Adverse Selection and Equity in Insurance Markets with Guaranteed Renewable Contracts: Evidence from Chile

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Abstract

In theory, guaranteed renewable (GR) insurance contracts can efficiently insure against reclassification risk without causing adverse selection on pre-existing conditions. In practice, however, adverse selection can still arise on other dimensions. In 2020, in response to protests demanding gender equality, Chile banned gender-based pricing in its private health insurance market. I investigate how this policy impacts Chile's health care system, which consists of a low-quality public option and a private market characterized by the use of GR contracts. I find that, if the ban is implemented, prices in the private market would increase by more than 30% as low-cost men switch to the public option and high-cost women enter. Overall, the regulation causes annual consumer surplus to increase \$373 per insured woman and decrease \$279 per insured man, which is around 2% and 1% of average annual per capita income, respectively. The ban is regressive, as high-income groups benefit more than low-income groups, creating a trade-off between gender-based equity and income-based equity. Subsidies that induce low-cost enrollees to remain in the private market are the most effective mitigation strategy to contain higher premiums. Finally, relative to non-GR contracts, the number of individuals choosing the private market is lower under guaranteed renewability.

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1 Introduction

Guaranteed renewable (GR) insurance contracts guarantee that the terms of a policy will not be cancelled or modified, even if the policyholder develops a medical condition. They are popular in insurance markets such as term life insurance and long-term care insurance. In theory, such contracts can mitigate reclassification risk—the exposure of individuals to substantial premium increases due to changes in health status—without causing adverse selection. The intuition is that consumers pay front-loaded premiums to guarantee affordable coverage in the future, regardless of any possible negative health shocks.

The theoretical literature tipically rules out adverse selection in long-term insurance contracts by allowing for screening on pre-existing conditions at enrollment (Ghili et al., 2022). In practice, however, adverse selection can arise on other dimensions.[1] For instance, policies designed to promote gender equality in insurance markets can introduce adverse selection on gender. A common example of this is gender-based pricing bans, which prevent insurers from charging higher prices to women than men, despite the fact that woman have higher health care costs on average. Gender-based pricing bans have been been implemented in health insurance markets in the U.S. and Europe, and, since 2020, in Chile.

This paper investigates how gender-based pricing bans impact insurance markets characterized by the use of GR contracts. To do this, I estimate a discrete-choice model of plan choice using detailed data from the Chilean private health insurance system between 2013 to 2016. I find that, under a conterfactual ban, prices in the market increase by more than 30% as high-cost women enter the system and low-cost young men leave. Overall, the regulation causes annual consumer surplus to increase \$373 per insured woman and decrease \$279 per insured man, which is around 2% and 1% of average annual per capita income, respectively. The ban is regressive,

[1] As another dimension of adverse selection, consumers might be forward looking and select high-quality plans before periods of costly elective medical spending. This is usually labeled as *selection on moral hazard* (*e.g.* Einav et al., 2013, Cabral, 2017, Diamond et al., 2021 and Shepard, 2022).

as high-income groups benefit more than low-income groups, creating a trade-off between gender-based equity and income-based equity. Subsidies that induce low-cost enrollees (young men) to remain in the private market are the most effective mitigation strategy to contain higher premiums. Finally, relative to non-GR contracts, the number of individuals choosing the private sector is lower under guaranteed renewability.

The Chilean health care system is ideal for this type of study for at least three reasons. First, Chile has one of the very few health insurance markets, in addition to Germany, featuring GR contracts. By law, Chilean workers must choose between a public option (generally considered of low quality) or a private market with contracts that offer guaranteed renewability. In contrast to the typical short-term health insurance contracts available in the U.S., premium changes in GR contracts have to be community rated; that is, premium changes over the lifecycle of a contract are independent of changes in policyholders' health status. This imples that the higher costs of adverse selection, induced by the ban, will be spread evenly across contracts. Second, in response to protests that started by the end of 2019 demanding gender equality in health care markets, Chile banned gender-based pricing in its private sector in 2020. In particular, before 2020, women in their 30s had to pay around 3 times more than men for the same plan. Third, unlike other insurance markets with GR contracts, the Chilean regulator gives researchers access to unusually rich individual-level data, thus allowing for a detailed study of the overall impact of the policy under examination.

I begin by providing several stylized facts regarding how a health insurance market offering GR contracts without a ban of gender-based pricing works. First, enrollees in the Chilean private sector are more likely to be high-income (3 times higher wages than enrollees in the public option), men (63%) and young (49% below age 35). The first two points are a consequence of a higher quality private system with gender-based pricing. The last point is contrary to what the theory of long-term contracts predicts (*i.e.* long tenure in a contract). Second, women pay higher premiums than men in the private market, conditional on plan quality, but they also spend more than men in health care. The latter implies that, if women have higher willingness-to-pay for insurance, adverse selection will emerge after the ban is implemented. Third, policyholders do not stick with their plans for long periods. Annual switching rates in the system are high (over 20%) and these rates are partially explained by changes in plan premiums. Thus, in spite of contracts' guaranteed renewability, policyholders are price sensitive and make frequent active choices in the market.

To quantify the impact of the ban on market outcomes (*e.g.* health-insurance premiums, market composition, and consumer surplus), and motivated by contracts' guaranteed-renewability and enrollees' response to premium changes, I estimate a two-stage discrete-choice demand model for plans in the private market using detailed administrative data from 2013 to 2016. The first stage determines the probability a policyholder makes an active choice of insurance plan in a year. This probability depends on announcements of premium increases, changes in personal income, and changes in family size. The second stage determines the choice of plan for the policyholder, which is a function of household characteristics, premiums, switching costs and the expected value of the hospital network. This last component is estimated using a hospital discrete-choice model and hospital admissions data, which also allow me to calculate expected costs per enrollee in each plan. The results of the second stage of the model show that women are relatively less price sensitive and have higher willingness-to-pay for coverage. These two facts together, in addition to women having higher health care costs, will drive adverse selection after gender-based pricing is banned. Importantly, including the first stage in the estimation matters. Switching costs are noticeably higher if the model is estimated without the first stage because in that case all the inertia in the market is attributed to switching costs. The two stages are separately identified by relying on exclusion restrictions.

I then solve for the equilibrium premiums during the same time period but under a counterfactual ban of gender-based pricing. In practice, the ban only applies to policyholders that decide to switch to a new plan. For that reason, the regulator spent considerable resources in promoting this policy, especially to women. The two-stage model allows me to force women to make active choices without removing switching costs. I show that, after the ban is implemented, premiums for private insurance plans increase as a result of adverse selection. The latter can be decomposed into intensive margin of adverse selection (movements of enrollees within the private market) and extensive margin of adverse selection (movements of enrollees in and out of the private market). In this setting, I find that extensive margin is the main driver of higher premiums. Without the ban, women below age 45 account for 28% of the private market, and that share jumps to 39% under the ban. In the case of men below age 45, the share goes from 47% to 37%. From a (remedial) policy perspective, subsidies that induce low-cost enrollees (young males) to remain in the private market are the most effective mitigation strategy to contain premiums. Monetary transfers between companies that balance expected costs are not as effective because they do not stop the movements of enrollees between the private and the public system.

The way GR contracts protect consumers from reclassification risk is by preventing insurers from changing prices of a given plan in response to changes in enrollees' health care costs. In contrast, short-term contracts without this kind of reclassification risk protection allow premiums of each plan to respond to changes in enrollment composition. This feature of non-GR contracts implies that, as a response to the higher costs of adverse selection, changes in prices are independent across plans.[2] Thus, premiums of individuals in low-quality plans will be higher under GR contracts (relative to a market with only non-GR contracts) because they must cross-subsidize selection on high-quality plans. Pairing this fact with the presence of a low-quality public option should lead to a lower number of enrollees choosing the private market than under non-GR contracts. In line with this hypothesis, I find that 60% of potential consumers select the private market after the ban of gender-based pricing is implemented under non-GR contracts compared to 52% who do so in a market with GR contracts.[3]

[2]As noted by Handel et al. (2015) and Azevedo and Gottlieb (2017), among many others, in a competitive market with short-term health insurance contracts, companies will set prices independently across plans; that is, high-coverage policies that become more adversely selected over time will experience a higher rate of increase in prices compared to low-coverage policies.

[3]In this particular analysis, non-GR contracts represent GR contracts with a temporary waiver that allows insurers to respond to compositional changes in each plan independently (until a new equilibrium is reached). This

The interaction between adverse selection on dimensions beyond pre-existing conditions and GR contracts in health insurance markets is an important topic not only for Chilean regulators, but for academics and policymakers in general. A recent literature studies the potential benefits of GR contracts and asks whether they should be implemented in health insurance markets in the U.S.[4] Ghili et al. (2022) charactize optimal long-term insurance contracts with one-sided commitment, as in Harris and Holmstrom (1982) and Hendel and Lizzeri (2003), and find that in certain scenarios, these contracts can achieve higher consumer welfare than ACA-like contracts. Similarly, Atal et al. (2020) show that GR contracts in Germany, despite not being optimally designed, obtain similar welfare outcomes as those in Ghili et al. (2022). These studies' favorable evaluation of GR contracts are based on assumptions that rule out the possibility of adverse selection. In practice, however, GR contracts can face adverse selection due to policy choice. Policymakers around the world are increasingly restricting insurers' pricing in favor of gender-based equity. This is because charging women higher premiums than men for the same level of coverage due to conditions such as pregnancy is considered unfair. As such, gender-based pricing is banned in the ACA Marketplaces in the U.S., and in all insurance industries in the European Union.[5] Similar restrictions exist in employer-sponsored health plans and in Medicare Advantage and Medicare Part D in the U.S., and in private health insurance markets in Australia, Colombia and South Africa.

Empirical studies of health insurance markets with long-term contracts are rare because few health insurance markets offer these contracts. Pauly and Herring (2006) show evidence of front-loaded prices in GR contracts in the individual market in the pre-ACA period. In the context

is how the short-term contracts available in the U.S. would respond to adverse selection. The reason I cannot make a direct comparison between GR contracts and short-term contracts is that, in the data, I do not observe individuals choosing between these two contracts. Thus, in the simulation of the ban under non-GR contracts, I keep consumer preferences for plans fixed.

[4]In the case of policy research in the U.S., to name some examples, Cochrane (2017) and Pope (2020) advocate for long-term contracts to replace the current short-term contracts in the individual market, and Duffy et al. (2017) from RAND posit the question of whether the individual market could perform better under long-term contracts.

[5]Plans in the Affordable Care Act (ACA) exchanges in the U.S. cannot price discriminate based on sex or medical history, and there are binding restrictions on how age can enter pricing. In the case of Europe, the European Union's high court ruled in 2011 that sex cannot enter premium determination in health insurance, life insurance, or annuities.

of the small group market pre-ACA, Fleitas et al. (2020) document limited dynamic pass through of expected medical costs into premiums, and provide evidence that GR contracts indeed give protection against reclassification risk. Browne and Hoffmann (2013) study the German private health insurance market and find that front-loading in premiums generates lock-in of consumers. Furthermore, they document that consumers that lapse (*i.e.* switch contracts) are healthier than those who do not. Closest to this paper is Huang and Salm (2019), who consider the impact of banning gender-based pricing in German's private health insurance market. Using survey data on enrollment composition in each system, they find the mandate increases the probability of switching from the public sector to the private system for women relative to men, which implies a worsening of the private sector risk pool. All of these papers use data from specific employers, insurance companies or surveys, whereas I use detailed data on both the supply and the demand side of the whole Chilean private health insurance system.[6]

The remainder of the paper is organized as follows. Section 2 illustrates the intuition behind the effects of banning gender-based pricing in a two-tiered system with GR contracts. Section 3 describes the main institutional details of the Chilean health insurance system and the regulation that is the focus of this paper. Section 4 introduces the data and provides stylized facts of the Chilean private sector before the ban was implemented. Section 5 presents a two-stage empirical demand model of plan choice. Section 6 discusses the parameter estimates and simulates Chile's gender-based pricing ban. Section 7 concludes.

2 Conceptual Model

In this section, I provide a conceptual model that illustrates the effects of banning gender-based pricing in health insurance markets, and how these effects vary under GR contracts and non-GR

[6]A few papers have used the same Chilean data to look at contract lock-in (Atal, 2019) and vertical integration (Cuesta et al., 2019).

contracts. In Section A in the Appendix, I develop a stylized theoretical model based on Einav et al. (2010) and Geruso et al. (2021) supporting the predictions of this section.

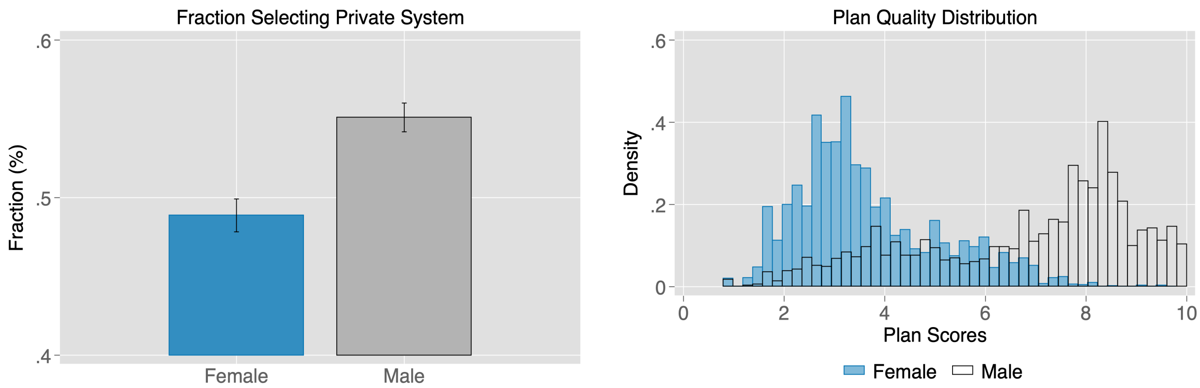
As described in Section 3, the Chilean health insurance market is a two-tiered system with a private sector and a safety net public option. For simplicity, here I assume that within the private market there is perfect competition with homogenous firms and zero administrative costs. Each firm from the private market sells two insurance plans, a high-coverage plan and a low-coverage plan. The public option offers a single plan that can be thought as lower coverage than any plan from the private market. The are only four consumer types in the market: "high-income males", "low-income males", "high-income females" and "low-income females". Gender determines health care costs, with female enrollees spending more in health care than male enrollees.[7] Income and gender together determine price sensitivity, with high-income groups and females being less price sensitive. Finally, I assume that females pay X times more for the same plan as their males counterpart (with $X > 1$). In Chile, before banning gender-based pricing, $X \approx 3$. At those prices, high-income males select high-coverage plans, low-income males and high-income females select low-coverage plans, and low-income females select the public option. Figure 1 shows that these choices are similar to the choices empirically observed in the Chilean health insurance market before the ban was implemented.

Under a ban of gender-based pricing, firms are forced to charge females the same prices they were previously charging to males.[8] If high-coverage plans are more expensive, conditional on enrollment, than low-coverage plans, then the difference in premiums between the two plans will go down. This implies that, in this scenario, high-income females can afford to buy high-coverage plans instead of low-coverage plans, which is called *adverse selection on the intensive margin.* Furthermore, the difference between the price of low-coverage plans and the public option will go down as well. This implies that low-income females are able to enter the private market instead

[7]See Figure 6 in Section 4.

[8]This is how the regulation was implemented in Chile in 2020. Another possibility would be to allow firms to increase prices of males such that they pay the same prices females are paying.

Figure 1: Gender-rated prices and selection



Notes: The left figure shows the fraction selecting the private system from a sample of single individuals that are realistically on the margin between the two systems (see Section E for details regarding sample construction). The right figure shows the distribution of plan scores (a measure of plan quality) from a sample of single individuals at the top income tercile (see Section 4.1 for details regarding plan scores).

of choosing the public option, which is called *adverse selection on the extensive margin*.

Since females have higher health care costs than males, firms will face pressure to increase premiums after these movements due to the zero profits condition. In response to higher prices in the private market, high-income males, that are less costly and more price sensitive than high-income females, switch from high-coverage plans to low-coverage plans, exacerbating *adverse selection on the intensive margin*. Conversely, low-income males move from the private market to the public option, exacerbating *adverse selection on the extensive margin*. These changes in enrollment composition put further pressure on firms to increase premiums again. This process of consumers switching and prices responding accordingly will continue until an equilibrium is reached. Overall, the private market is more adversely selected and with higher premiums after the ban is implemented. These market predictions are summarized in Figure 2.

How would the outcomes of banning gender-based pricing change in a health insurance market offering non-GR contracts? The way GR contracts protect consumers from reclassification risk is by preventing insurers from changing prices of a given plan in response to changes in

Figure 2: Private market predictions: banning gender-based pricing

	Share Policyholders Private System		Premiums Private System
	Female	Male	
Baseline	Lower	Higher	Lower
Under ban	Higher	Lower	Higher

enrollees' health care costs. Therefore, the higher costs of adverse selection will be spread evenly across contracts and premiums of both high-coverage plans and low-coverage plans must increase at similar rates. This implies that low-coverage plans cross-subsidize selection in high-coverage plans.

In contrast, non-GR contracts without this kind of reclassification risk protection allow premiums of each plan to respond to changes in enrollment composition such that profits in each plan are zero (Azevedo and Gottlieb, 2017). Therefore, in response to the higher costs of adverse selection, the price of high-coverage plans will increase at a higher rate than under GR contracts to reflect the higher health care costs of high-income females. The opposite will hold for the price of low-coverage plans because it does not have to cross-subsidize selection on high-coverage plans. This implies that, after gender-based pricing is banned, the number of enrollees choosing the private market should be higher under non-GR contracts as more price sensitive consumers are able to buy low-coverage plans. Figure 3 below summarizes the differences between the two cases.[9]

To summarize, there are two main channels that explain higher prices in the private market after a ban of gender-based pricing. First, an increase in the *intensive margin of adverse selection* (movements within private market). Second, an increase in the *extensive margin of*

[9]In Azevedo and Gottlieb (2017) the setting is a market with short-term contracts in which firms set plan prices equal to their annual average costs. In this setting, I am assuming that the same will hold even though this is a market with long-term contracts. A way to think about this assumption is that firms will set plan prices equal to their long-term average costs. Thus, when defining expected costs, I actually mean long-term expected costs, and profits actually mean long-term expected profits.

Figure 3: Private market predictions: GR versus non-GR contracts

	Premiums		Share Policyholders Private System
	Low Quality Plan	High Quality Plan	
GR contracts	Higher	Lower	Lower
Non-GR contracts	Lower	Higher	Higher

adverse selection (movements between systems). To quantify the importance of each channel, an empirical model is needed. The effectiveness of additional policies to mitigate higher premiums, such as subsidies to low-income groups (targeting the extensive margin) or monetary transfers between companies (targeting the intensive margin), depends on which channel matters the most. Furthermore, under non-GR contracts, prices of high-coverage plans are higher, prices of low-coverage plans are lower, and a higher number of enrollees choose the private sector.

The actual outcome in the Chilean health insurance market after implementing the ban is an empirical question that depends on the observed preferences of both males and females. For example, if males do not actually lapse or switch their plans when premiums increase, then the degree of adverse selection will be lower. Estimating these preferences, and extending this simple framework to a more realistic setting with multiple demographic and income groups, and with multiple heterogenous firms and health plans, is the objective of Section 5. Importantly, an empirical model allows for consumer welfare assessments of the ban.

3 Institutional Framework

The insurance system in Chile combines public and private provision.[10] The safety net public option, FONASA, is a pay-as-you-go system financed by the contributions of affiliates and public

[10] The details of the Chilean health care system have already been described elsewhere, in particular Duarte (2012), Atal (2019), Cuesta et al. (2019) and Pardo (2019). I draw from those papers heavily in this section. See Section B in the Appendix for more details on how the public option interacts with the private system.

resources. The private sector—operated by a group of insurance companies—is a regulated health insurance market. In 2015, FONASA covered 77.3% of the population and the private system covered 15.1%. The remainder of the population is presumed to be affiliated with special healthcare systems such as those of the Armed Forces or to not have any coverage at all.[11]

Workers and retirees have the obligation to contribute 7% of their wages to the public system, or to buy a plan that costs at least 7% of their wages in the private system, with a cap of $207 per month.[12] The two systems differ in many respects, including provider access, premiums, coinsurance structure, exclusions, and quality. Unlike the private sector, in FONASA there are no exclusions based on pre-existing conditions, nor pricing based on age or gender, and there is no additional contribution for dependents. As a consequence, the private sector serves the richer, healthier, and younger portion of the population (Pardo and Schott, 2013).

The private health insurance market is comprised of 13 insurance companies, which are classified into two groups: six *open* (available to all workers) and seven *closed* (available only to workers in certain industries). This paper focuses only on *open* insurers, which account for 96% of the private market. Contracts in the private sector are, for the most part, individual arrangements between the insured and the insurance company. A key feature of these contracts is that they offer guaranteed renewability, meaning that enrollees can stay in their health insurance plans as long as they wish. Furthermore, insurers cannot change the characteristics of these plans over time. Only the price can change but in a limited way in order to protect consumers from reclassification risk (see details below). Once a policyholder has been in a contract for one year, she may lapse her contract and switch to another company. Switching plans within an insurer is allowed at any time.

The monthly premium for individual i under plan j in year t, P_{ijt}, is a combination of a

[11] See Figure A.7 for historical market shares in each segment of the health insurance market in Chile.
[12] All monetary amounts are measured in U.S. dollars using the exchange rate on December 2016.

base premium P^B_{jt} and a risk-rating factor r_i so that:

$$P_{ijt} = P^B_{jt} \times r(enroll\ age_i, gender_i) \tag{1}$$

where $r(enroll\ age_i, gender_i)$ is the risk-rating factor, which is a function of age at enrollment and gender. These factors are fixed over time as long as enrollees stay in their plans. For dependents, there is a similar $r(enroll\ age_i, gender_i)$ function and the full premium of the plan in that case is the base price P^B_{jt} multiplied by the sum of the risk-rating factors r_i of each member of the family. In the empirical model in Section 5, this is the premium policyholders observe in each plan. A couple of features of the market restrict the extent to which private firms can risk-rate their plans when individuals enroll. First, base premiums are set at the plan (and not the individual) level. Second, the r function is not individual-specific: each firm can have at most two r functions.

Several features of the plan determine the base premium P^B_{jt}. A plan has two main coinsurance rates, one for inpatient care and another for outpatient care. Unlike in the U.S., plans do not include deductibles and out-of-pocket maximums. Additionally, plans offer either unrestricted open networks or tiered networks.[13] Hospitals in Chile cannot deny health care to patients, and therefore all consumers have access to all hospitals, although they may have zero coverage from their plan.[14]

Base premiums are indexed to inflation, and adjustments to the base premium in real terms can be made once a year. In March of each year, companies must inform the regulator of their projected premium increases for the year. Each company must also inform their clients (through letters) about these increases, justify their reasons for the changes, and offer alternative

[13]Unrestricted network plans provide the same coverage for all hospitals. Tiered networks offer differentiated coverage across sets of private hospitals, as PPO plans in the U.S.. Few plans offer restricted networks, as HMO plans in the U.S., and they are rarely observed in the data and not offered publicly. I do not consider them in my analysis.

[14]Other important characteristics of the plans are: a) Capitation scheme: Plans can either be capitated or not, b) Maternity-related expenses: Some plans do not have coverage for maternity-related expenses (in 2019 the regulator prohibited companies from selling these plans anymore). As these two characteristics also contribute to the determination of the base premium of the plan, I control for them in the demand model of Section 5.

contracts to their clients that keep monthly premiums more or less constant but that often imply lower coverage.

Reclassification risk

Reclassification could occur if firms could adjust the base premium P^B_{jt} of any given plan j based on the health status of the pool of enrollees in j. However, the market regulation involves also a restriction that limits the extent of reclassification of individuals already in a contract: the increase in P^B_{jt} of any particular plan j of insurer k cannot be higher than 1.3 times the weighted average price increase of all plans of insurer k. Formally

$$\frac{P^B_{jt+1} - P^B_{jt}}{P^B_{jt}} \leq \frac{1.3}{|J_k|} \sum_{j' \in J_k} \frac{P^B_{j't+1} - P^B_{j't}}{P^B_{j't}} \tag{2}$$

where J_k is the set of plans of company k.

