Lock-in in Dynamic Health Insurance Contracts: Evidence from Chile

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Abstract

Long-term health insurance contracts have the potential to efficiently insure against reclassification risk, but at the expense of other limitations like provider lock-in. This paper empirically investigates the workings of long-term guaranteed-renewable contracts, which are subject to this tradeoff. Individuals are shielded against premium increases and coverage denial as long as they stay with their initial contract, but those that become higher risk are subject to premium increases or coverage denials upon switching, potentially leaving them locked-in with their original network of providers. I provide the first empirical evidence on the importance of this phenomenon using administrative panel data from the universe of the private health insurance market in Chile, where competing insurers offer guaranteed-renewable plans. I fit a structural model to yearly plan choices, and am able to jointly estimate evolving preferences for different insurance companies and supply-side underwriting in the form of premium risk-rating and coverage denial. To quantify the welfare effects of lock-in, I compare simulated choices under the current rules to those in a counterfactual scenario with no underwriting. The results show that consumers would be willing to pay around 13 percent more in yearly premiums to avoid lock-in. Finally, I study a counterfactual scenario where guaranteed-renewable contracts are replaced with community-rated spot contracts, and I find only minor general-equilibrium effects on premiums and on the allocation of individuals across insurers. I argue that these small effects are the result of large levels of preference heterogeneity uncorrelated to risk.

Keywords; Health Insurance, Guaranteed Renewability, Lock-in
JEL: D82, G22, I11

1 Introduction

When health insurance contracts are of limited duration, changes in health status might lead to substantial increases in premiums or subsequent coverage denial.[1] Ensuring affordable coverage for individuals reclassified by the market into a higher risk group was among the most important goals of the Affordable Care Act (ACA). The ACA eliminates barriers to purchasing insurance faced by sick individuals by prohibiting all forms of differential pricing or coverage denial based on preexisting conditions.[2] However, ruling out this type of discrimination (known as "community rating") leads more costly individuals to sort into more comprehensive plans, which in turn prices out lower risk individuals (Akerlof (1970), Handel *et al.* (2015a)). The ACA tackles this adverse-selection problem by making the purchase of health insurance mandatory —one of the most controversial aspects of the regulation.[3]

In theory, an unregulated marketplace with properly designed long-term contracts can also deliver protection against reclassification risk without adverse selection. In particular, Pauly *et al.* (1995) show that long-term individual agreements with guaranteed renewability can provide full insurance against medical expenses and reclassification risk. By paying a premium higher than what they would otherwise pay under a short-term contract, individuals acquire the guarantee of affordable coverage in the future, regardless of any potential negative health shocks. However, if individuals leave their long-term contract to buy another in the spot market, they lose that guarantee and must pay premiums according to their current health status. This financial incentive to remain in the long-term contract potentially leaves participants inefficiently tied to their original plan and/or health service provider. For the remainder of this paper, I will use the term "locked-in" to refer to an individual who would prefer to switch provider networks if the offers she faced across insurers were not differentially risk-rated, but is unable (due to coverage denial) or unwilling to do so given the discrepancy between the premium she pays under her guaranteed renewable contract and those faced in the spot market.

This paper quantifies the inefficiency from insurer lock-in generated by guaranteed renewable contracts. Consider an individual that enters a contract with a narrow network of providers while healthy, but later develops a chronic condition (such as cancer) that would be better treated in a specialty clinic outside the network. Absent reclassification in the spot market, the individual would switch to a contract with a more appropriate network. In the presence of reclassification, however, the individual might

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[1]Hendren (2013) cites that between 2007 and 2009, prior to the implementation of the Affordable Care Act, one in seven applications to the four largest insurance companies in the US non-group market were rejected. See Hendren's paper for the theoretical rationale for coverage denial.

[2]Under the ACA premiums can only be adjusted by age and geographic location

[3]The individual mandate requires that most individuals obtain health insurance or pay a tax penalty

find it prohibitively expensive to switch, and might even be denied coverage outside of her current contract. An individual who does not switch because of this underwriting is effectively locked-in with her network, generating a welfare loss.

Although health insurance contracts in most markets are short term, there are a couple of practical experiences of markets with guaranteed-renewable (GR) arrangements. Prior to the ACA, GR contracts were particularly common in the US individual health insurance market, and were required by the federal Health Insurance Portability and Accountability Act (HIPAA) of 1996 (Herring and Pauly (2006), Pauly and Herring (1999)). However, lack of regulation with respect to the evolution of non-price features made these contracts generally unappealing to sick customers (Handel *et al.* (2015b)). GR contracts are also present in the German private health insurance market (Hofmann and Browne (2013)).

Proponents of guaranteed renewability have recognized that the inability of riskier individuals to switch insurers is potentially welfare-reducing (Patel and Pauly (2002)). However, quantifying its importance is empirically challenging, and requires individual-level panel data on health insurance purchases and claims, with the ability to observe individuals after they switch insurers. This paper, which is the first to my knowledge to quantify the welfare effects of lock-in, takes advantage of a unique panel data set from the universe of the private health insurance market in Chile in which contracts are guaranteed-renewable. The data contains individualized claim records for all enrollees (and their dependents) in each of the private health insurance companies that operate in Chile. Importantly, the claims data contains detailed procedure codes and identifiers of each health service provider.

It is *a priori* plausible that valuations over private insurance companies in Chile differ across individuals, and that individual's preferences may change over time, as they develop specific health conditions. Four stylized facts from the data support this idea. First, individuals enrolled in different insurance companies access different heath care providers. Second, networks differ in the extent to which they give access to different providers for different types of claims. For example, two networks can have similar providers for routine claims but different providers for cancer-related procedures.[4] Third, switching companies strongly predicts seeing a new health care provider : the probability that the same individual sees a new health care provider after switching insurance company increases by around 40% the month after switching. Fourth, high-risk switchers generally switch to different companies than low-risk switchers.

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[4]For instance providers labeled as "P_1", "P_5" and "P_{11}" in the data are the major three providers for routine claims for insurance companies "A" and "B", with an accumulated share of approximately 40% routine claims in each company. For cancer-related treatment, another provider "P_4" is the most frequent provider for company B with a share of 33 percent, although P_4 represents only 9 percent of those claims in Company A (These numbers were computed using the claims data for the providers in the Metropolitan Region of Santiago during 2011.).

Individuals's valuations for these companies are also likely to change as individuals move geographically. The market share of each of these companies varies substantially across geographical regions, and is strongly correlated with the presence of in-network providers (details in section 4.1).

In order to show why welfare-reducing lock-in could occur in this market, I begin by developing a simple two-period model of guaranteed-renewable contracts with evolving preference heterogeneity. This model will also allow me to identify the data objects needed to empirically assess the magnitude of this inefficiency. The shape and evolution of preferences for companies over time will determine the share of individuals that would eventually switch companies absent reclassification. The extent of premium risk-rating and coverage denial in the spot market, and the path of health expenditures over an individual's lifetime determine the share of potential switchers that are effectively locked-in.

I then show that the main features of guaranteed-renewable contracts are present in the Chilean private insurance market, and provide reduced-form evidence of lower switching rates among the highest risk individuals. This result is implied by the theory of guaranteed-renewable contracts, since healthier individuals are not subject to coverage denial or premium increases due to risk-rating in the spot market, and thus are not constrained in switching insurance contracts.

In order to quantify the welfare losses resulting from lock-in, I use a structural model that jointly estimates plan choices and underwriting in the spot market. The model incorporates heterogeneous and evolving preferences for firms that are correlated with health status and geographic location. Individuals also evaluate the potential benefits of switching plans by the degree of overlap between their current provider network and that of the alternative offers they face. I account for guaranteed-renewability by allowing the plan that an individual chooses in year t to always be available to that individual in year $t+1$ regardless of any changes in health status. However, individuals also receive risk-rated offers in the spot market each year. I estimate the level of risk-rating in the spot market by empirically linking each plan's characteristics to the health risks of those who switch into that plan. The arrival rate of offers from competing insurers in the spot market depends on an individual's preexisting conditions, consistent with the possibility that insurance companies may deny coverage based on these conditions. Finally, the model also allows for "choice inconsistencies" (*à la* Abaluck and Gruber (2011)) and "inertia" —two well-known behavioral biases affecting health insurance purchase (see e.g. Handel (2013) and Abaluck and Gruber (2013)). Inertia is potentially an important factor in choice persistence in this market where search costs are likely to be high. In the spirit of Ching *et al.* (2009) and Grubb and Osborne (2015), I model inertia as inattention that restricts the choices that individuals actually consider in each period.

Finally, I estimate age and gender specific health transition matrices that allow me to simulate the path of health expenditures over an individual's lifetime.

I estimate the parameters of the structural model by adapting the Geweke-Hajivassiliou-Keane (GHK) simulator (Keane (1993, 1994), Hajivassiliou *et al.* (1996), and Geweke and Keane (2001)) to an environment where, as a result of guaranteed renewability, the evolution of options available in each period is dependent on the choices made in the preceding periods, and where the first period choice is not necessarily observed (left-censored choices). To quantify the welfare loss resulting from lock-in, I use the estimated parameters of the model along with the estimated risk profiles to simulate the path of choices over time. Then, I compare predicted choices under the current underwriting rules against a counterfactual scenario in which coverage denial based on preexisting conditions is banned and there is no premium risk rating in the spot market (as recently regulated by the ACA)

The results suggest that around 5% of individuals end up locked-in with their insurance company, but an individual on average would be willing to pay 13% of the average yearly premium to avoid the possibility of this lock-in. Locked-in individuals would be willing to pay on average 2.5 times the premium to switch plans. I find that most of the lock-in is due to coverage denial based on preexisting conditions, and only mildly caused by spot premiums which have been adjusted to reflect current health status. The results depend mostly on the estimated level of coverage denial in the spot market. My estimates suggest that one in five individuals with a preexisting condition is denied coverage in the spot market. Next, I investigate potential market unraveling following endogenous sorting across insurance companies if a community rating policy were adopted. I simulate a counterfactual situation without underwriting in the spot market, but allowing for the overall level of premiums in each company to be adjusted in order to maintain profits per enrollee at their current level. In this counterfactual scenario, guaranteed-renewable contracts are replaced with community-rated spot contracts, but premiums are adjusted at the insurer level to reflect the changes in each insurer's risk pool. I find only minor general-equilibrium effects on prices and allocation of individuals across insurers.

I use the estimated parameters to interpret these findings and to shed light on how different aspects of preference heterogeneity affect the desirability of guaranteed-renewability. Although time-varying preferences generate lock-in, preferences that are persistent over time have the opposite effect, showing another margin of interaction between preference heterogeneity and health insurance design (Bundorf *et al.* (2012) and Geruso (2013)). I use the stylized model of Einav and Finkelstein (2011) to formalize this insight: in this static setting, preference heterogeneity within health status reduces the share of high-risk individuals willing to enroll in a contract, compared to

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a situation in which health status and preferences are perfectly correlated. This limits the mechanical effects of banning coverage denial and the resulting adverse selection, as the share of risky individuals that enroll when allowed is smaller than in the case in which health status is the only determinant of preferences.[5]

This paper is related to two strands of literature. First, it draws from the theoretical literature of pricing in one-sided commitment contracts with adverse selection. It highlights the advantage of "time consistent" contracts suggested by Cochrane (1995), which eliminate reclassification risk and ensure access to health insurance for sick people through a severance payment payable after the diagnosis of a long-term illness. Time-consistent contracts are fully portable (and thus do not generate lock-in), but at the expense of potentially large up-front borrowing (Handel *et al.* (2015b)). By quantifying the presence of lock-in and resulting welfare loss, this paper puts in perspective the advantages of time consistent contracts relative to guaranteed-renewability in relation to their portability.

Second, the paper contributes to the sparse empirical literature on the dynamics of health insurance contracts. Koch (2011) and Handel *et al.* (2015a) focus on the tradeoff between adverse selection and reclassification risk by analyzing consecutive short-term marketplaces, like the ACA. Instead, I focus on long-run guaranteed renewable arrangements. These contracts have been empirically studied by Herring and Pauly (2006) and Marquis *et al.* (2006), who demonstrate that the relationship between premiums and health claims shows the patterns predicted by the theory in the individual US market for health insurance. Handel *et al.* (2015b) study the welfare implications of the financial aspects of different long-term arrangements. In particular, they quantify the welfare loss resulting from the inability to effectively smooth consumption which is implied by front-loading vis-à-vis other market arrangements in a setting with imperfect capital markets. Instead, my focus is on lock-in due to evolving preference heterogeneity, assuming away capital market imperfections. Also, Crocker and Moran (2003) show that employment-based health insurance can facilitate the existence of long-term contracts even in the absence of front-loading. Adverse selection is reduced since healthy individuals would have to switch jobs to drop their health insurance contract and buy another that does not cross-subsidize the riskier.

Relatedly, Hendel and Lizzeri (2003) provide evidence of front-loading in life-insurance contracts, and show that more front-loading is associated with higher retention rates (less "lapsation") which allows for the retention of a healthier risk pool. Finkelstein *et al.* (2005) focus on the long-term care insurance market, and show that lower risk individuals are most likely to leave the contracts. This selective lapsation generates

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[5]Studies that find high levels of market unravelling produced by community rating generally analyze environments in which insurance contracts are purely a financial product (e.g. Handel *et al.* (2015a)).

dynamic inefficiencies, as individuals who stay in the contract have to pay a premium consistent with dynamic adverse selection, which undermines the protection against reclassification risk. This paper contributes to this line of research by providing further evidence of selective switching, and explicitly using data on both supply and demand for health insurance to estimate how it relates to welfare.

Finally, this paper is also related to Pardo and Schott (2012, 2013) who use survey data to analyze enrollment decisions across the private and public sector in Chile, and the role of preexisting conditions in these decisions. Their results, complementary to this paper, suggest that few individuals would switch sectors if restrictions on preexisting conditions were eliminated. They argue that most of the sorting across sectors can be explained by heavy asymmetries in the premium structure, since the public sector offers important cross-subsidies for families, women, and low-income users. This paper focuses instead in lock-in within the private sector, which permits me to estimate heterogeneity in preferences for insurance companies with the same structure of financial incentives. Also, I have access to detailed administrative claims data which permit good assessment of health conditions and to study the general-equilibrium effects of counterfactual policies.

The remainder of the paper is organized as follows. Section 2 intuitively explains the working of guaranteed-renewable contracts and the sources of welfare loss implied by these contracts when preferences vary over time. In section 3, I provide an overview of the main institutional details of the Chilean health insurance system. Section 4 describes the data and provides reduced-form evidence to support the idea that preferences for Chilean private health insurance companies are heterogeneous and evolve over time. Section 5 presents empirical evidence that the main features of guaranteed-renewability are present in the Chilean market, making it a suitable environment for empirical analysis. I also provide reduced form evidence of the link between health risk and switching rates across companies. Section 6 presents a structural model of plan choice that incorporates the main features of guaranteed-renewability and underwriting in the spot market. Section 7 discusses the parameter estimates, quantifies lock-in and its welfare implications, and simulates a counterfactual policy with community rating. Section 8 concludes.

2 Economics of guaranteed-renewable contracts and welfare consequences of lock-in

In this section, I use a simple model with two firms and two periods to highlight the main welfare consequences of lock-in in markets with guaranteed renewable contracts. In start with a simple adaptation of the seminal work on guaranteed renewability by

Pauly *et al.* (1995) that assumes no preference heterogeneity (section 2.1), and then incorporate the features that generate lock-in (section 2.2).

2.1   No preference heterogeneity

There are two periods and two health types (L, H), with corresponding probability of an adverse health event p_L or $p_H > p_L$. An adverse event entails a monetary loss equal to C. In period $t = 1$ everyone is of type L. Individuals become type H in period $t = 2$ if they have a negative health event in period one, otherwise they stay type L. Importantly, there is one side-commitment (i.e. individuals cannot be forced to stay in the contract in period two) and symmetric information between insurers and consumers (such that all insurers can observe the resolution of uncertainty regarding the period-2 status). Individuals are risk-averse, and there is no discount rate.[6]

In this setting, Pauly *et al.* (1995) show that a competitive marketplace can offer long-term contracts that provide full insurance against medical expenditures and against reclassification risk. In period one, insurers will sell contracts to healthy individuals at a premium that is equal to the expected value of their period-two claims, and guarantee the renewability at a premium equal to the expected value of their period-1 claims. That is, the sequence of premiums $(P_{t=1}^{GR}, P_{t=2}^{GR})$ offered in $t = 1$ is front-loaded: $P_{t=1}^{GR} = p_L C(1 + (p_H - p_L))$ and $P_{t=2}^{GR} = p_L C < P_{t=1}^{GR}$.

Insurance companies selling these guaranteed-renewable contracts can provide full coverage each period and break-even in expectation, since the price in period one covers the expected loss in period two and the price in period two covers the expected loss in period one. Although several premium profiles would make the firms break-even, this particular profile also complies with *no-lapsation constraints*. The lack of consumer commitment requires that, in every state in the second period, the consumers prefer to stay in the long-term contract rather than switching to a competing insurance company. In fact, individuals receive offers for short-term (spot) contracts in period two. Because of perfect competition, these contracts are offered at a premium that is equal to period-two expected claims conditional on each individual's updated type. Formally, spot contracts are offered in period $t = 2$ for individual i at $P_{i,t=2}^{SPOT} = p_i C \geq P_{t=2}^{GR}$. With prices $(P_{t=1}^{GR}, P_{t=2}^{GR})$, all individuals (and in particular the healthy) have incentives to purchase the long-term contract in period one and remain in the contract in period two, since spot contracts in period two are (weakly) more expensive.

The above results explain why guaranteed-renewable contracts attain the first-best allocation when there is one-sided commitment, and non-binding borrowing con-

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[6]A more general theoretical analysis is provided by Krueger and Uhlig (2006). In particular they show that the relative discount rates between the principal (insurance company) and the agent (individual) is crucial in determining the level of insurance for the agent in the long run.

straints.[7] In the absence of non-financial plan characteristics, individuals do not switch in equilibrium, effectively eliminating reclassification and adverse selection. In the next section I extend this model by incorporating evolving preference heterogeneity.

2.2 Evolving preference heterogeneity

As already suggested by Patel and Pauly (2002), guaranteed renewable contracts are not perfect

> "[...] since some high risk individuals could find themselves locked in with an insurance they *have come to dislike*" (Patel and Pauly (2002), pp. 289, emphasis added).

Those individuals that become high risk are reclassified in the spot market, and would be required to pay a potentially much higher premium if they were to switch insurers.

To formalize Patel and Pauly's observation I extend the previous model by allowing for preferences for insurers that are heterogeneous across the population, and are permitted to change from period one to period two. In this extension, there are two firms, A and B. Each firm offers a guaranteed-renewable contract in period $t = 1$ (when everyone is healthy) and risk-rated (type-specific) spot contracts in $t = 2$. Contracts are distinguished only by the premium and the firm that offers them (all other characteristics are the same).

Panel (a) of Figure 1 shows the distribution of the relative willingness to pay for firm A in the population in each period. The y-axis represents the willingness to pay in period one, and the x-axis the willingness to pay in period two. Evolving preference heterogeneity is represented by an imperfect (although positive) correlation between the willingness to pay in each period, leading to an ellipsoidal shape oriented to the north-east.

I assume that preferences and the competition environment are such that the price (and marginal costs) in period one and period two of the guaranteed renewable contract are the same for both firms. This simplification is not essential but it facilitates the graphical analysis. Also, I assume individuals do not take into account the uncertainty about period-two taste shocks in their period-one decision, or that the distribution of taste shocks in period two is such the optimal strategy in period one corresponds to the optimal strategy of a myopic individual. [8]

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[7]When it is costly for individual to pay this front-loaded set of premiums, long-term contracts provide only imperfect insurance against reclassification risk (Hendel and Lizzeri (2003)) and Handel *et al.* (2015b)

[8]This could happen for instance if individuals are fully myopic or if the distribution of taste shocks in period 2 is symmetric around zero. I will return to discuss the plausibility of this assumption in Section 6.

