation. Darker colors report smaller actuarial values. The figure shows an insurer's choice of actuarial value is correlated across states.