Figure A.8 in the Appendix suggests that this regulation works in limiting the extent of reclassification risk. For the season 2013/2014, which is representative of the pattern for all years in the sample, 5 out of 6 companies applied the same percentage price increase to all their plans, and the sixth firm increased its prices within a narrow window of 2.2% and 2.6%. Moreover, in Figure A.9 I plot the evolution of base prices by plan quality, showing that they all increase at similar rates within a company. This practice limits the correlation between individual health status and individual price increases, which implies limited reclassification.

Pre-existing conditions

Each new potential insured has to fill a “Health Declaration” before signing a new contract with a private firm. The companies are allowed to deny coverage of any pre-existing condition during the first 18 months of enrollment, or even to reject the prospective enrollee altogether. Although there is no available data on the extent to which insurers deny coverage, anecdotal evidence and conversations with industry actors suggests that this is a regular practice.

Hospitals in Chile

The health care system combines public and private provision. The public hospital network is broader than the private one, with 191 public hospitals compared to 83 private hospitals in 2016 (Chile, 2016). The private and public sectors are mostly segmented. Private insurers primarily cover admissions to private hospitals, whereas the public option mostly covers admissions to public hospitals. In fact, 97% of private insurer payments are to private hospitals, whereas only 3% are to public hospitals (Galetovic and Sanhueza, 2013). An important feature of this market is price transparency, as consumers are often able to obtain price quotes before choosing a hospital.

In the analysis of the network of health insurance plans, I focus on a particular geographic segment of the market. Specifically, I focus on the private hospitals in the city of Santiago, which is the largest health care market in the country and where more than a third of private hospitals and around half of the capacity is located (Galetovic and Sanhueza, 2013). Additionally, I only consider inpatient care, which represents more than half of health care expenditure. This segment is comprised of remarkably fewer players than the outpatient care sector, with more pronounced differences on prices and quality, and therefore strategic concerns associated with choosing the right network are more relevant in this segment.[15]

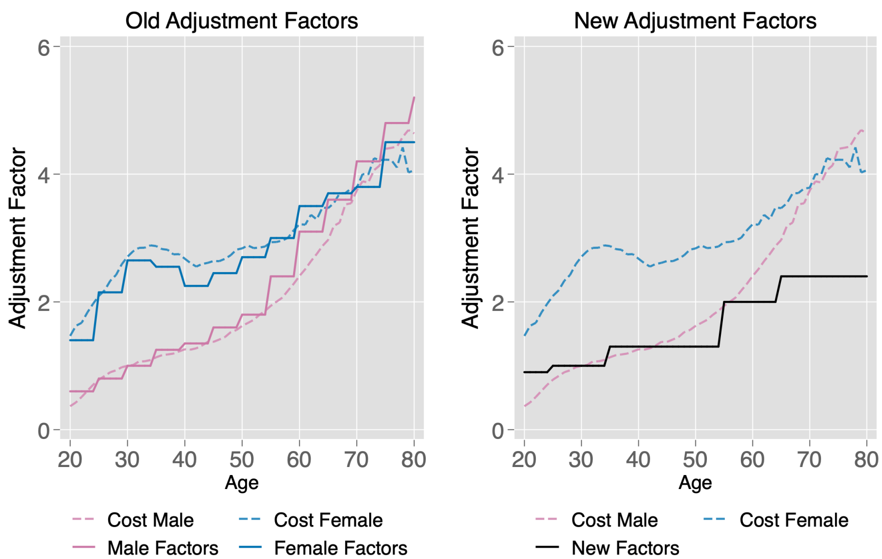
3.1 New Price Regulation

In March of 2020, in response to a wave of protests that erupted by the end of 2019 demanding, among other things, more gender equality, the regulator of the private health insurance market, *Superintendencia de Salud*, implemented a new policy banning gender-based pricing and adding restrictions on age-based pricing. Specifically, now the r function cannot depend on gender, and

[15]Plans are advertised and differentiated mostly on the inpatient hospital network offered. This is because outpatient procedures are less expensive and more homogenous. A limitation of this is that I can only predict inpatient health care costs. However, these predictions are at the group level (*e.g.* low-income young males), and at that level the correlation of spending between inpatient health care and outpatient health care is quite high.

it can only depend on enrollment age in a predetermined way common across companies, allowing for much less price differentation between age groups (in the paper I refer to this regulation as *the ban of gender-based pricing*). The change is shown in Figure 4, where I plot the old risk-rating factors for a representative company in 2016 (left figure), the new risk-rating factors implemented in 2020 (right figure) and health care costs by gender and age (relative to a 30-years old male) across enrollees in the private market in 2016.[16]

Figure 4: Risk-rating factors for one firm



Notes: This figure shows the old risk-rating factors for a representative company in 2016 (left figure), the new risk-rating factors implemented in 2020 (right figure) and health care costs by gender and age (relative to a 30-years old male) across enrollees in the private market in 2016

Under the new risk-rating factors, as described in Section 2, firms from the private sector will face pressure to increase premiums due to the higher costs of adverse selection, both on the intensive margin (which plan to buy within private market) and extensive margin (private versus public system). The simulation in Section 6 allows for these two mechanisms to play a role in

[16]Figure A.5 in the Appendix repeats this excercise for the six companies together. Figure A.6 shows in detail the change of the r function for a particular firm. These are the changes in the factors of policyholders. A similar change was also implemented for dependents. In the simulation of the policy in Section 6, these two changes are taken into account.

explaining higher prices in the system.

But what actually happened after the regulation was implemented in 2020? Even though a full empirical analysis is impossible due to the recency of the policy and a lag in the availability of the data, in Section F in the Appendix I provide anedoctal evidence indicating that costs in the private system have skyrocketed since the new risk-rating factors were implemented.[17]

Interestingly, a similar regulation was implemented in the German private health insurance market in 2011, the only other health insurance market in the world with GR contracts. Using survey data from both the private health insurance (PHI) sector and the social health insurance (SHI) sector, Huang and Salm (2019) find that women started switching from SHI to PHI at higher rates and more men were switching from PHI to SHI once the regulation was enacted, even though the latter result is not significant, likely because switching from PHI to SHI is highly restricted in Germany. In terms of prices, they show descriptive evidence that they increased at a much faster rate after the policy, in line with the results of this paper.

4 Data and Stylized Facts

4.1 Data

I exploit administrative data collected by the *Superintendencia de Salud* containing the universe of insureds in the private market for the period of 2013-2016 (Superintendencia, 2006).[18] Insurers must report data on individual claims to the regulatory agency. These data cover every health service provided to a private plan policyholder in 2013–2016, including financial and medical

[17]The simulation in Section 6 corresponds to the equilibrium in the market after implementing the ban, which, in practice, could take many years.

[18]In practice, I have data from 2007 to 2016. The reason I focus most of the analysis in the period 2013-2016 is that these were stable years in this market (*e.g.* the regulator did not pass any important mandate during this period) and data from one of the companies is unreliable before 2013.

attributes along with consumer, plan and hospital identifiers. Additionally, I have data on all private plans offered during the period of analysis. This includes data on plans' company name, base prices, risk-rating function r, preferential networks, extra plan characteristics, availability in the market over time, and the date at which the plan was introduced in the market. Furthermore, I can match plans and their enrollees and observe basic demographics of policyholders and their dependents.[19]

I use administrative claims data to construct hospital admissions. I restrict the analysis to the 14 hospitals with highest market share, which account for 86% of the admissions in the data. The remaining hospitals are relatively small, and I group them into the outside option along with public hospitals. All these hospitals receive patients from all insurers in the market. Using claim dates and patient identifiers, I identify unique medical episodes of inpatient care which I label as admissions. The data contain detailed financial and medical information for each admission. Financial information includes the hospital charges, insurer coverage, and consumer copayment. Medical information includes the diagnosis and the list of claims for different services provided by the hospital. I code admissions to diagnoses using ICD-10 codes, resulting in medical episodes that cover 16 diagnoses groups.[20] These diagnoses account for 90% of admissions and 92% of hospital revenue. Finally, I combine these data with plan attributes and consumer covariates, such as age, income, gender, and the number of dependents.

Even though plans in this market are differentiated by the coverage rate offered in each of the main hospitals of the capital, those rates are not available in the data. Instead, an online platform called *QuePlan.cl* provided me with access to their administrative plans database, allowing me to observe the actual contract of each plan. Thus, I can extract the actual coverage rate of each plan in each hospital. In Section D of the Appendix, I provide further details about how I

[19] One caveat is that I am not able to match spouses with different plans to the same household. That is, a low-income policyholder might actually be part of a high-income household and I cannot observe that.

[20] The list of diagnoses covers infections and parasites, neoplasms, blood diseases, endocrine diseases, nervous system diseases, ocular diseases, ear diseases, circulatory diseases, respiratory diseases, digestive diseases, skin diseases, musculoskeletal diseases, genitourinary diseases, pregnancy, perinatal treatments, and congenital malformation.

construct these coverage rates. In addition, *QuePlan.cl* gave me access to "plan scores", a measure of plan quality. I use this variable in Section 4.2.[21]

Finally, in order to obtain information about households that are in the public option, I use the Chile National Socioeconomic Characterization Survey (CASEN) of 2017. The survey contains data on basic demographic and socieconomic characteristics of a representative sample of Chilean families, along with their health information (*e.g.* whether they have pre-existing conditions or not) and their choice of insurance system. I use this information in the simulation of the policy in Section 6.

4.2 Stylized Facts

In this subsection, I present five stylized facts of the Chilean health insurance system under gender-based pricing. I focus on differences in enrollment composition between the public option and the private system, and differences in premiums paid for private plans between demographics groups. These differences are economically justified by comparing health care spending between these groups. Finally, I also document switching rates across consumers in the private market, and I study whether premium changes can explain these switching rates.[22]

First, Table 1 presents descriptive statistics of individuals in the public option and the private market in 2016 (see Section E for details regarding sample construction). Monthly wages of policyholders in the private market are, on average, 2.71 times higher than in the public option and they pay 3 times more for health insurance plans. Regarding market composition, females account for 45% of total enrollment in the public option, but only 37% in the private sector.

[21]The "plan score" is a standarized measure that goes from 0 to 10, where 10 represents a plan with almost perfect coverage for the most expensive private hospitals of Santiago. As the score goes down, the coverage rate for private hospitals goes down as well. The reason I do not use this variable in the empirical model of Section 5 is that I can only match scores to a subset of plans available in the market.

[22]Table A.3 in the Appendix presents descriptive statistics for the hospitals in the sample. Moreover, Table A.4 shows market shares for multiple demographic and socioeconomic groups.

Strikingly, while enrollees below 35 years old (26%) and above 55 years old (25%) account for similar shares in the public option, in the private system they represent 49% and 9% of the market, respectively. This last point is contrary to what the theory of long-term contracts predicts (*i.e.* long tenure in a contract). These differences between the two systems are in line with previous literature documenting that the private sector serves the richer, healthier, and younger portion of the population (Pardo and Schott, 2013).

Table 1: Descriptive statistics public and private market

	Wages (1000s US$)	Premium Paid (1000s US$)	Female %	Below 35 %	Above 55 %
Public	0.71	0.05	0.45	0.26	0.25
	(0.25)	(0.17)			
Private	1.93	0.15	0.37	0.49	0.09
	(0.86)	(0.09)			

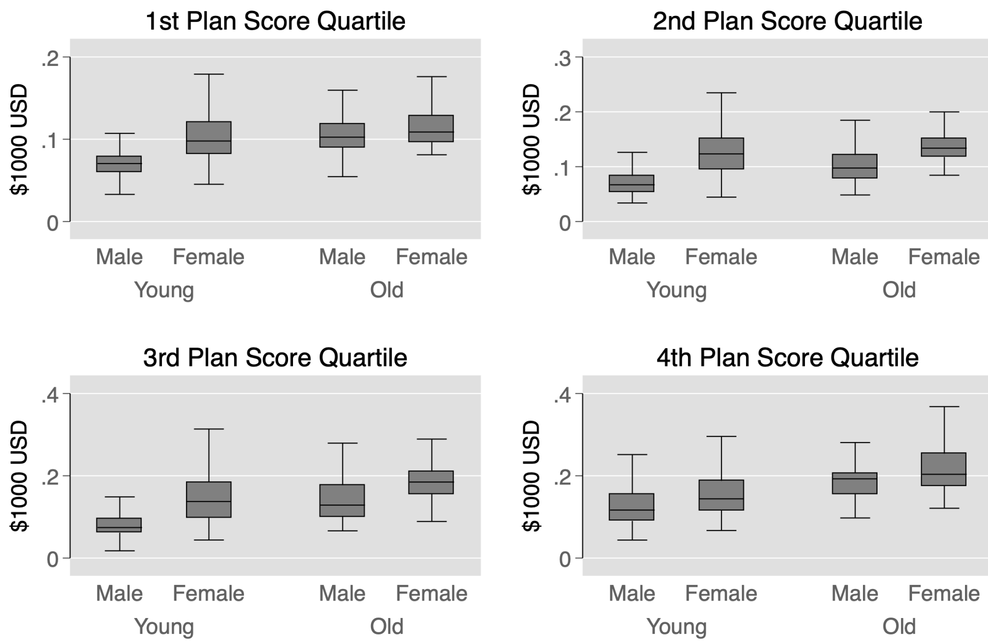
Notes: This table shows descriptive statistics for my simulation sample. Only households without pre-existing conditions and with income high enough to consider the private system are in the public option sample (see Section E for details regarding sample construction). For wages and premiums paid, means are reported and standard deviations are in parentheses. Monetary values are measured in thousands of U.S. dollars for December, 2016.

Second, conditional on plan quality (plan scores), premiums paid differ greatly between demographic groups. Specifically, Figure 5 shows that, for policyholders signing a new contract in 2016, young females pay much higher premiums for plans with similar quality than young males. For example, for a policy in the lowest plan score quartile, a young male pay around $71 dollars per month on average and a young female pay $105 dollars. Similar differences exist between young males and old males.[23] Third, female and old enrollees spend the most in health care. Figure 6 shows that these two groups are more likely to file a claim in a particular year and to spend more on health care, conditional on having positive spending. These two facts, differences by age and gender in premiums paid and health care spending, are in line with the adjustment factors and expected costs shown in Figure 4. Importantly, if women and older people also have higher

[23]In Table A.5 in the Appendix, I document that, beyond plan quality and firm fixed-effects, gender and age explain most of the variation in premiums paid across policyholders.

willingness-to-pay for insurance, which is estimated in Section 5, then adverse selection will emerge after banning gender-based pricing.

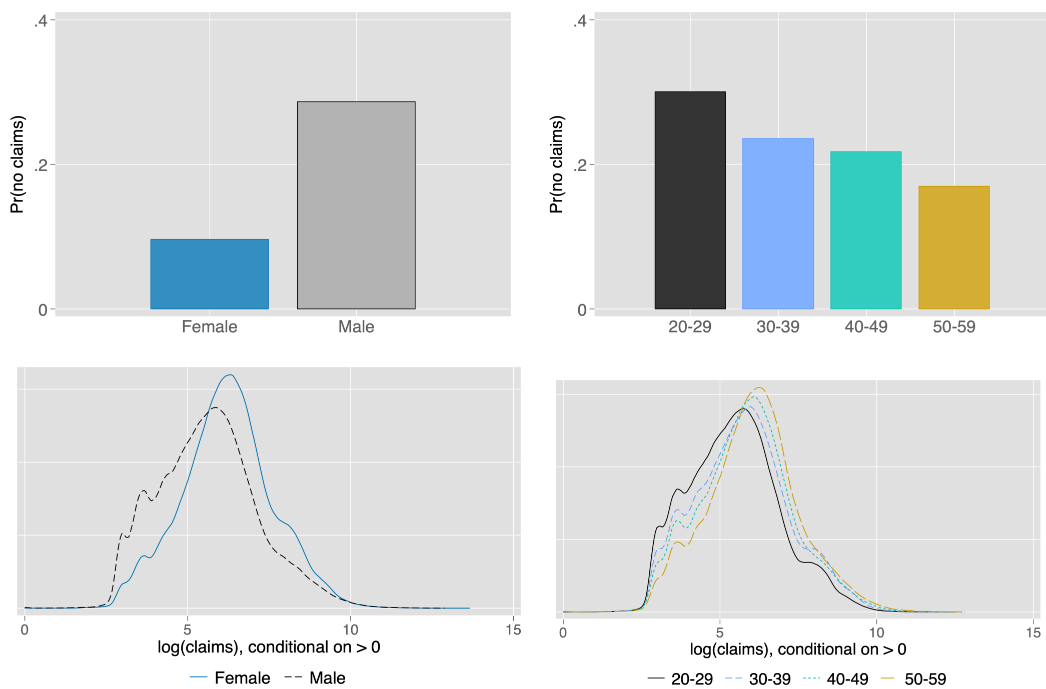
Figure 5: Premiums paid private market



Notes: This figure shows a box plot of premiums paid by policyholders signing a new contract in the private market in 2016. Young is defined as an individual with 45 years old or less. Old is an individual with age above 45 years old. Prices are measured in thousands of U.S. dollars for December, 2016.

Fourth, the switching rates in the private system are remarkable, especially considering that this is a market with GR contracts. Specifically, as documented in Table 2, almost 21% of policyholders lapse their plans during a year, with 11.7% switching plans within their companies, 6% switching companies, and 9.5% leaving the private market in order to go the public option. For comparison, the annual switching rate in Medicare Advantage is 8% and in Medicare Part D is 10%, which are similar private health insurance markets with a public option but with short-term contracts. Furthermore, in Figure A.10 in the Appendix, I show that only around 29% of enrollees stay in the same contract after 70 months, which undermines, in theory, the effectiveness of long-term contracts. In the next subsection, I explore one of the reasons why people lapse their

Figure 6: Health care costs by gender and age groups



Notes: The upper figures show the probability of having zero claims in 2016 by gender (left upper figure) and age groups (right upper figure). The lower figures show the distribution of $log(claims)$ conditional on having positive claims during 2016 by gender (left lower figure) and age groups (right lower figure).

plans at such a high rate: changes in premiums.

Table 2: Switching rates private market

Switching Rates (%)	
Within company switching	11.71
Company switching	5.95
Public option switching	9.54
Any switching	20.76

Notes: This table shows switching rates across policyholders in the data in 2016.

4.3 Evidence of Lapsing

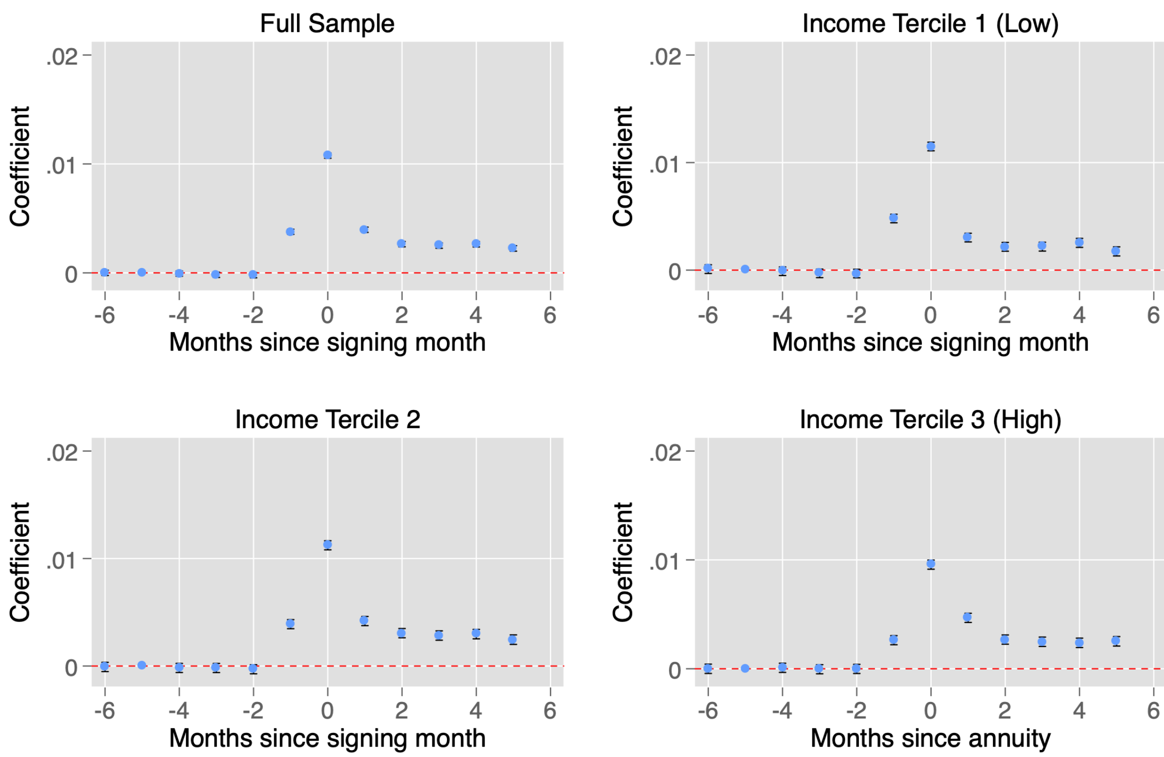
It is expected that companies will increase prices after the ban of gender-based pricing is implemented because of the higher costs of adverse selection. Thus, it is important to identify consumers' price sensitivity in this market as it is possible that, due to the guaranteed renewability of their contracts, policyholders will stick with their plans even after their premiums increase. Therefore, in this subsection, I explore whether policyholders in this market lapse their insurance plans in response to premium changes.

To answer this question, I examine the relationship between premium increases and the probability of switching plans within a company.[24] Figure 7 shows the results of an event study regression where the dependent variable is a dummy equal to one if the consumer switches plans within an insurer, and the event is the month in which the contract was signed in the first place. In Chile, the signing month is the month in which premium changes are applied to each policyholder. Importantly, given the nature of the contracts, these premium changes are the sole reason for enrollees to switch plans in this month in particular (*i.e.* it is the only characteristic of the plan

[24] I do not examine switching companies because this type of switching can only be done after being one full year in your current company. Thus, a spike in switching one year after enrollment could be attributed to premium changes or to the fact that policyholders could not switch before that. In the structural model, I can incorporate any type of switching because a period is defined as a year.

that is changing in the contracts). Furthermore, I also control for policyholder fixed effects and date (month-year) fixed effects, meaning that I am looking at the effect of the signing month on lapsing at the individual level, controlling for dates in which lapsing might be higher (or lower) than average. In order to have a clean panel of policyholders, I restrict the estimation sample to enrollees that do not switch insurance companies and that do not leave the private market and re-enter in later dates. This exercise is done on a 10% random sample of policyholders.

Figure 7: Probability of switching plans due to price changes



Notes: This figure shows an event study regression where the dependent variable is a dummy equal to one if a consumer switches plans within an insurer. The event is the month in which price changes are applied to health plans. Controls include individual fixed effects and date (month-year) fixed effects. I restrict the estimation sample to policyholders that do not switch insurance companies and that do not leave the private market and re-enter in later dates. Additionally, I drop individuals with zero or missing income at any month. This exercise is done on a 10% random sample of policyholders.

As documented in the figure, I find a large spike in the probability of switching plans in response to premium changes, and the effect appears consistent across income terciles. In terms of magnitude, the lapsing probability goes from 0.3% on average in any month of the year to 1.2% during the signing month. In Figure A.11, I look specifically at the plans to which policyholders lapse, finding that they switch to lower quality plans to keep their premiums paid roughly constant.[25] Finally, in Figure A.12, I repeat the same exercise but with the dependent variable now being switching from the private market to the public option. I show that policyholders on the lowest income tercile are prone to leave the private sector in response to premium changes.

These results are not only relevant for this particular setting, but also for the literature of insurance with long-term contracts in general. In theoretical models, lapsing only occurs by healthy consumers trying to find a lower price in the spot market. This holds by assuming that income paths are flat or that consumers have perfect foresight of their income paths.[26] Nonetheless, recent papers in other industries show that there might be additional reasons why individuals lapse their long-term contracts (*e.g.* Gottlieb and Smetters, 2021). The lapsing evidence presented above motivates the choice of a two-stage empirical model, estimated in Section 5. That is, due to front-loading and guaranteed renewability (Atal, 2019), policyholders have incentives to remain passive in their contracts, but they will make active choices in the market if they face premium changes in their plans (in the model I also add changes in personal income and changes in family size as explanatory variables). Furthermore, decomposing inertia into switching costs and remaining passive matters for the simulation in Section 6 because it allows me to force women to make active choices after implementing the ban without removing switching costs.