[FIGURE 1 AROUND HERE]

Under these assumptions, individuals in the two upper quadrants choose firm A in period one. Because of guaranteed-renewability, those individuals have the option of staying with firm A in period two by paying a premium equal to the expected cost of type-L individuals (expected loss from period one), regardless of their health status.

The offer that enrollees in A get from B in period two depends on their health status. Panel (a) of Figure1 represents the case of type-L individuals (healthy enrollees), who are also offered a spot contract in firm B at the same price as the price they pay in period two under the long-term contract in A. Absent any choice frictions (like search or switching costs), healthy individuals in the left quadrant will choose firm A in period two, whereas those in the right quadrant will choose firm B. By the same argument, each quadrant representing two-period preferences also represents the choices of health individuals. Since marginal costs are the same, it follows that healthy individuals are efficiently allocated across companies.

Consider now those individuals who had an adverse health event in period one and therefore are reclassified as type H (risky) in period two, as represented in Panel (b) of Figure 1. These individuals pay an extra premium ΔP to switch across companies, equal to difference between the premium of the spot contract for the risky and the guaranteed-renewable contract, $\Delta P = (p_H - p_L)C$. In the figure, the distance between the dashed lines and the x-axis corresponds to this difference.

Risky individuals in the upper left quadrant chose firm A in period one and would switch to firm B in period two if they were charged the guaranteed-renewable price in both firms. However, as shown in the figure, a share of those individuals will stay with firm A even they prefer firm B in period two, since they are not willing to pay the extra premium to switch. The dashed area of the left-upper quadrant represents these individuals, who I define as being "locked-in to firm A". Similarly, individuals represented by the dashed area in the lower-right quadrant are "locked-in to firm B": they chose B in period one and would have switched to firm A had they been charged the same price in both companies.

As it is typically done in the literature of guaranteed-renewable contracts, I have assumed an environment in which health type is revealed over time symmetrically to all market participants. In this case, a firm and a risk-averse agent will always be willing to trade at a premium equal to the expected cost, regardless of the risk type. However, Hendren (2013) shows that failures to this assumption (i.e. when applicants to an insurance contract hold private information) can explain enrollment denial. Another potential reason for coverage denial, and also potentially relevant for this paper - is firm's inability to fully risk-rate their plans through legal impediments or menu costs.

I analyze the effect of denying enrollment on lock-in in Panel (c).[9] In that case, all individuals in the upper left and bottom-right quadrant cannot switch away from the firm they picked in period one even if it would be efficient for them to do so.

In this simple analysis, the degree of inefficiency produced by lock-in depends on the following factors: First, it is contingent on the shape of preference heterogeneity dynamics, as depicted by the shape of the shaded area in Figure 1. It also depends on the share of individuals who are subject to reclassification (i.e those for which the relevant situation is described in panel (b) of Figure 1), and the extra premium they pay upon switching, ΔP. Finally, inefficiency resulting from lock-in depends on the share of individuals who are denied coverage if they were willing to switch, as represented by the share of individuals in situation described by panel (c) of Figure 1. In section 6 I describe the main empirical framework to quantify these objects in the data.

The existence of welfare losses in guaranteed-renewable contracts is at odds with previous theoretical analysis that has shown that they achieve pareto-optimality. That analysis makes the strong assumption of no preference heterogeneity for providers, so it abstracts from any non-financial motive to switch plans over time. This is also true if preferences are heterogeneous but constant over time, as would be the case when the shaded area of Figure 1 shrinks to a line, as shown in panel (d) of Figure 1. In that case, there are no individuals willing to switch companies over time and thus no possibility of lock-in.

3   Institutional Framework

The Chilean health-care system is divided into a public and private system.[10] The public regime, FONASA, is a pay-as-you-go system financed by the contributions of affiliates and public resources. The private sector —operated by a group of insurance companies known as "Instituciones de Salud Previsional" or ISAPRES—is a regulated health insurance market.[11] FONASA covers more than two thirds of the population (about 11 million people), while ISAPRES covers around 17 percent. 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 (Bitran *et al.* (2010)).

Workers and retirees have the obligation to contribute 7 percent of their wages to the public system, or to buy a plan that costs at least 7% of their wages in the private

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[9]See Cabral (2015) for dynamic inefficiencies caused by dynamic asymmetric information.

[10]The details of the Chilean health care system have already been described elsewhere, in particular Duarte (2012) and Dague and Palmucci (2015). I draw from those papers heavily in this section.

[11]From this point forward, I will refer to a private insurer that is part of this group as an "ISAPRE", and the group of insurers collectively as "ISAPRES".

system.[12] The two systems differ in many respects, including provider access, premiums, coinsurance structure, insurer payment caps, exclusions, and quality. Affiliates of FONASA are classified into four groups based on wages and family composition. These groups determine copayment for each service (which ranges from 0-20 percent), but otherwise benefits are unrelated to income. Unlike the private sector, there are no exclusions based on preexisting 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 (2012)).

The private health insurance market is comprised of 13 ISAPRES, which are classified into two groups: six "open" (available to all workers) and seven "closed" (available only to workers in certain industries). Open ISAPRES account for almost 95 percent of the private market. When workers enroll in a health insurance contract under an ISAPRE, they must immediately select a specific plan. Contracts in the private sector are, for the most part, individual arrangements between the insured and the insurance company. The contracts are yearly, although those who have already been enrolled for one year may switch to another ISAPRE or to the public sector at any time.

The monthly premium P is a combination of a base price P_B and a risk-rating factor r so that

$$P = P_B \times r \tag{1}$$

where r is a gender-specific and discontinuous (step) function of age.

Several features of the plan determine the base price P_B. A plan has two main coverage features: coinsurance rates (one for inpatient care and another for outpatient care) and coverage caps (insurer payment caps). Every plan assigns the insurer a per-service payment cap, and these caps apply to each visit. Coinsurance rates and the insurer payment caps remain constant across visits and do not accumulate over time. For any particular claim, a person pays her coinsurance rate until the amount that the insurance company contributes reaches the cap for that service. After hitting the cap, the patient pays the rest. The basic formula to determine the copay is therefore:

$$copay = price - minimum([price \times (1 - coinsurance)], cap)$$

Base prices are indexed to inflation, and adjustments to the base price in real terms can be made once a year. Three months before the end of the contract year, ISAPRES must inform the regulator of their projected price increases for the year. Each company must also inform their clients about these increases, justify their reasons for the changes

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[12]With a cap of 186 USD per month

and offer alternative contracts to their clients that maintain monthly premiums but that often imply lower coverage.

A couple of features of the market restrict the extent to which private firms can risk-rate their plans. First, base prices are set at the plan (and not the individual) level. Also, since a major reform to the system in May 2005 —the "ley larga de ISAPRES" —each firm can have at most two r functions. However, there is a large number of plans in the market (around 52 thousand with active enrollees and around 18 thousand actually offered in the market at a given point in time), so the effective number of insureds per plan is fairly small (on average 28). A large share of plans has only one insured (40 % as of January of 2011). Although the spirit of the regulation is not to allow risk-rating through the base price, I evaluate this issue empirically.

The "ley larga" introduced a major restriction that limits the extent of reclassification of individuals already in a contract: the price increase of each particular plan j in ISAPRE k cannot be higher than 1.3 times the average price increase of all plans of ISAPRE k.[13] Formally,

$$\Delta\%P_{jk} \leq 1.3 \times \overline{\Delta\%P_k} \qquad (2)$$

where $\Delta\%P_{jk}$ is the percentage change in the base price of plan j in ISAPRE k and $\overline{\Delta\%P_k}$ is the average price increase for all plans in ISAPRE k.

As shown in section 4, rule (2) effectively limits the variation in price increases and therefore the extent of reclassification risk.

Preexisting 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 preexisting 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 ISAPRES deny coverage, anecdotal evidence and conversations with industry actors suggests that this is a regular practice. Note that preexisting conditions are relevant for switching across ISAPRES or into an ISAPRE from the public sector, but not within a given ISAPRE.[14]

Networks Individuals have access to different types of plans with respect to the provider network. "Preferred-provider" plans are tied to a specific network, although enrollees can use providers outside of their insurers network at a higher price (similar

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[13]There is a small share of plans (5%) that are not subject to this rule. In the empirical part I use only the sample of plans for which this rule applies

[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. Policyholders can opt for these plans and pay a lower premium.

to PPO in the US). Individuals can also choose - at a higher premium - plans with an unrestricted network of providers. Under these "free choice" plans, coverage is not tied to the use of a particular clinic or health care system, similar to a traditional fee for service indemnity plan in the United States. Companies also offer a small share of "closed network" plans, where enrollees can only use the services of the plan providers or must pay full price (the equivalent of the U.S. HMO).

4   Data

I have access to an administrative dataset containing the universe of insureds in the private market for the period 2009-2012. This dataset is sent by ISAPRES to the regulatory agency (*Superintendencia de Salud*) and was made available through a research partnership. The data contains the stock of policyholders each month (around 1.5 million per month), including basic demographics (age, gender, number of dependents, district of residency), wage (capped to the contribution limit) and plan choice. I have access to the universe of claims in each month for each individual and his or her dependents. Claim information includes total cost, insurer cost, copayment, provider identification and geographical location, and a claim (procedure) code. The data also includes biannual information on the stock of all "active" plans in the market, which is updated in January and July. Active plans are defined as those that are either currently sold in that month or that have been discontinued but are still held at least by one enrollee. The information on the plans include the company, premiums, the adjustment factor f, and the date at which the plan was introduced in the market. I provide the main descriptive statistics of the data in section 6.5 when I describe the construction of the data for estimation.

4.1   Provider differentiation and provider switching

In this section I provide empirical evidence suggesting that the valuation for private insurance companies in Chile differ across individuals, and that individual's preferences change over time, in particular as they develop specific health conditions and as they move geographically. This evidence supports the notion that evolving preference heterogeneity—the main driver of lock-in—is likely to be important in the context analyzed in this paper, and motivates the remainder of the paper.

First, enrollees to health insurance companies that are subject to this study access different networks, particularly for some types of conditions. To illustrate this fact with a concrete example, in table 1 I list the most frequent providers of cancer treatment for each of the six companies and the shares of cancer-related claims of each company

treated by these providers in the Metropolitan region of Santiago[15]. For each company, the list includes the largest cancer treatment providers in descending order up to the point where providers jointly account for 80 % of the treatment or more. I also include, for each provider in each company, the share of claims related to other procedures. Companies are labeled as A, B, .., F and providers as P_1, P_2, ..., P_{16}.

Although there are some discrepancies across companies, a few common patterns emerge from this table: First, cancer-treatment procedures are concentrated in a handful of providers: more than 80% of the claims are treated by 5-7 providers, depending on the company. These are most likely big hospitals with a high degree of complexity. While these hospitals treat an important share of cancer-related procedures, their participation in treating other types of claims is on average significantly smaller. The cumulative share of other procedures treated by these providers is fairly small in some of the companies (12 % percent in company F and 10 % in company D), although higher in companies C and E (58% and 41 % respectively).

The relative importance of each provider varies across insurance companies and depends on the type of claim. Consider for instance the case of companies E and F, and how they are linked to providers P_7 and P_4. Provider P_7 is the main provider seen by patients enrolled in a plan under E for cancer-related procedures: 55 percent of such procedures are performed by provider P_7 (along with 14 % of other types of procedures). Provider P_7 is, however, an infrequent destination of enrollees in company F: it treats 5 % of cancer-related claims and 3 % of non-cancer claims. Most of the cancer claims of enrollees from company F (56 %) are treated by another provider, P_4, that does not treat a significant share of other types of claims in F, nor a significant share of claims of enrollees in E. Thus, differences between P_7 and P_4 are likely to be especially relevant in shaping the preferences over companies E over F for individuals in need of cancer treatment. However, a healthy individual comparing these two companies upon entering a contract might not consider her taste for P_4, since she is unlikely to utilize it unless she develops cancer.

This table suggests that the provider networks vary across insurance companies, and that network differences are specific to the nature of the treatment. However, it does not rule out that individuals sort perfectly across insurance companies in relation to their contingent preferences for a given network.

In practice, though, individuals *do* switch companies. Do individuals that switch companies also switch providers? I answer this question by constructing a monthly panel data sample of individuals from 2009-2012, and follow their enrollment as well as the providers they see. This dataset contains a 10% random sample of enrollees in

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[15]This region corresponds to nearly 2/3 of the Chilean private market. These figures were computed using all the claims data from 2011

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companies A-E by january 2009 (including enrollees in the entire country). For reasons I explain later, I exclude enrollees from company F.[16] To evaluate whether individuals that switch companies also switch providers, I run an event-study specification, where the event corresponds to an insurance-company switch, and the outcome of interest is whether the individual sees a provider she hasn't seen before.[17] Specifically, I run:

$$newprovider_{it} = \sum_k \beta_k D_{it}^k + \psi_t + \theta_i + \epsilon_{it} \qquad (3)$$

where $newprovider_{it}$ is a dummy variable equal to 1 if t is the first time that individual i sees the provider seen in month t. Since the records of provider utilization are left-censored in january 2009, I construct the variable $newprovider_{it}$ using the entire time span but estimate the parameters only on data from the years 2011 and 2012.[18] In ψ_t I include month-year time dummies, θ_i is an individual effect, and ϵ_{it} is an error term.

The D_{it}^k are a series of "event-time" dummies that equal one when an individual switches company k periods away. Formally,

$$D_{it}^k = \mathbb{1}(t - s_i = k)$$

where s_i is the month individual i switched.

The β_k coefficients represent the time path of the probability of seeing a new provider relative to event of switching insurance company. [19] I estimate equation 3 by ordinary least squares and I normalize $\beta_{-1} = 0$, since the inclusion of individual fixed-effects make the D's perfectly collinear. I also place the following endpoint restrictions:

$$\beta_k = \begin{cases} \bar{\beta} & \text{if } k \geq 7 \\ \underline{\beta} & \text{if } k \leq -6 \end{cases}$$

Figure 2 plots the estimated β_k coefficients from a regression of the form given in Equation 3, where the dependent variable is the dummy for new provider, with the corresponding 95% percent cluster-robust confidence intervals. The results show a significant increase in the probability of seeing a new provider after switching insurance companies. From a baseline probability of 35%, the probability increases by 13 percentage points the month after switching. The probability of seeing a new provider continues to be higher than the baseline for 5 months after switching, after which it

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[16]Since an individual may see more than one provider in a month, I use the provider with the largest amount of claims in the month per individual.

[17]This specification follows closely Kline (2012).

[18]Although this issue should be largely addressed with the time dummies, the results are robust to running OLS only on the 2012 data.

[19]For simplicity, I drop all the observations after an individual switches companies for a second time during the period, which corresponds to about 4 % of observations.

stabilizes to its pre-switching level. This result emphasizes that individuals do switch companies, and when they switch, they do see different providers. This is evidence against the simplifying assumptions that make guaranteed-renewable contracts "perfect", which require no heterogeneity across companies or stable preferences for them over time.

As another piece of reduced-form evidence showing that lock-in with a given insurer is potentially important, I show that destination companies among switchers are different across individuals with different pre-switching health status. That is, high-risk switchers generally switch to different companies than those preferred by the low-risk when they switch. First, I show this evidence by calculating differences by health status in the net flows into each company. I define net flow into company k as the difference between the number of people switching into k and the number of people switching out of k, as a share of total switchers. The net flows for the monthly panel sample are in table 2. For instance, during the sample period, healthy individuals switch in net out of company B, with a net flow of -8.5 % . On the other hand, individuals with preexisting conditions disproportionately switch into company B, with a net flow of 6.1 %. Differences in net flows across health status are statistically significant for all companies except for company A. As an additional test, I show in Appendix 9.1 the results of estimating a multinomial logit on the sample of switchers for the probability of choosing each of the companies, as a function of health status and other demographics. Several specifications robustly show that pre-switching health condition is a statistically significant determinant of the destination company.

Finally, the data shows that geographical location is also a potentially important determinant of individual valuation's for each company. Chile is split in 346 districts, which belong to one of 53 provinces, which in turn belong to one of 15 regions. Panel (a) of Figure 3 plots the market share of the 6 open ISAPRES by region for the 10 largest regions in terms of number of insureds. For instance, while company 1 has around 20 percent of the market share in the largest region, it has only 10 percent of the market in the second largest. In panel (b) I show the market shares of each company also varies substantially across districts of region 1 (Metropolitan Area). Company 1 has a market share of around 30 percent in the largest district, 18 percent in the second largest and around 12 percent in the third largest. Overall, these pictures suggests that there are substantial differences across districts in the relative valuation for difference insurance companies. To understand the variation of preferences across geographic in Appendix 9.2 I show that market shares at the district level are positively correlated with the presence of in-network providers in each district. The presence of an in-network provider in the district is associated with a 12 higher market share.

5 Empirical evidence on guaranteed renewability

In this section I show evidence that the main features of guaranteed-renewable contracts are present in the Chilean health plans. The findings in this section motivate the remainder of the paper that estimates the welfare consequences of these contracts using a structural choice model. In particular I show evidence that 1) there is low reclassification for individuals who remain in their contract, 2) premiums are front-loaded, and 3) individuals buy contracts in a "spot market". In the estimation section, I also show that premiums in the spot market are correlated with an individual's previous health expenditures even after controlling for plan generosity.

Reclassification risk   Private firms are not permitted to unilaterally cancel an individual's contract. Moreover, they cannot change the contract's characteristics. However, in principle, they could effectively force out an enrollee by a large enough increase in her premium. The rule described by equation 2) aims to eliminate this possibility, by constraining the variance of price increases: the price increase of a single plan cannot exceed 1.3 times the average price increase in the corresponding company.

There are many ways in which ISAPRES could effectively comply with this constraint. To show how this constraint works in practice, in Figure 4 I show histograms with the distribution across plans of yearly (real) price increases (in percentage points) for the period 2010/2011, which is representative of the pattern for all years in the sample.[20]   Although there are many possible ways to comply with 2, Figure 4 shows that in practice companies pick only a handful of price increases to apply to most of the contracts. This practice limits the correlation between individual health shocks and individual price increases, which implies very limited reclassification.

[FIGURE 4 AROUND HERE]

Front-loading   I show evidence of front-loading by looking at the evolution of premiums relative to health claims for individuals who stay with their insurance company. Let h_{it} be the total claims (insurer cost) in period t of individual i, and P_{it} the corresponding premium. I show that the ratio $rat_{it} = h_{it}/P_{it}$ is increasing in t.[21] This test is

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[20]In the interest of space, I do not show the distribution for other years, but they are available upon request

[21]As Herring and Pauly (2006) argue, front-loading does not necessarily imply a decreasing premium schedule. Premiums can increase only to reflect the increase in the spot price of the healthy individuals. Instead, front-loading means that the (expected) markup decreases as individuals stay in the contract. Since the theory predicts full insurance, there is no distinction between total cost and insurer cost. However, since individuals that stay in the same contract keep their coverage rates, the distinction is not relevant for testing the dynamics of either one relative to premiums. The results of table 3 are robust to using total cost instead of insurance costs.

equivalent to Hendel and Lizzeri (2003)'s, who report that the ratio of yearly premium to probability of death in the life insurance market shows a decreasing pattern over time. Similarly, Marquis *et al.* (2006) show evidence of front-loading in California's individual market by showing that among longer-term enrollees, families that include an adult who contracts a chronic medical condition after enrolling in the individual market pay less than families with a chronically ill adult at enrollment.