In summary, the stylized facts documented in this section provide a clear picture of the Chilean private health insurance market before the ban of gender-based pricing was implemented. First, the market is mainly composed by rich, young and male policyholders. Second, females and

[25]Additionally, in Figure A.13 I look at switching by age and gender groups, finding that they all lapse in response to premium changes.

[26]Theoretical models with long-term contracts treat policies as securing a certain level of income (or consumption), which is feasible by assuming *ex-ante* known income paths. However, if income paths are uncertain, then insurance against these income shocks is needed as well, which is not provided by real applications of long-term insurance policies (*e.g.* the GR health insurance contracts offered in Chile and Germany).

older enrollees pay higher prices than young males for the same plans, but they also spend the most in health care. Third, for a market offering GR contracts, switching rates are non-trivial and they are explained, at least partially, by changes in premiums. Thus, if prices increase after the ban is in place, lapsing will be triggered in the market. These facts will be part of the empirical model and the simulation of the ban in the following sections.

5 Empirical Model

The evidence provided in Section 4 does not allow me to quantify the welfare effects among consumers of banning gender-based pricing in the private health insurance market. To allow for such quantification, I formulate a two-stage econometric model of how individuals choose which contract to enroll in. The first stage determines whether a policyholder makes an active choice of insurance plan in a year. The second stage, conditional on making an active choice, determines the choice of plan for the policyholder. The choice of plans is a function of household characteristics, premiums, the expected value of the hospital network in the upcoming year, and switching costs. The two stages are estimated simultaneously.[27] For the calculation of the expected value of the hospital network, I separately estimate a hospital discrete-choice model (Capps et al., 2003 and Ho, 2006). Importantly, this model allows me to calculate expected costs per enrollee in each plan.

I note that, besides the expected value of the hospital network in the upcoming year, the demand model abstracts away from forward-looking behavior. Forward-looking generates an option value that may affect current choices, since they affect the set of feasible future choices. Specifying a dynamic demand model would require to specify individual's perceptions about the distribution of their future preference shocks, supply-side behavior, and discount rate.[28] Nevertheless, in Section

[27]Abaluck and Adams (2021) and Heiss et al. (2021) estimate similar models to explain inertia in Medicare Part D. In my setting, this model is even more compelling because what they call *inattention* might be rational behavior in an insurance market with GR contracts due to front-loading. That is also the reason why in this paper I use the terms *active* versus *passive* instead of *attention* versus *inattention*.

[28]The complexity of choice in health-insurance as well as the evidence showing choice inconsistencies in this

C of the Appendix I study the effects of a regulation implemented in 2011 that changed the incentives of consumers to be forward-looking. I find no structural change, on aggregate, on how policyholders choose plans after this regulation. Thus, this behavior does not seem to be a first order issue in this market.

5.1 Discrete-Choice Demand Model

First-Stage

The first stage of the demand model determines the probability, s^a_{ft}, that an incumbent household f makes an active choice of insurance plan in year t ($a_{ft} = 1$). This probability depends on announcements of premium increases, changes in personal income, and changes in family size. It takes the following logit form:

$$s^a_{ft} \equiv Pr(a_{ft} = 1 | \mathbf{x_{0t}}) = \frac{exp(\mathbf{x_{0t}} \tau^{\mu})}{1 + exp(\mathbf{x_{0t}} \tau^{\mu})} \tag{3}$$

where $\mathbf{x_{0t}}$ is a vector containing the percentage increase in the premium of the household's own plan, an indicator for changes above 30%, in either direction, in personal income, and an indicator for changes in family size (typically indicates birth of a new child). τ^{μ} are the corresponding first stage parameters to be estimated.

Second-Stage

Conditional on making an active choice, an incumbent household f considers all health insurance plans in their choice set $\mathcal{Y}_{ft}$. To change plans, however, they must incurr in a switching cost γ_f. Each year after signing a GR contract, the incumbent household f's utility from choosing plan j

market is arguably a main reason why most recent papers estimating health insurance demand in dynamic settings do not incorporate forward-looking behavior. A recent literature uses Medicare part D dynamic pricing incentives to estimate discount factors and myopia in drug purchases, finding strong levels of myopia (*e.g.* Abaluck et al., 2018 or Dalton et al., 2020).

in period t takes the following form:

$$u_{fjt} = \alpha_f p_{fjt} + \beta_f \sum_{i \in f} EU_{ijt} + \phi X_{fj} + \gamma_f y_{fjt-1} + \epsilon_{ijt} \tag{4}$$

where ϵ_{ijt} is distributed Type 1 EV. Utility thus depends on the plan premium p_{fjt}, EU_{ijt} and X_{fj}, explained below, switching cost γ_f, and an indicator for remaining in the same plan y_{fjt-1}.[29] EU_{ijt} is the expected utility of consumer i of household f from the hospital network of plan j at time t, which depends on how sick consumers expect to be and the plan coverage in the hospitals they expect to go. I separately estimate EU_{ijt} using a hospital discrete-choice model and hospital admissions data, a standard procedure in the health insurance literature (Capps et al., 2003 and Ho, 2006). Importantly, this model also allows me to calculate expected costs for each household in each plan of the market, which I then use in the simulation of the ban to calculate profits. See Section D of the Appendix for details about the estimation of this model and how EU_{ijt} is calculated. Finally, X_{fj} includes additional plan characteristics, such as whether the plan is capitated and whether the plan covers maternity-related expenses, and firm fixed effects interacted with household characteristics in order to control for segmentation at the company level.

Under these assumptions, the conditional probability that household f chooses plan j from choice set $\mathcal{Y}_{ft}$ in year t given they make an active choice is:

$$s^y_{ftj} \equiv Pr(y_{ft} = j | a_{ft} = 1; \gamma_f, .) = \frac{\alpha_f p_{fjt} + \beta_f \sum_{i \in f} EU_{ijt} + \phi X_{fj} + \gamma_f y_{fjt-1}}{\sum_{k \in \mathcal{Y}_{ft}} \alpha_f p_{fkt} + \beta_f \sum_{i \in f} EU_{ikt} + \phi X_{fk} + \gamma_f y_{fkt-1}} \tag{5}$$

For new households entering the private market, the main difference is that they do not have a default plan, and, hence, they do not have switching costs. Policyholders are assumed to choose the plan that gives them the highest utility. Notice that this formulation assumes that beneficiaries

[29] In this particular case, switching costs could be paperwork or enrollment costs, acclimation costs, and even reclassification risk. The latter could occur if families with sick members find it harder to switch plans, maybe due to the possibility of being denied coverage. Importantly, the coefficients themselves may pick up both true switching costs and persistent unobserved heterogeneity. For my purposes, it is not clear that is important to distinguish these factors. Doing so would matter primarily for dynamic price competition, which I do not model.

choose the option with the highest "perceived" utility, which may not necessarily correspond to the "best" plan for them from an actuarial risk-protection perspective (Abaluck and Gruber, 2011, Abaluck and Gruber, 2016). For the analysis of risk allocation and choices in the simulation of the ban, however, this "perceived" utility is exactly the object of interest.

Household preferences for health insurance may reflect both health risks, as well as horizontal tastes and risk aversion. Importantly, these differences in willingness-to-pay for insurance between demographic groups will determine the degree of adverse selection in the market after the ban is implemented. To capture these features of insurance demand in the model, I include rich observed heterogeneity in the specification of marginal utility. Specifically, I allow preferences for plan characteristics, α_f and β_f,to vary by two age groups, gender, two income groups (low- and high-income) and household size. Additionally, in the case of switching costs γ_f, I allow them to depend on pre-existing conditions in order to capture lock-in (Atal, 2019).

5.2 Identification and Choice Sets

In this subsection, I go through the sources of identification for all the components of the discrete-choice model outlined above. Additionally, I explain how I deal with the problem that choice sets are unobserved in the data.

The simplest explanation for why a policyholder decides to stay in the default plan is that she carefully compared plans and came to the conclusion that her default plan is the most attractive one available for the next year. Given the incentives for policyholders to remain passive in their GR contracts (*e.g.* front-loaded premiums), this alone is unlikely to be the only reason that explains choosing the default plan. In the second stage of the model, I account for a large part of the plan characteristics that should be relevant to a policyholder's decision of what plan to choose. Allowing for preference heterogeneity provides a comprehensive model of deliberate plan choices. The remaining persistence that cannot be explained by plan features and preference heterogeneity is what I call inertia and attribute to switching costs and remaining passive.

For identification, I exploit the fact that, each year, there are new cohorts of consumers entering the private market and that are forced to make an active choice. This implies that I observe policyholders choosing with and without frictions from the same menu of contracts. On the one hand, the preference parameters that enter in the second stage utility are identified from the choices of consumers who enter the market under the assumption that unobservables are uncorrelated with premiums and plan characteristics. Given the rich set of observables included in the model, this assumption should be reasonable. On the other hand, the difference in behavior between households with default plans and without default plans is attributed to inertia (Handel, 2013).

First stage parameters τ^{μ} are identified by the fact that the explanatory variables driving the probabilities of making an active choice (first stage) are quite different than the ones explaining the plan choices (second stage), creating exclusion restrictions that add to the identification of the model. For example, if the premium of the $t-1$ plan increases in t—a change that is made salient by letters sent from insurers—my model implies an increase in the probability of becoming active, so the policyholder starts comparing alternatives. Conversely, if the level of the premium of the $t-1$ plan is high for year t relative to the alternatives, a fact that is only apparent after comparing plans, this might contribute to overcoming switching costs and changing the plan (Heiss et al., 2021).[30]

Regarding contract characteristics, these are identified by variation in premiums and offered hospital networks across plans within an insurer and household type. Still, endogeneity of premiums might threaten identification. In particular, insurers could provide coverage for additional services that are not captured by offered hospital networks. If these extra services affect

[30] Another identification issue arises in dynamic panel data models with lagged dependent variables if unobserved initial conditions and unobserved heterogeneity are correlated. However, this is not a problem in my setting since I am using data from 2013-2016 to estimate the model, while still having data back from 2007.

premium setting, it would cause an endogeneity concern. However, this is not a big problem in this setting because I observe in detail the characteristics of each plan, which allows me to add them to X_{fj} in the demand model.

Finally, in the case of the choice set of policyholders, it is unrealistic to believe that consumers observe all the plans for each company, especially given that there are thousands of plans available each year. Due to the mandatory rule of spending at least 7% of your wage in a health insurance plan, the choice set that each individual faces is restricted to only plans with a premium equal or higher than 7% of their wages. Additionally, according to the function r, the price of plans depends also on the age and gender of the policyholder. In practice, each firm offers betweeen 2 to 4 plans to consumers, conditional on a year, preferences for plan type (*i.e.* tiered network or unrestricted choice), hospital network offered, and their income and demographics. Therefore, for estimation purposes, I split the sample of consumers into different groups depending on the year, age group, gender, income group, and household size. Within each group, I find the most popular plans purchased in a year, conditional on plan type, network of providers offered and premium deciles. These are the plans, along with the default plan, that enter the choice set of each household.[31][32]

5.3 Maximum Likelihood Estimation

Given my parametric specification, I can estimate all model parameters simultaneously using maximum likelihood. For notational convenience, I collect all parameters in the vector θ. Since I assume independence across households, the likelihood function is the product of the individual likelihood contributions $\mathcal{L}_f(\theta)$. The observed outcome for household f is the sequence of plan

[31] Companies usually offer a plan at your 7% income level and the other plan(s) offered are priced above that 7% (either around 10% of your income level or even above that in some cases). In practice, then, conditional on plan type and hospital network, I include three plans in the choice set of each policyholder, one at 7% of their income, one between 7% and 10%, and one above 10%.

[32] Cuesta et al. (2019) and Robles-Garcia (2022)) follow similar strategies in their settings with unobserved choice sets.

choices made in years $t = 1, \ldots, T$ (making active choices is unobserved). Let j_{ft} denote the observed plan choice in year t. Thus, the likelihood contribution of each household is given by:

$$\mathcal{L}_f(\theta) = Pr(y_{f1} = j_{f1}, ..., y_{fT} = j_{fT} | \theta, d_f) \tag{6}$$

where d_f collects the histories of all the observed covariates. Further, conditional on these covariates, the time-constant switching cost component γ_f, and whether the policyholder is active or not a_{ft}, the household choices are independent over time. I can therefore write:

$$Pr(y_{f1} = j_{f1}, ..., y_{fT} = j_{fT} | \theta, d_f) = \prod_{t=1}^{T} Pr(y_{ft} = j_{ft} | \theta, d_f, a_{ft}, y_{ft-1}) \tag{7}$$

These probabilities are readily available given my assumptions on the first and second stages. First, I obtain the choice probabilities for period t:

$$Pr(y_{ft} = j_{ft} | \theta, d_f, a_{ft}, y_{ft-1}) = s^a_{ft} Pr(y_{ft} = j | a_{ft} = 1, d_f, y_{ft-1}) \tag{8}$$

$$+ (1 - s^a_{ft}) Pr(y_{ft} = j | a_{ft} = 0, d_f, y_{ft-1}) \tag{9}$$

This expression involves probabilities that condition on making active choices ($a_{ft} = 1$), which is not observable. By plugging in s^a_{ft} and s^y_{ftj} from equations (3) and (5), respectively, it is easy to see that the choice probabilities have different forms depending on whether the household has a default plan or not and whether the household stay in the default plan or switch to a different plan, which are both observable events. If I_{ft} is an indicator for a household having a default plan, then for households without a default plan ($I_{ft} = 0$), the probability of making an active choice is $s^a_{ft} = 1$, thus the probability of choosing plan j is equal to s^y_{ftj}. For a household with a default plan ($I_{ft} = 1$), I either observe that they switch plans (and thus choose a plan j with $y_{ft-1} \neq j$) or that they stay in their default plan (and choose plan j with $y_{ft-1} = j$). Switching (choice of j for $I_{ft} = 1 \wedge y_{ft-1} \neq j$) can only occur if the household is active. The probability of choosing a plan j that is not the default plan is therefore $s^a_{ft} s^y_{ftj}$. Staying in the default plan (choice of j for

$I_{ft} = 1 \wedge y_{ft-1} = j$) can occur either if the household is not active (with probability $(1 - s^a_{ft})$) or if they are active (with probability s^a_{ft}) and choose the default plan j as the preferred option (with probability s^y_{ftj} for $y_{ft-1} = j$).

Putting everything together, for any plan j:

$$Pr(y_{ft} = j|.) = \begin{cases} s^y_{ftj} & \text{if } I_{ft} = 0 \\ s^a_{ft} s^y_{ftj} & \text{if } I_{ft} = 1 \wedge y_{ft-1} \neq j \\ s^a_{ft} s^y_{ftj} + (1 - s^a_{ft}) & \text{if } I_{ft} = 1 \wedge y_{ft-1} = j \end{cases} \tag{10}$$

To obtain the probability of household f's entire choice sequence, I plug this expression into equation (7).

6 Estimation Results and Simulation

6.1 Parameters Estimates

Table 3 displays the results for the first stage of the demand model.[33] The estimates suggest that policyholders start making active choices in the market in response to changes in premiums, changes in personal income and changes in family size. Moreover, the average household is active in a particular year with a probability of about 30%, and hitting all enrollees with the average premium change (6.4%) would increase their probability of making an active choice by 15.5%.

Table 4 documents the results of the second stage of the demand model. Specifically, the first panel of the table highlights the premium coeffients,[34] the second panel shows the expected

[33] Section E in the Appendix provides details about the construction of the sample used in the estimation of the model.

[34] See Figure A.15 for estimated premium elasticities across my sample.

Table 3: Parameters estimates - First stage

Variable	Coeff	S.E.	Average Marginal Effect
$\%\Delta$ Premium	0.037	(0.002)	15.52%
$\mathbb{1}\{\lvert\Delta Income\rvert \geq 30\%\}$	1.020	(0.029)	82.75%
$\mathbb{1}\{\lvert\Delta Family\rvert > 0\}$	1.896	(0.058)	158.88%
Constant	-1.316	(0.023)	
Mean Active		29.82%	
Observations		3,706,628	

Notes: This table shows the first stage logit estimates of the discrete-choice model. Average marginal effects for the price are computed by simulating the increase in the probability of making an active choice after imposing that all enrollees are hit by the average premium change on in the sample. For the income change (or the family size change), the average marginal effect is computed by simulating the increase in the probability of making an active choice in the case where no one has an income change (or family size change) versus when every enrollee face an income change (or family size change). Standard errors are in parenthesis.

utility of health care coefficients, and the third panel displays the switching costs coefficients. Each row represents a different estimate for a different household group. Different columns indicate a different specification. Columns (1) and (3) consider insurer fixed effects, and columns (2) and (4) consider insurer fixed effects interacted with household groups. Additionally, columns (3) and (4) include the first stage in the maximum likelihood estimation. Column (4) is my preferred specification.[35]

The main conclusions from the table are: (i) females and older enrollees are relatively less price sensitive; (ii) females and older enrollees have a higher relative preference for higher "quality" plans (in terms of coverage and hospital networks); (iii) including the first stage in the estimation matters, especially in the case of the switching costs estimates. Points (i) and (ii) together will drive adverse selection after gender-based pricing is banned, that is, the two groups with higher health care costs also have the higher willingness to pay for better insurance plans.

To highlight the effect of including the first stage in the model, in Figure 8 I plot the

[35] Table A.6 in the Appendix assesses which model has a better fit to the data. The full model that includes the first stage and insurer-household group fixed effects provides the best fit according to multiple tests.

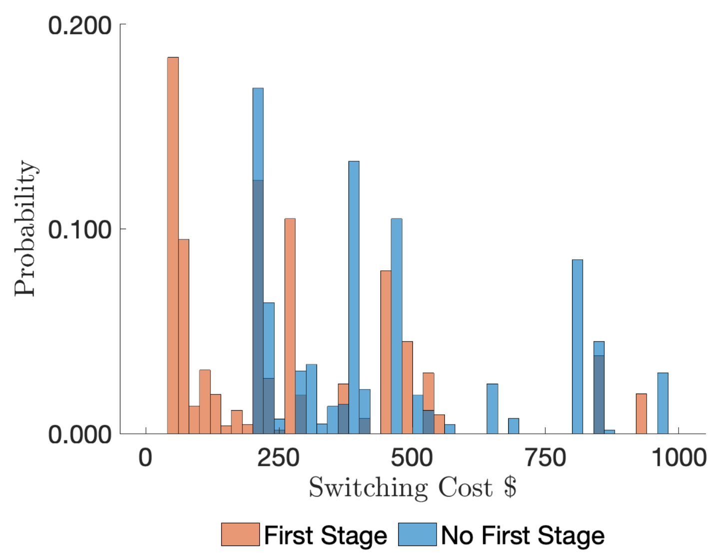
Table 4: Parameters estimates - Second stage

Variable	(1) Coeff	(1) S.E.	(2) Coeff	(2) S.E.	(3) Coeff	(3) S.E.	(4) Coeff	(4) S.E.
α_f - Plan premium p_{fjt}								
age ≤ 45	-21.928	(0.283)	-22.579	(0.300)	-27.422	(0.402)	-28.096	(0.421)
age > 45	-16.466	(0.315)	-17.625	(0.338)	-22.917	(0.476)	-23.885	(0.488)
Single female	2.807	(0.218)	3.319	(0.231)	2.223	(0.306)	3.102	(0.309)
Family	8.373	(0.238)	8.661	(0.260)	9.851	(0.333)	9.694	(0.350)
High-Income	5.659	(0.255)	7.733	(0.278)	8.697	(0.406)	11.350	(0.433)
β_f - WTP network EU_{ijt}								
age ≤ 45	-0.651	(0.209)	2.295	(0.276)	-1.646	(0.269)	2.170	(0.335)
age > 45	-0.753	(0.195)	3.603	(0.291)	-1.747	(0.277)	2.886	(0.388)
Single female	1.775	(0.163)	1.119	(0.278)	2.713	(0.202)	1.895	(0.338)
Family	0.999	(0.170)	-0.470	(0.298)	1.621	(0.206)	0.347	(0.368)
High-Income	6.144	(0.164)	-1.649	(0.253)	6.265	(0.197)	-2.155	(0.300)
γ_f - Lagged plan y_{fjt-1}								
age ≤ 45	4.555	(0.017)	4.626	(0.020)	1.168	(0.111)	1.509	(0.083)
age > 45	5.283	(0.029)	5.405	(0.047)	2.435	(0.097)	2.679	(0.078)
Single female	-0.078	(0.021)	-0.141	(0.038)	0.234	(0.041)	0.189	(0.051)
Family	-0.737	(0.022)	-0.708	(0.040)	-0.405	(0.044)	-0.389	(0.041)
High-Income	1.257	(0.022)	1.053	(0.000)	2.368	(0.080)	2.085	(0.059)
Pre-existing condition	0.341	(0.024)	0.330	(0.024)	0.271	(0.046)	0.287	(0.042)
Observations	3,706,628		3,706,628		3,706,628		3,706,628	
First Stage	N		N		Y		Y	
Plan Characteristics	Y		Y		Y		Y	
Insurer FE	Y		N		Y		N	
Insurer-Demographics FE	N		Y		N		Y	

Notes: This table shows the logit estimates of the discrete-choice model. The first panel displays the premium coeffients, the second panel shows the expected utility of health care coefficients, and the third panel shows the switching costs coefficients. Estimates vary across age groups, household composition, and income. Different columns indicate a different specification. Columns (1) and (3) consider insurer fixed effects, and columns (2) and (4) consider insurer fixed effects interacted with household groups. Additionally, columns (3) and (4) include the first stage in the maximum likelihood estimation. Standard errors are in parenthesis.

distribution of annual switching costs (in dollars) across enrollees for specifications (2) and (4) from the table. These switching costs are calculated by dividing the switching costs parameters with the premium parameters (and adjusting for annual costs). The differences are striking. In the case of the demand model including the first stage, the average annual switching costs ($376) account for only 21% of average premiums paid. On the contrary, when the demand model is estimated without the first stage, the average annual switching costs ($890) account for almost 50% of average premiums paid. The intuition behind this result is that estimating a discrete-choice model with a dummy variable for the default plan, but without a first stage, implies that each policyholder compares the available plans in each year and deliberately makes a choice—which seems unrealistic when the availability of a default contract with guaranteed renewability invites *passiveness*.

Figure 8: Switching costs



This figure shows the distribution of annual switching costs (in dollars) across enrollees in the estimation sample. These switching costs are calculated by dividing the switching cost parameters with the premium parameters (and adjusting for annual costs). Orange bars represent switching costs for the demand model including the first stage. Blue bars represent switching costs for the demand model without the first stage. Prices are measured in U.S. dollars for December, 2016.

6.2 Simulation

6.2.1 Description of Simulation

With the parameter estimates from the demand model, I can now simulate a gender-based pricing ban in the Chilean private health insurance market. Specifically, for the year 2016, I change the old risk-rating factors by the new risk-rating factors that will determine the final premium of each plan. In this subsection, I describe the steps taken in order to perform this simulation.

First, in practice, the regulation only implements new risk-rating factors to enrollees if they switch to a new plan, but for incumbents that decide to stay in their old plans, they keep their old risk-rating factors. This means that the ban does not change premiums of default plans, which implies that, in the simulation, few policyholders will make active choices. That is not realistic as the regulator spent considerable resources in promoting this policy, using targeted advertising to women and the elderly population (see Figure A.16 for an ad example). The two-stage model allows me to force women and older people (above 55 years old) to make active choices without removing switching costs.

Second, in the case of households from the public option, I only select consumers that are realistically on the margin between the two systems, and I include them in the simulation. *Realistically on the margin* means that their income is not sufficiently low such that they would never enter the private sector even if prices drop by a high amount, nor do they have pre-existing conditions such that they could be denied coverage by private insurers. Additionally, I also assume that potential consumers from the public option are actively making plan choices in every iteration of the simulation. In Section G in the Appendix, I study how the results change if instead only 50% of these households are active in each iteration.