Still, decreasing markups is a *strong* test of front-loading, as even in its the presence, markups could increase over time if individuals display enough inertia (as is often the case in health insurance markets, see e.g. Handel (2013) and Abaluck and Gruber (2011, 2013)). In markets with consumer inertia, firms are expected to use an "invest-then-harvest" pattern for prices, i.e. start charging a low price and increase it over time (Farrell and Klemperer, 2007).[22] In the context of one-sided commitment, guaranteed renewable contracts combined with an "invest-then-harvest" strategy do not imply unambiguous price patterns. Intuitively, inertia relaxes the no-lapsing constraint that is needed to incentivize the healthier to stay. Therefore, firms can charge in period two a price that is above the actuarially fair premium for the healthy type. This increased revenue in period two is passed on to the first period in the form of lower premiums.[23] Moreover, the evidence I provide is limited to the first 4 years of enrollment.

I test the hypothesis of increasing markups using the monthly panel of the sampled individuals enrolled in January 2009 and followed until December 2012.

As is common in health expenditures data, h_{it} (and therefore rat_{it}) has a significant zero mass and is heavily skewed. In this setting, the use of generalized linear models (GLM) has become popular to deal with the undesirable properties of standard OLS methods or two-part models.[24] I estimate the model using the method of generalized estimating equations (GEE), which extends GLM to take into account potential within-individual correlation (Blough *et al.* (1999) and Nedler (1989)). I specify a log link and gamma distribution with an AR(1) process. In a first specification I estimate

$$log(E(rat_{it})) = \alpha + \beta \times T_{it} \tag{4}$$

with $r_{it} \sim \Gamma$. I also investigate whether the parameter β varies across age groups by interacting T_{it} with three age groups (as of January 2009) ; 20-35, 36-45, and 45+ :

$$log(E(rat_{it})) = \sum_g \mathbb{1}(agegroup_i = g)(\alpha_g + \beta_g \times T_{it}) \tag{5}$$

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[22]Indeed, Ericson (2012) shows that premiums in Medicare Part D plans follow this pattern.

[23]Thus, a test for invest-then-harvest pricing strategies in the context of guaranteed renewability would look for the presence of potential savings that healthy enrollees would make conditional on switching

[24]See Buntin and Zalavsky (2004) for a review of the methods handling skewed health care cost.

The parameter estimate pooling age groups is $\hat{\beta} = .078(0.007)$ corresponding to a marginal effect of an extra year enrolled of $.050(0.005)$. The results allowing different slopes for each age group, in the second column of Table 3, indicate that the slope of rat_{it} is not statistically different across groups.

Overall, these results indicate that markups decrease over time as individuals stay enrolled in the same plan, as suggested by the theory of guaranteed renewable contracts.

[TABLE 3 AROUND HERE]

Spot markets   One key aspect of markets with guaranteed-renewability is that consumers buy contracts in a spot market, where contracts are tailored to their risk. I argue that in the Chilean market environment this spot market exists.

Plans are constantly created. Between January 2009 and December 2011, ISAPRES created on average more than 5400 plans per year. The constant creation of plans allows ISAPRES to potentially have plans with slightly different features but different coverage rates and premiums.

A couple of features of this market support the notion that insureds are not free to shop across all the plans, and their choice set is restricted to the offers made by insurance companies to them. First, there is no centralized resource where price quotes are available from all the plans offered by different companies. Survey data on plan choice in this market shows that around 70 % of individuals chose among a few options offered by a sales agent (Criteria Research (2008)).

The dynamics of plan purchase are also consistent with the existence of an active spot market. To show how the purchase of plans relate to the date at which plans launched in the market, I split plans into different "plan cohorts", defined as a function of the date when they were created. In particular, I split plan into 6 different groups: group 1 contains all plans created before July 2007, group 2, plans created between July 2007 and June 2008, and so on, until group 6, which contains plans created between July 2011 and June 2012.

In Figure 5 I show the share of switchers in date t that switch to plans of each cohort. This exercise is conducted for the same random sample of enrollees in January 2009. It shows, for instance, that almost 90% of individuals who switched in January 2009, did so to plans created between july 2007 and june 2008 and almost 10% switched to plans created after July 2008 (a negligible share of individuals switched to older plans). The pattern is repeated over time: the majority of switchers in a given moment in time switch only to relatively new plans. Figure 6 shows a similar pattern for switchers within insurance companies.

[FIGURE 5 and 6 AROUND HERE]

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5.1 Switching and health status

It is expected in GR contracts that switching rates will be decreasing in health expenditures. To test this hypothesis, I estimate a proportional hazard model for the probability of switching companies using the monthly panel of individuals enrolled in January 2009.[25]

I identify individuals with a preexisting condition using the claims data. The data contains a detailed procedure code that I link to medical conditions that are typically considered by ISAPRES as preexisting conditions. [26] In Table 4 I show a list of the six conditions considered, as well as their prevalence in the data (column 2). As shown in Table 4, the prevalence rates compare well with self-reported prevalence rates derived from survey data shown and shown in column (1).[27]

[TABLE 4 AROUND HERE]

I estimate a proportional Cox model for the hazard rate of switching companies, λ_{it}, as a function of a set of covariates X_{it}

$$\lambda_{it} = \lambda_{0t} \times exp(\beta X_{it}) \tag{6}$$

where λ_{0t} is a time-specific baseline hazard rate The results are found in Table 5, for different specifications. In Column (1) I only include a dummy for preexisting conditions, which is equal to 1 for every period after the first realization of a procedure related to conditions listed in Table 4, $\mathbb{1}(preex)_{it}$. The estimated hazard ratio is 0.74, indicating that individuals with preexisting conditions are 26% less likely to switch companies. Column (2) shows that this result is robust to including a quadratic term on age and a dummy for gender. In Column (3) I add controls for contemporary measures of healthcare utilization. I compute three-month moving averages of health expenditures and create a) the logged amount of spending on preexisting conditions, $\mathbb{1}(h_{it}^{preex} > 0) \times log(h_{it}^{preex})$, and b) an indicator for any health expenditure $\mathbb{1}(h_{it} > 0)$ and its interaction with the logged value of all health expenditures $\mathbb{1}(h_{it} > 0) \times log(h_{it})$. The results reflect interesting patterns: the presence of a preexisting condition is strongly (negatively) correlated with switching rates even after controlling for the amount of contemporary expenditures. Total expenditures on preexisting conditions among individuals with preexisting conditions are slightly correlated with switching

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[25]In the subsample of individuals for whom I observe a complete spell within an insurance company in the period.

[26]For instance "Simple vascular access for hemodialysis" is considered to indicate Renal Insufficiency.

[27]I use the 2009 wave of Social Protection Survey, which is a nationally representative survey on a variety of issues related to social protection. This survey asks individuals if they were diagnosed with a variety of conditions, as well as health insurance enrollment. More information in `http://www.previsionsocial.gob.cl/subprev/?pageid=7185`

rates. On the contrary, other types of health expenditures only have an effect in the extensive margin : positive health expenditures do not predict lower switching rates, but among those with positive expenditures, higher total expenditures does predict lower switching. I interpret these results as reflecting that higher health care utilization does in general cause lower switching rates, but that preexisting conditions cause lower switching rates beyond the increased expenditures they produce. This is consistent with a model in which individuals who have claims do not want to switch companies (so as not to lose their provider) and/or higher expenditures imply higher prices in the spot market, but also that insurance companies also limit the extent to which individuals with preexisting conditions are able to switch. I will incorporate all these possibilities into the structural analysis in the next section.

6 Structural Estimates

The reduced form evidence revealed differences in switching rates across health groups. In this section I turn to a structural model to jointly estimate the demand-side decision to enroll in a plan and the supply side plan offers from insurance companies depending on health status. The structural model allows me to quantify the welfare consequences of lock-in and simulate counterfactual scenarios, at the cost of several modeling assumptions.

6.1 Discrete Choice Model

The demand-side of the model —plan enrollment given a choice menu—follows mainly Abaluck and Gruber (2011), who provide the micro-foundations that allow to conveniently specify utility as a linear function of plan's characteristics, and at the same time incorporate realistic departures from full optimization under full information. In addition, I incorporate heterogeneous and time-varying preferences for plans, which is the fundamental source of lock-in.

Individuals face different money lotteries and maximize flow expected utility. Let OOP_{it}^{jk} be out-of-pocket costs for individual i in period t under plan j of company k. $E\left(OOP_{it}^{jk}\right)$ and $Var\left(OOP_{it}^{jk}\right)$ are a function of the individual's health risk and the financial characteristics of plans (copays and caps). Assuming CARA utility with risk-aversion parameter γ and normally-distributed cost process, Abaluck and Gruber (2011) show that an individual's utility for plan (j, k) in period t, $U_{i,t}^{j,k}$ can be approximated by (ignoring heterogeneity in non-financial characteristics across plans):

$$U_{it}^{jk} \simeq -P_{it}^{jk} - E\left(OOP_{it}^{jk}\right) - \frac{\gamma}{2}Var\left(OOP_{it}^{jk}\right) \tag{7}$$

Equation 7 implies three main restrictions to the parameters governing utility, namely (1) a one dollar decrease in premiums is equivalent to a one dollar decrease in expected out-of-pocket expenses, (2) a $\gamma/2$ dollar increase in premiums is equivalent to a one dollar increase in the variance of out-of-pocket expenditures, where γ is the risk-aversion parameter, and (3) financial characteristics of plans should not matter beyond their effect on the mean and variance of out-of-pocket expenditures.[28]

Following Abaluck and Gruber (2011), I use a more flexible alternative that allows for "choice inconsistencies" by relaxing the above restrictions on the parameters.

$$U_{it}^{jk} = -\beta_0 P_{it}^{jk} - \beta_1 E\left(OOP_{it}^{jk}\right) - \beta_2 Var\left(OOP_{it}^{jk}\right) + \lambda \mathbf{f^{jk}} \tag{8}$$

where $\mathbf{f^{jk}}$ are the financial characteristics of the plans. I also allow for individual-specific tastes for each insurance company ("brand intercepts", Berry (1996)). These intercepts, which I denote by α_{it}^{jk}, capture consumer heterogeneity in tastes for each firm based on factors that are unobserved. These include individual-specific heterogeneity over tastes for the provider network of each company, among other factors that make an insurance company more attractive to an individual but are not directly observed in the data. By including other observable dimensions of heterogeneity in plans, X_{it}^{jk}, and idiosyncratic taste shocks, u_{it}^{jk}, the final demand specification is:

$$U_{it}^{jk} = \alpha_{it}^k - \beta_0 P_{it}^{jk} - \beta_1 E\left(OOP_{it}^{jk}\right) - \beta_2 Var\left(OOP_{it}^{jk}\right) + \delta X_{it}^{jk} + \lambda \mathbf{f^{jk}} + u_{it}^k \tag{9}$$

In general, the brand intercepts α_{it}^k are aimed to capture unobserved attributes for which people have heterogeneous tastes that are constant over time (Keane (2013)). It is particularly important to incorporate these factors when analyzing lock-in because stable preference heterogeneity for ISAPRES decreases the extent to which individuals would like to switch over time. However, I also allow these intercepts to vary *deterministically* as a function of time-varying covariates Z_{it}, in order to capture potential sources of lock-in associated with changes in these observables. In particular, I allow health expenditures and individual geographic location to be included in Z_{it}, so that preferences for different firms are allowed to depend on an individual's region of residency and risk profile. These brand intercepts α_{it}^k are assumed to be normally-distributed, with

$$\alpha_{it}^k \sim \mathcal{N}(\alpha_0^k + \sum_{s=1}^{S} \lambda_s^k Z_{its}, (\sigma^k)^2)$$

where λ_s^k is the differential valuation for company k after a one-unit increase in the

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[28]Abaluck and Gruber (2011) and Abaluck and Gruber (2013) show that all of these restrictions are violated in the market of Medicare Part D.

characteristic Z_{ts}.

The idiosyncratic taste shocks u_{it}^{jk} are assumed to arise from unobserved attributes of plans for which people have heterogeneous tastes that vary over time Keane (1997). This interpretation motivates an AR(1) specification (Keane, 2013). I allow for autocorrelation within insurance companies as well as autocorrelation within plan, such that $u_{it}^{jk} = \kappa_2 u_{it-1}^{jk} + \sqrt{1 - \kappa_2} v_{it}^{jk}$ and $u_{it}^{j'k} = \kappa_1 u_{it-1}^{jk} + \sqrt{1 - \kappa_1} v_{it}^{j'k}$ with $v_{it}^{jk} \sim \mathcal{N}(0,1)$ and $v_{it}^{j'k} \sim \mathcal{N}(0,1)$.

In X_{it}^{jk} I include an individual-specific measure of the utility derived from the provider network of the plan. I assume that the utility of having a plan with a restricted network of providers instead of an unrestricted network is given by $-\beta_{RN}$. When switching plans from a restricted network-plan (j,k) to a restricted network (j',k'), I assume that the disutility of doing so, denoted by ψ, is proportional to a "provider-distance" measure d (to be defined in more detail in the following section)

$$\psi\left(N_{it-1'}^{j'k}, N_{it}^{jk}\right) = -\beta_{RN}\mathbb{1}(RN_{it}^{jk}) - \beta_d \mathbb{1}(RN_{it}^{jk}) \times \mathbb{1}(RN_{it-1}^{j'k'}) \times d^{jk,j'k'}$$

The term β_{RN} captures the disutility of having a restricted provider network, whereas β_d captures the extra disutility of switching to a plan that has a different provider network than the source plan. Finally, I allow for variation in the coefficients β_{RN} and β_d as a function of health status, to capture the fact that the "distance" across providers could matter differentially for individuals with different levels of utilization of care. Specifically, I allow $\beta_{RN,it} = \beta_{RN0} + \delta_{RN} \times log\left(1 + h_i^t\right)$ and $\beta_{d,it} = \beta_{d0} + \delta_d \times log\left(1 + h_i^t\right)$.

6.2   Forward-looking behavior

This 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 regarding reclassification, and discount rates.[29]

I mostly worry about individuals that predict being locked-in because of high future health expenditures decide on their insurance company accordingly. As a reduced-form test for this behavior, I look at active enrollment decisions (choice of ISAPRE) in 2009 and how they correlate with future health expenditures in 2010 and 2011 controlling for current health expenditures using a multinomial logit with score $s_{it}^k = \beta X_i + \gamma_0 log(1 + $

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[29]The complexity of choice in health-insurance as well as the evidence showing choice inconsistencies in this market is arguably a main reason why most recent papers estimating health insurance demand in dynamic settings do not incorporate forward-looking behavior (e.g. Handel (2013) or Abaluck and Gruber (2013)). A recent literature uses Medicare part D dynamic pricing incentives to estimate discount factors and myopia in drug purchases, and finds strong levels of myopia (see e.g. Dalton *et al.* (2015), Abaluck *et al.* (2015))

$h_{i,t}) + \gamma_1 log(1 + h_{i,t+1}) + \gamma_2 log(1 + h_{i,t+2}) + \beta X^k$. I cannot reject the null that $\gamma_1 = 0$ and $\gamma_2=0$ (see Table 21 in Appendix).

6.3   Construction of key explanatory variables

Some of the key variables that enter in the demand model described above are not directly observed in the data. In this section I briefly explain how I construct each of them.

Financial characteristics: effective coverage rate   Plan-specific coverage rates are only partially observable in the dataset. Plans typically specify outpatient and inpatient copayment rates as well as per-service caps that can depend on the provider and the specific service. Since I only have access to a general copayment rate for outpatient and inpatient rate, I calculate an "effective coverage rate" c (or "actuarial value"), as the share of health care costs that a health plan effectively covers using the claims data. Specifically, for each plan I calculate c as the sum of all copayments and divide by total claims (insurer cost + copayment):

$$c_p = 1 - \frac{\sum_{i \in I_p} \sum_{s \in S_i} Copayment_{is}}{\sum_{i \in I_p} \sum_{s \in S_i} (Copayment_{is} + InsurerCost_{is})}$$

where I_p is the set of individuals i enrolled in plan p

and S_i is the set of claims of individual i. For plans with a restricted provider network, I calculate a different coverage rate for in-network providers ($c_{p,in}$) and out-network providers ($c_{p,out}$). In the choice model, I estimate the weight w that individuals put on each coverage rate. Specifically, financial characteristics of the plan enter as

$$\mathbf{f} = \beta_c \times (\mathbb{1}(RN = 0) \times c_p + \mathbb{1}(RN = 1) \times (w \times c_{p,in} + (1 - w) \times c_{p,out}))$$

Out-of-pocket expenditures   I use a rational-expectations assumptions to model out-of-pocket expenditures for each individual in each plan (see e.g Abaluck and Gruber (2011) and Handel (2013)). Under this assumption, individuals predict their future health shocks based on current information available. For new enrollees, I calculate the mean and variance of health expenditures within each decile for the year following enrollment, conditional on 10 deciles of health expenditures during the month of enrollment, within gender and 5-year age bins. For incumbents, I calculate the mean and variance in year t conditioning on health expenditures during year $t - 1$.[30]

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[30]I do not observe cohort "0" expenditures in 2008 to predict their claims in 2009. However, since for this cohort I only estimate choices in 2010 and 2011 conditional on the choices in 2009, this is not problematic.

Network - distance across plans Claims data allow me to determine the set of in-network providers for a given plan, as each claim identifies the provider and whether it corresponds to an in-network or an out-of-network claim. Let N^{jk} be the set of in-network providers for plan j in company k. I define the "distance" between two RN plans, in terms of their provider networks, as the number of providers that are in (j,k) and (j',k') over the number of providers that are in (j,k) or in (j',k'). Formally,

$$d\left(N^{jk}, N^{j'k'}\right) \equiv 1 - \frac{\left|N^{jk} \bigcap N^{j'k'}\right|}{\left|N^{jk} \bigcup N^{j'k'}\right|}$$

The measure d is equal to 1 when all the plans in the network of (j,k) are also in the network of (j',k'). On the contrary, if there are no plans in the network of both plans, d is equal to 0. In to visualize the outcome of this exercise, Figure 7 graphs each plan in a Euclidean two-dimensional space, where the coordinates have been calculated to reflect pairwise distances across plans.[31]

The average d across distinct plans in the sample is 3.1%, but there is substantial variation in the data, both within and across insurance companies. The company with the least diversified network is company F with an average d within its plans of 20%, while the company with the most diversified network is company C with an average d of only 3%. Although generally plans within the same company are closer to each other than plans across companies, companies 3 and 5 have similar networks. The variation of d within and across companies allows me to identify the role of the provider network separately from individual-specific brand-related tastes for insurance companies.

[FIGURE 7 AROUND HERE]

6.4 Choice sets

As suggested by the survey evidence regarding plan choice in Criteria Research (2008), the large number of plans and the impossibility of searching across all potential plans in the market means that, for most individuals, the choice set is *de facto* restricted to the menu offered by the sale agents. In this scenario, allowing individuals to choose among all plans available in the market is unlikely to recover consistent demand parameters. I handle this problem by explicitly restricting each individual's choice set before estimating demand.

First, I form each choice set to comply with the guaranteed-renewable environment. As such, the plan chosen by individual i in year t is always available to individual i in $t+1$ at the corresponding guaranteed price. On top of their guaranteed-renewable plan, individuals receive offers in the spot market that depend on their observable

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[31]The representation is only determined up to location, rotations and reflections.

characteristics $\mathbf{D}$. The vector $\mathbf{D}$ includes age and gender to account for risk-rating through the f function, and wage, to comply with the 7 % rule. I also allow potential offers to depend on an individual's geographic location and family composition.

Offers received in the spot market are subject to underwriting. By including age and gender in $\mathbf{D}$, I account for risk-rating through the r risk-rating function. In order to allow for potential risk-rating through the base price P_B, I also include in $\mathbf{D}$ the overall health status, captured by individual's health expenditure quintile between $t-1$ and t, h_{it}. The extent to which firms are able to discriminate through the base price is an empirical question, but the myriad of plans available and constantly created suggest that this possibly cannot be ruled out *ex-ante*.

I allow coverage denial as a second form of underwriting, to account for the possibility that individuals with preexisting conditions are not offered plans from other firms in the spot market because of their health declaration. Specifically, incumbent individuals enrolled in company k receive spot offers from other companies $k' \neq k$ with a probability that depends on whether the individual has a preexisting condition, denoted $\rho^s(\mathbb{1}(Preex_{it})$. In particular, I parametrize ρ^s as:

$$\rho^s \left(1(Preex_{it}) = 2 \times (1 - \Phi(\theta_s \times \mathbb{1}(Preex_{it}))\right)$$

The parameter θ_s, to be estimated, captures the degree of dependency of offer rates on the presence preexisting conditions. The offer rate is equal to 1 (plans are offered to anyone regardless of preexisting conditions) when θ_s is equal to 0, and it decreases as θ_s increases. In the interest of reducing the number of parameters to be estimated, this specification makes two simplifying assumptions. First, ρ^s is not permitted to depend on the insurance company, even if there might be differences in the underwriting procedures across these firms. Also, I estimate a single parameter for all preexisting conditions, although I expect that some conditions classified as preexisting, like depression, entail lower levels of coverage denial compared to conditions like cancer that are more expensive to treat. As such, ρ^s reflects the average offer rate across ISAPRES for the average individual with a preexisting condition.

I summarize the supply behavior of each company k as an "offer-policy",

$$\mathbb{M}^k \left(\mathbf{D}, h, \mathbb{1}(Preex_{it})\right) = \left\{ P^k \left(\mathbf{X}^k, \mathbf{D}, h\right), \mathbf{X}^k \left(\mathbf{D}, h\right), \rho^s \left((Preex_{it})\right) \right\} \qquad (10)$$

The offer policy is a function that maps demographics and health status to the characteristics of offers in the spot market. In each period t, an incumbent individual is confronted with an offer from each company k complying with the corresponding offer policy, and the guaranteed renewable plan, M_{it}^{GR}. The argument $\rho^s(Preex_{it})$ is meant to capture that an individual enrolled in company k receives spot offers from companies

$k' \neq k$ with probability ρ^s.

Finally, the model allows for inertia, which is a widely-documented phenomenon in health insurance purchase (see for instance Handel (2013); Abaluck and Gruber (2013)). In this market, inertia is potentially important considering the large number of plans available. Therefore, I model inertia as arising from "inattention", such that individuals may not necessarily see all the choices in their potential choice set when deciding to renew their plan. Arguably, other reasons besides inattention (or search costs) might cause inertia, such as habit formation, learning, or real switching costs (like hassle costs of paperwork involved) (see Handel (2013)). In practice, it is empirically difficult to disentangle among alternative explanations without direct measures of these costs or strong assumptions. In practice, I model inertia as the probability of making an active choice in every period after the first enrollment period, similar to Grubb and Osborne (2015) and Ching *et al.* (2009). Specifically, in every period after the first, individuals actively choose between guaranteed-renewable plans and the spot offer received from their insurance company with probability ρ^w. Also, among those that actively choose within their insurance company, some also search across all other insurance companies with probability ρ^a.[32] This specification of inertia thus operates through the plans that individuals consider in their choice set. In one of the specifications I allow ρ^w and ρ^a to depend on the individual's potential savings for switching in terms of premiums, ΔP, so that $\rho^w = \rho_0^w + \rho_{sav}^w \times \Delta P$ and $\rho^a = \rho_0^a + \rho_{sav}^a \times \Delta P$. I also allow ρ^a to depend on age, so that $\rho^a = \rho_0^a + \rho_a \times (age/\overline{age} - 1)$, where $\overline{age}$ is the average age in the sample.

Putting together the supply and demand features, I have a probabilistic choice set model for incumbent individuals. In period $t = 1$, an entrant individual makes an active choice considering offers from all the companies. However, in every period $t > 1$, an individual previously enrolled in plan j of company k will have a choice set that matches one of three mutually exclusive possibilities C_{it}^1, C_{it}^2, or C_{it}^3:

- $C_{it}^1 = M_{it}^{j1} \cup M_{it}^{j2} ... \cup M_{it}^{jK} \cup M_{it}^{GR}$: guaranteed renewable contract and spot contracts within and across insurance companies. This happens if the individual searches within and across insurance companies and is offered a plan in each. All new clients are assumed to have this choice set when they pick a plan for the first time.

- $C_{it}^2 = M_{it}^{jk_{t-1}} \cup M_{it}^{GR}$ guaranteed renewable contract and spot contract within their insurance company. This occurs if the individual (a) searches only within her insurance company or (b) searches within and across insurance companies but is not offered a plan in the other companies.

- $C_{it}^3 = M_{it}^{GR}$: only guaranteed renewable contract.

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[32]This is equivalent to assuming that individuals have infinite search cost with probability ρ^w and ρ^a for switching within and across, respectively.

Let $\mathbb{C}_i$ be the set of all potential choice sequences and C_i^s an element of $\mathbb{C}_i$.[33] Since the probability of a given choice sequence depends on the choice set C_i drawn by the individual, the overall choice probability is

$$Pr\left(\mathbf{d_i}\right) = \sum_{\mathbb{C}} Pr\left(\mathbf{d}|C_i = C_i^s\right) Pr\left(C_i = C_i^s\right) \tag{11}$$

6.5 Identification

Here I discuss identification of the key parameters of the model. A common identification issue in choice models in panel data is how to disentangle between the roles of state dependence from autocorrelation. I do so with functional form assumptions and exclusion restrictions that leverage time-varying covariates. Autocorrelation, modeled as an AR(1) process, implies that the probability of repeating a choice that has small observed utility decreases over time. The main exclusion restriction that allows more robust identification is that lagged premiums do not affect current utility. In the absence of state dependence, a transitory change in premiums causes at most a transitory change in the outcome, while in the presence of state dependence a transitory shock has a persistent effect in the outcome (see Hyslop (1999)).

Another identification issue is separately identifying preference heterogeneity from state dependence. In this setting, individual-specific plan characteristics help to identify preference heterogeneity using the cross sectional data because of the presence of alternative-specific premiums and coverage rates (that vary within insurance companies which is the level at which I allow unobserved preference heterogeneity). Also, the covariate-specific brand intercepts are identified from the presence of different plans in a given firm and individual-specific prices. Still, I also impose a parametric model as it is typically done to identify state dependence from preference heterogeneity Keane (1997). In this paper, I model state dependence by assuming that individuals choose actively with a probability that is constant over time (or depends deterministically on age and potential savings) as in Grubb and Osborne (2015). The preference parameters that enter in the flow utility are identified from the choices of individuals who enter the market (see e.g. Handel (2013)), under the assumption that unobservables are uncorrelated with premiums and characteristics.

The inertia parameters ρ^w and ρ^a are identified by the switching rates of healthy individuals within firms and across firms. The parameter governing offer rates θ is identified based on the assumption that inertia does not depend on having a preexisting condition, which is the key identification assumption of the model. If individuals

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[33]For instance, an individual entering the market in 2009 and observed in 2009, 2010 and 2011 has 9 potential choice set sequences; the combination of the 3 options listed above in 2010 and the same 3 options in 2011.

become more aware about their plans and their incentives to search increase after acquiring a preexisting condition, the θ would be negatively biased. On the other hand, if individuals with preexisting conditions are discouraged to search because they correctly predict lower offer rates, θ would be positively biased. I discuss the sensitivity of the results to the estimated θ.

As is common in these models, incumbent individuals are assumed to have the same preferences as individuals who are new entrants to the market, so that inertia is identified from differences in choice between observationally equivalent incumbents and new entrants. Although covariates of incumbent individuals do differ from new individuals entering the market, empirically there is a substantial degree of overlap. In particular, I show the kernel density estimates of age for incumbents and new entrants (by pooling all new entrants across years) in figure 8.

Finally, δ_{RN} and δ_d are identified from the gradient in switching rates across health expenditures and plan distances, using the variation in network distances within and across insurance companies.

To set the level of utility, I normalize the intercept $\alpha_{it}^5 = 0$ in equation (9). Normalizing the scale requires normalizing the variance of one the composite error terms, which I achieve by setting $\sigma^4 = 0$, so that $var(\epsilon^4) = 1$.

6.6 Construction of estimation sample and descriptive statistics

I construct a yearly panel, where the year t is defined to begin in September of each corresponding calendar year. I define three cohorts of "new clients" that enter the system between October of $t - 1$ and September of year t for years $t = 2009, 2010, 2011$.[34]

From a universe of approximately 1.5 million enrollees, there are approximately 120 thousand new enrollees each year. I perform a few sample restrictions among the new clients: I keep only individuals that have individual plans, with contracts under "open" ISAPRES (so enrollment is not limited to specific industries), and whose plans are subject to the standard pricing regime, which correspond to around 100 thousand of new enrollees per year. I only keep individuals older than 25 and younger than the corresponding legal retirement age (60 for females and 65 for males) leaving around 70 thousand new enrollees each year. Besides these sample restrictions, I drop observations with invalid or missing wages, or plan characteristics. Due to miscoded plan identifiers

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[34]For each individual, I the date when she entered into a contract with her current insurer, but the date when she entered the overall system. I identify individuals that enter the system for the first time in period t, as those that entered a contract with a firm in t and cannot be found contributing to the system in any earlier period. This method yields a cohort in 2009 that is substantially larger than those of 2010 and 2011. Since there are no structural reasons for this to be the case, I use a matching technique to get a subsample of cohort 2009 of the same size as of cohort 2010 with similar demographic distribution.

that resulted in difficulties in matching plans to their characteristics for one of the 6 insurance companies included in the analytical dataset, individuals buying their first plan with that company are eliminated from the sample. [35]

To the universe of new clients described above, I add a 10% random sample of incumbent clients as of September 2009 who are followed until 2011. I label these as "cohort 0". Cohort 0 is subject to the same sample restrictions detailed above. I also drop those that enrolled in the system before july 2005, before the major law ("ley larga described in section 3) substantially changed the pricing rules of plans. The inclusion of cohort 0 permits a richer and more representative support on the health expenditures distribution. However, as explained in Section 9.4, choices of cohort 0 in 2009 cannot be estimated with an autocorrelated error structure. The likelihood of the choices of cohort 0 in 2010 and 2011 are estimated conditional on their choices in 2009

The final sample consists of approximately 313,000 individual-year pairs. The main demographic characteristics are summarized in Table 6.

[TABLE 6 AROUND HERE]

Around 60% of the individuals in the sample are men, and the average age is 34 years old. Almost two-thirds of individuals live in Santiago. In the estimation sample, between 13 and 20 percent of individuals have a preexisting condition, depending on the cohort and year. Cohort 0 is older, has higher wages, and a higher share of individuals with preexisting conditions. On average, around 80 percent of individuals remain in the same plan from t to $t + 1$ and around 13 percent of individual switch within the same insurance company, so that on average 7 percent switch across insurance company from year to year.

The panel dataset contains plan choices for each individual in the estimation sample. Each individual has one (potential) spot offer from each insurance company, with the exception of those living in seven (out of fifteen) "special regions", where insurer "C" has a negligible market share. Individuals living in one of these regions are assumed to receive offers only from the other 4 companies.[36] Also, the guaranteed-renewable plan is always in the choice set of incumbent individuals. The main characteristics of the plans in the choice set are described in the Table 7

[TABLE 7 AROUND HERE]

Spot offers made to each individual in the sample are constructed by assigning to each individual, in each period, a plan within the set of plans to which an individual

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[35]Individuals switching to that company, or to other plans not considered in the sample are treated as "leaving the sample"

[36]regions 1-4,11,12, and 15

with her same characteristics D switched during a window of 12 months. In practice, I assign a spot offer to each individual from each insurance company by finding an exact match on gender, age, region, and health expenditure quintiles, and a nearest-neighbor match on wage, where the neighbor of individual i is found among those individuals with weakly higher wages, to be consistent with the "7% rule".

With the sample of spot offers I can evaluate empirically the presence of risk-rating *via* spot prices. I do so with the OLS estimates of log of premium on health expenditure quintiles, after controlling for demographics and for plan's characteristics as in the following specification,

$$log\left(P_{it}^{jk}\right) = \alpha_j + \beta_h h_{it} + \beta_D D_{it} + \beta_X X_{it}^{jk} + \epsilon_{it}^{jk} \tag{12}$$

where h_{it} are health expenditures quintiles during year $t-1$, X_{it} are plan characteristics besides premium, and $\mathbf{D_{it}}$ is the set of demographic characteristics.

Column 1 of Table 8 shows the results of a specification in which only plan characteristics are added as controls: insurer dummies, effective coverage, quality, and a dummy for unrestricted network. The fit of this model is only 20%, and the restricted network coefficient has the incorrect sign. When age category and gender interactions are included, the fit of the model increases substantially, and the unrestricted network coefficient has the expected sign. This reflects the risk-adjustment on age and gender though the r function. Column (3) includes health expenditure quintile dummies, and shows an increasing relationship between health expenditures in the previous period, suggesting some moderate level of risk-rating via spot prices: individuals in the highest quintile of health expenditures pay on average 9.0% more in premiums for plans with equivalent characteristics. I will incorporate this empirical level of risk-rating when simulating choice sets under the current scenario.

[TABLE 8 AROUND HERE]

6.7   Estimation Procedure

I estimate the model using the Geweke-Hajivassiliou-Keane (GHK) multivariate normal simulator (Geweke and Keane (2001), Keane (1993, 1994), and Hajivassiliou *et al.* (1996)). GHK is convenient over standard accept/reject simulators since it requires the simulation of choice probabilities only for the chosen sequence. The algorithm consists of drawing the composite errors for each of the alternatives in each period from a normal distribution that is consistent with the chosen sequence. GHK permits the incorporation of cross-sectional correlation (present because an individual in period t might face two offers from the company she picked in $t-1$) and time-series correlation (because of the AR(1) structure of the error term). The details of this procedure are

in section 9.4, but a few important modifications to the standard procedure are worth mentioning here. First, the guaranteed-renewability of contracts makes the choice set in a given period dependent on past choices. In particular, the company chosen in period t defines the company of the guaranteed-renewable contract in period $t+1$ and therefore the correlation of its random components with those of each spot contracts. In practice, this makes the structure of the variance-covariance matrix of the composite error term $\alpha_i + u_{it}$ to be individual-specific. Also, the standard GHK procedure assumes that the econometrician observes the entire choice sequence. In order to incorporate "cohort 0" into the analysis (those incumbents individuals in the first period), I adapt the algorithm to allow for a truncation in the observed past choices. In section 9.4 I show that a simple extension to the standard procedure, writing the likelihood for the choices in 2010 and 2011 conditional on the observed choice in 2009, allows for the use of the information provided by the choices of this cohort.[37]. Finally, in order to incorporate random choice sets, I jointly simulate the choice set and the error terms. In each repetition of the simulation, I simulate a choice set sequence and then the set of random normal terms. I use standard maximization techniques with $R = 200$ repetitions.

7 Results

7.1 Parameter Estimates

Table 9 lists the estimates for the main parameters of the model for three different specifications. The first specification, in Column (1), restricts $\rho^a = \rho^w = \rho^s = 1$, so that the choice set the individual confronts is always the full set of potential choices. Column (2) shows the results of a specification in which ρ^a, ρ^w, and ρ^s are estimated. The third specification allows ρ^a and ρ^w to depend on potential savings from search, and ρ^a to also depend on age.

[TABLE 9 AROUND HERE]

The price coefficient is between -0.25 and -0.18 depending on the specification. This implies a premium elasticity that is lower than what has been found in previous work.[38]

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[37]This solution is in the same spirit of Wooldridge (2005)'s solution to the initial conditions problem in dynamic panels. However, in this case, the problem arises from the guaranteed-renewability environment that makes individual-specific covariance matrices in year t to depend on the choices in year $t-1$.

[38]Abaluck and Gruber (2011) find an elasticity close to -1. I estimated the model using the control function approach of Petrin and Train (2009) , with a "marginal cost" instrument derived from the average covered expenditures for individuals in the plan. The price coefficient is not altered significantly in the IV models, and since I am not confident that the exclusion restriction is satisfied, I continue to estimate the model without an instrument

However, a likelihood-ratio test strongly rejects the first specification where the price elasticity is the smallest.

The estimated probability of searching within is $\hat{\rho}_0^w = 0.43$, and a probability of searching across (conditional on searching within) is estimated to be $\hat{\rho}_0^a = 0.80$. Lower potential savings in the spot market decrease the probability of searching, but the result is not economically meaningful: the estimated probability of searching is higher by 1 percentage point for an individual with no potential savings than for an individual with the average (negative) potential savings.

To interpret the rest of the demand coefficients I calculate the marginal effects using simulation. I simulate the market shares for each company across four groups defined by health status and geographic region: healthy individuals v.s. individuals with preexisting conditions, and Santiago v.s. other regions. The effect of health status on preferences, as estimated in the model, results from by comparing the predicted market shares in column (a) to those in column (b). This effect varies across firms. The effect is larger for company D that is predicted to have a 12.3 market share among the risky in Santiago compared to 8.8 among the healthy in Santiago. The effect is the smallest in company E where both market shares differ by less than 1 percentage point. Since the model does not allow for interaction in the Z variables (health status and region), the pattern described above also holds for market shares in other regions. On the other hand, market shares are predicted to vary significantly across regions, particularly for company D that has a market share around 30 percentage points larger in regions different than Santiago.

[TABLE 10 AROUND HERE]

On the supply side, the average individual with a preexisting condition is offered a contract with probability $\rho^s = 0.82$, which implies that on average one in five individuals with preexisting conditions is denied coverage in the spot market.

7.2 Health status by age

Along with the structural parameters estimated above, a key input for quantifying lock-in is the share of individuals subject to underwriting in the spot market. In this section I explain my empirical approach to simulate the evolution health status over and individual's lifetime, to determine the type of offers they receive in the spot market.

As stated in Section 10, offer policies map an individual's health status (as well as other demographics) to a potentially offered premium and plan characteristics, as well as a coverage decision. Specifically, I have modeled throughout that premiums and characteristics depend on 5 health expenditure quintiles, and the coverage decision depends on the presence of a preexisting condition. Therefore, the supply response is

determined by 10 different and mutually exclusive states for status, corresponding to the combination of 5 different health expenditure quintiles and a preexisting condition indicator.

I estimate the probability of being in each of the 10 states during an individual's lifetime by assuming that the health process is a Markov Chain with transition probabilities that depend on age and gender. For each age and gender, I use the actual transition rates across the 10 states as estimates of the transition probabilities. I calculate a separate transition matrix for each age and gender. Then, I use each of these age-gender specific 10 by 10 transition matrices for simulating health paths from age 25 until retirement (60 for females and 65 for males).[39].

Tables 11 and 12, present, as an example, the transition matrices at age 25 for females and males respectively, and tables 13 and 14, the corresponding transition matrices at age 55. States 1 to 5 correspond to 5 quintiles of health expenditures with no preexisting conditions, with states 6 to 10 corresponding to 5 quintiles of health expenditures but with preexisting conditions. On-diagonal entries reflect persistence in health status. For instance, the first element in Table 11 shows that 41 % of 25 year-old females that are in the healthiest group are expected to remain in that category at age 26. States 6-10 (with preexisting conditions) represent only a small share of cases at age 25, and the vast majority transition to states 1-5 (without preexisting conditions) in the next period. On the other hand, persistence at the sickest states is high at age 55 : 40 % of females and 48 of males in the sickest state at age 55 are expected to remain in state 10 at age 56.