As noted in Section 2, these movements from female and older enrollees will put pressure on private insurers to increase premiums. There are two main reasons for this: (1) adverse selection on the intensive margin, and (2) adverse selection on the extensive margin. Fully modelling the supply side of a health insurance market with GR contracts is a complicated task that remains an open challenge in the literature (*e.g.* Atal, 2019) and is beyond the scope of this paper. Instead, I allow firms to adjust prices following two simple rules. First, following existing regulation of GR contracts, the rate at which they increase premiums has to be the same for all their plans (*i.e.* protection against reclassification risk). Second, they must keep their profits constant relative to the sample period (2013-2016).[36] That is, in each iteration, insurers will raise prices, in a restricted way, until profits are back to sample period levels. Profits are calculated using prices, expected costs per enrollee in each plan (obtained from the hospital discrete-choice model in Appendix Section D) and enrollment. In Section G in the Appendix, I report results from a sensitivity analysis where I run multiple simulations with different profit levels.[37]

The moment companies increase their prices, consumers might start making active choices in response to these changes. Once active in the market, they decide whether to remain in their default plans or to switch to a new, likely cheaper, plan. Furthermore, some of them, especially low-income enrollees, might decide to even leave the private market altogether. If these switchers also have relatively lower health care spending, costs in the private market will further raise, putting further pressure on firms to increase premiums again. I repeat this process until I reach convergence, which in this case means that companies do not have incentives to change prices. This is what I call an *equilibrium* in the market.

Mitigation policies

[36] Specifically, I calculate profits for each firm in each year from 2013 to 2016. Then, I calculate the median profit for each firm across those years. These are the profit levels that insurers must keep constant. Importantly, when updating prices, I am only considering *static* changes in costs in each iteration. If, instead, firms take into account the *long-term* changes in costs in order to set premiums, then prices might increase even further.

[37] I keep the set of contracts fixed throughout the simulation, meaning that insurers are not allowed to create new health insurance plans after the ban is implemented. In practice, however, companies can create new plans if they wish. This assumption will bias my results if companies use this channel as a way to practice "cream-skimming" in the market. In Section F of the Appendix, I discuss and show evidence that this was not the case in the Chilean private sector in the years following the ban.

I perform two additional simulations of the private sector under the ban, but with mitigation policies that address the higher costs of adverse selection. Particularly, I simulate two strategies that are commonly used in health insurance markets in other countries but that have not been implemented in Chile yet. The first strategy is risk adjustment transfers (or monetary transfers between companies). The objective of this policy is to address adverse selection on the intensive margin by balancing the expected costs across insurers such that, the most adversely selected firms, in relative terms, do not have more incentives to increase premiums than the least adversely selected firms. In short, firms with a pool of high-cost enrollees, relative to the market, receive money from firms with a pool of low-cost enrollees, until all companies have the same expected costs.

The second mitigation policy is subsidies to low-income enrollees in the private market. The purpose of this policy is that a higher share of those enrollees remain in the private system because they are the ones that are likely to leave after premiums increase. Importantly, they are also the consumers with the lowest expected health care costs (young men). Thus, by keeping them in the private sector, costs will not increase as much as they would otherwise. In other words, this strategy is targeting adverse selection on the extensive margin.

Notice that the effectiveness of each policy depends on which margin of selection is more important once the ban is implemented. If most of the increase in costs is due to adverse selection on the intensive margin, then risk adjustment transfers will be more effective. If adverse selection on the extensive margin explains most of the rising costs, then subsidies will be more effective. If both margins are important, then it is probably a good idea to use both policies at the same time.[38]

Non-GR contracts

[38] One caveat of this analysis is that subsidies are politically much harder to implement because, unlike risk adjustment transfers, they are not a budget neutral policy.

Finally, I simulate an scenario in which the ban is implemented and premiums of each plan are allowed to reflect enrollment composition in that plan (*i.e.* non-GR contracts). According to Section 2, the number of enrollees in the private market should be higher under these kind of contracts as low-quality plans do not have to cross-subsidize selection in high-quality plans, which is exactly the case under GR contracts.

To conduct these counterfactual simulations, I need a method to find new equilibrium premiums in each plan as the enrolled population changes. Under the assumption of a perfectly competitive individual insurance market, Azevedo and Gottlieb (2017) provide an algorithm to compute this equilibrium.[39] In brief, I augment the pool of households with a mass of "behavioral consumers" who incur zero covered health costs and choose each available contract with equal probability; the inclusion of these behavioral types ensures that all contracts are traded. I then apply a fixed point algorithm in which, in each iteration, consumers choose contracts according to their preferences, taking prices as given. Prices are adjusted up for unprofitable contracts and down for profitable contracts until an equilibrium is reached.[40]

In my setting, this method is an imperfect approximation because it assumes perfect competition. Therefore, and following Dickstein et al. (2021), to determine equilibrium premiums in this counterfactual environment, I apply a modified version of the algorithm from Azevedo and Gottlieb (2017) that includes a fixed markup by plan (the markup is fixed in that it does not vary with the equilibrium outcome). In addition, this approach of fixed markups per plan does not allow cross-subsidization of plans within an insurer, that is, an insurer cannot subsidize an unprofitable high-quality plan with a profitable low-quality plan. As discussed in Azevedo and Gottlieb (2017), one can micro-found this restriction with a strategic model with differentiated

[39]The model in Azevedo and Gottlieb (2017) features an insurance market with short-term contracts. As in the main simulation of the ban under GR contracts, I assume that insurers respond to *static* changes in profits. If that is the case, I can apply then the algorithm provided by Azevedo and Gottlieb (2017) to find equilibrium prices.

[40]Given the large number of plans available in the market, to simplify the algorithm, within each firm I pool similar plans into "plan groups", according to their plan scores and plan characteristics. Therefore, firms adjust prices independently across "plan groups", but they apply the same price change for plans within each "plan group".

products. If an insurer taxes one plan to subsidize another, it risks being undercut on the taxed plan and only selling the money-losing option.

6.2.2 Simulation Results

In Figure 9, I decompose, approximately, how much of the rise in premiums after banning gender-based pricing is due to adverse selection on the intensive margin or adverse selection on the extensive margin. First, I simulate an escenario in which I implement the new risk-rating factors only for female and older enrollees without allowing for consumer switching ("Ban without switching").[41] Second, I simulate the implementation of the new risk-rating factors and allowing for switching, but only within the private market ("Ban with within market switching"). Third, the last scenario ("Ban with full switching"), is the full simulation of the ban. As shown in the figure, adverse selection on the extensive margin is the most important channel in explaining the rise in prices compared to intensive margin adverse selection. Specifically, extensive margin adverse selection accounts for 56% of the price increase and adverse selection on the intensive margin accounts for only 16%. This implies that subsidies should be a more effective tool than risk adjustment transfers in containing the rise in premiums.

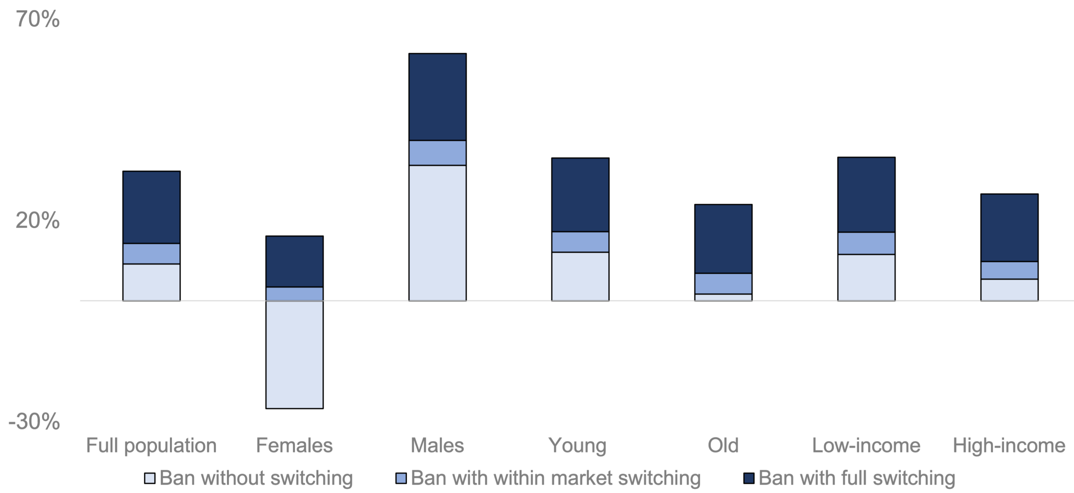
Table 5 shows the full results of the simulation. The first panel of the table displays the share of the simulation sample that is in the public option,[42] the second panel shows the percentage change in overall prices, and, the last panel documents the (annual) change in consumer surplus.[43]

[41] Prices increase, on average, in the full population in this scenario because median profits across 2013-2016 are higher than profits in 2016.

[42] For the simulation, I impose that high-income policyholders stay within the private market. The reason is that, for them, it is not a rational decision to go to the public option, even if prices are higher in the private system. My preferred specification of the empirical model supports this prediction as well, but because of logit shocks, a small share of policyholders would choose the public option in the simulation. In the data, high-income policyholders rarely move to the public option, and when they do is mostly due to large income shocks.

[43] For consumer surplus I use the compensating variation metric of change in expected consumer surplus as derived in Small and Rosen (1981). In general, the change in expected consumer surplus for household f from a change in the characteristics of the choice set from J to J' is (conditional on the household-specific parameters of the utility function θ_f):

Figure 9: %Δ in prices after ban: decomposition



This figure shows how much of the premium increases after simulating the ban of gender-based pricing are due to intensive margin adverse selection and extensive margin adverse selection. To perform this, first I simulate an escenario implementing the new price factors only for female and older enrollees without allowing for consumer switching ("Ban without switching"). Second, I simulate an escenario in which I implement the new price factors and allowing for switching but only within the private market ("Ban with within market switching"). The last scenario ("Ban with full switching") is the full simulation of the ban.

Each row in each panel is a different scenario (*i.e.* a different simulation) and each column is a different demographic or income group. All changes are relative to the baseline scenario under the old risk-rating factors in 2016.

The ban causes an influx of women from the public option to the private market—the share of women choosing the public option drops from 47 to 38 percent. At the same time, it causes men to move in the opposite direction—the share of men choosing the public option increases from 39 to 55 percent. The net effect is an increase in the total share choosing the public option from 43 to 48 percent. Most of these movements are from young women and young men. Particularly, in terms of composition, without the ban, young men account for 47% of the private market and

$$\Delta E[CS_f|\theta_f] = \frac{1}{\alpha_f}\left[ln\Big(\sum_{j'\in J'} exp(v_{fj'})\Big) - ln\Big(\sum_{j\in J} exp(v_{fj})\Big)\right]$$

where v_{fj} is the part of the utility function in Equation (4) without the unobserved portion ϵ.

Table 5: Simulation results

	Total	Women	Men	Young	Old	Single	w/ Dependents	Low-income	High-income
Share in Public Option (%)									
Baseline	42.67	47.39	39.44	40.09	49.20	47.67	31.31	69.05	-
Ban	47.88	37.71	54.81	44.92	55.36	52.61	37.22	77.63	-
Ban + Risk Adjustment	47.61	36.79	54.98	44.51	55.43	52.28	37.07	77.19	-
Ban + Subsidies	44.83	36.05	50.81	41.97	52.05	48.99	35.46	72.68	-
Ban + RA + Subsidies	42.23	36.16	46.37	38.60	51.41	45.86	34.06	68.47	-
%Δ in Overall Prices - Relative to Baseline									
Ban	32.23	-10.60	61.45	35.51	23.94	34.34	27.47	35.72	26.60
Ban + Risk Adjustment	32.22	-10.58	61.42	35.38	24.22	34.24	27.67	36.02	26.10
Ban + Subsidies	21.41	-17.83	48.18	24.45	13.71	23.35	17.03	24.42	16.56
Ban + RA + Subsidies	13.16	-23.30	38.04	15.91	6.22	14.91	9.24	16.19	8.30
Δ in Consumer Surplus ($) - Per enrollee per year - Relative to Baseline									
Ban	-15	373	-279	-73	132	-30	19	-68	71
Ban + Risk Adjustment	0	396	-269	-57	144	-18	41	-59	97
Ban + Subsidies	66	481	-217	-14	268	10	192	-16	198
Ban + RA + Subsidies	126	556	-167	30	370	42	316	21	296

Notes: This table shows the results of the simulation implementing the ban of gender-based pricing. The first panel of the table displays the share of the simulation sample that are in the public option, the second panel shows the percentage change in overall prices relative to the baseline and the last panel documents the change in consumer surplus relative to the baseline. Each row in each panel is a different scenario (*i.e.* a different simulation), and each column is a different demographic or socioeconomic group.

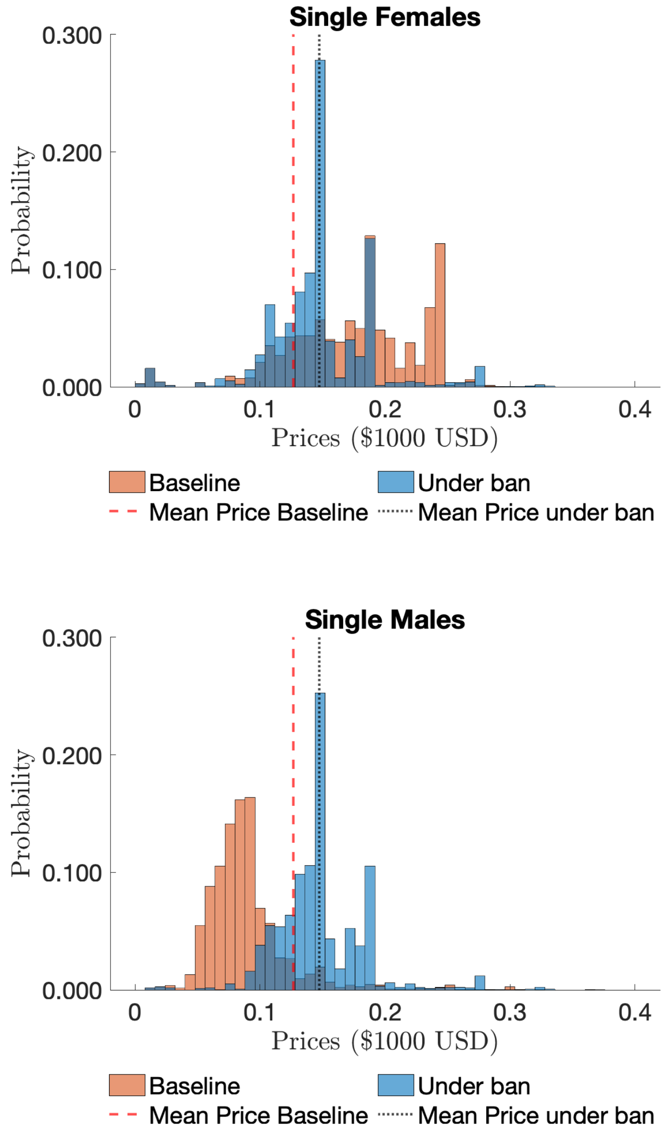
young women for 28%. After the ban, these shares change to 37% and 39% respectively. These two factors—women entering the private market and males leaving—are the main reason prices go up more than 30% in the private sector (the second panel). Figure 10 plots the distribution of premiums for single females and single males, before and after implementing the ban. In the baseline scenario, female premiums are higher than male premiums, which is in line with the factors displayed in Figure 4. Once the ban is implemented, as expected, premium distributions are much more homogenous between the two groups. Importantly, as noted by the vertical dashed lines in the figure, the average premium shifts to the right due to the higher costs of adverse selection.

The pattern of consumer welfare changes mirrors those for premium changes: there is little average change for the whole population, but surplus shifts sharply from men to women. The regulation causes average annual consumer surplus to increase \$373 per insured woman and decrease \$279 per insured man, which is around 2% and 1% of average annual per capita income, respectively. Splitting the sample by income, surplus shifts from relatively low-income to relatively high-income enrollees. This is because the women who benefit from price cuts are, on average, higher income than the men who face price increases, and the women who gain private market coverage are on average higher income than the men who lose this coverage. Additionally, high-income women are one of the groups with the highest willingness-to-pay for insurance.[44]

Mitigation policies, risk adjustment transfers and subsidies, have a positive effect on surplus. However, as expected given the results in Figure 9, subsidies are much more effective. The intuition behind this is that, by keeping young males in the private market, costs do not increase as much as they would otherwise, mitigating then adverse selection on the extensive margin. Importantly, the gain in consumer surplus from the subsidies (over \$3 millions) outweighs the costs of them (\$1.5 millions). Implementing both strategies at the same time delivers the best outcome for consumers. In this scenario, low-income groups have a positive change in consumer

[44] In terms of government revenue, I find that, with the implementation of the ban, the government would gain more than 10 million dollars (in 2016 dollars). This is between 0.1% and 0.2% of what the public option spent on enrollees' health care in 2016 (FONASA, 2019).

Figure 10: Histogram of premiums by gender



This figure shows the distribution of premiums for both single females (top plot) and single males (bottom plot) in the baseline (red bars) and under the ban of gender-based pricing (blue bars). Red dashed vertical lines despict the average premium across the two groups in the baseline and black dashed lines despict the average premium under the ban. Prices are in thousands of dollars of 2016.

surplus, which makes the ban less controversial. This result is in line with the two margin problem described in Geruso et al. (2021); addressing one margin of selection (*e.g.* intensive margin) can exacerbate the other margin (*e.g.* extensive margin), therefore the best solution is to address both margins at the same time.

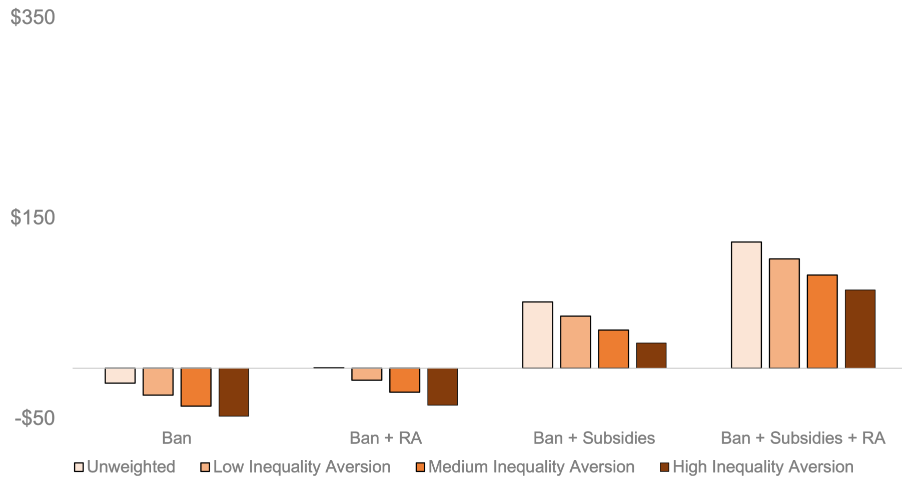
Finally, notice that the average consumer surplus results in Table 5 do not account for inequality, that is, this is an unweighted welfare measure. In contrast, in Figure 11 I show the consumer surplus impact of the ban if I introduce different levels of aversion to inequality. More specifically, to assess the equity implications of banning gender-based pricing, I rely on income as the measure of inequality and consider alternative welfare weights for different income groups. Following Handel et al. (2021), the consumer surplus of an individual in income group y_δ, where $y_\delta = 1$ for low-income and $y_\delta = 2$ for high-income, is weighted by $y_\delta^{-\epsilon}/(\sum y_\delta^{-\epsilon}/2)$ for $\epsilon = 0.5$, $\epsilon = 1.0$ and $\epsilon = 1.5$.[45] As shown in the figure, consumer surplus is lower the higher the aversion to inequality. This is intuitive because low-income groups have a lower change in surplus than high-income groups. Thus, when the regulator cares more about income inequality, banning gender-based pricing looks less appealing.

A different way to assess the implementation of the ban is instead to assume that the regulator has aversion to health care spending inequality. To do this, I split enrollees into four groups depending on their age (young and old) and gender (female and male), and rank them according to their health care costs. That is, the consumer surplus of an individual in group y_δ is weighted by $y_\delta^{-\epsilon}/(\sum y_\delta^{-\epsilon}/4)$ for $\epsilon = 0.5$, $\epsilon = 1.0$ and $\epsilon = 1.5$. In Figure 12 I show the results using this variant of the Atkinson index of inequality. In contrast to the results in Figure 11, now the (weighted) average consumer surplus is positive for all scenarios and is quite large for high aversion to inequality. This follows because the groups that benefit the most from the ban are also

[45] This is called the Atkinson index of inequality (Atkinson, 1970), which uses a social welfare function of the form $y_i^{1-\epsilon}$ with $\epsilon \geq 0$ as measure of inequality aversion. Here, I follow Handel et al. (2021) and I weigh the welfare gain for each household depending on the income group they are in by $y_\delta^{-\epsilon}/(\sum y_\delta^{-\epsilon}/2)$, which ensures comparability with the unweighted case.

the ones with highest health care spending (*i.e.* female and older enrollees).[46]

Figure 11: Consumer surplus impact and income inequality aversion



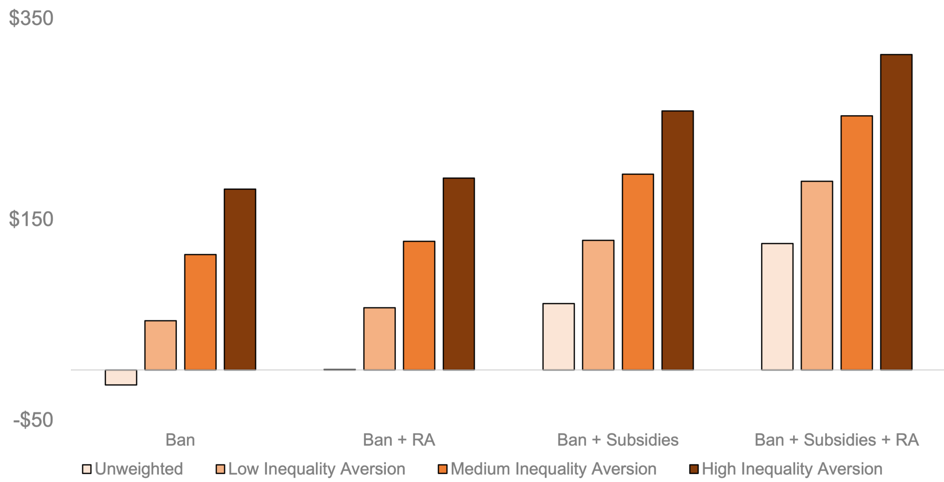
This figure shows the average consumer surplus change (in annual US per household) of implementing the ban of gender-based pricing with and without mitigation policies. The consumer change impact is calculated with equal weights for both income groups, low inequality aversion, medium inequality aversion and high inequality aversion. Weights y_δ are computed as $y_\delta^{-\epsilon}/(\sum y_\delta^{-\epsilon}/2)$ for $\epsilon = 0.5$, $\epsilon = 1.0$ and $\epsilon = 1.5$.

6.2.3 Banning gender-based pricing under non-GR contracts

One of the predictions of the conceptual model in Section 2 is that the number of enrollees in the private market would be lower under GR contracts with protection against reclassification risk compared to non-GR contracts without that protection. Figure 13 below confirms this prediction by comparing the share of the simulation sample that is in the public option in (i) the baseline with the old risk-rating factors and under GR contracts, (ii) after the new risk-rating factors are implemented and under GR contracts, and, (iii) after the new risk-rating factors are implemented and under non-GR contracts. Particularly, as shown by the left bars of the figure, the share of enrollees in the public option goes from 43% to 48% after implementing the new risk-rating factors under GR contracts, but it goes down to 40% under non-GR contracts. These results are driven

[46]In unreported results, I also use income net of health care spending as a measure of inequality. The results in this case are quite similar to the ones in Figure 11 because accounting for health care spending creates almost no change in the ranking of consumers in terms of income.

Figure 12: Consumer surplus impact and health spending inequality aversion

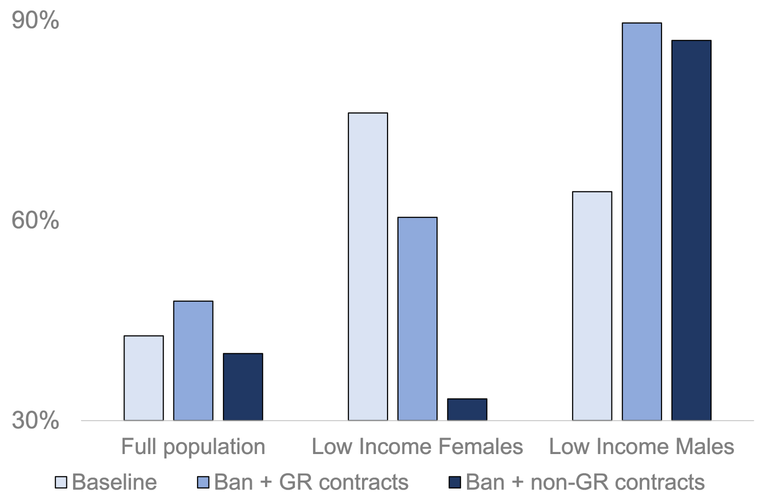


This figure shows the average consumer surplus change (in annual US per household) of implementing the ban of gender-based pricing with and without mitigation policies. The consumer welfare change is calculated with equal weights for the four health spending groups, low health spending inequality aversion, medium health spending inequality aversion and high health spending inequality aversion. Weights y_δ are computed as $y_{\bar{\delta}}^{-\epsilon}/(\sum y_{\bar{\delta}}^{-\epsilon}/4)$ for $\epsilon = 0.5$, $\epsilon = 1.0$ and $\epsilon = 1.5$.

mostly by consumers that are on the margin between the two systems, such as low-income females and low-income males, who are more likely to either remain in the private market or to enter this system from the public option when firms are allowed to price plans independently.