The most important outcome from these tables is the predicted share of individuals with preexisting conditions at each age. To assess the accuracy of this procedure in forecasting the prevalence of such conditions over time, figure 9 compares the empirical share of males and females with preexisting conditions by age (full line), and the simulated share of males and females with preexisting conditions (dashed line). Overall, this procedure achieves a good fit. Males start with a prevalence of preexisting condition of around 6% at age 25. The prevalence among men rises to around 50 % by the age of 65. The prevalence among females at 25 is slightly higher than for males, starting at around 13 %, but it increases less steeply than for males. At age 60, I estimate that around 38 % of females have a preexisting condition.[40] Note that total health expenditures enter in the demand model, in particular in individual's valuation for each company. Total health expenditures are also simulated non-parametrically, by drawing a random number from the empirical distribution of health expenditures conditional on each state.

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[39]Handel *et al.* (2015b) take a similar approach

[40]In the interest of space I do not show this comparison for all 10 states, but they all show a good fit. These figures are available upon request

7.3 Lock-in

With simulated health expenditures, the estimated level of underwriting, and the estimated preferences, I can now quantity the share of individuals locked-in because underwriting in the spot market. I use the estimated preferences and underwriting rules, to simulate the choices of individuals over their lifetime. Each individual's health status, which impacts their preference and potential choices, are simulated with the methodology described in the previous section.

Formally, let $K_i(\Theta_{it}, \mathbb{M}, H_{it}) = \{k_1, k_2, ..., k_T\}$ be the sequence of companies chosen by individual i under the current offer policy $\mathbb{M}$, preference parameters Θ_{it}, and health-status process H_{it}. Let $\mathbb{M}'$ be a different policy and $K_i'(\Theta_{it}, \mathbb{M}', H_{it}) = \{k_1', k_2', ..., k_T'\}$. I define an individual's *willingness to pay for policy $\mathbb{M}'$ over policy $\mathbb{M}$ in period t* as w_{it}:

$$w_{it}\left(\mathbb{M}', \mathbb{M}, \Theta_{it}, H_{it}\right) \equiv max\left(\frac{u_{it}^{k_t'} + \beta_P P^k - \left(u_{it}^{k_t} + \beta_P P^{k'}\right)}{\beta_P}, 0\right) \qquad (13)$$

The willingness to pay w_{it} can be interpreted as the dollar amount that makes agent i indifferent between her current policy $\mathbb{M}$ and paying w_{it} for receiving offers from policy $\mathbb{M}'$. I quantify this object by simulating K_i and K_i' for a representative sample of individuals that enter in the market at 25 years old and stay for 35 years.

To quantify lock-in, I calculate the willingness to pay for an offer policy $\mathbb{M}'$ that eliminates risk-rating in the spot market, so that a) premium risk-rating is eliminated and b) coverage denial is eliminated. In this exercise I assume away any potential changes to the overall level of premiums associated with the new policy $\mathbb{M}'$. In that sense, calculating w_{it} does not answer a full welfare analysis question, but it is instructive to calculate how much a single individual would be willing to pay to eliminate her underwriting while keeping everyone else's. I return to the question of full welfare analysis in general equilibrium in the next section, when I allow prices to adjust to the new policy.

The simulation procedure to recover K_i for a given offer policy $\mathbb{M}$ is as follows:

1. Set t = 0 and set $D_{i0} = (age_0, gender_0, region_0)$ equal to the empirical D_i for individuals entering in the market at age 25 in 2009.

2. Draw $H_{it} = (h_{it}, Preex_{it})$ and Z_{it} from the empirical (joint) distribution $F_H(D_{it})$ and each $z_i \in Z_i$ from the empirical distribution $F_z(D_i)$

3. Construct the choice menu by drawing offers from each company, $M_{ik} \in \mathbb{M}^k(D_{it}, h_{it}, Preex_{it})$, by

   (a) Drawing $X^k(D_{it}, h_{it}, Preex_{it})$ from the empirical distribution of spot offers in each company and

(b) calculating spot prices using the estimates of spot prices from equation 8.

4. If $t > 0$, add $k_{i,t-1}$ to the choice menu.

5. Draw u_{it}^{jk} and choice k_{it} for each i among her choice menu.

6. Update D_{it} and return to step 2.

The left Y-axis of figure 10 shows the share of individuals with positive willingness to pay for the policy described above over the current policy. I also include the average willingness to pay in the right Y-axis.

Individuals with $w_{it} > 0$ are those locked-in to their plans: they are enrolled in plan k under policy $\mathbb{M}$ but would be enrolled in plan $k' \neq k$ under an alternative policy $\mathbb{M}'$ that bans underwriting. The share of locked-in individual reaches around 5 percent after 35 years and is increasing over time, as preexisting conditions become more prevalent. On average, an individual would be willing to pay around 13 % of the current average premium for policy $\mathbb{M}'$.

[FIGURE 10 AROUND HERE]

I use the estimated parameters of the model to shed light on the relative importance of the two potential sources of underwriting in the market: coverage denial and premium risk-rating. To calculate the level of lock-in produced only by risk-rating of premiums, I simulate the share of individuals with $w_i^t > 0$ and willingness to pay for a policy $\mathbb{M}''$ where everyone gets risk-rated offers. In practice, I leave the current level of risk rating but use $\rho^s = 1$, to shut down the coverage-denial mechanism. The purpose of this exercise is only to describe the relative importance of both sources of lock-in rather than answering a general-equilibrium question, so I leave the level of risk-rating at the original parameter estimates. The results of this simulation are in figure **??**, which shows that most of the lock is due to preexisting conditions: the simulations predict that less than one percent of individuals would be locked-in if we set $\rho^s = 1$ while keeping risk-rating in spot premiums.

[FIGURE 10 AROUND HERE]

Thus, the level of lock-in results is mostly sensitive to the estimated coverage denial rates rather than the level of premium risk-rating. My estimates indicate that 1 in 5 individuals with preexisting conditions are denied coverage in the spot market. Since around 50 % of males and 40 % of females are expected to end-up with a preexisting condition by age 60, mechanically, the share of individuals facing coverage denial in the spot market is 10 % of males and around 8% for females.

To show how higher coverage-denial rates translate into higher lock-in, I simulate the economy assuming that everyone with a preexisting condition is denied coverage in

the spot market, that is by setting now $\rho^s = 1$. The results are in figure 10. Under this alternative assumption, the share of locked-in individuals would be around 16 % at the age of 60.

7.4 Repricing effects

The share of locked-in individuals calculated in the previous section do not necessarily correspond to the share of switchers if policy $\mathbb{M}'$ is implemented. Mechanically, 5 % of individuals would switch if prices of plans remain fixed at their original level. However, the prices of contracts are expected to change in response to those switchers, creating a general-equilibrium effect in the allocation. Prices of contracts to which individuals with preexisting conditions switch are expected to increase, decreasing the share of those who would effectively want to switch, and also potentially generating the result that some healthy individuals would want to switch out of those contracts.

Predicting price responses to policy $\mathbb{M}'$ would require that I specify and estimate a full supply model, which is outside of the scope of this paper. Instead, I make use of simple supply-side assumptions that allow me to use the already estimated parameters to quantify these effects. I find the equilibrium under $\mathbb{M}'$ by assuming that the average markup per enrollee of each company does not change after the policy. This simulates, for instance, a scenario in which all extra payments made by enrollees in the counterfactual scenario go to a common pool that is distributed to each company accordingly (so there is "risk-adjustment" relative to the original policy). Also, I assume that the change in markup at the company level is compensated with a uniform price increase of all plans at the company.

Formally, let $\mathbf{A}_t(\mathbb{M}, \Theta)$, the $I \times K$ allocation matrix whose element $A_t(i, k, \mathbb{M}, \Theta)$ is equal to 1 if individual i is enrolled in company k in period t and 0 otherwise, given policy $\mathbb{M}$ and demand parameters Θ. Let $J(k)$ be the collection of plans of firm k. The average markup in period t of company k under allocation $\mathbf{A}_t$ is given by

$$\mu_k^t (\mathbf{A}_t | \Theta, \mathbb{M}) = \frac{\sum_{i=1}^N \sum_{j \in J(k)} A_t (i, k | \mathbb{M}, \Theta) \times \left(P_{it}^{jk} (\mathbb{M}) - c^k(h_{it}, X_{it}^{jk}) \right)}{\sum_{i=1}^N \sum_{j \in J(k)} A_t (i, k)}$$

Definition An allocation $\mathbf{A}'_t$ is an *equilibrium allocation under a counterfactual offer policy* $\mathbb{M}'$ if

1. Markups are equal to current markups

$$\mu_k^t \left(\mathbf{A}'_t | \Theta, \mathbb{M}' \right) = \mu_k^t \left(\mathbf{A}_t | \Theta, \mathbb{M} \right)$$

2. Individuals choose company/plan optimally given Θ and $\mathbb{M}'$, so that for all plans

$$\tilde{j}, \tilde{k} \in \mathbb{M}'$$

$$A_t(i, j, k|\Theta, \mathbb{M}') = \mathbb{1}(U_{it}^{jk} > U_{it}^{\tilde{j}\tilde{k}})$$

The difference between the share of locked-in individuals and the share of switchers under the equilibrium allocation quantifies the general equilibrium effect of the policy. I calculate the equilibrium allocation using the following algorithm:

1. Set $t = 0$

2. Set $r = 0$, $P_{it}^{jk,(r)} = P_{it}^{jk}$ and $\mathbf{A}_t^{(r)} = \mathbf{A}_t$, i.e. start with prices and allocations under current offer policy $\mathbb{M}$.

3. Simulate $\mathbf{A}_t^{(r+1)}$ given offer policy $\mathbb{M}'$, and prices $P_{ik}^{(r)}$.

4. Construct $\delta^{(r)} = |\mathbf{A}_t^{(r+1)} - \mathbf{A}_t^{(r)}|$ where $||$ is a norm. If $\delta^{(r)} < \epsilon$: stop. Else,

   (a) calculate

   $$\Delta\mu_t^{k,(r)} \equiv \frac{\sum_{i=1}^N \sum_{j \in J(k)} A_t^{(r+1)} \times \left(P_{it}^{jk,(r)} - h_{it} \right)}{\sum_{i=1}^N \sum_{j \in J(k)} A_t} - \frac{\sum_{i=1}^N \sum_{j \in J(k)} A_t^{(r)} \times \left(P_{it}^{jk,(r)} - h_{it} \right)}{\sum_{i=1}^N \sum_{j \in J(k)} A_t}$$

   (b) update prices $P_{ik}^{(r+1)} = P_{ik}^{(r)} + \Delta\mu_t^{k,(r)}$

   (c) go back to step (2) with $r + 1 \to r$

Figure 12 compares the share of locked-in individuals under $\mathbb{M}$ to the share of individuals that would switch under policy $\mathbb{M}'$, after prices adjust. The results show that the differences between the two are small and almost indistinguishable.

[FIGURE 12 AROUND HERE]

7.5 Preference heterogeneity, lock-in, and adverse selection

A recent literature has focused on the interaction between preference heterogeneity and regulation in static health insurance contracts (Einav and Finkelstein (2011), Bundorf *et al.* (2012) and Geruso (2013)). In guaranteed-renewable contracts, preference heterogeneity plays two opposing roles in determining the level of lock-in. As discussed in Section 2, evolving preference heterogeneity is the main source of lock-in. On the other hand, when preferences are stable, individuals are less prone to lock-in in the guaranteed-renewable environment, since it reduces the share of individuals for whom reclassification in the spot market is relevant.

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The general equilibrium effects of transitioning to community rating also depend on preference heterogeneity.[41] In the situation analyzed in this paper, preference heterogeneity over companies may arise from several reasons uncorrelated to health expenditures. I discuss this issue in more detail using static framework of Einav and Finkelstein (2011), where I analyze the impact of stable preference heterogeneity in both the mechanical and general equilibrium effect of banning underwriting.

As in Bundorf *et al.* (2012), an individual's relative valuation for insurance is given by $u(h, \epsilon)$ where $h \in [0, \infty)$ is health risk and $\epsilon \in (-\infty, \infty)$ summarizes other determinants of valuation that are orthogonal to h, with $E(\epsilon) = 0$. The presence of ϵ in the utility function is intended to capture preference heterogeneity. The degree of preference heterogeneity is captured by $\partial u / \partial \epsilon$, which is assumed to be weakly positive. I assume that there is adverse-selection, so that $\partial u / \partial h > 0$. Here h is private information, in the sense that firms cannot price based on h.

Preference heterogeneity within health status decreases the average cost at any price, as show in panel (a) of figure 13. Intuitively, starting with a situation in which everyone is enrolled in a plan, the marginal enrollees that would drop out of the contracts after a price increase are unambiguously the healthiest if preferences are perfectly correlated with health status (so that the healthiest are those that have the lowest valuation for the contract). On the contrary, with preference heterogeneity, some marginal enrollees are high-risk individuals with low valuation for the plan because of reasons uncorrelated to health (I provide a simple formal proof in the Appendix).

[FIGURE 13 AROUND HERE]

The competitive equilibrium is found at the intersection of the demand curve and the respective average cost curve (AC). For a given demand curve, higher preference heterogeneity will therefore imply lower premiums and a higher number of enrollees in equilibrium. [42] As shown in the shaded area in panel (b), the standard marginal cost curve (depicted by MC_1) is replaced by a marginal cost *correspondence* (MC_2), to reflect the heterogeneous costs of the marginal enrollees[43]

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[41]As an example, Einav and Finkelstein (2011) show that if risk-aversion is negatively correlated with health risk, a uniform pricing may induce advantageous selection. Contrary to the standard model of health insurance markets, health insurance is more valuable for healthier individuals.

[42]Even if the demand and the cost curve are tightly linked in insurance markets, the degree of this linkage depends on the degree of preference heterogeneity. Thus, two different utility functions, with different degrees of preference heterogeneity, can yield the same demand curve and different average cost curves. For instance $u_1 = h + \epsilon$ and $u_2 = 2h$ with $h \sim U[0, 1]$ and $\epsilon \sim U[0, 1]$ produce the same demand curve but different AC curves.

[43]This figure provides an explanation complementary to Bundorf *et al.* (2012)'s to why preference heterogeneity makes a uniform price policy inefficient at any price. Any price above P_h does not produce the efficient outcome because a lower price would generate marginal enrollees who have a marginal cost below their willingness to pay. On the other hand, any price below P_l is also inefficient because increasing the

Assume that preexisting conditions take the form of denying coverage to anyone with $MC > c^*$. The share of individuals who are locked-in corresponds to the number of individuals with preexisting conditions who are not allowed to enroll in the plan if preexisting conditions are introduced, but that would otherwise enroll. The mechanical effect is represented by a leftward shift of the demand curve of a magnitude that is equal to the number of individuals with preexisting conditions who would have bought the plan at any price. Panel (b) of Figure 13 shows that preference heterogeneity decreases the share of such individuals, and therefore produces a smaller leftward shift in demand when preexisting conditions are introduced. Panel (c) shows the leftward shift in demand, represented by the new demand curve D', in the case of no preference heterogeneity. Panel (d), shows a smaller shift, corresponding to the case with heterogeneity. The mechanical effect is represented by the decrease in quantity from the original equilibrium Q^* to the new quantity Q_{mec}, corresponding to the new curve and the original average cost curve (AC). The "GE" effect is represented by a movement along the new demand curve, toward its intersection with the new AC curve (AC').

In my empirical model, stable preference heterogeneity is captured by the terms α_{i0}, σ_k, and the autocorrelation terms κ_1 and κ_2. When these terms are higher (in an absolute value sense for α_{i0}), individuals are predicted to switch less during their lifetime, even in the absence of underwriting.

To shed light on the importance of stable preference heterogeneity in reducing lock-in, I simulate the economy assuming that $\alpha_{i0} = 0$ and $\kappa_1 = 0$ and $\kappa_2 = 0$ instead of the estimated parameters. The results are in Figure 10, which shows the share of locked-in individuals under these new assumptions, for the case of $\rho^s = 1$. The share of locked-in individual increases from 16 percent to 19 percent at age 60.

8   Conclusions

This paper contributes to the literature with an empirical evaluation long-term health insurance contracts. Specifically, I evaluate the workings of guaranteed-renewable contracts in the Chilean private health insurance market, where individuals potentially receive offers from different health insurance companies.

Theoretically, guaranteed-renewable contracts have the potential to fully eliminate adverse selection and reclassification risk as long as individuals do not have incentives to switch across these companies for non-financial reasons. However, in reality, contracts have non-financial characteristics —like the provider network —which vary across com-

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price will make individuals who have a marginal cost above their willingness to pay opt out of the contract. Moreover, all prices between P_l and P_h do not yield the efficient outcome either, since under these prices there are some individuals who are inefficiently enrolled in the plan and some inefficiently not enrolled.

panies. Individuals switch every year —7 % on average in the Chilean market—but switching rates are significantly higher among the healthier. Sick individuals that come to dislike their insurance company but cannot switch because of the financial incentives imbedded in these contracts suffer a welfare loss.

I estimate that the welfare loss resulting from lock-in in Chile reaches around 13% of the yearly premium by the time individuals reach age 60. Around 5% of individuals are locked-in to their insurer at this point, although 60% of individuals experience a lock-in event in their lifetime. The estimated incidence of lock-in depends crucially on the rate at which individuals with preexisting conditions are denied coverage in the spot market, which I estimate to be around 20 %. Small levels of lock-in also imply minor general-equilibrium effects upon transitioning to a community rating scheme.

Even if the presence of lock-in in this particular market is relatively small, the degree of lock-in in long-term arrangements is an empirical question that depends on context-specific levels of differentiation across insurers as well as the evolution of preferences over time. This paper provides a systematic way of empirically evaluating this issue in other markets.

This paper does not deal explicitly with a few important aspects of guaranteed-renewability. First, despite incorporating behavioral biases in estimating demand, I do not study in detail the consequences of consumer mistakes in the evaluation of guaranteed-renewability. However, the problem of lock-in adds an important layer to the design of health insurance markets with behavioral agents. Arguably, the lack of portability of contracts is more problematic when individuals cannot forecast their future preferences or needs.[44] Relatedly, individuals suffer more from lock-in if it is difficult to make a good initial choice before a learning period. Although there is a great deal of consensus that individuals have difficulties in choosing plans, there is limited empirical evidence on whether they learn over time.[45]

Finally, when evaluating the desirability of long-term contracts that generate lock-in, it is important to incorporate other margins of response in the supply that might be not contractible at the start.[46] In health insurance markets, insurance companies generally revise the terms of their agreements with providers (Shepard (2015)). In fact, in April 2015, two of the companies analyzed in this paper went through negotiations with a group of providers that resulted in major changes in their networks. Changes in provider networks have important consequences for individuals who face underwriting. It is an open question to study the dynamic relationship between insurance companies and providers when the demand is subject to long-term contracts with lock-in.

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[44]As Pauly and Herring (1999) warn, the lock-in should "induce more care in the initial choice [...]".

[45]Ketcham *et al.* (2012) and Abaluck and Gruber (2013) evaluate learning in Medicare Part D

[46]See Farrell and Shapiro (1989) for a theoretical analysis of long-term contracts with switching costs and unenforceable quality.

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Firm	Provider	Share Claims cancer (c)	other (o)	Ratio (c/o)	Firm	Provider	Share Claims cancer (c)	other (o)	Ratio (c/o)
A	P1	0.42	0.07	6.0	B	P4	0.33	0.01	40.0
A	P2	0.18	0.01	17.4	B	P1	0.25	0.11	2.2
A	P3	0.10	0.00	28.3	B	P6	0.19	0.00	48.9
A	P4	0.09	0.00	43.9	B	P5	0.04	0.15	0.3
A	P5	0.06	0.16	0.4					
A	**Cum.**	**0.85**	**0.24**		B	**Cum.**	**0.81**	**0.27**	
C	P7	0.29	0.04	6.9	D	P4	0.54	0.01	43.6
C	P5	0.18	0.21	0.8	D	P12	0.21	0.07	2.8
C	P8	0.15	0.11	1.4	D	P13	0.04	0.00	1541.7
C	P9	0.09	0.00	23.7	D	P2	0.03	0.01	3.7
C	P10	0.07	0.04	2 .0					
C	P11	0.06	0.17	0.3					
C	**Cum.**	**0.84**	**0.58**		D	**Cum.**	**0.82**	**0.10**	
E	P7	0.55	0.14	3.8	F	P4	0.56	0.01	91.1
E	P9	0.09	0.01	15.2	F	P7	0.05	0.03	1.7
E	P10	0.09	0.05	1.7	F	P14	0.05	0.06	0.9
E	P8	0.05	0.16	0.3	F	P6	0.05	0.00	37.3
E	P5	0.04	0.08	0.5	F	P13	0.04	0.00	288.1
					F	P15	0.03	0.01	4.7
					F	P16	0.03	0.01	2.1
E	**Cum.**	**0.82**	**0.44**		F	**Cum.**	**0.81**	**0.12**	

Table 1: **Share of claims by provider and type in each company**
Note: This table shows, for each company, the share of claims related to cancer and to other all other (non-cronic) health conditions, for all claims in 2011. For instance, 42% of cancer-related claims of individuals enrolled in company A where treated by provider P_1. That provider treated 7% of the "other" claims for enrollees in the same company.

Firm	($h_{it}^{preex} = 0$)	($h_{it}^{preex} = 1$)	Difference
A	−2.6%	−1.6%	1.0%
B	−8.5%	6.1%	−14.7%***
C	4.8%	0.9%	3.8%***
D	−2.2%	−5.1%	2.9%***
E	8.6%	−0.4%	9.0%***
N obs.	13482	3461	

Table 2: **Net flow depending on health status**
Note: Table shows the net flow (*entry − exit*) to each company among switchers, as a share of total switchers, for individuals with preexisting conditions and without preexisting conditions, for a sample of enrollees in january 2009 and followed until december 2012
***: Difference is significant at the 95% confidence level.

	(a)		(b)	
	Parameter Estimate	Marginal Effect	Parameter Estimate	Marginal Effect
T_{it}	0.078***	0.05***		
	(0.007)	(0.005)		
$T_{it} \times (age \leq 35)$			0.077***	0.05
			(0.009)	(0.006)
$T_{it} \times (35 < age \leq 45)$			0.066***	0.043
			(0.013)	(0.008)
$T_{it} \times (45 < age \leq 60)$			0.091***	0.058
			(0.016)	(0.01)
N obs	1,185,346		1,185,346	
N groups	45,212		45,212	

Table 3: **Front-loading evidence**
Note: This graph shows GLM estimates of equation (4) to show the increasing relationship between tenure in a plan T_{it} and the ratio between total claims and premium, $r_{it} = h_{it}/P_{it}$, on a 4-year monthly panel of enrollees by January 2009. Panel (a) pools all age groups. Panel (b) shows the results by interacting tenure with 3 age groups.
Standard errors in parentheses, clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01

	Prevalence self reported in SPS [%]	Patients with related procedure in ISAPRES claims dataset [%]
Diabetes	4	8
Depression and Chronic Psyc. Disorder	5	7
Arthritis	3	3
Hypertension and cardiovascular diseases	10	7
Cancer	1	1
Chronic Renal Insufficiency	1	0.1

Table 4: **Prevalence of Preexisting Conditions**
Note: This table shows the prevalence of the 6 major preexisting conditions. It compares the prevalence found in the ISAPRES dataset of this paper, using the procedure claims associated with each condition to the self-reported prevalence in the Social Protection Survey of 2009.

	(1)	(2)	(3)
$\mathbb{1}(h_{it}^{preex} > 0)$	0.743***	0.776***	0.850***
	(0.039)	(0.041)	(0.047)
age		1.017	1.025
		(0.024)	(0.025)
age2		1.000	1.000
		(0.000)	(0.000)
gender		1.277***	1.263***
		(0.065)	(0.065)
$\mathbb{1}(h_{it}^{preex} > 0) \times log(h_{it}^{preex})$			1.057*
			(0.034)
$\mathbb{1}(h_{it} > 0)$			0.948
			(0.048)
$\mathbb{1}(h_{it} > 0) \times log(h_{it})$			0.872***
			(0.018)
N	165409	165409	155668

Exponentiated coefficients; Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: **Cox Proportional Hazard Model Estimates**

Note: This table shows the estimates of a proportional cox hazard model for the event of switching company, as a function of preexisting conditions and other demographics. Exponentiated coefficients.

Standard errors in parentheses, clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

cohort =	all	0	0	2009	2009	2009	2010	2010	2011
year =	all	2010	2011	2009	2010	2011	2010	2011	2011
gender	0.62	0.62	0.65	0.61	0.62	0.64	0.61	0.63	0.61
age	34.05	37.50	38.11	33.10	33.89	34.66	33.42	33.87	33.03
Nr. Dep.	0.44	0.85	0.84	0.33	0.37	0.41	0.43	0.42	0.39
Insurer = A	0.18	0.19	0.19	0.17	0.18	0.18	0.18	0.19	0.19
Insurer = B	0.26	0.22	0.21	0.26	0.25	0.24	0.27	0.26	0.29
Insurer = C	0.05	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.04
Insurer = D	0.22	0.25	0.26	0.21	0.22	0.24	0.21	0.23	0.21
Insurer = E	0.29	0.28	0.28	0.31	0.30	0.29	0.30	0.29	0.27
Santiago	0.57	0.62	0.65	0.56	0.58	0.60	0.53	0.55	0.55
Has Preex Cond.	0.15	0.20	0.21	0.13	0.15	0.17	0.13	0.15	0.13
Pick GR plan	0.39	0.77	0.82	0.00	0.79	0.80	0.00	0.82	0.00
Switch Within	0.06	0.14	0.11	0.00	0.13	0.11	0.00	0.13	0.00
N	313,462	20,333	15,577	56,613	45,301	34,616	51,580	36,292	53,150

Table 6: **Descriptive Statistics of Estimation Sample**
Note: Sample means for key variables in the estimation dataset

cohort =	0	0	2009	2009	2009	2010	2010	2011
year =	2010	2011	2009	2010	2011	2010	2011	2011
Premium (Ths.USD)	1.33	1.42	1.17	1.29	1.40	1.20	1.32	1.29
Coverage in-network	0.83	0.82	0.85	0.84	0.83	0.84	0.83	0.83
Coverage out-network	0.62	0.61	0.65	0.65	0.64	0.64	0.63	0.63
Unrestricted Network	0.37	0.36	0.41	0.41	0.39	0.37	0.39	0.34
Distance	0.84	0.84	0.00	0.82	0.82	0.00	0.82	0.00
N	121,998	93,462	283,065	271,806	207,696	257,900	217,752	265,750

Table 7: **Descriptive Statistics of Plans**
Note: Sample means for key variables in the estimation dataset

	(1)	(2)	(3)
c_p	0.402***	2.047***	2.037***
	(0.082)	(0.074)	(0.074)
Free Network	-0.052*	0.178***	0.178***
	(0.028)	(0.023)	(0.023)
$log(wage_t)$		0.227***	0.222***
		(0.009)	(0.009)
$h_{it-1} = 2$			0.007***
			(0.003)
$h_{it-1} = 3$			0.030***
			(0.003)
$h_{it-1} = 4$			0.059***
			(0.004)
$h_{it-1} = 5$			0.088***
			(0.005)
Year fixed effect	Yes	Yes	Yes
ISAPRE fixed effect	Yes	Yes	Yes
age x gender fixed effects	No	Yes	Yes
N	320190	320190	320190
R^2	0.216	0.735	0.738

Table 8: **Spot prices as a function of plan's and individuals' characteristics**
Note: OLS estimates of equation , that quantifies the correlation between log of price and plan and individual characteristics. The sample of plans correspond to "spot" plans.

β_P	-0.18	(0.016)	-0.26	(0.027)	-0.22	(0.026)
β_c	0.57	(0.075)	0.82	(0.119)	0.79	(0.116)
μ_A	-0.37	(0.078)	-0.23	(0.069)	-0.22	(0.066)
μ_B	0.05	(0.044)	0.05	(0.064)	0.05	(0.056)
μ_C	-1.00	(0.094)	-1.15	(0.258)	-1.16	(0.513)
μ_D	0.47	(0.039)	0.49	(0.041)	0.49	(0.041)
$log(\sigma_A)$	-0.28	(0.146)	-0.77	(0.283)	-0.79	(0.272)
$log(\sigma_B)$	-2.27	(0.774)	-2.25	(2.564)	-2.25	(2.643)
$log(\sigma_C)$	-0.99	(0.62)	-0.75	(0.783)	-0.71	(1.54)
ρ_0^w			0.43	(0.025)	0.42	(0.024)
ρ_0^a			0.76	(0.077)	0.80	(0.074)
ρ_s			0.83	(0.083)	0.82	(0.08)
κ_1	0.73	(0.015)	0.56	(0.067)	0.58	(0.042)
κ_2	1.00	(0.001)	0.88	(0.037)	0.86	(0.031)
Axstgo	-0.12	(0.062)	-0.14	(0.06)	-0.15	(0.06)
Axhealth	-0.13	(0.044)	-0.14	(0.067)	-0.15	(0.067)
Bxstgo	-0.19	(0.052)	-0.19	(0.057)	-0.20	(0.056)
Bxhealth	-0.11	(0.037)	-0.08	(0.058)	-0.08	(0.058)
Cxstgo	-0.06	(0.076)	0.08	(0.099)	0.07	(0.058)
Cxhealth	-0.12	(0.063)	-0.22	(0.109)	-0.21	(0.085)
Dxstgo	-1.26	(0.053)	-1.38	(0.058)	-1.38	(0.057)
Dxhealth	0.10	(0.038)	0.30	(0.055)	0.30	(0.054)
ρ_{age}^a			-0.16	(0.355)	-0.18	(0.388)
$\rho_{savings}$					0.22	(0.047)
Log L		15637.70		14554.40		14490.90
N		84507.00		84507.00		84507.00

Table 9: **Parameter estimates**

Note: Table shows the parameter estimates of the structural model for three different specifications

		Healthy	Risky
	A	21.5	19.5
	B	23.5	22.5
Santiago	C	7.9	6.5
	D	8.8	12.3
	E	38.3	39.2
	A	15.9	13.4
	B	18.8	16.4
Other Regions	C	3.9	3.0
	D	37.9	44.7
	E	23.5	22.4

Table 10: **Predicted market shares as a function of time-varying observables**
Note: This table shows the predicted market shares for healthy v/s risky and Santiago v/s Other regions based on the structural estimates

s_t/s_{t+1}	1	2	3	4	5	6	7	8	9	10
1	0.41	0.29	0.13	0.05	0.04	0.00	0.02	0.03	0.01	0.01
2	0.18	0.33	0.21	0.09	0.09	0.00	0.02	0.04	0.02	0.02
3	0.08	0.24	0.24	0.15	0.16	0.00	0.02	0.04	0.04	0.04
4	0.05	0.15	0.19	0.19	0.23	0.00	0.01	0.03	0.05	0.08
5	0.06	0.17	0.22	0.22	0.19	0.00	0.01	0.03	0.05	0.06
6	0.23	0.32	0.10	0.06	0.00	0.00	0.13	0.10	0.06	0.00
7	0.14	0.28	0.18	0.07	0.06	0.00	0.09	0.07	0.07	0.04
8	0.11	0.20	0.19	0.11	0.09	0.00	0.04	0.11	0.09	0.06
9	0.03	0.09	0.15	0.12	0.14	0.00	0.03	0.11	0.15	0.18
10	0.04	0.09	0.14	0.18	0.16	0.00	0.01	0.05	0.14	0.19

Table 11: **Health status transition from one year to the next, females at age 25**
Note: Table show the shares of women that are in state s_{t+1} at age 26 among those that were in state s_t at age 25.

s_t/s_{t+1}	1	2	3	4	5	6	7	8	9	10
1	0.65	0.20	0.07	0.03	0.03	0.00	0.01	0.01	0.01	0.00
2	0.33	0.31	0.16	0.08	0.06	0.00	0.02	0.02	0.01	0.01
3	0.18	0.27	0.22	0.14	0.12	0.00	0.01	0.03	0.02	0.02
4	0.13	0.19	0.21	0.21	0.16	0.00	0.01	0.03	0.03	0.03
5	0.17	0.20	0.20	0.16	0.19	0.00	0.01	0.01	0.03	0.04
6	0.48	0.21	0.08	0.00	0.06	0.02	0.06	0.05	0.05	0.00
7	0.35	0.24	0.11	0.04	0.05	0.01	0.11	0.05	0.02	0.01
8	0.16	0.24	0.17	0.10	0.07	0.00	0.04	0.09	0.09	0.04
9	0.07	0.14	0.15	0.12	0.11	0.00	0.03	0.09	0.17	0.11
10	0.07	0.09	0.14	0.13	0.15	0.00	0.03	0.06	0.13	0.22

Table 12: **Health status transition from one year to the next, males at age 25**
Note: Table show the shares of men that are in state s_{t+1} at age 26 among those that were in state s_t at age 25.

s_t/s_{t+1}	1	2	3	4	5	6	7	8	9	10
1	0.42	0.24	0.13	0.05	0.02	0.00	0.04	0.05	0.03	0.02
2	0.17	0.29	0.21	0.09	0.05	0.00	0.04	0.07	0.05	0.03
3	0.09	0.22	0.23	0.15	0.07	0.00	0.03	0.07	0.09	0.05
4	0.05	0.10	0.21	0.23	0.14	0.00	0.01	0.05	0.12	0.10
5	0.05	0.11	0.16	0.20	0.20	0.00	0.01	0.04	0.10	0.15
6	0.28	0.05	0.13	0.03	0.03	0.08	0.23	0.18	0.03	0.00
7	0.14	0.17	0.10	0.05	0.04	0.01	0.17	0.17	0.10	0.05
8	0.05	0.10	0.13	0.09	0.04	0.01	0.08	0.22	0.21	0.08
9	0.02	0.05	0.10	0.10	0.06	0.00	0.03	0.13	0.31	0.20
10	0.02	0.05	0.05	0.08	0.09	0.00	0.02	0.07	0.21	0.41

Table 13: **Health status transition from one year to the next, females at age 55**
Note: Table show the shares of women that are in state s_{t+1} at age 56 among those that were in state s_t at age 25.

| s_t/s_{t+1}	1	2	3	4	5	6	7	8	9	10
1	0.56	0.19	0.08	0.03	0.03	0.00	0.03	0.03	0.02	0.03
2	0.22	0.28	0.18	0.09	0.06	0.00	0.04	0.06	0.04	0.03
3	0.10	0.19	0.22	0.16	0.09	0.00	0.02	0.06	0.08	0.07
4	0.06	0.10	0.15	0.22	0.17	0.00	0.01	0.04	0.12	0.13
5	0.05	0.07	0.11	0.17	0.26	0.00	0.01	0.03	0.10	0.20
6	0.19	0.20	0.07	0.02	0.01	0.07	0.16	0.18	0.07	0.02
7	0.16	0.16	0.07	0.04	0.02	0.02	0.20	0.17	0.10	0.07
8	0.06	0.10	0.11	0.07	0.04	0.01	0.10	0.21	0.18	0.13
9	0.02	0.04	0.08	0.10	0.07	0.00	0.02	0.11	0.31	0.25
10	0.02	0.02	0.04	0.08	0.13	0.00	0.01	0.05	0.17	0.48

Table 14: **Health status transition from one year to the next, males at age 55**
Note: Table show the shares of women that are in state s_{t+1} at age 56 among those that were in state s_t at age 55.

(a) Allocation of healthy individuals
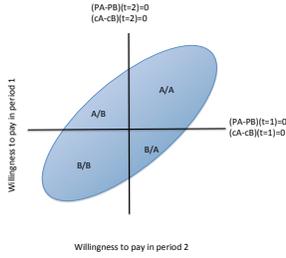
(b) Allocation of risky individuals
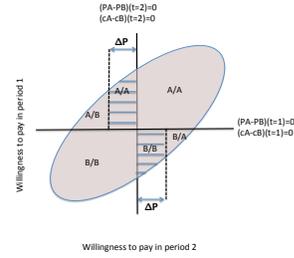
(c) Allocation of risky individuals
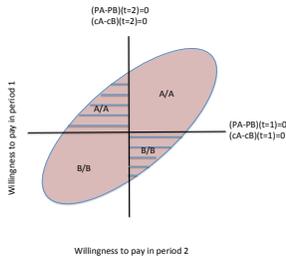
(d) Stable preference heterogeneity
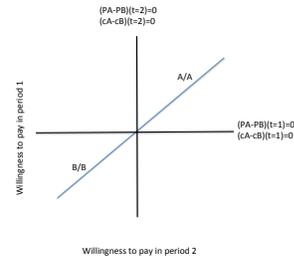
Figure 1: **Allocation with evolving preference heterogeneity and guaranteed-renewability**.

Note: Panel (a) and (b) show the allocation across firms in two time periods, of individuals that have heterogeneous and time-varying preferences for two companies A and B. Panel (a) shows that the allocation of healthy individuals is efficient since in both periods the price they pay in each company is the same. Panel (b) shows that some risky individuals inefficiently stay with their company because they are reclassified in the spot market.
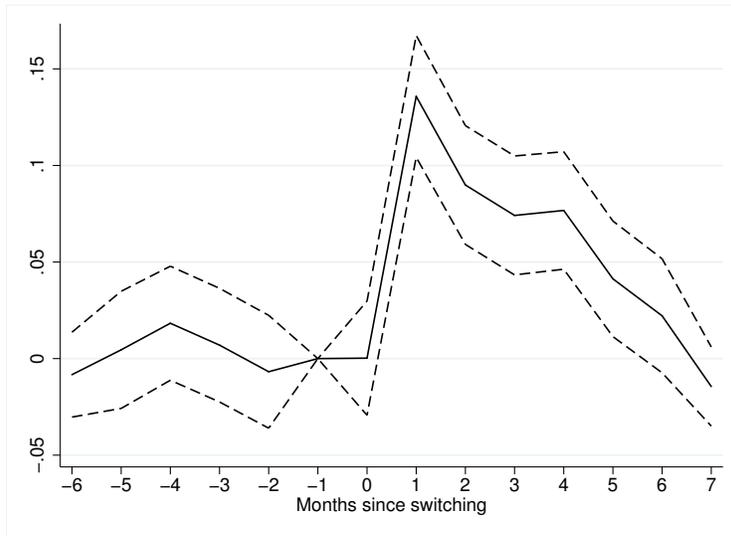
Figure 2: **Probability of seeing a new provider**

Notes: Figure plots the estimated coefficients from an event-study regression of the form given in equation 3. The dependent variable is a dummy indicator for seeing a new health service provider and time zero is the month of switching company. The bands around the point estimates are 95% cluster-robust confidence intervals (clustered at the individual level. The probability of seen a new health service provider after switching company is about 13 percentage points above the baseline the month after switching ISAPRE.

(a) Market share by region

(b) Market share by district with region 1
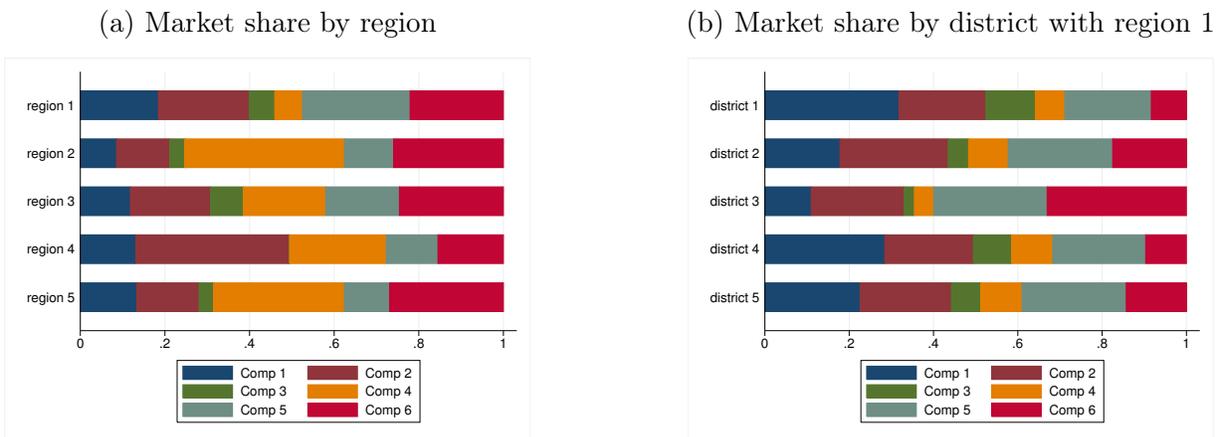
Figure 3: **Market shares by geographic location**.