What explains this result? The reason price sensitive consumers are able to choose the private sector at higher rates under non-GR contracts is that in this scenario prices of low-quality plans are lower as they do not have to cross-subsidize selection in high-quality plans. This can be seen in the upper panel of Figure 14, where I plot the distribution of prices for the cheapest plans in the market (less than $100 USD per month) for single young enrollees after implementing the ban under GR contracts and under non-GR contracts. By allowing firms to price plans independently, premiums of low-quality plans can better reflect the lower costs of their enrollees. On the contrary, and as predicted in Section 2 and shown in the lower panel of Figure 14, premiums of high-quality plans are much higher in this scenario, with some of them even unravelling (*i.e.* no enrollee is willing to purchase them). Finally, in terms of consumer surplus, Figure A.17 in the Appendix

Figure 13: Share in public option with and without ban



This figure shows the share of policyholders in the public option with and without banning gender-based pricing in Chile. Lighter bars represent shares before implementing the ban under GR contracts. Medium-light bars represent shares after implementing the ban under GR contracts that provide protection against reclassification risk. Darker bars represent shares after implementing the ban under non-GR contracts that do not provide protection against reclassification risk.

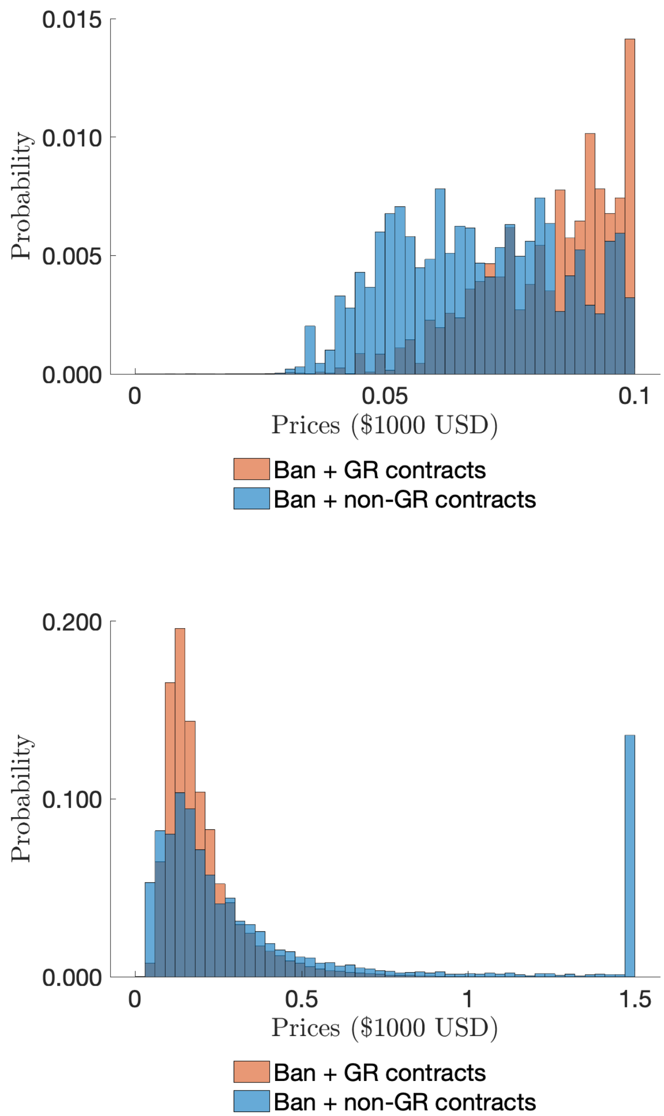
shows that enrollees are better-off when the ban is implemented under non-GR contracts as more affordable plans enter the choice set of most consumers.[47]

It is important to emphasize that this result is not stating that protection against reclassification risk is not desirable. This analysis is not taking into account the long-term benefits that this protection provides to enrollees (Handel et al., 2015). What this shows is simply that, in the case of banning gender-based pricing, contracts that allow premiums to reflect enrollment composition in each plan are better equipped to limit the number of consumers choosing the public option than contracts that do not allow for this.[48]

[47]Unlike the result stating that the number of consumers in the private market should be higher under non-GR, the consumer surplus result is likely to be highly dependent on this particular empirical setting.

[48]For similar reasons, an important caveat of this analysis is that, if consumers understand and value the protection against reclassification risk provided by GR contracts, then their preferences might change as well under non-GR contracts without that protection. Therefore, here I am assuming that this change in consumer preferences would not affect plan choices drastically.

Figure 14: Distribution of plan prices



This figure shows the distribution of prices after banning gender-based pricing in Chile, only for cheap plans (less than $100 USD per month) in the upper plot and for all prices in the lower plot (plans above $1,500 USD per month are clustered at that price). Premiums are restricted for single young enrollees only. Red bars represent prices under GR contracts that provide protection against reclassification risk. Blue bars represent prices under non-GR contracts that do not provide protection against reclassification risk.

7 Conclusion and Further Comments

Guaranteed renewable insurance contracts have the potential to mitigate reclassification risk without causing adverse selection on pre-existing conditions. However, adverse selection on gender will arise in these contracts if policymakers restrict insurers' pricing in favor of gender-based equity. This paper studies how a regulation banning gender-based pricing impacts the Chilean health insurance system, which is characterized by a private market offering GR contracts and a safety net public option.

First, I present several stylized facts of the Chilean health insurance system under gender-based pricing. Female enrollees pay higher prices than males for the same plans in the private system, but they also spend more in health care. If women have higher willigness-to-pay for insurance, this will drive adverse selection after implementing the ban. In addition, for a market offering GR contracts, switching rates are non-trivial and they are explained, at least partially, by changes in premiums. Motivated by these facts, I estimate a two-stage discrete-choice demand model for plans in the private market using detailed administrative data from 2013 to 2016. The first stage of the model determines whether a policyholder will make an active choice in the market, and the second stage determines, conditional on making an active choice, which plan the policyholder will choose. After estimating the model, I simulate a ban of gender-based pricing in the private system.

Overall, I find that women benefit from the regulation and men are negatively impacted by it. Since in my sample gender is also correlated with income, I find that low-income enrollees benefit less than high-income enrollees. Subsidies that induce young men to remain in the private market are the most effective mitigation strategy to contain higher premiums as extensive margin adverse selection is the main driver of adverse selection. Lastly, under the ban, a market offering non-GR contracts would increase the number of consumers choosing the private market instead of the public option.

The findings of this paper are relevant to policymakers as recent research is considering whether GR contracts should be implemented in the health insurance individual market in the U.S. A limitation of this literature is that, for tractability, they ignore the possibility of adverse selection on dimensions beyond pre-existing conditions. However, insurance markets around the world are increasingly implementing restrictions on insurers' pricing in favor of gender-based equity. Therefore, to seriously consider whether to implement these contracts in the U.S., a better understanding of the interaction between these contracts and adverse selection on gender is required. This paper helps to fill that gap.

Regarding the lapsing evidence presented in Section 4.3, an interesting topic for further research is to explore in detail whether lapses in markets with GR contracts are explained by reasons beyond health shocks. The literature of insurance with long-term contracts assumes that lapsing only occurs by healthy consumers trying to find a lower price in the spot market. If, in practice, lapses are also explained by premium changes or income changes, researchers might question then the effectiveness of long-term contracts. Importantly, if insurers foresee this, they could potentially based their pricing strategies on these lapses, an issue that has been studied before in the term life insurance industry (Gottlieb and Smetters, 2021).

Finally, one important caveat in the analysis of this paper is that I do not observe consumers choosing between GR contracts and short-term contracts in the data. Instead, I simulate how the Chilean private market will respond to the ban under contracts with a temporary waiver that allows insurers to respond to compositional changes in each plan independently (until a new equilibrium is reached). This is how the short-term contracts available in the U.S. would respond to adverse selection. Quantifying willingness-to-pay for long-term contracts (on top of short-term contracts) is a challenging but important avenue for future research.

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A Stylized Model

In this section, I develop a simple stylized model of insurance contract choice and insurer pricing that highlights the effects of a ban of gender-based pricing in health insurance markets, and how the effects of the ban change under GR contracts and non-GR contracts.

The general setting of the model follows the one in Einav et al. (2010) and Geruso et al. (2021). First, I assume perfect competition in the private market (zero profit condition) and that each company has zero administrative costs. This means that, in a competitive equilibrium, if allowed, firms will set plan prices equal to their average costs.[49] Second, I will consider two fixed contracts offered by each firm, $j = \{H, L\}$, where H is a high-coverage policy and L is a low-coverage policy. Finally, there is a safety net public option U, which has lower coverage than any plan in the private market. A price vector is defined as $P = \{P_H, P_L, P_U\}$.

Demand and costs

The model's primitives are consumers' willingness-to-pay (WTP) for each plan and expected insurer costs for consumers of specific types in each plan. Regarding demand, let $W_{i,H}$ be WTP of consumer i for plan H, and $W_{i,L}$ be WTP for L, both defined as WTP relative to U ($W_{i,U} \equiv 0$). I make the following assumptions:

Assumption 1. *Vertical Ranking*: $W_{i,H} > W_{i,L} > 0 \ \forall i$

The vertical ranking assumption implies that the products are vertically ranked for all consumers. Notice that this does not allow for plans being horizontally differentiated, which is one of the reasons why an empirical model is needed.

[49] In Einav et al. (2010) the setting is a market with short-term contracts in which firms set plan prices equal to their annual average costs. Here, for simplicity, I am assuming that the same will hold even though the plans in this market are long-term contracts. A way to think about this assumption is that firms will set plan prices equal to their long-term average costs, thus, when defining expected costs, I actually mean long-term expected costs, and profits actually mean long-term expected profits.

Assumption 2. *Single dimension of WTP heterogeneity and only 4 types*: there are only four types of consumers in the market; "high-income males" ($i = HM$), "low-income males" ($i = LM$), "high-income females" ($i = HF$) and "low-income females" ($i = LF$). These types can be ranked based on declining WTP, with $W_{HF,L} > W_{HM,L} > W_{LF,L} > W_{LM,L}$ and $(W_{HF,H} - W_{HF,L}) > (W_{HM,H} - W_{HM,L}) > (W_{LF,H} - W_{LF,L}) > (W_{LM,H} - W_{LM,L})$.

This assumption implies that consumers' WTP for H and L—which in general could vary arbitrarily over more dimensions—are assumed to collapse to a single-dimensional type s with $s = \{HM, LM, HF, LF\}$. Thus, if $W_{s,H} - W_{s,L} > P_H - P_L$, then consumer type s selects plan H, and if $W_{s,L} > P_L - P_U$ and $W_{s,H} - W_{s,L} < P_H - P_L$, the consumer chooses plan L. In any other case, the consumer would choose U.

In terms of expected insurer costs for consumers, I define "type-specific costs" for each plan j as $C_j(s) = E[C_{ij}|s_i = s]$ with $C_H(s) > C_L(s)$ and $C_L(s) > C_U(s)$ $\forall s$. Supported by empirical evidence in Figure 6, I assume that females have higher health care costs than males, thus $C_j(HF) = C_j(LF) > C_j(HM) = C_j(LM)$ $\forall j$. Notice that this implies adverse selection as consumers with higher willingness to pay also have higher health care costs. Relatedly, plan-specific average costs $AC_j(P)$ are defined as the average of $C_j(s)$ for all types who buy plan j at a given set of prices.

Initial condition and equilibrium under gender-based pricing

Assumption 3. *Initial condition and dynamic price adjustments:* there is a period $t = 0$, at the onset of the market, in which insurers set prices equal to average costs across all potential enrollees. After that, premiums are adjusted dynamically until an equilibrium is reached.

The assumption implies that, under a ban of gender-based pricing, at $t = 0$, $P_H = \frac{C_H(HF)+C_H(HM)+C_H(LF)+C_H(LM)}{4}$ and $P_L = \frac{C_L(HF)+C_L(HM)+C_L(LF)+C_L(LM)}{4}$. This allows for dynamic price adjustments, after consumers start selecting into plans, until an equilibrium is reached.

Under GR contracts, the assumption forces cross-subdization between plans. In the case of non-GR contracts, the assumption is inconsequential.

The main problem with the assumption is that it prevents forward-looking behavior from insurers, which might not be realistic in this simple setting with only two vertically differentiated policies and four consumer types. However, in practice, health insurance markets have multiple plans differentiated both vertically and horizontally, and multiple consumer types. Moreover, the way companies adjust prices over time after creating new plans in the ACA Marketplaces and in the Chilean private market (before and after the ban) provides strong support for the assumption. Nonetheless, as the ban in Chile was implemented after the market was created, for the empirical application of this paper, the assumption is not required. The assumption is only needed in order to generalize the results to markets that start with new plans under a ban and GR contracts.

If gender-based pricing is allowed in the market, plans can charge females X times more than males for the same plan. In Chile, before the ban, $X \approx 3$. I take the equilibrium under gender-rated prices as given and study how the equilibrium changes under a ban and GR contracts, or under a ban and non-GR contracts. Particularly, for this case, based on empirical evidence in Figure 1, I assume that in equilibrium high-income males select H, low-income males and high-income females select L, and low-income females select U. Prices for males and X are set such that profits in each plan, and for each gender, are equal to zero.

Banning gender-based pricing

Compared to the last scenario, in a market with a ban of gender-based pricing and $t = 0$, both $P_H - P_L$ and $P_L - P_U$ will be lower for females. In that case, $P_H = \frac{C_H(HF)+C_H(HM)+C_H(LF)+C_H(LM)}{4}$ and $P_L = \frac{C_L(HF)+C_L(HM)+C_L(LF)+C_L(LM)}{4}$. Given consumers' ordering of WTP, high-income females select H and low-income females choose to enter the private market and select L.[50] Notice that

[50]Here I assume that, at these prices, low-income females will not choose plan H, that is, $W_{LF,H} - W_{LF,L} < P_H - P_L$, $W_{LF,L} > P_L - P_U$.

for males the opposite is true, that is, $P_H - P_L$ and $P_L - P_U$ are higher. For expositional reasons, I will assume that, at those premiums, $W_{HM,L} > P_L - P_U$ and $W_{HM,H} - W_{HM,L} < P_H - P_L$, and $W_{LM,L} > P_L - P_U$ and $W_{LM,H} - W_{LM,L} < P_H - P_L$ Thus, both high-income males and low-income males select L. Even though this is a strong assumption, it is an approximation to the actual response of consumers to premium changes observed in Section 6.

As females have higher health care costs than males, after these choices, firms will face pressure to increase prices due to the zero profit condition. The way they do that depends on whether the market offers GR contracts or non-GR contracts. I will start with the common case of non-GR contracts, such as the short-term contracts offered in health insurance markets in the U.S., and then move to the setting with GR contracts.

Non-GR contracts: no reclassification risk protection

In this scenario, firms will set plan prices equal to their average costs (Handel et al., 2015 and Azevedo and Gottlieb, 2017). In that case, $P_H = AC_H(P) = C_H(HF)$ and $P_L = AC_L(P) = \frac{C_L(LF)+C_L(HM)+C_L(LM)}{3}$. Now, either this is the final equilibrium or high-income females switch to L after the increase in $P_H - P_L$ (*i.e.* plan H unravels). For the purposes of this model, this is inconsequential.

GR contracts: reclassification risk protection

In this scenario, firms are not allowed to change prices based on the enrollees that select into each plan (*i.e.* protection against reclassification risk). Instead, the percentage price increase of both plans must be the same. Therefore, $P_H = P_{H,t-1} + \Delta^{\%} P_{H,t-1}$ and $P_L = P_{L,t-1} + \Delta^{\%} P_{L,t-1}$, where $\Delta^{\%} = \frac{P_H - P_{H,t-1}}{P_{H,t-1}} = \frac{P_L - P_{L,t-1}}{P_{L,t-1}}$ and $t-1$ stands for prices before the current premium adjustment. The main difference between this scenario and the previous scenario with non-GR contracts is that now firms must cross-subsidize selection in plan H with plan L. Premiums will keep adjusting in this manner until an equilibrium is reached. The main implication of the model is:

Proposition 1. *In a health insurance market with a ban of gender-based pricing:* P_L*(GR contracts)* $>$ P_L*(non-GR contracts) and* P_H*(GR contracts)* $<$ P_H*(non-GR contracts)*

Proof. Both of these inequalities follow directly from the zero profit condition and cross-subsidization. In the case of L, $P_L(\text{non-GR contracts}) = AC_L(P) = \frac{C_L(HM)+C_L(LF)+C_L(LM)}{3} < \frac{C_L(LF)+C_L(LM)}{2} + \Delta^{\%}(\frac{C_L(LF)+C_L(LM)}{2}) = P_L(\text{GR contracts})$. This can be easily shown after some algebra by finding $\Delta^{\%}$ that solves $P_L(\text{GR contracts}) + P_H(\text{GR contracts}) = C_H(HF) + \frac{C_L(HM)+C_L(LF)+C_L(LM)}{3} = AC_H(P) + AC_L(P)$ and replacing it in the inequality. Once the first inequality has been proven, the second one for H is trivial because if $P_L(\text{GR contracts}) > AC_L(P)$, then profits for L are positive. Thus, profits for H must be negative such that the zero profit condition holds, meaning that $P_H(\text{GR contracts}) < AC_H(P) = P_H(\text{non-GR contracts})$. □

This proposition can be further generalized, but the most important takeaway is that prices of low-coverage plans should be higher under GR contracts and prices of high-coverage plans should be lower in that scenario. This happens because low-coverage plans are forced to cross-subsidize adverse selection in high-coverage plans. Notice that this implies that the number of price sensitive consumers choosing the private market should be lower as some of them are not able to afford the higher premiums in low-coverage plans.

Corollary 1. *Share of consumers in the private market will be lower under GR contracts than under contracts non-GR contracts.*

The empirical outcome of banning gender-based pricing in the Chilean private health insurance market is much more complicated than what is outlined in this simple model. First, the private sector in Chile features multiple plans per firm, with multiple coverage levels, that differ not only on price and coverage, but also on characteristics such as the hospital network offered or the firm's brand (*i.e.* horizontal differentiation). Second, by law, policyholders must spend 7% of their income in health insurance plans, meaning that high-income consumers are likely to remain in the private market purchasing high-coverage plans even if prices go up. Finally, enrollees in the private market, and in the public option, differ not only by gender, but also by age, family composition, and income, and each of these "consumer-types" has different WTP for insurance and expected costs. Therefore, quantifying the actual difference in outcomes of implementing the ban under GR contracts or under non-GR contracts is an empirical question. However, as long as enough healthy consumers remain in low-coverage plans in the private market, none of these features should affect the main predictions of the model: higher prices of high-coverage plans under non-GR contracts, lower prices of low-coverage plans, and a higher share of enrollees in the private market. The reason is that these healthy enrollees will keep the costs, and, hence, the prices of low-coverage plans, at low levels.[51]

[51] If only high-cost enrollees remain in the private market under non-GR contracts, then it might happen that the price of low-coverage plans is actually higher in this scenario than under GR contracts, contradicting then the prediction of the model. This last scenario seems implausible given the multitude of plans and consumer types in the Chilean setting. Nevertheless, generalizing this simple theoretical model in order to provide clear predictions in a more complicated environment, such as the Chilean market, is an interesting area for future research. This is out of the scope of the current paper.

B Details about How Public and Private Sectors Interact

The public and private health systems seem to operate in practice in a remarkably isolated fashion.[52] For instance, most of the consumers that purchase insurance in the private sector are also provided health care services mostly by private sector hospitals. A substantial 97% of all payments by private insurers are collected by private hospitals, while only 3% are collected by public hospitals (Galetovic and Sanhueza, 2013). Research on sorting across sectors points towards the remarkable differences in premium structures across sectors as the most relevant determinant of consumers' choice between public and private insurance (Pardo and Schott, 2013).

In terms of the evolution of their market shares, Figure A.7 shows that, since 2000, there has been a slight increase in the market share of public insurance, from 66% to 76%, while the market share of private insurers has remained almost unchanged at around 18%. The increase in the public insurance market share originates mostly from a reduction in the share of consumers with either no insurance or other forms of insurance. An interesting margin of study in this market is that of switching across the private and public sector. Data availability only allows for looking at switching out of the private sector. Duarte (2011) provides preliminary evidence showing that the public sector operates mostly as a safety net, as one of the major determinants of a consumer's decision to switch is job loss (or income shocks more generally).

There are some aspects that are worth studying in further detail in term of the relationship between these two sectors. Specifically, additional policies and regulations have been enacted since the 2000s that have changed the dynamics between the two systems.

Ley larga de Isapres

Through law 20,015, enacted in May, 2005, the government introduced a number of regulations to the private insurance sector. The focus of these was to reduce the extent for risk pricing

[52] Some parts of this section are taken from Cuesta et al. (2019).

by private insurers. Two relevant constraints on pricing that were introduced by this law were already described in the main text: (i) the number of risk-rating functions r was limited to 2 per insurer, and (ii) the extent to which premiums could be adjusted through time was limited to 1.3 of the average premium change, reducing then the extent for risk reclassification. Additionally, this law arguably increased the cost of vertical integration. This, as it explicitly established that insurers are not allowed to participate in the provision of health care services. This is the reason why vertical integration in this market is organized through common ownership of insurers and hospitals by holdings, rather than through direct ownership of hospitals by insurers (see Cuesta et al., 2019 for more details).

AUGE-GES plan

Through law 19,966, enacted in September, 2004, the government made mandatory the coverage of a list of health conditions dictated by the Ministry of Health. This regulation implied that since June, 2005, both public and private insurers are required to provide adequate treatment and insurance for consumers under conditions included in the list. The four elements considered by the law were (i) access to adequate treatment, (ii) certification of the quality of treatment by hospitals, (iii) financial protection of consumers through the imposition of thresholds below which there is a 20% coinsurance rate and beyond which such rate is set to 0%, and (iv) opportunity, by imposing maximum wait times for consumers to be treated by the system. The list started by including 25 conditions since July, 2005, and then was extended to 40 and 56 by July, 2006 and July, 2007 respectively. See Pardo (2019) for an analysis of how this reform changed selection dynamics between the two sectors.

C Forward-Looking Behavior

Even though it is hard to conclusively prove that consumers do not exhibit forward-looking behavior in this market, it is possible to show that this is not a first order issue, meaning that the estimates from the demand model in Section 5 will not be strongly biased by omitting this factor. To do that, I exploit a policy implemented in 2011 that completely changed dynamic incentives, particularly among new enrollees, and show that new consumers did not change their purchasing behavior in response to this regulation.

Before March of 2011, insurers were able to update (increase) the premium of enrollees according to their age in a predetermined way. Specifically, as policyholders aged, firms would increase their premiums by moving down the rows in the left table of Figure A.6. Thus, for example, if a male signed a new contract at age 34, he would get a factor of 1. But once he turned 35, his factor, and, hence, his premium, would have increased by 1.05. This caused public outraged, especially because insurers would only update the premium of consumers when this meant a higher price, but not when it meant a lower price. The regulator then decided to intervene, and by the end of 2010 enacted a policy that prohibited this kind of updating. Instead, as long as consumers stay in their plans, companies must keep the age factor fixed.