*Note:*Panel (a) shows the market share of each ISAPRE in the 10 biggest regions of Chile. Panel (b) shows the market share of each ISAPRE in the 10 biggest district of the Santiago region

(a) Company "A"

(b) Company "B"

(c) Company "C"

(d) Company "D"

(e) Company "E"
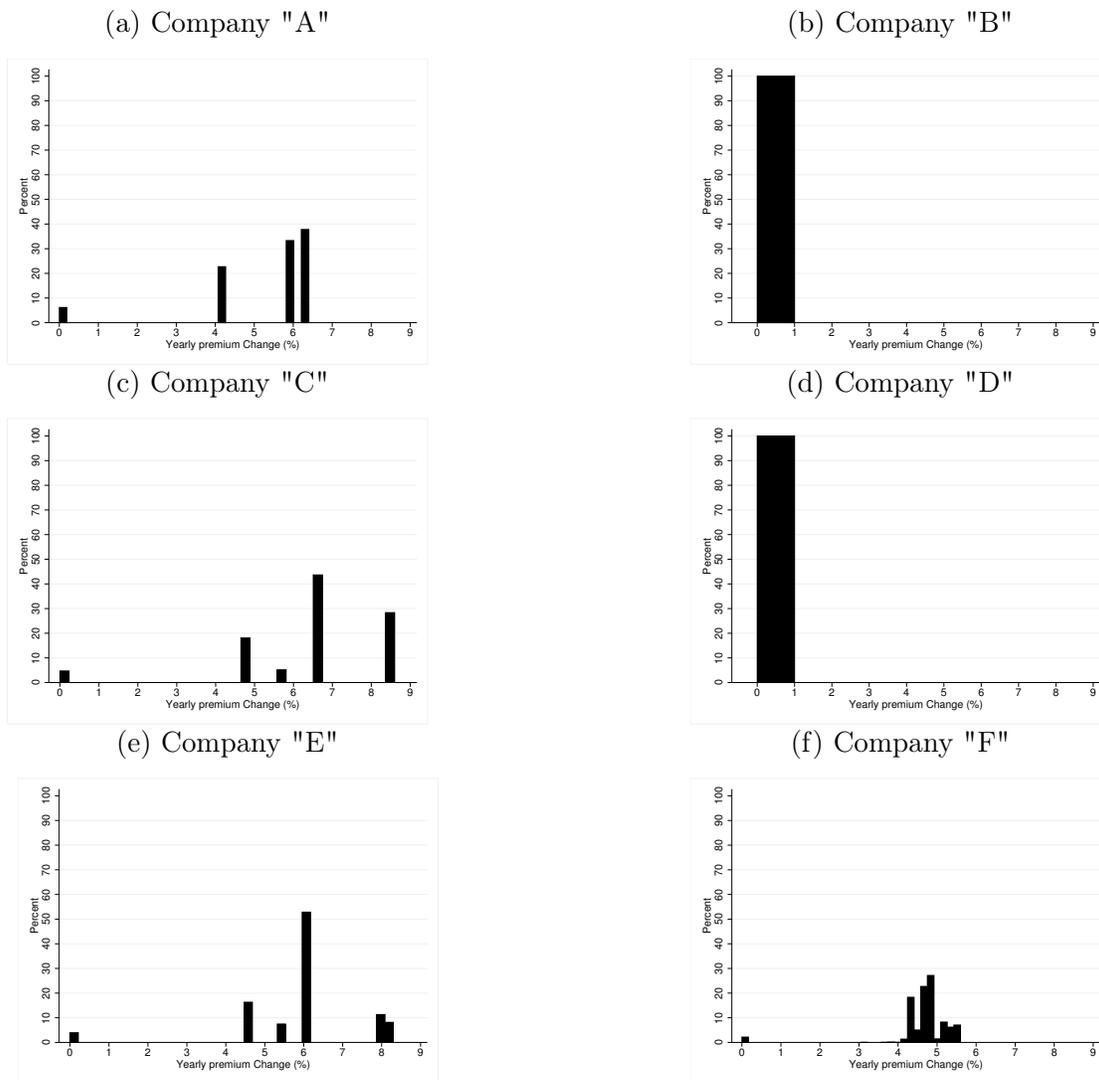
(f) Company "F"

Figure 4: **Premium change by Insurance Company and Year**
Note: This figure shows the histogram of yearly price increases from 2010 to 2011 for each of the six ISAPREs in this study. It shows the practical workings of the "1.3" rule" described in the text that limits the variance of premium increases of contracts.
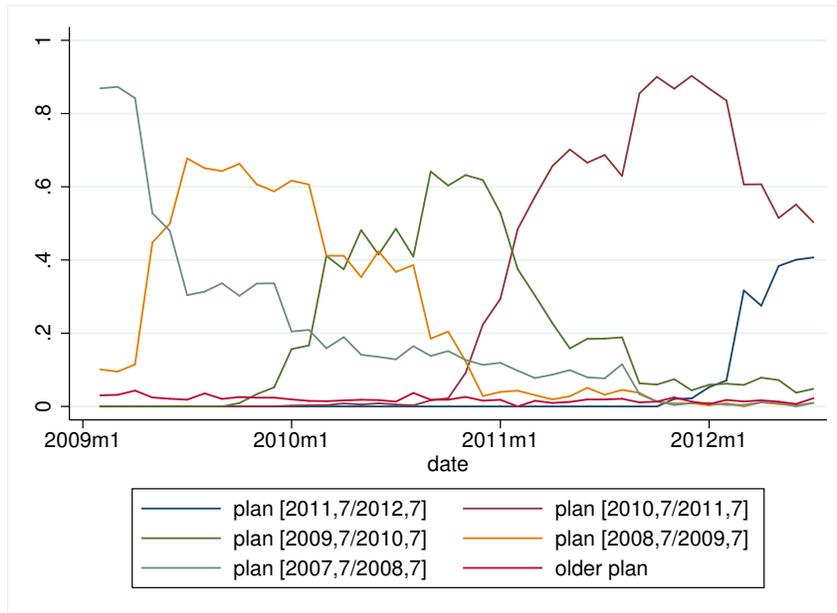
Figure 5: **Cohort of destination plan among switchers across Isapres, by month**
Note: Figure shows the share of switchers across Isapres by cohort of the destination plan at each point in time.
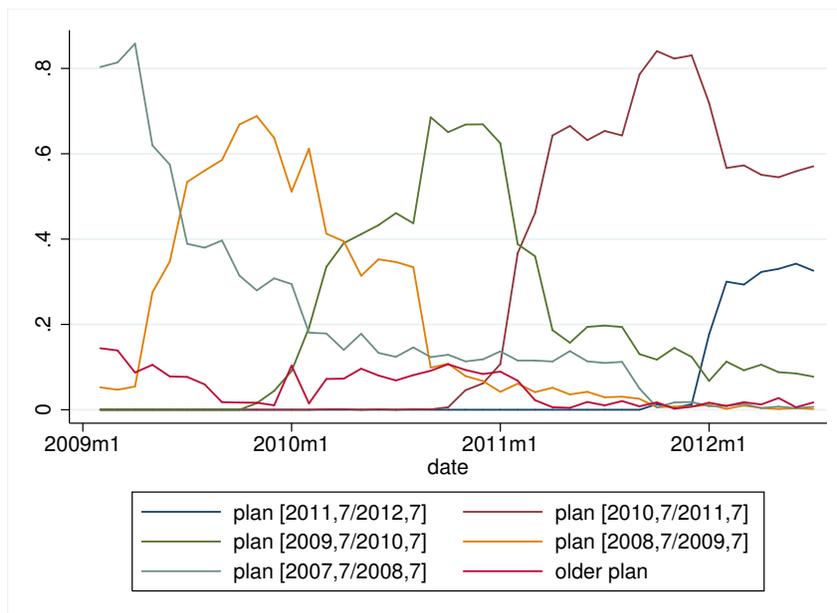

Figure 6: **Cohort of destination plan among switchers across Isapres, by month**
Note: Figure shows the share of switchers within Isapres by cohort of the destination plan at each point in time.
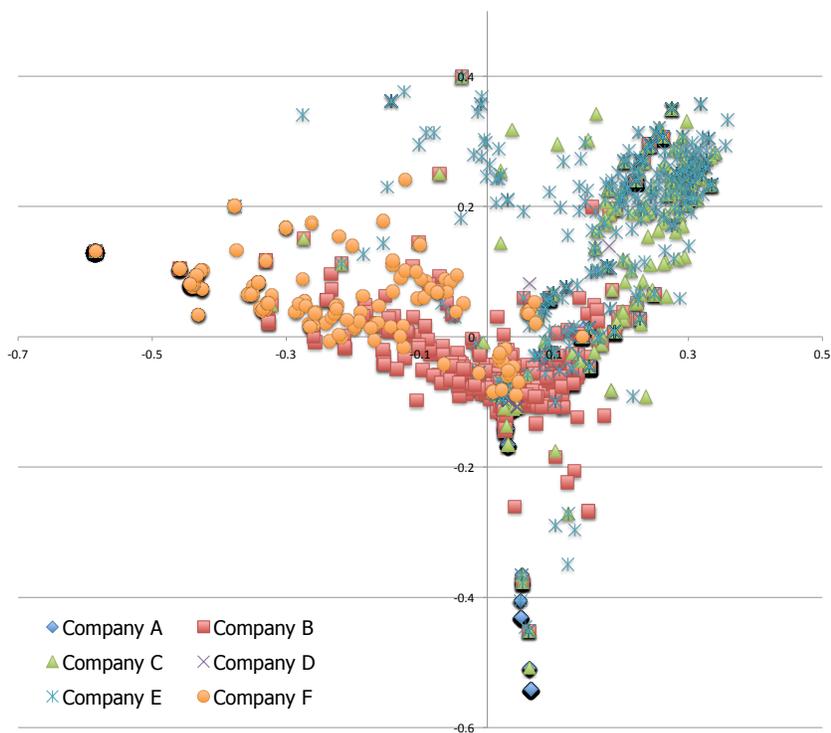
Figure 7: **Provider distance across plans**
Note: Each dot is a restricted network plan in a euclidean plane to represent their distance $d \in [0,1]$ in terms of the provider network. $d = 1$ if two plans do not share any providers. $d = 0$ for two plans with the same network. Colors represent different ISAPRES. 10 % subsample of plans
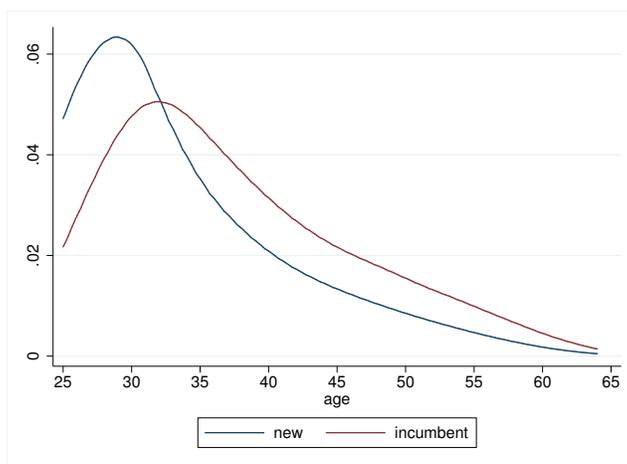
Figure 8: **Age distribution of new and incumbent clients**
Note: kernel density estimate of age distribution among "cohort 0" and new enrollees
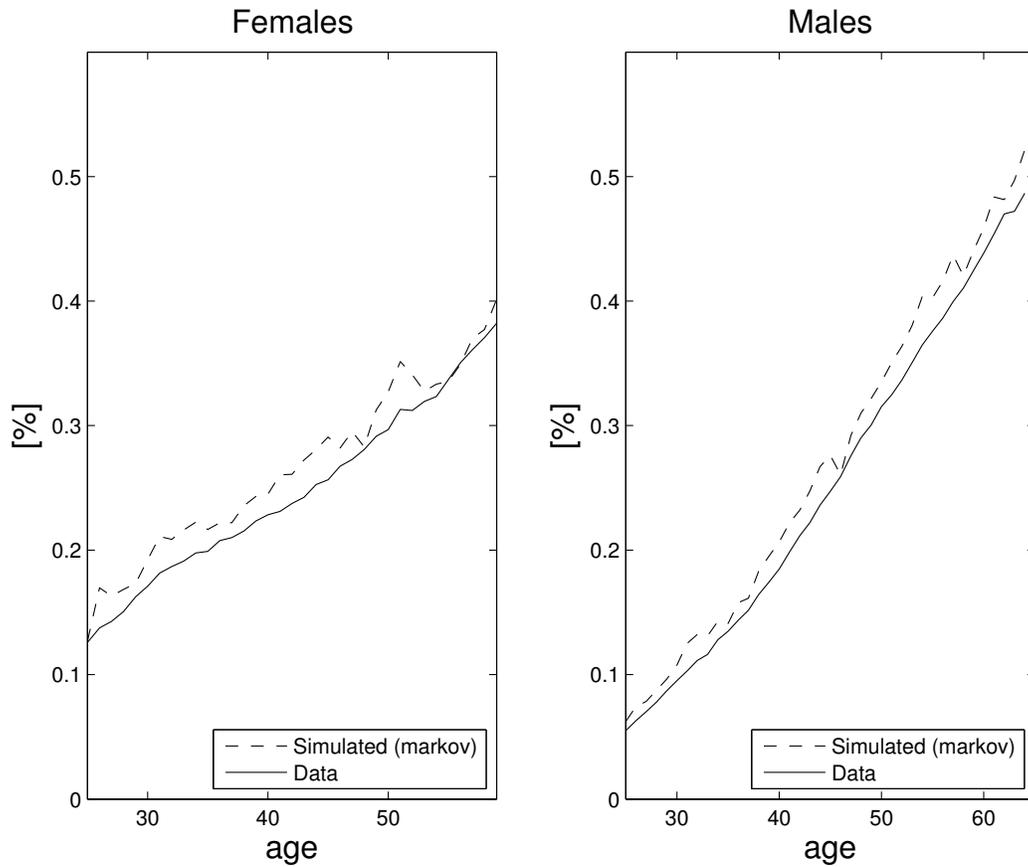
Figure 9: **Predicted and actual prevalence of preexisting conditions**
Notes: This graph shows the real and simulated probability of having a preexisting condition. The left panel is form females and the right panel for males.
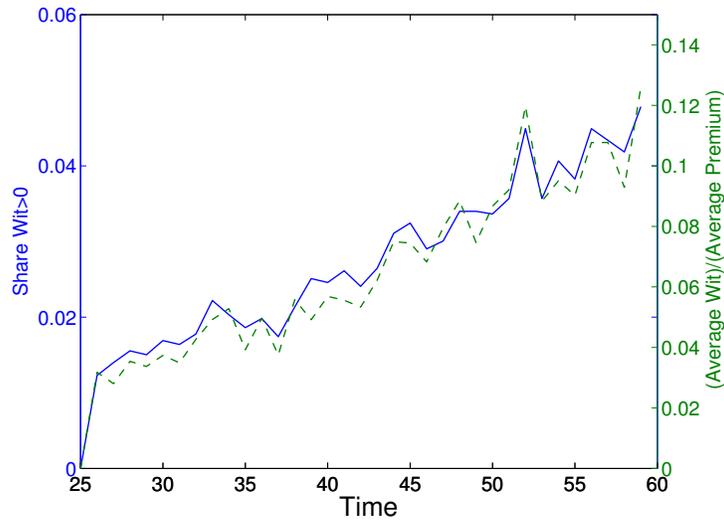
Figure 10: **Share of individuals with $w_i^t > 0$ and average w_{it}**
*Notes:* The full line (left Y axis) shows the share of individuals with w_{it}, as defined by equation 13 using the simulation method described in the text, representing the simulated share of individuals that would have picked a different company if preexisting conditions and risk-rating were banned. The dashed line (right Y axis) shows the average w_{it}
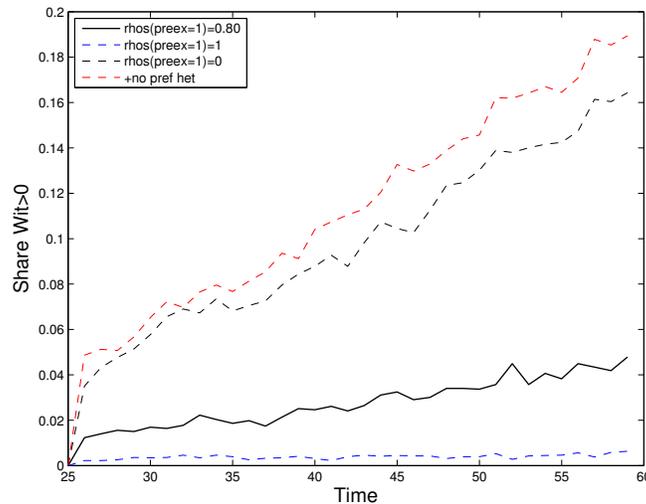
Figure 11: **Share of locked-in individuals under different parameters**
Note: This figure shows the sensitivity of the lock-in result to the parameter estimates. The main results are represented by the full black line, that reproduces the result shown in figure 9. The dashed blue line represents the result assuming no coverage denial, and only assuming premium risk-rating. The black dashed line represents the results in the case of full coverage denial, so that all individuals with preexisting conditions are denied coverage in the spot market. Finally, the red dashed line shows the result with full coverage denial and assuming that there is no stable preference heterogeneity
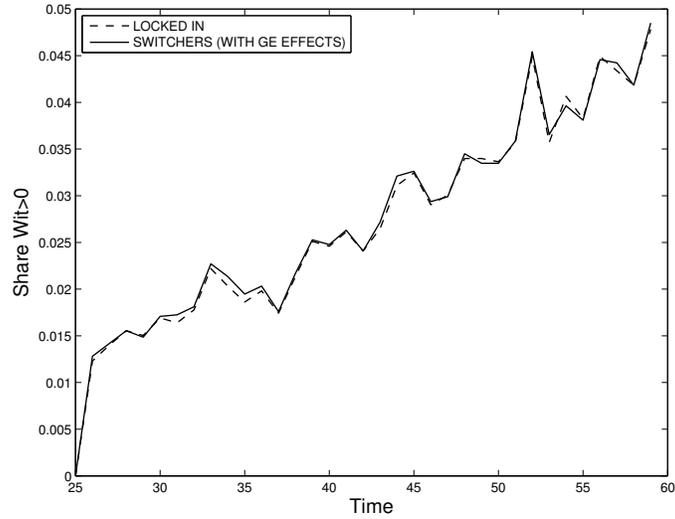
Figure 12: **Simulated difference in switching rates between current policy and counterfactual policy**

Notes: Figure shows the simulated switching rates of the counterfactual policy that bans preexisting conditions and underwritting relative to the simulated switching rates under current policy. Full line corresponds to switching rates across insurance companies and dashed line to switching rates within company.