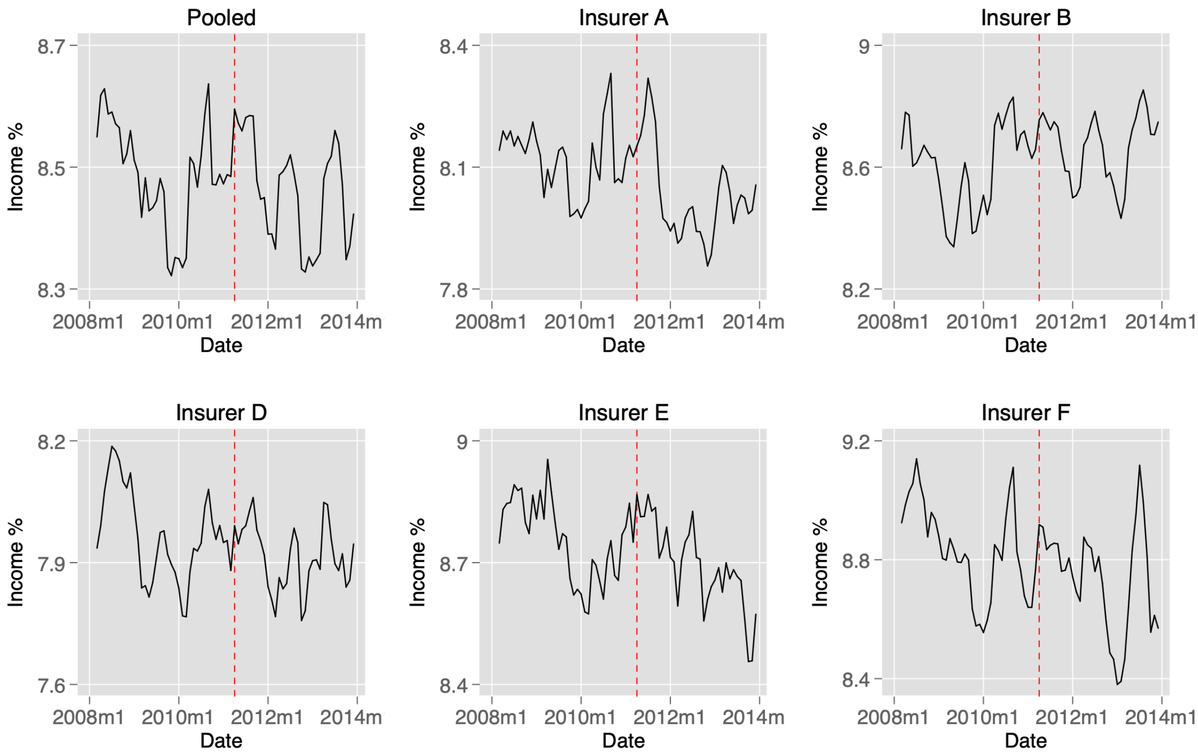
This policy drastically changed dynamic incentives when purchasing a new plan in the market. Specifically, policyholders know that they are likely to remain in their plans for longer because their age factors will not increase as they age. If consumers, then, are forward-looking, I should observe a structural change of how they choose plans in the private market after the regulation was implemented. In Figure A.1 below I plot the premium paid by new enrollees as a percentage of their income, probably one of the most relevant variables to examine. The data is smoothed using a 3-month moving average.

As can seen from the figure, policyholders do not seem to change their behavior when choosing new plans. Besides some normal fluctuations, there is no clear structural change in how much they are spending on health insurance plans before and after the policy was implemented. In addition to this variable, I also look at other measures such as raw premium or type of plan chosen, among others, finding similar results. That is, this is evidence that, at least on aggregate, consumers in this market do not exhibit strong forward-looking behavior. This is in line with findings from the Medicare part D literature, where, for example, Abaluck et al. (2018) and Dalton et al. (2020) have found strong levels of myopia.

Certainly, this is not meant to be a rigorous test of forward-looking behavior among consumers in this market. But the lack of evidence showing a clear change of behavior after the policy was implemented suggests that this is not a first order issue in the Chilean private system, and, hence, my demand estimates will not be significantly affected by omitting this feature in the estimation of the structural model.[53]

[53]An interesting area of study for future research would be to use this policy for a more sophisticated test of forward-looking behavior. However, this is out of the scope of the current paper.

Figure A.1: Premium paid as a percentage of income - New enrollees 2008-2014



Notes: This figure shows premiums paid by new enrollees as a percentage of their income between 2008 and 2014. The vertical red dashed line represents the introduction of a new policy that fixed the age function to the age at which the policyholder initially enrolled in her health insurance plan. The data is smoothed using a 3-month moving average. Data for insurer C before 2013 is questionable. Therefore, I do not include that firm in the analysis.

D Hospital Choice Model

Construction of coverage rates for hospitals

Prices faced by consumers when choosing a hospital have two main components: the actual price charged by the hospital and the coverage rage offered by the insurance plan. This subsection describes how I construct these coverage rates for each plan in each hospital.

A big portion of this task was completed manually. Specifically, the platform *Queplan.cl* gave me access to their database of contracts for each plan in the market, allowing me to retrieve each contract file and gather information about the coverage rate offered in each hospital. This manual procedure was done for all plans with tiered networks. For hospitals outside these preferred network, and for plans with unrestricted open networks, coverage rates are more complicated to retrieve manually as they involve visit payments cap by insurers. Therefore, for those cases, I impute the coverage rates using the observed empirical coverage rates from the enrollees in those plans in the claims data.[54] Finally, for each plan, I create only four coverage rates: one for the top 5 most expensive hospitals that are part of a preferred network, one for the top 5 most expensive hospitals that are not part of a preferred network, one for the other hospitals that are part of a preferred network, and one for the other hospitals that are not part of a preferred network. I do this by taking the average coverage rates across hospitals.

The final outcome of this procedure is four coverage rates for each health insurance plan in the private market. These are the rates c_{jh} I use to estimate the hospital choice model. Notice that the main advantage of using the *Queplan.cl* information is that I do not have to rely extensively on empirical coverage rates, which are likely to be biased, especially for the most expensive hospitals.

[54]For a few plans that I could not find their respective contract in the platform or that did not have enough claim information, I extrapole their coverage rates using similar plans. Specifically, I group plans by company, hospital network offered, and extra plan characteristics. Then, for plans with missing coverage rates, I look at plans from the same group but without missing information and I impute the missing coverage rate using the base price difference between these plans.

Construction of hospital prices

In order to construct hospital prices I follow Shepard (2022) closely. Therefore, for the interested reader, I recommend looking at his article for more details. The main difference with the current paper is that I only focus on inpatient care because in Chile there are too many outpatient units, making it almost impossible to identify each one of them in the data.

For inpatient care, the most natural service unit is the diagnosis-related group (DRG), which is the standard measure used in hospital price analyses. Nonetheless, because not all admissions are DRG-paid and because even DRG payment allows exceptions due to outlier adjustments, I estimate a pricing model that allows quantity to vary within a DRG or diagnosis based on other patient severity observables. Essentially, this method defines the quantity associated with each hospital admission in a continuous way based on a projection of spending onto DRG/diagnosis categories and other patient observables.

Consider a particular admission a – for enrollee i in plan j in year t for DRG (or diagnosis) d at hospital h. I regress log total payments ($log(Paid_{a,i,j,t,d,h})$) on insurer-hospital dummies ($\alpha_{h,j}$), year dummies (β_t), DRG/diagnosis fixed effects (γ_d), and patient severity factors ($Z_{a,i,t}$) comprised of gender x age groups (in 5-year bins), income groups and diagnoses groups:

$$log(Paid_{a,i,j,t,d,h}) = \alpha_{h,j} + \beta_t + \gamma_d + Z_{a,i,t}\delta + u_{a,i,j,t,d,h} \tag{11}$$

Using estimates from this regression, I define the quantity unit as the component of payment arising from DRG/diagnosis and severity:

$$\tilde{Q}_{a,i,t} \equiv exp(\hat{\gamma}_d + Z_{a,i,t}\hat{\delta}) \tag{12}$$

The remainder of the regression is defined as price:

$$\tilde{P}_{a,i,j,t,h} \equiv exp(\hat{\alpha}_{h,j} + \hat{\beta}_t) \tag{13}$$

The price I use then in the hospital choice model is $p_{ijhdt} \equiv \tilde{P}_{a,i,j,t,h} \times \tilde{Q}_{a,i,t}$. That is, with this procedure I get rid of the residual portion of the total payment to the hospital. This makes sense because the variable I want to create is the *expected price* for a particular diagnosis in a hospital in a year for a particular group (*e.g.* low-income young males).[55]

D.1 Empirical Model

In this subsection I describe the hospital choice model I estimate in order to construct the expected utility for a consumer from the hospital network offered by a specific plan, that is, EU_{ijkt}. These models are now standard in the health insurance literature and, hence, I will brief in each part of the model. For more detailed descriptions, see both Cuesta et al. (2019) and Shepard (2022), which I follow closely.

In the specification used in this paper, the choice of a hospital is conditional on the diagnosis and the health insurance plan of the individual. Specifically, an enrollee with a certain health condition will choose a hospital among those available in her choice set, and this choice will depend on how much she needs to pay to treat that condition in each hospital, on the distance between her house and each hospital, and on the quality of each hospital. That is, the utility of consumer i in period t with plan j for choosing hospital h to treat diagnosis d takes the following form:

$$u^H_{ijhdt} = \alpha^H_i c_{jh} p_{ijhdt} + \beta^H_i Dist_{ih} + \delta_h + \epsilon_{ijhdt} \tag{14}$$

[55]See Table A.3 for descriptive statistics showing the results of this decomposition for the 14 main private hospitals in Santiago.

where $c_{jh}p_{ijhdt}$ is how much consumer i must pay to treat condition d at hospital h. This amount will depend on both the coverage offered by her insurance plan in that hospital, c_{jh}, and the price charged by the hospital to treat that condition to consumer i, p_{ijhdt}. $Dist_{ih}$ is the distance between consumer i's house and hospital h. Finally, δ_h are hospital fixed effects.[56] As in the plan choice model of Section 5, coefficients in the utility function vary by demographic and socioeconomic groups.

The outside option in this case means going to a public hospital or to a smaller private hospital.[57] Specifically, the utility in case of choosing the outside option takes the following form:

$$u^H_{ij0dt} = \alpha^H_i c_{j0}p_{ij0dt} + \upsilon_{l(i)} + \epsilon^H_{i0hdt} \tag{15}$$

where $\upsilon_{l(i)}$ are county fixed effects in order to control for the fact that the quality of the outside option might vary between counties. Similarly to the model in Section 5, this hospital choice model is estimated by maximum likelihood.

Results

Table A.1 below describes the main results from the hospital choice model. Specifically, the first panel of the table displays the premium coeffients and the second panel shows the distance coefficients. Each row represents a different estimate for a different consumer group. Different columns show estimates considering a different set of fixed effects. Column (1) does not allow for any type of fixed effects. Column (2) considers hospital fixed effects, and column (3) includes hospital fixed effects interacted with diagnoses, which is also my preferred specification.

The main takeaways from the table are the following: (i) women, older and richer people are less price sensitive when it comes to choosing a hospital, and (ii) older and richer people dislike

[56] In the preferred specification I use diagnoses interacted with hospital fixed effects.

[57] The choice set consists of the 14 main private hospitals in the capital Santiago. Any other private hospitals falls into the outside option. The same goes for any public hospital.

more to travel to hospitals. These results are now standard in the health insurance literature, which is reassuring that my specification is correct. Moreover, in Figure A.2 I plot the hospital fixed effects from column (2) of Table A.1 against the final accreditation grade assigned by the regulator to each hospital as a proxy for quality.[58] The high correlation between these two variables supports the fact that hospital fixed effects are capturing the quality of each hospital.

Table A.1: Parameters estimates - Hospital choice model

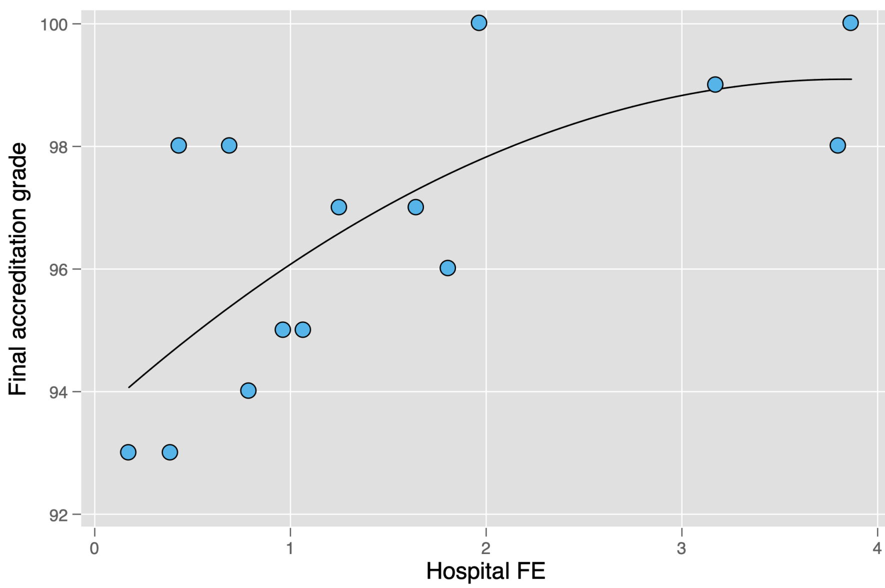
	(1)		(2)		(3)	
Variable	Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
α^H - Hospital Price						
age ≤ 35	-2.183	(0.020)	-3.192	(0.020)	-3.266	(0.020)
age $\in (35, 45]$	-1.879	(0.020)	-2.831	(0.020)	-2.869	(0.020)
age $\in (45, 55]$	-1.843	(0.020)	-2.697	(0.020)	-2.668	(0.020)
age > 55	-1.736	(0.021)	-2.544	(0.020)	-2.488	(0.020)
Single female	0.347	(0.010)	0.371	(0.011)	0.336	(0.011)
Family	0.021	(0.012)	-0.030	(0.012)	-0.049	(0.013)
Income 2nd Tercile	0.403	(0.021)	0.345	(0.020)	0.343	(0.020)
Income 3rd Tercile	1.398	(0.018)	1.393	(0.017)	1.352	(0.017)
β^H - Distance to hospital						
age ≤ 35	-0.153	(0.002)	-0.180	(0.003)	-0.177	(0.003)
age $\in (35, 45]$	-0.160	(0.002)	-0.183	(0.003)	-0.179	(0.003)
age $\in (45, 55]$	-0.171	(0.002)	-0.196	(0.003)	-0.181	(0.003)
age > 55	-0.189	(0.003)	-0.209	(0.003)	-0.189	(0.003)
Single female	0.007	(0.001)	0.026	(0.002)	0.016	(0.002)
Dependents	0.016	(0.001)	0.031	(0.002)	0.012	(0.002)
Income 2nd Tercile	-0.009	(0.002)	-0.016	(0.002)	-0.010	(0.002)
Income 3rd Tercile	-0.031	(0.002)	-0.037	(0.002)	-0.028	(0.002)
Observations	2,726,739		2,726,739		2,726,739	
Hospital FE	N		Y		N	
Hospital-diagnosis FE	N		N		Y	

Notes: This table shows the logit estimates of the hospital choice model. The first panel displays the premium coeffients and the second panel shows the distance coefficients. Estimates vary across age groups, household composition, and income. Different columns show estimates considering a different set of fixed effects. Column (1) does not allow for any type of fixed effects. Column (2) considers hospital fixed effects. Column (3) considers hospital fixed effects interacted with diagnoses. Standard errors are in parenthesis.

Once I have the estimates from the hospital choice model, I can construct the expected

[58]The final accreditation grade is a score assigned by the regulator after they do a thorough inspection on each hospital. This is mandatory in order to be able to operate in the country.

Figure A.2: Hospital fixed effects and accreditation grade



This figure plots the hospital fixed effects from column (2) of Table A.1 against the final accreditation grade of each hospital. The latter is a score assigned by the regulator after they do a thorough inspection on each hospital. This is mandatory in order to be able to operate in the country. Each dot is an observation and the line is a quadratic fit.

utility obtained from each health insurance plan j for each consumer i as follows:

$$EU_{ijkt} = \sum_{d \in D} \gamma_{di} \log \sum_{h \in H} \exp(\alpha_i^H (c_{jh} p_{ijhdt} - c_{j0} p_{ij0dt}) + \beta_i^H Dist_{ih} + \delta_h - \upsilon_{l(i)}) \tag{16}$$

where γ_{di} is the probability of consumer i of being diagnosed with condition d. In practice, this is calculated using a frequency estimator of admission probabilities for each diagnosis for multiple demographic groups. EU_{ijkt} is the variable that is then used in the plan choice demand model of Section 5.

Finally, I also use this model, and the price and quantity variables constructed above, to measure expected costs for each enrollee in each insurance plan. In particular, let s^H_{ijhdt} be the probability of consumer i in period t with plan j of choosing hospital h to treat diagnosis d. Then, $\rho_{ijhdt} = \tilde{P}_{a,i,j,t,h} \times s^H_{ijhdt}$ is the weighted price that this consumer will pay to treat her diagnosis. In order to get the total payment, I have to sum over each hospital and then multiply this by my quantity measure:

$$C_{i,j,d,t} = \tilde{Q}_{a,i,t} \sum_{h \in H} \rho_{ijhdt} \tag{17}$$

I weight this by γ_{di} in order to get the final measure of expected costs for consumer i in plan j in year t:

$$\tilde{c}_{i,j,t} = \sum_{d \in D} \gamma_{di} C_{i,j,d,t} \tag{18}$$

This is the variable I use in the simulation to construct profits for each insurer. Notice that, as opposed to Shepard (2022), there is no problem in creating this variable because enrollees in Chile are able to access every hospital, no matter the plan they have, thus, within each insurer, I have enough observations to know the average costs for each group of consumers in each plan.[59]

[59]The problem in Shepard (2022) is that the hospital network *within* a plan is changing, and, so, it is less realistic to create an expected cost variable that can measure the change in costs after that change. This is because the

E Sample Construction

Several adjustment are made to the dataset in order to get the sample of enrollees that are actually used for estimation. This section describes the steps that are taken to do this.

1. I keep only individuals that are enrolled in individual plans, with contracts under *open* insurers (*i.e.* enrollment is not limited to specific industries) and whose plans are subject to the standard pricing regime.[60]To have a clean panel, I also drop from the sample those enrollees that at some point between 2007 and 2016 move to any of those plans or to a *closed* insurer.

2. I drop policyholders younger than 20 years old and older than 80 years old (less than 2% of policyholders), and non-employees, such as independent workers or retirees (less than 17% of policyholders). The reason behind the last restriction is that these individuals do not have reliable income data. For the same reason, I also drop observations with invalid or missing wages.

3. I focus only on enrollees in Santiago, the capital of Chile. This is due to the fact that it is hard to know how the choice set looks for someone living in a different city. They might want access to their local hospitals, but also access to a high quality hospital in the capital in case of a major surgery. Therefore, to avoid choice set misspecification, I drop them from the analysis. Importantly, however, most policyholders live in Santiago (over 60% of them).

4. Finally, for computational reasons, the estimation of the demand model, described in Section 5, uses a 10% random sample. For the simulation of the policy in Section 6 I use a 5% random sample.

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author does not know how consumers will change their behavior once they are allowed to go to a different hospital (*e.g.* moral hazard).

[60]Firms also offer other type of plans such as partnership plans or employer-based plans. These other plans normally follow different pricing rules, among other differences, so I drop them from the analysis. These plans account for less than 23% of all policyholders in the market.

F Health Insurance Plans and Cream-Skimming

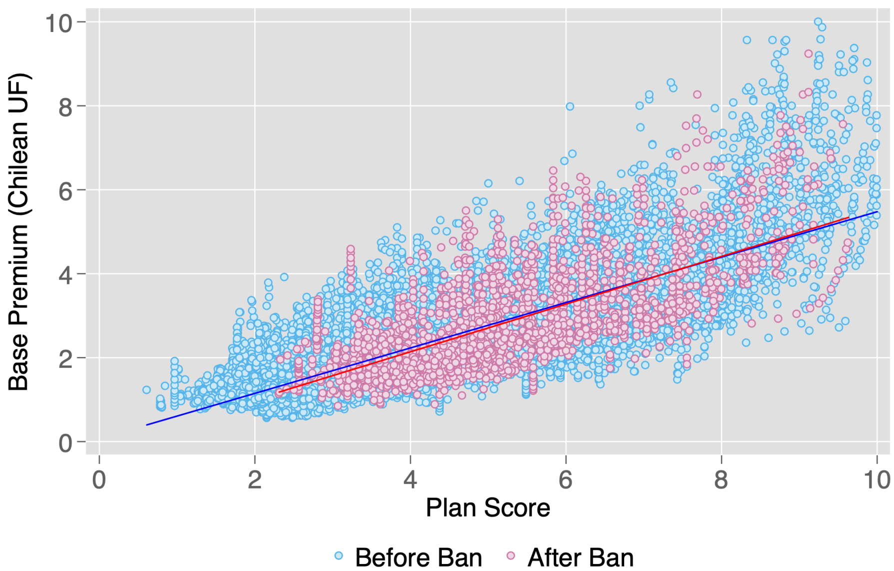
In this section, I explore the creation of new plans as a channel used by firms to respond to the regulation banning gender-based pricing. This is important because if companies use this as a way to practice "cream-skimming" in the private market, then the results of the simulation in Section 6 will be biased (*e.g.* companies create expensive but low quality plans only for females). Luckily, data on plans are publicly available from the regulator even after 2020. However, as noted in Section 4.1, these data do not have detailed information regarding real coverage rates for each plan. Instead, as a measure of quality, I use "plan scores" provided by the platform *QuePlan.cl*.

According to the regulator, the main reason to create new plans in the market is to respond to the fact that companies must have plans available with prices close enough to the 7% of their potential enrollees' income. Moreover, plan quality is by far the strongest predictor of base premiums. If firms use the creation of new plans as a channel to discriminate after implementing the ban, I should observe a change in the relationship between plan quality and base premiums. The intuition is that they would create new plans solely for women with low quality and higher base premiums, thus disrupting the positive, and strong, relationship between these two variables.

Figure A.3 tests this hypothesis descriptively by plotting base premiums of health plans against their plan scores, separately for plans created before and after 2020. A clear positive and strong relationship emerges from the figure, that is, better plans tend to have higher quality. Importantly, the slope of this relationship does not appear to have changed after the policy change, which goes against the hypothesis of firms using the creation of new plans as a way to practice "cream-skimming".

Formally, in Table A.2 I run a regression model with base premiums as the dependent variable and plan scores as the dependent variable. The main variable of interest is an interaction of plan scores with a dummy equal to one for plans created after 2020. Additionally, I control

Figure A.3: Base premiums and plan quality



This figure plots the base premiums of plans against their plan scores. Blue dots refer to plans created before 2020 and red dots refer to plans created after 2020. A linear trend is added to each set of plans.

for insurer FE, plan characteristics and year FE. The main results of the table are the following. First, as mentioned above, higher plan scores are the main predictor of base premiums. This can be seen by comparing the R-squared among regressions. Second, plans created after the ban do not appear to have different base premiums than plans created before. Third, and most importantly, there is no evidence of a change in the relationship between base premiums and plan scores. The coefficient in the interaction is negligible and statistically non-significant, which is evidence that companies do not use the creation of plans as a way to practice "cream-skimming".[61]

Anecdotal Evidence Post-Regulation

Some additional anecdotal evidence appears to suggest that changes in prices have been the main mechanism used by firms in response to, among other things, the ban of gender-based pricing. First, firms are not currently allowed anymore to create plans that do not cover maternity expenses,

[61] I find similar results if I use logged variables instead.

Table A.2: Regression results - Base premiums and plan quality

	(1)	(2)	(3)	(4)	(5)	(6)
Plan score	0.542	0.536	0.564	0.574	0.574	0.597
	(0.019)	(0.015)	(0.015)	(0.017)	(0.021)	(0.021)
$\mathbb{1}$(plan after ban)				-0.240	-0.228	-1.310
				(0.274)	(0.160)	(0.073)
Plan score x $\mathbb{1}$(plan after ban)					-0.002	-0.032
					(0.074)	(0.073)
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Plan Characteristics	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes
R^2	0.63	0.66	0.67	0.67	0.67	0.71
Observations	18,866	18,866	18,866	18,866	18,866	18,866

Notes: This table shows the results of a regression of plan scores on a dummy equal to one if the plan was created after the banning of gender-based pricing, controlling for base prices, plan characteristics, company fixed effects, and date fixed effects. Each column is a different specification with different controls. Standard errors are in parenthesis and are clustered at the firm level.

thus forbidding this type of discrimination. Second, in March 2022, as a reaction to pressure from companies to increase prices due to the ban and COVID-19 related expenses, the regulator announced a cap of 8% on how much firms could raise premiums. The firms complained that the cap was too low given the higher costs in the system, as they wanted to increase prices three times more than the cap. This has started an intense debate in the country where insurance companies are demanding higher prices in order to match higher health care costs or otherwise, according to them, the whole private market will become unsustainable (see La Tercera, 2022).

In conclusion, anecdotal evidence suggest that, as a result of banning gender-based pricing, (i) health care costs in the private market have skyrocketed, and (ii) companies have responded to that pressure by trying to increase prices and not by lowering plans' quality. Thus, this evidence supports the analysis and results of the simulation in this paper. Nevertheless, endogenizing the creation of new plans is an interesting topic for future research.

G Sensitivity Analysis

In this section, I briefly describe how the results change when I modify some of the steps taken in Section 6.2 in order to implement the simulation of the ban. Particularly, I focus on the level of profits that firms have to keep constant, the percentage of people from the public option that are active in each iteration of the simulation, and the percentage of female and old enrollees from the private market that are active right after implementing the ban.

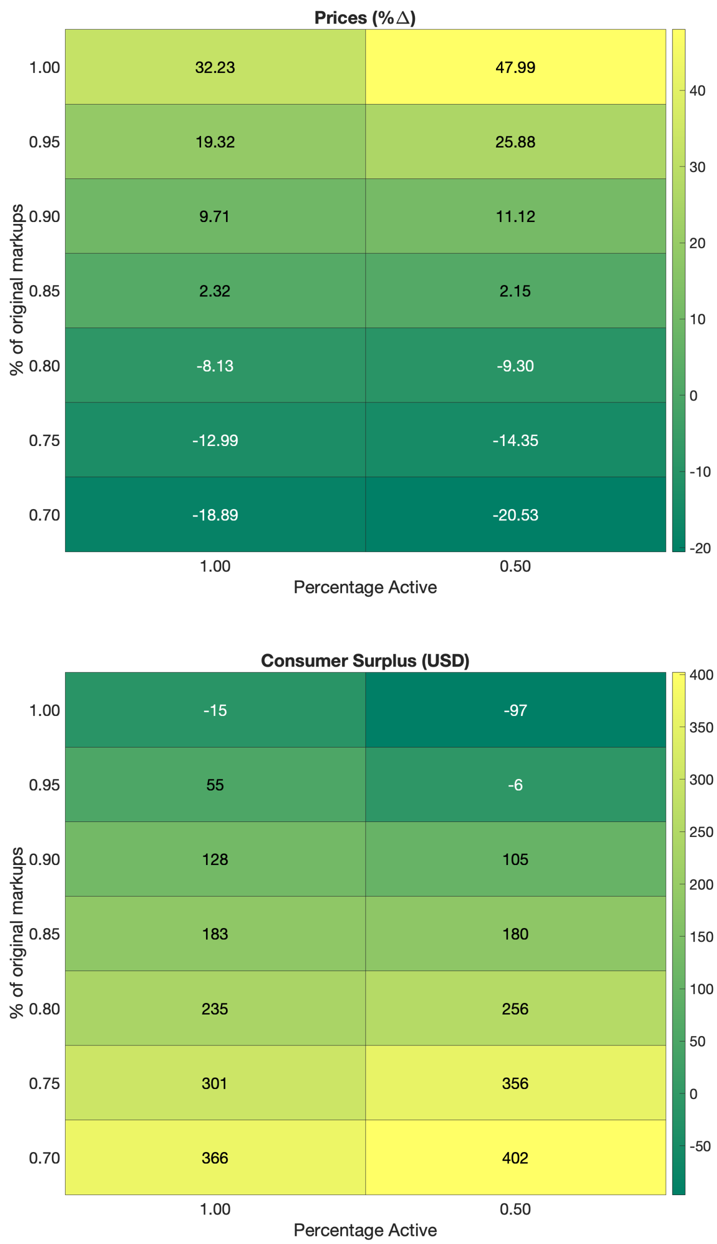
Figure A.4 below shows the percentage change in prices and the change in consumer surplus, relative to the baseline without the ban, for different scenarios. Each row represents what percentage of the original profits used in Table 5 firms have to keep constant throughout the simulation. Therefore, the first row is the status quo and each row below that is a lower level of profits. In the case of the columns, they represent the percentage of people from the public option that are active in each iteration of the simulation. Hence, the first column is the status quo and the second column represents a case in which (a random) 50% of the people from the public option are active. Additionally, in this case, I only allow 50% of female and old enrollees from the private market to be active right after implementing the ban. This means that the top left block in each plot is the same result as the one documented in Table 5.

In the case of lower profits the results are straightforward. Lower profits for firms are just a transfer to consumers. Hence, it is not a surprise that consumer surplus increases as profits go down. Importantly, 90% of the original profits (the third row) is around the lowest level the profits have ever been for these companies during the years of my data, so any level lower than that would mean that firms would obtain less profits that they have ever done before. As expected as well, prices go down as I reduce profits to the point where the overall price change would be negative if profits are too low.

The results are more interesting when I only allow half of the population in the public option to be active in each iteration, and only 50% of female and old enrollees to be active right after implementing the ban. On the one hand, when profits are close to the original ones, surplus is lower and prices are higher as less people are active. On the other hand, when profits are low, surplus is higher and prices are lower as less people are active. In the first scenario, the intuition is that some young females from the public option are not able to enter the private market because they just never become active but a large portion of young males are still leaving the private market. Therefore, the share of old people in the private system is higher than otherwise, and these groups have higher health care costs than young females, explaining then the higher prices and lower surplus. In the second scenario, still some young females remain in the public option, but now young males, which are less costly than young females, are able to stay at higher rates in the private market, and this force dominates the results.

In sum, the main takeaway of the sensitivity analysis is that, as profits are lower, the benefits from banning gender-based pricing will be higher. This is not surprising as it is just a transfer from firms to consumers. Additionally, if less people from the public option are active in each iteration, the benefits from banning gender-based pricing will be lower if profits are close to the original ones and the opposite is true if profits are lower.

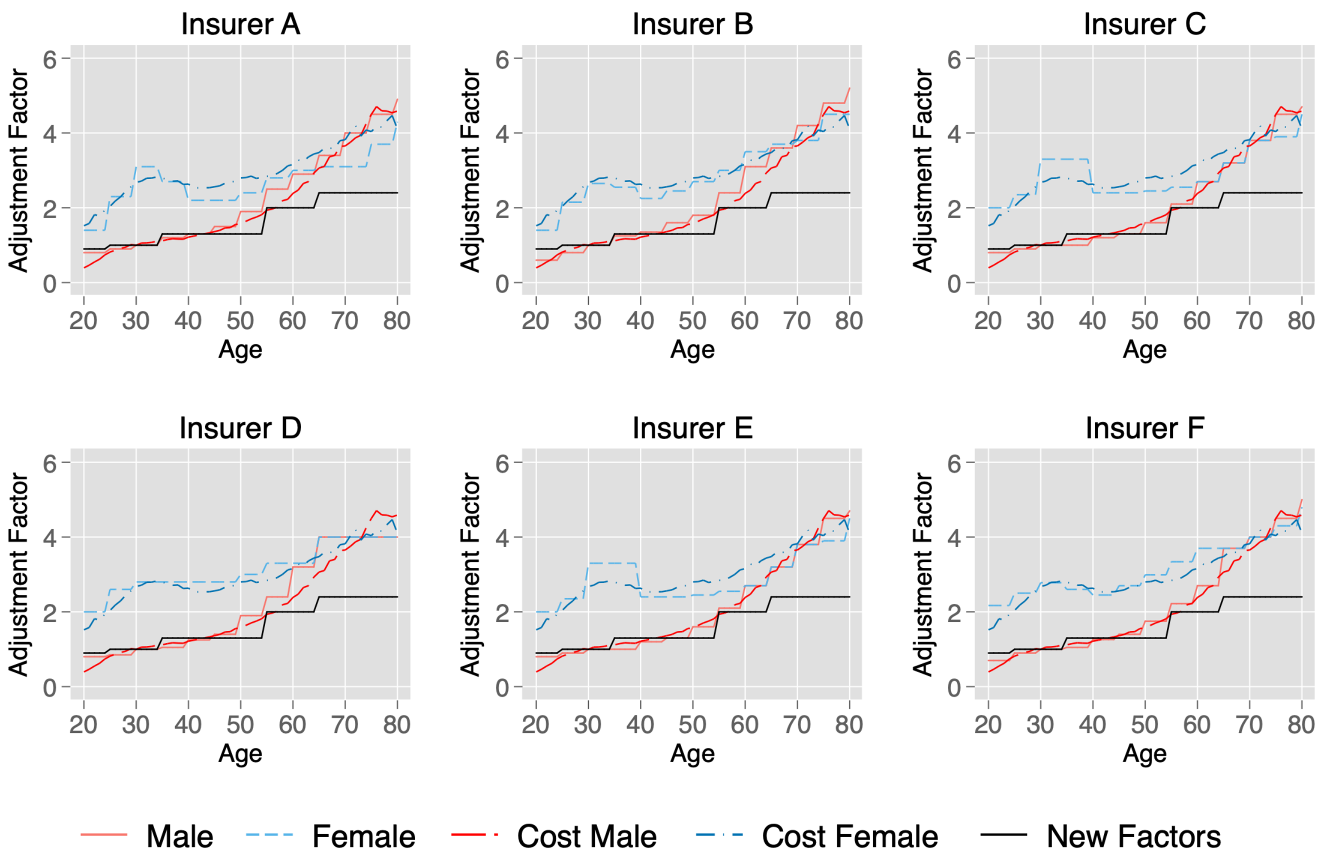
Figure A.4: Sensitivity to lower profits and % of active people



This figure shows prices (top plot) and consumer plus (bottom plot) for multiple scenarios regarding lower profits and lower percentage of people active from the public option. Specifically, each row represents what percentage of the originals profits used in table 5 are being considered. Therefore, the first row is the status quo and each lower row is a lower level of profits. In the case of the columns, they represent the percentage of people from the public option that are active in each iteration of the simulation (and also the percentage of female and old enrollees from the private market that are active right after implementing the policy). Hence, the first column is the status quo and the second column represents a case in which (a random) 50% of the people from the public option are active. Numbers inside each block are the percentage change in prices and the change in consumer surplus for each scenario, relative to the baseline without the ban.

H Additional tables and figures

Figure A.5: Risk-rating factors



Notes: This figure shows the old risk-rating factors by gender for the six companies, health care costs (relative to a 30-years old male) across enrollees in the private market and the new risk-rating factors implemented in 2020.

Table A.3: Descriptive statistics for hospitals

	Raw Data	Hospital Model		Market
	Avg. Total Payment	Relative Price	Relative Severity	Shares
Hospital 1	7.31	1.89	0.90	5.61%
Hospital 2	6.15	1.39	1.07	9.61%
Hospital 3	5.06	1.27	0.94	0.60%
Hospital 4	4.47	1.16	0.92	13.81%
Hospital 5	3.95	1.14	0.84	11.06%
Hospital 6	4.49	1.14	0.81	1.47%
Hospital 7	3.86	1.08	1.04	2.78%
Hospital 8	4.30	0.94	1.17	5.53%
Hospital 9	3.16	0.88	0.93	4.23%
Hospital 10	2.99	0.77	1.02	15.85%
Hospital 11	2.52	0.71	0.84	3.53%
Hospital 12	2.67	0.69	1.05	4.13%
Hospital 13	2.30	0.69	0.90	4.08%
Hospital 14	2.74	0.66	1.10	7.27%

Notes: This table shows descriptive statistics for the main 14 private hospitals in Santiago using the hospital admissions dataset. The first column includes the hospitals, which are anonymized in the data. The second column documents average total payment per hospitalization. The third and fourth column show the decomposition of these total payments in prices and quantity (severity), which are standarized such that the mean across hospitals is 1. See Section D for more details about this decomposition. Finally, the last column focuses on the market shares for each hospital. All prices are measured in thousands of U.S. dollars for December, 2016.

Table A.4: Market shares by gender and income

Females	Low-income	Medium-income	High-income	Total
Insurer A	17%	18%	22%	19%
Insurer B	26%	25%	24%	25%
Insurer C	3%	2%	5%	3%
Insurer D	18%	23%	21%	21%
Insurer E	20%	17%	18%	18%
Insurer F	17%	15%	10%	14%
Males	**Low-income**	**Medium-income**	**High-income**	**Total**
Insurer A	10%	12%	16%	13%
Insurer B	22%	22%	20%	21%
Insurer C	2%	2%	6%	3%
Insurer D	13%	17%	18%	16%
Insurer E	21%	23%	24%	23%
Insurer F	32%	24%	16%	24%

Notes: This table shows market shares for the six open insurers in December of 2016 by gender and income group.

Table A.5: Regression results - Premiums paid

log(premiums)	(1)	(2)	(3)	(4)	(5)
Plan score	0.080	0.101	0.133	0.070	0.147
	(0.010)	(0.022)	(0.008)	(0.010)	(0.015)
Gender					0.441
					(0.035)
Firm FE	No	Yes	Yes	Yes	Yes
Plan Characteristics	No	No	Yes	Yes	Yes
Income Deciles FE	No	No	No	Yes	Yes
Age FE	No	No	No	No	Yes
R^2	0.13	0.28	0.39	0.56	0.83
Observations	55,521	55,521	55,521	55,521	55,521

Notes: This table shows the results of a regression of log of premiums paid on plan scores, firm fixed effects, plan characteristics, income deciles fixed effects, gender and age fixed effects. Each column is a different specification with different controls. The sample is composed by policyholders signing a new contract in the private market in 2016. Standard errors are in parenthesis and are clustered at the firm level.

Table A.6: Model fit

	Model			
	(1)	(2)	(3)	(4)
Log likelihood	135,930	133,720	132,350	130,430
LR test against model (4)	11,000	6,580	3,840	-
AIC	271,910	267,670	264,758	261,098
BIC	272,238	269,179	265,139	262,660
Parameters	25	115	29	119
Observations	3,706,628	3,706,628	3,706,628	3,706,628
First Stage	N	N	Y	Y
Plan Characteristics	Y	Y	Y	Y
Insurer FE	Y	N	Y	N
Insurer-Demographics FE	N	Y	N	Y

Notes: This table shows multiple tests to assess which model provides a better fit to the data. Different columns indicate a different specification. Columns (1) and (3) consider insurer fixed effects, and columns (2) and (4) consider insurer fixed effects interacted with household groups. Additionally, columns (3) and (4) include the first stage in the maximum likelihood estimation.

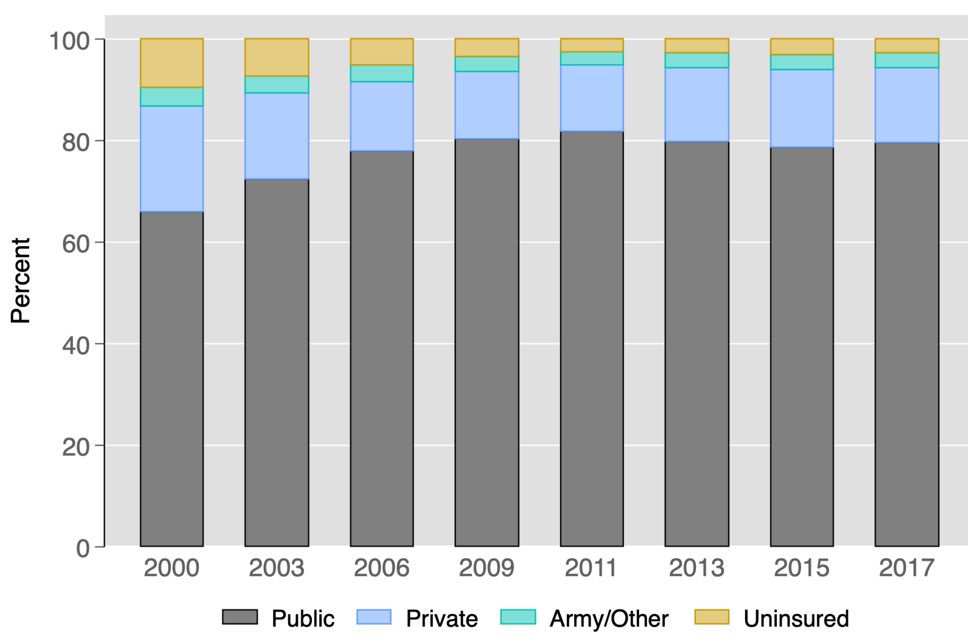
Figure A.6: Risk-Rating factors before regulation (for one firm) versus after regulation

Age groups	Policyholders	
	Male	Female
[0-2)	1.84	1.86
[2-5)	0.87	0.81
[5-10)	0.70	0.66
[10-15)	0.60	0.65
[15-20)	0.66	0.95
[20-25)	0.73	1.87
[25-30)	0.87	2.29
[30-35)	1.00	3.01
[35-40)	1.05	2.91
[40-45)	1.26	2.43
[45-50)	1.38	2.47
[50-55)	1.72	2.65
[55-60)	2.22	2.92
[60-65)	2.79	3.12
[65-70)	3.63	3.42
[70-75)	4.03	3.70
[75-80)	4.66	4.08
[80-	4.97	4.55

Age groups	Policyholders
[0-20)	0.60
[20-25)	0.90
[25-35)	1.00
[35-45)	1.30
[45-55)	1.30
[55-65)	2.00
[65-	2.40

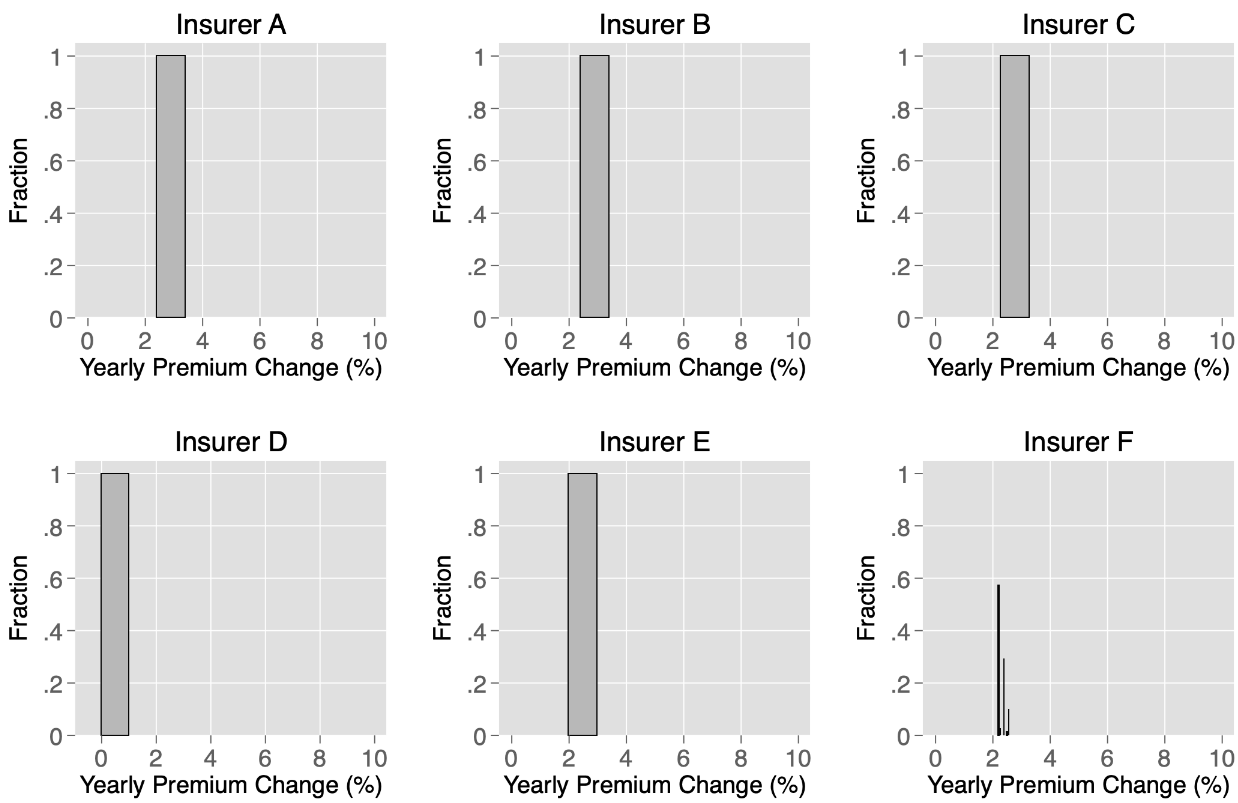
Notes: This figure shows the risk-rating factors before the regulation for one firm (on the left) and the new risk-rating factors (on the right).

Figure A.7: Historical market shares across segments



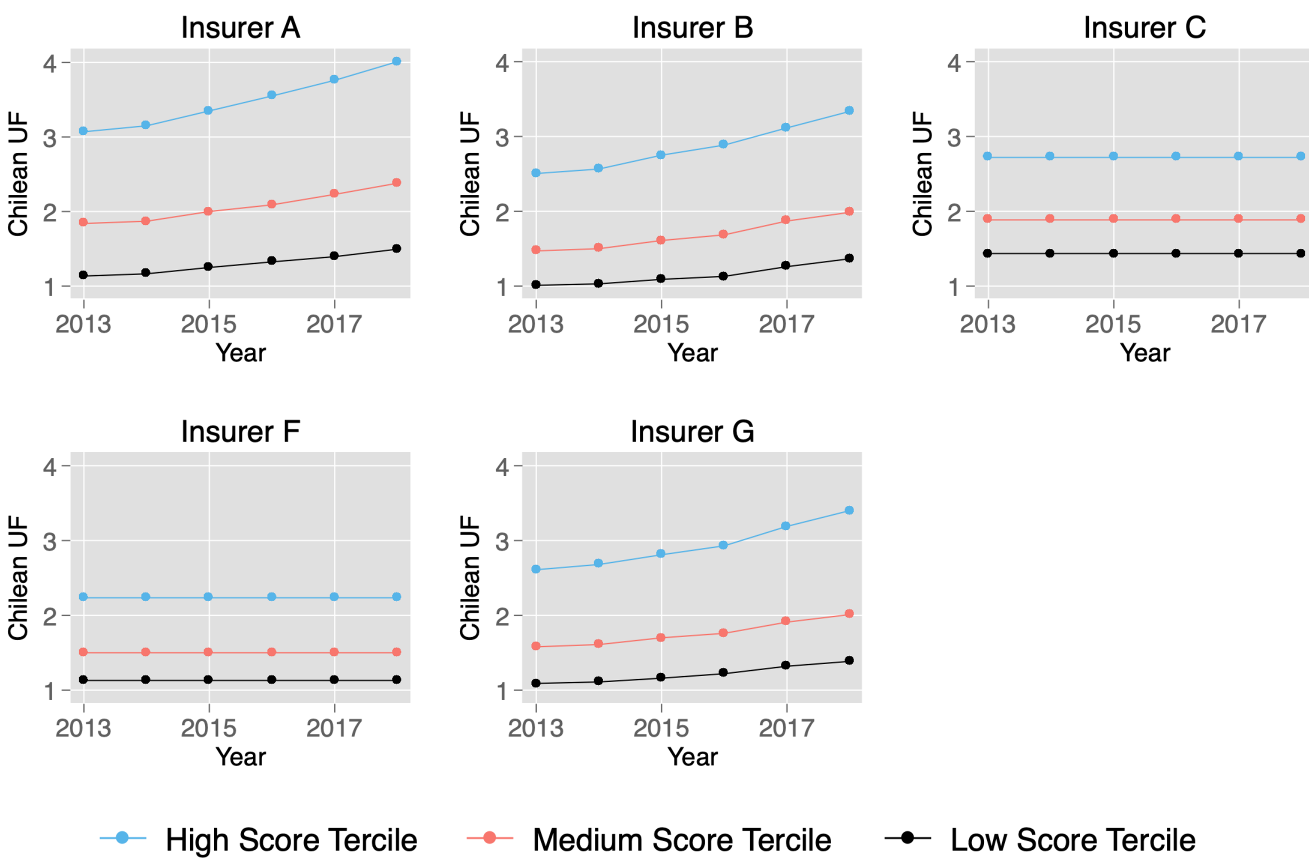
Notes: This figure shows the historical market shares across segments in the health insurance market in Chile. The data come from the Chile National Socioeconomic Characterization Survey (CASEN).

Figure A.8: Base price changes 2013/2014



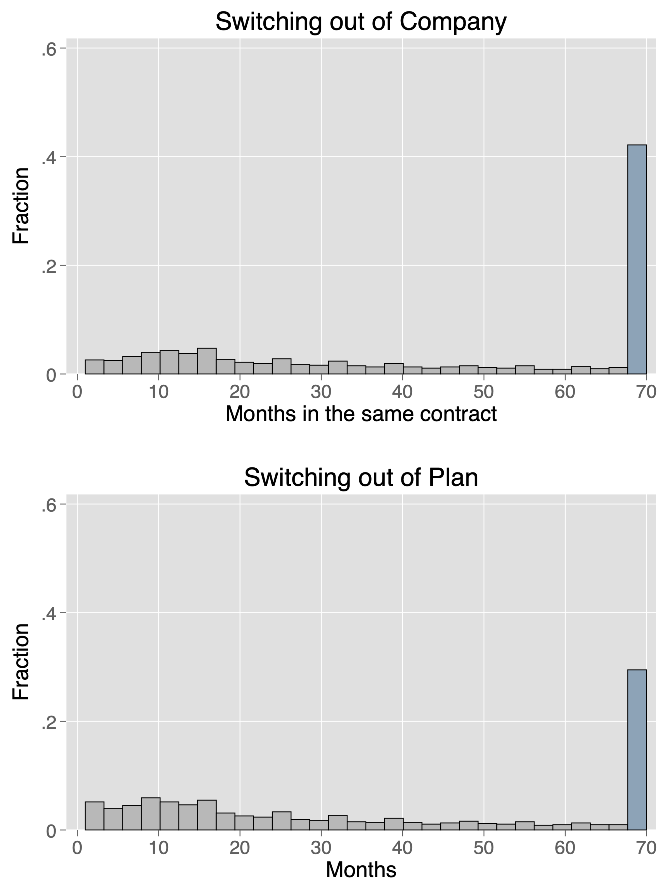
Notes: This figure shows an histogram of the annual base price changes for the six insurance companies in Chile for the period 2013/2014. Plans with less than 50 policyholders by January 2013 are excluded from the figure.

Figure A.9: Base price evolution



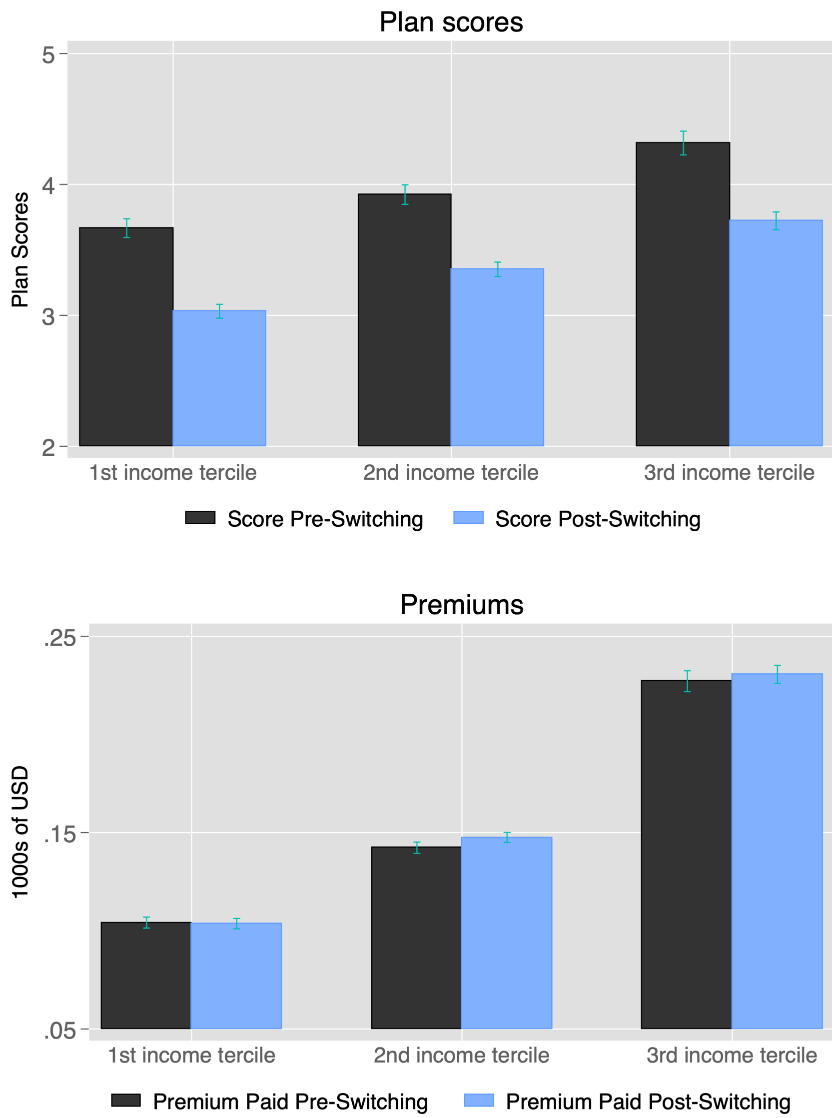
Notes: This figure shows the evolution of base prices for five of the six insurance companies in Chile for the period 2013-2018. The company missing filed for bankruptcy in 2017. Plans are divided into terciles according to their plan scores. Chilean UF is the unit, indexed to inflation, in which base prices are measured in Chile.

Figure A.10: Tenure in GR contracts



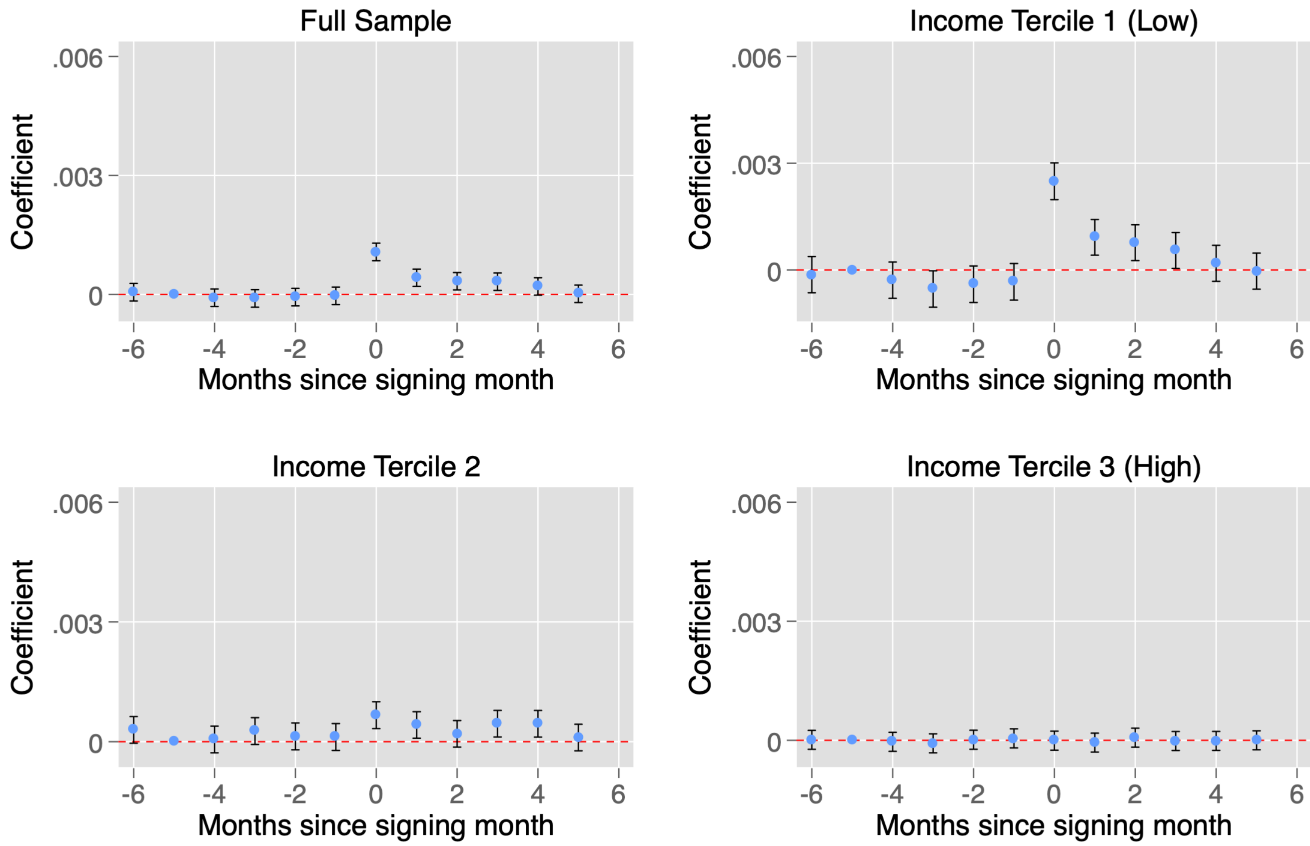
Notes: This figure shows histograms of how many months policyholders stay in their contracts. The top figure shows this for the case where switching plans within the company is not considered. The bottom figure shows the case in which any switching is considered. This exercise is done for policyholders that signed a new contract in May 2011.

Figure A.11: Plans before and after switching



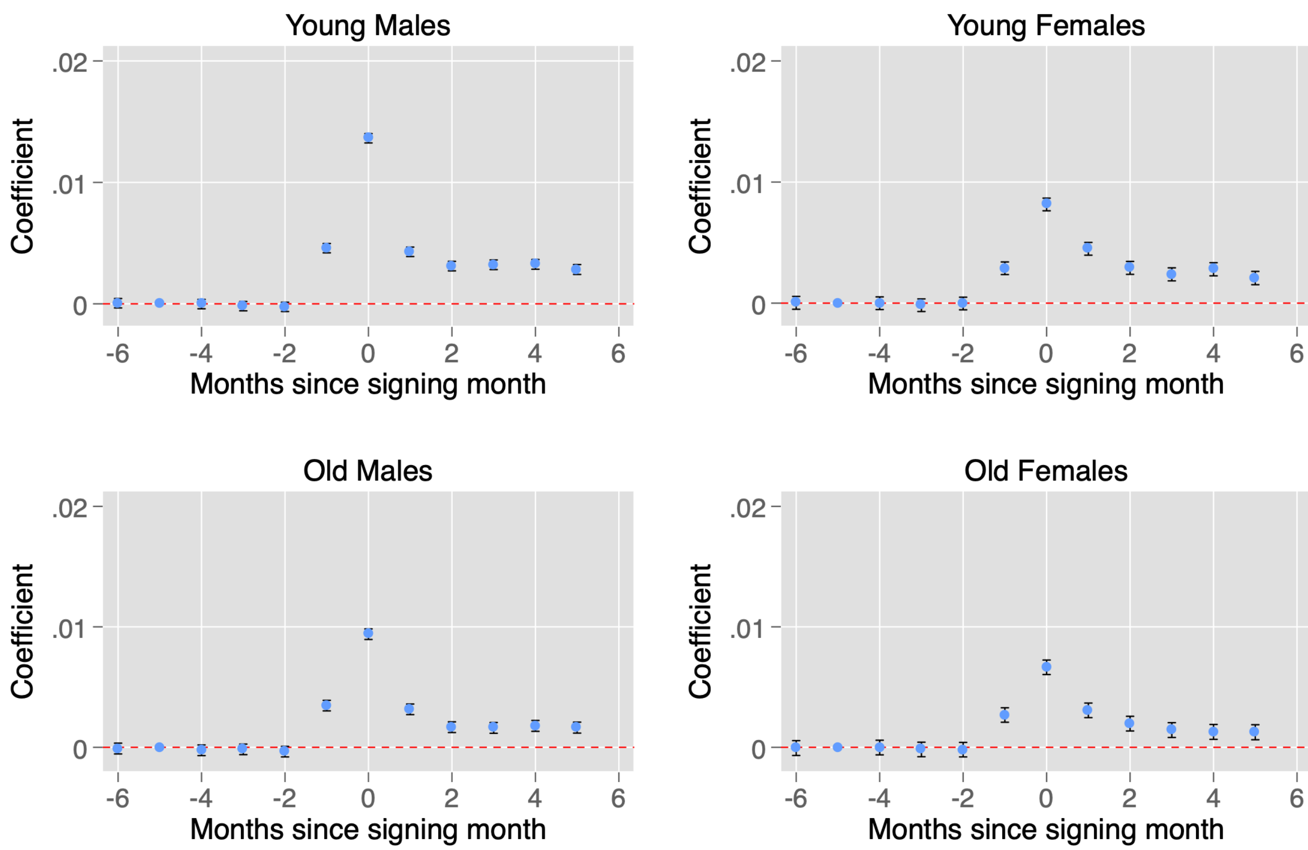
The upper figure shows the plan scores before and after switching during the signing month of the contract. The lower figure shows premiums paid by policyholders before and after switching during the signing month of the contract. Green lines report the 95% interval.

Figure A.12: Probability of leaving the private market due to price changes



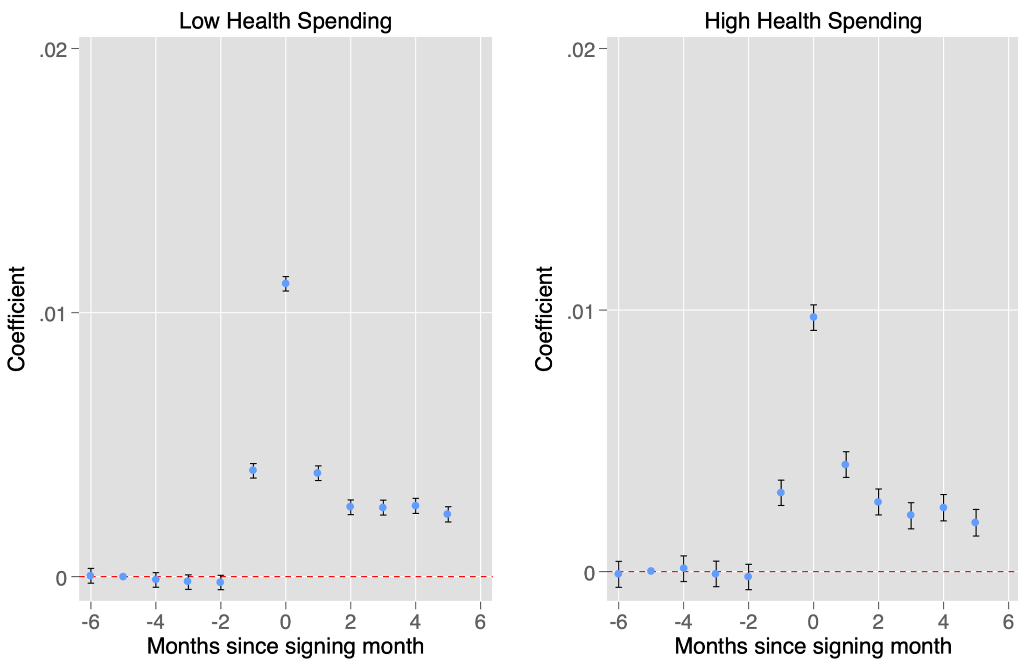
Notes: This figure shows an event study regression where the dependent variable is a dummy equal to one if a consumer leaves the private market and do not re-enter in the future. The event is the month in which price changes are applied to health plans. Controls include individual fixed effects and date (month-year) fixed effects. I restrict the estimation sample to policyholders that are active in the data for at least 12 months and that do not leave the private market and re-enter in later dates. Additionally, I drop individuals with zero or missing income at any month. This exercise is done on a 10% random sample of policyholders.

Figure A.13: Probability of switching plans due to price changes - Demographics



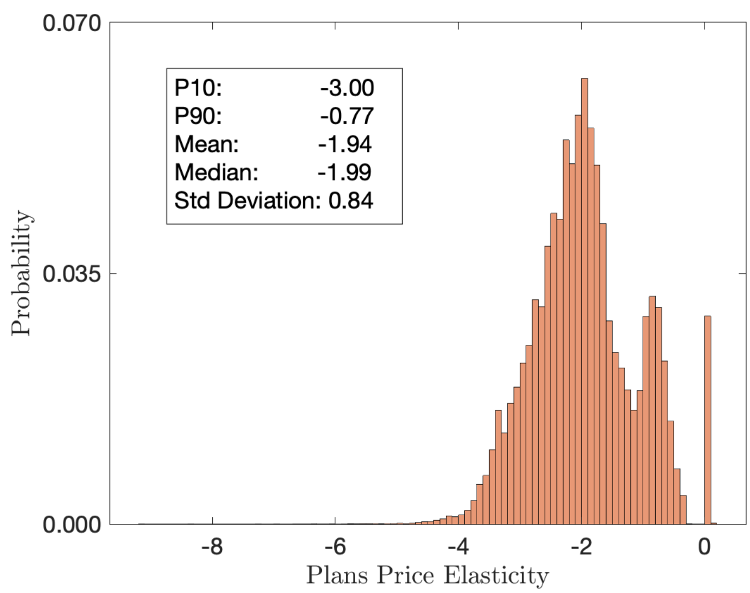
Notes: This figure shows an event study regression where the dependent variable is a dummy equal to one if a consumer switches plans within an insurer. The event is the month in which price changes are applied to health plans. Controls include individual fixed effects and date (month-year) fixed effects. I restrict the estimation sample to policyholders that do not switch insurance companies and that do not leave the private market and re-enter in later dates. Additionally, I drop individuals with zero or missing income at any month. This exercise is done on a 10% random sample of policyholders. Enrollees are split according to their age and gender.

Figure A.14: Probability of switching plans due to price changes - Health Spending



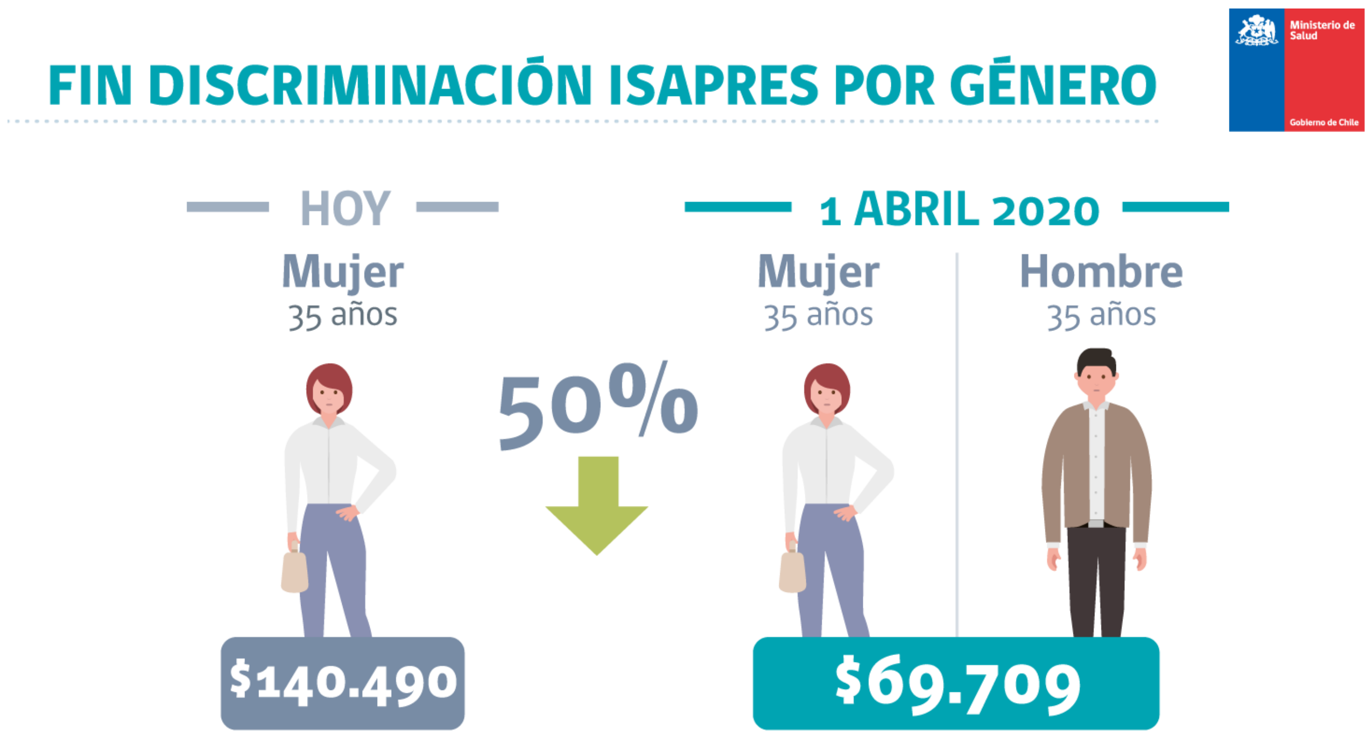
Notes: This figure shows an event study regression where the dependent variable is a dummy equal to one if a consumer switches plans within an insurer. The event is the month in which price changes are applied to health plans. Controls include individual fixed effects and date (month-year) fixed effects. I restrict the estimation sample to policyholders that do not switch insurance companies and that do not leave the private market and re-enter in later dates. Additionally, I drop individuals with zero or missing income at any month. This exercise is done on a 10% random sample of policyholders. Enrollees are split according to how much they spend on health care during their time in the sample.

Figure A.15: Premium elasticities



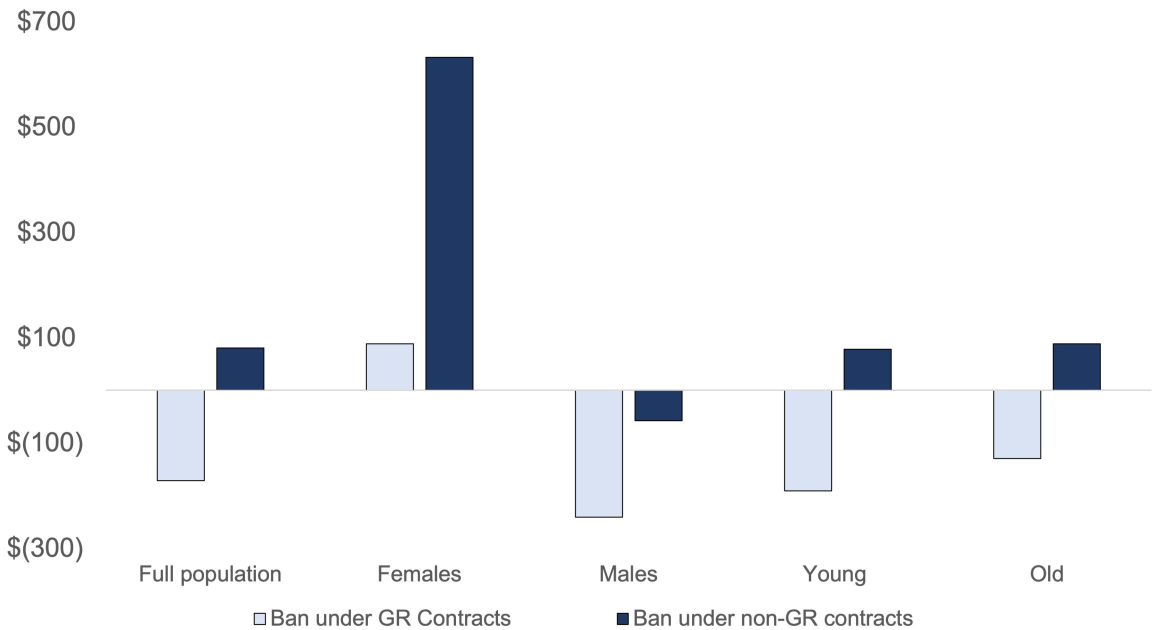
This figure shows the estimated premium elasticities for the chosen plans derived from the demand model in Table 4. Elasticities are calculated as $\hat{\eta}_{fjt} = \hat{\alpha}_f p_{fjt}(1 - \hat{s}_{fjt})$, where $\hat{s}_{fjt}$ is the predicted choice probability of plan j by household f in time t.

Figure A.16: Ban of gender-based pricing: advertisement



This figure shows an ad from the regulator promoting the ban of gender-based pricing to women. The ad explains that, by switching plans, a woman of 35 years old would pay 50% lower premiums (the same as her male counterpart). Prices are in Chilean pesos.

Figure A.17: Change in consumer surplus - Reclassification risk protection



This figure shows the median change in consumer surplus after banning gender-based pricing, relative to the baseline of no ban, for multiple demographic groups. The numbers are in USD of 2016.