(a) Average Cost Curves

(b) Marginal Cost

(c) Introducing Preexisting Conditions, No Preference Heterogeneity

(d) Introducing Preexisting Conditions, WIth Preference Heterogeneity
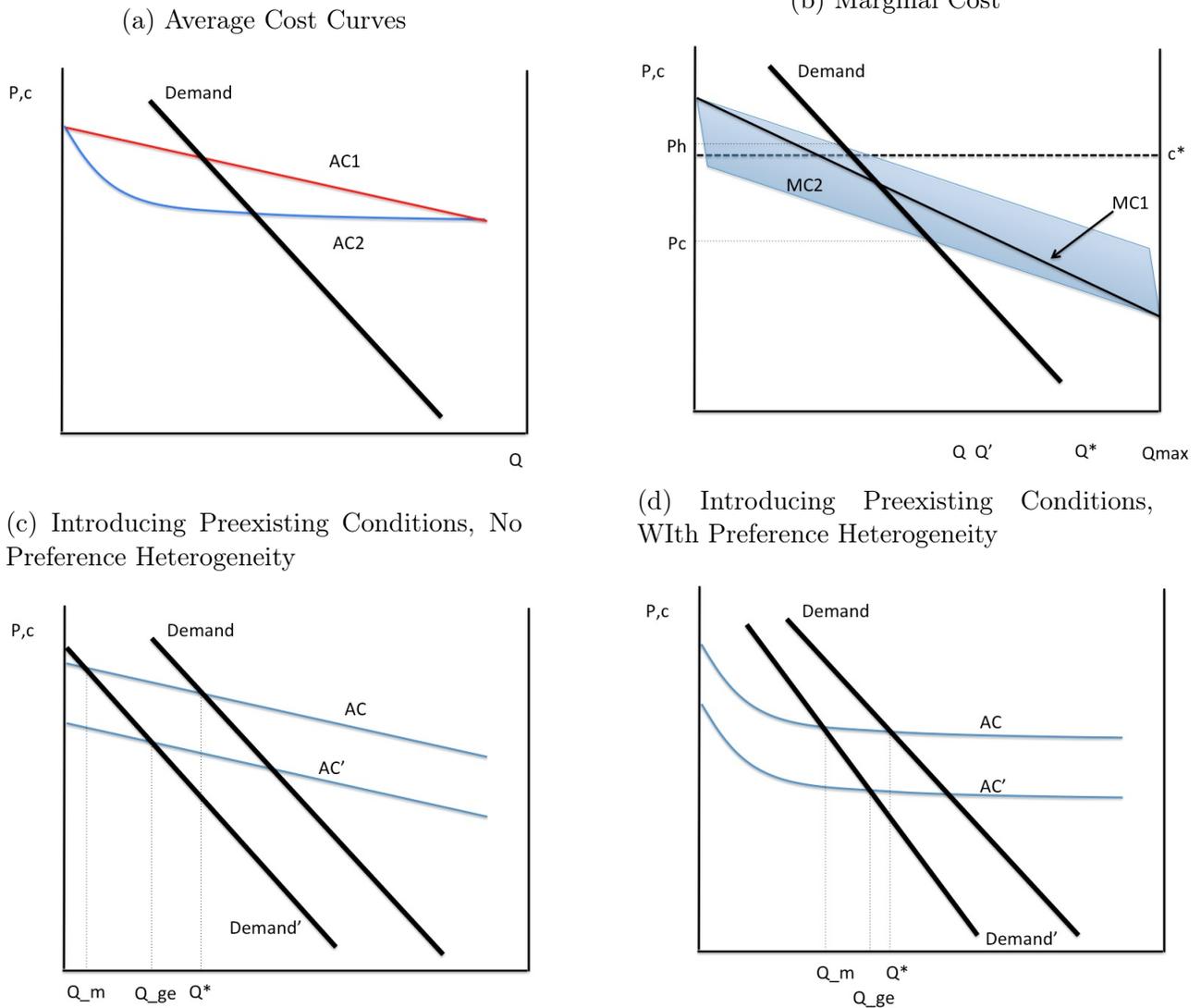
Figure 13: **Equilibrium effects of preference heterogeneity and preexisting conditions**

Notes: Panel (a) shows average cost curves for the case of no preference heterogeneity within risk (AC_1) and for the case of preference heterogeneity within risk (AC_2). Panel (b) shows the respective marginal cost curve (MC_1) and marginal cost correspondence (MC_2). Panel (c) shows the mechanical effect and general-equilibrium effect of introducing preexisting conditions in the case of no preference heterogeneity. Panel (d) performs the same exercise in the case of preference heterogeneity.

9 Appendix

9.1 Multinomial logit for destination company

I specify the multinomial logit among switchers, for the probability that individual i chooses firm k upon switching, as:

$$p_i^k = \frac{e^{X_i'\beta^k}}{\sum_{l=1}^{K} e^{X_i\beta^l}}$$

where β^k are firm-specific coefficients and X_i are individual-specific regressors that include pre-switching health status as well as other demographics. Table 15 shows the estimated β coefficients as well as the χ^2 statistic for the null that all health coefficients are equal to zero. Column (1) corresponds to a specification that only includes a dummy $preex = 1$ of a preexisting condition (equal to one if at any point in the past the individual received treatment related to any condition). Column (2) adds age, gender and (the log) wage. Column (3) replaces the preexisting condition dummy by a dummy of a preexisting condition in the three months prior to switching, $preex_{3m} = 1$. Finally (4) replaces this variable by $log(1 + healthpreex_{3m})$, where $healthpreex_{3m}$ summarizes the total health expenditures related to preexisting conditions in the previous three months. The tables shows the X_4^2 statistic and p-value for the Wald test that all variables related to pre-switching health expenditures are equal to zero.

	(1)	(2)	(3)	(4)
Firm = B				
$preex = 1$	0.139**	0.091		
	(0.054)	(0.063)		
$preex_{3m}$			-0.070	
			(0.121)	
$log(1 + healthpreex_{3m})$				0.044
				(0.176)
Firm = C				
$preex = 1$	-0.096	-0.319***		
	(0.081)	(0.098)		
$preex_{3m}$			-0.627***	
			(0.212)	
$log(1 + healthpreex_{3m})$				-0.685*
				(0.402)
Firm = D				
$preex = 1$	-0.004	-0.009		
	(0.059)	(0.066)		
$preex_{3m}$			-0.245*	
			(0.132)	
$log(1 + healthpreex_{3m})$				-0.228
				(0.226)
Firm = E				
$preex = 1$	-0.228***	-0.241***		
	(0.059)	(0.068)		
$preex_{3m}$			-0.299**	
			(0.132)	
$log(1 + healthpreex_{3m})$				-0.664***
				(0.234)
Demographics	No	Yes	Yes	Yes
N	16943	12971	12971	12427
χ^2_4	47.0	37.6	13.1	12.6
$(p-value)$	(0.00)	(0.00)	(0.01)	(0.01)

Table 15: **Mutinomial logit for destination company among switchers**
Note: Table shows the coefficients of a mulitnomial model estimated by maximum likelihood of the probability of switching to each firm B-E among switchers, as a function of health conditions and other demographics. Firm A is the baseline category. $preex = 1$ is a dummy variable equal to 1 if the individual was treated for a preexisting condition at any point in time before switching. $preex_{3m}$ calculates this indicator using the 3 months before switching. $log(1 + healthpreex_{3m}$ is the log of 1 plus the total health expenditures related to preexisting conditions in the 3 months prior to switching.The χ^2_4 corresponds to the null hypothesis that all coefficients related to health status are jointly equal to zero. The corresponding p-value is in parenthesis. Robust standard errors for multinomial-logit coefficients in parentheses
* p<0.10, ** p<0.05, *** p<0.01

9.2 Market shares for each geographical region

To understand the variation of preferences across geographic areas I investigate the role of "in-network providers". I exploit the geographic variation in the presence of in-network providers of different companies, and show that providers matter for the decision to enroll in a given insurance company.[47] Specifically, I investigate the relationship between in-network providers and market share within each district by estimating:

$$ln\left(mshare_{kd}\right) = \eta_k + \beta NP_{kd} + \epsilon_{kd} \tag{14}$$

where η_k are insurer fixed-effects, NP_{kc} is an indicator variable that is equal to 1 if insurer j has a network provider in district d and ϵ_{kc} is an error capturing other determinants of market share.

Column (1) of the following Table shows the results of estimating equation 14 for all 1934 districts. Column (2) restricts the sample to districts in which all ISAPREs have at least one client (78% of the districts) while column (3) restrict the sample to districts in which also the market is higher than 500 individuals (894 districts).

	(1)	(2)	(3)
NP	0.258***	0.259***	0.321***
	(0.048)	(0.049)	(0.062)
N	1934	1620	894

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 16: **Market share an in-network providers**
Note: Table shows OLS estimates of equation 14

In all three specifications we find that a network provider significantly increases the market share of an insurance company, between 26 % and 32 % depending on the specification. In the following Table we investigate the same relationship with narrower sources of identification by adding region fixed effects (column 2) and province fixed effects (column 3) to equation 14. Using only within-region variation or within province variation we find smaller but still significant effects.

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[47]I identify the presence of in-network providers with the claims data, since claims are classified either done at an "in-network" or at an "out-network" provider.

	(1)	(2)	(3)
NP	0.321***	0.189***	0.118**
	(0.062)	(0.047)	(0.054)
N	894	894	894

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Table 17: **Market share an in-network providers**
Note: Table shows OLS estimates of equation 14

9.3 multinomial logit for initial choice - testing forward-looking behavior

I test for forward looking behavior regarding insurance company enrollment, by testing future health shocks on the current decision of health insurance company using a multinomial logit specification.

	A	B	C	D
$log(1 + h_{i,t})$	0.011	-0.004	0.089**	0.015
	(0.029)	(0.026)	(0.030)	(0.026)
$log(1 + h_{i,t+1})$	0.02	-0.016	0.021	0.014
	(0.017)	(0.017)	(0.024)	(0.017)
$log(1 + h_{i,t+2})$	0.011	0.024	0.024	0.017
	(0.019)	(0.017)	(0.023)	(0.016)
wage	0.000	0.000	-0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
age	-0.031***	-0.029*	-0.034***	-0.029***
	(0.009)	(0.011)	(0.008)	(0.007)
gender	0.302	0.428	2.024***	-0.275
	(0.359)	(0.472)	(0.286)	(0.283)
stgo	-0.365	-0.22	-0.113	-1.713***
	(0.251)	(0.288)	(0.231)	(0.173)
Plan Controls	Yes	Yes	Yes	Yes

Table 18: **Mulitnomial Logit - Active choice as a function of future health expenditures**

9.4 GHK algorithm

Here I give details on the steps to apply the GHK algorithm to a setting with varying choice sets. I adapt the methodology outlined by Geweke *et al.* (1997) and Train (2009).

Assume the following model for U_{it}^{jk}, where j denotes plans and k companies.

$$U_{it}^{jk} = \alpha_i^k + V_{it}^{jk} + u_{it}^{jk}$$

where the α_i^k are treated as random utility $\alpha_i^k \sim N\left(\mu^k, \sigma^k\right)$. Here I incorporate all the (deterministically) time-varying portion of preference heterogeneity discussed in the text in V_{it}^{jk}.

I define $\epsilon_{it}^{jk} = \alpha_i^k + u_{it}^{jk}$ as the composite random error term. I assume that u is an AR(1) process, where I allow autocorrelation within the same plan, and also autocorrelation across plans within a same company. Therefore the composite error has cross-sectional correlation for plans of the same company and time-series correlation for plans of the same company and within the same plan.

Since in the choice set there is only one plan per insurance plus the guaranteed-renewable plan, I drop from here on the j subscript, and denote the GR plan as the GR option. I also drop the i subscript to simplify notation.

Let $\tilde{s} = \{k_1, k_2\}$ be the sequence of chosen options in period 1 and 2 and $E(s)$ the define the vector of stacked error terms across time periods for each individual as

$$E\left(\tilde{s}\right) = \left(\epsilon_1^1, ..., \epsilon_1^K, \epsilon_2^1, ..., \epsilon_2^K, \epsilon_2^{GR}\left(\tilde{s}\right), \epsilon_3^1, ..., \epsilon_3^K, \epsilon_3^{GR}\left(\tilde{s}\right)\right)'$$

This vector depends on $\tilde{s} = \{k_1, k_2\}$ because the ϵ_2^{GR} and ϵ_3^{GR} are defined by the individual's choice sequence. Similarly define

$$A\left(\tilde{s}\right) = \left(\alpha_1^1, ..., \alpha_1^K, \alpha_2^1, ..., \alpha_2^K, \alpha_2^{GR}\left(\tilde{s}\right), \alpha_3^1, ..., \alpha_3^K, \alpha_3^{GR}\left(\tilde{s}\right)\right)'$$

and

$$U\left(\tilde{s}\right) = \left(u_1^1, ..., u_1^K, u_2^1, ..., u_2^K, u_2^{GR}\left(s\right), u_3^1, ..., u_3^K, u_3^{GR}\left(\tilde{s}\right)\right)'$$

I can write succinctly,

$$E\left(\tilde{s}\right) = A\left(\tilde{s}\right) + U\left(\tilde{s}\right)$$

Let $\Omega\left(\tilde{s}\right) = cov\left(E\left(\tilde{s}\right)\right)$. Since u and α are assumed to be uncorrelated

$$\Omega\left(\tilde{s}\right) = cov\left(A\left(\tilde{s}\right)\right) + cov\left(U\left(\tilde{s}\right)\right)$$
$$= \Gamma\left(\tilde{s}\right) + \Sigma\left(\tilde{s}\right)$$

Let $E^K\left(\tilde{s}\right) = M^K \times E\left(\tilde{s}\right)$ where M^K is the matrix such that we are taking differences

with respect alternative K in each period. The M^K matrix is defined as

$$M^K = \begin{bmatrix} M_1^K & 0 & 0 \\ 0 & M_2^K & 0 \\ 0 & 0 & M_3^K \end{bmatrix}$$

where M_1^K is a $K-1$ identity matrix with an added column of $-1's$ in the Kth position. Similarly, M_2^K and M_3^K is a K identity matrix with an added column of -1s in the K position (periods 2 and 3 include in the last column the guaranteed-renewable contract). Let $\Omega^K(\tilde{s})$ be the corresponding covariance matrix

$$\Omega^K(\tilde{s}) = M^K \Omega(\tilde{s})$$

For each sequence $\tilde{s}$, calculate the Choleskly factor $L^K(\tilde{s})$ such that

$$\Omega^K(\tilde{s}) = L^K(\tilde{s})' L^K(\tilde{s})$$

Then I calculate for each sequence $\tilde{s}$ the Cholesky factor of the undifferentiated errors by adding a row of zeros in the Kth row corresponding of each period, resulting in matrix $L(\tilde{s})$. (Train (2009)).

For each choice k in t I define the matrix M_k^t as the N_t identity matrix with an extra column of -1's added in the Kth column. Note that $N_1 = K - 1$ and $N_t = K \ \forall t > 1$ (since the choice in every period after the first includes the choice from each company and the guaranteed-renewable contract). For a given sequence $s = \{k^1, k^2, k^3\} = \{\tilde{s}, k^3\}$, I define the matrix $M(s)$ as

$$M(s) = \begin{bmatrix} M_{k_1}^1 & 0 & 0 \\ 0 & M_{k_2}^2 & 0 \\ 0 & 0 & M_{k_3}^3 \end{bmatrix}$$

I calculate for each sequence $s = (\tilde{s}, K_3)$ the covariance matrix as

$$\Omega(s) = (M(s) L(\tilde{s})) (M(s) L(\tilde{s}))'$$

Finally, I take the Choleksy decomposition of $\Omega(s) = L(s)' L(s)$. [48]

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[48]Note that with this procedure, the $L(K, K, K) = L_K$, the cholesky decomposition of the matrix Ω_K we used to parametrize the model

The matrix $L(s)$ is a $K - 1 + (T - 1) \times K$ lower-triangular matrix.

$$L(s) = \begin{bmatrix} L^{11} & 0 & 0 \\ S^{21} & L^{22} & 0 \\ S^{31} & s^{32} & L^{33} \end{bmatrix}$$

The first $(K-1) \times (K-1)$ elements, L^{11}, correspond to the Cholesky decomposition of the differentiated errors in period 1 for an individual that chose k_1 consistent with s. Then S^{21} is the Cholesky decomposition of the error terms in period 2 with respect to period 1 errors, and so on. Therefore, the the stacked $E(i)$, can be write as a function of series of vector $K - 1 + (T - 1) \times K$ iid errors η_i as

$$\epsilon_i = L(s) \times \eta_i$$

where η_i is a normal iid.

Then, for period 1, we perform the following steps (see Geweke *et al.* (1997))

step

(1)   draw $\eta_1^{1,r}$ s.t. $\tilde{V}_1^1\left(\eta_1^{1,r}\right) < 0$

    $\vdots$

$(c_1 - 1)$ draw $\eta_1^{c_1-1,r}$ s.t. $\tilde{V}_1^{c_1-1}\left(\eta_1^{1,r}, ..., \eta_1^{c_1-1,r}\right) < 0$

(c_1) skip $\eta_1^{c_1,r}$

$(c_1 + 1)$ draw $\eta_1^{c_1+1,r}$ s.t. $\tilde{V}_1^{c_1+1}\left(\eta_1^{1,r}, ..., \eta_1^{c_1-1,r}, \eta_1^{c_1+1,r}\right) < 0$

    $\vdots$

$(K - 1)$ draw $\eta_1^{K-1,r}$ s.t. $\tilde{V}_1^{K-1}\left(\eta_1^{1,r}, ..., \eta_1^{c_1-1,r}, \eta_1^{c_1+1,r}, ...\eta_1^{K-1,r}\right) < 0$

Similarly, for period 2,

step

(1)   draw $\eta_2^{1,r}$ s.t. $\tilde{V}_2^1\left(\eta_1^{1,r}, ..., \eta_1^{K-1,r}, \eta_2^{1,r}\right) < 0$

    $\vdots$

$(c_2 - 1)$ draw $\eta_2^{c_2-1,r}$ s.t. $\tilde{V}_2^{c_2-1}\left(\eta_1^{1,r}, ..., \eta_1^{K-1,r}, \eta_2^{1,r}, ..., \eta_2^{c_2-1,r}\right) < 0$

(c_1) skip $\eta_2^{c_2,r}$

$(c_1 + 1)$ draw $\eta_2^{c_2+1,r}$ s.t. $\tilde{V}_2^{c_2+1}\left(\eta_1^{1,r}, ..., \eta_1^{K-1,r}, \eta_2^{1,r}, ..., \eta_2^{c_2-1,r}, \eta_2^{c_2+1,r}\right) < 0$

    $\vdots$

(K) draw $\eta_2^{K,r}$ s.t. $\tilde{V}_2^K\left(\eta_1^{1,r}, ..., \eta_1^{K-1,r}, \eta_2^{1,r}, ..., \eta_2^{c_2-1,r}, \eta_2^{c_2+1,r}, ..., \eta_2^{K,r}\right) < 0$

and for period 3

step

(1) draw $\eta_3^{1,r}$ s.t. $\tilde{V}_3^1\left(\eta_1^{1,r},...,\eta_2^{K,r},\eta_3^{1,r}\right)<0$

$\vdots$

(c_2-1) draw $\eta_3^{c_3-1,r}$ s.t. $\tilde{V}_3^{c_2-1}\left(\eta_1^{1,r},...,\eta_2^{K,r},\eta_3^{1,r},...,\eta_3^{c_3-1,r}\right)<0$

(c_1) skip $\eta_3^{c_3,r}$

(c_1+1) draw $\eta_3^{c_3+1,r}$ s.t. $\tilde{V}_3^1\left(\eta_1^{1,r},...,\eta_2^{K,r},\eta_3^{1,r},...,\eta_3^{c_3-1,r},\eta_3^{c_3+1,r}\right)<0$

$\vdots$

(K) draw $\eta_3^{K,r}$ s.t. $\tilde{V}_3^K\left(\eta_1^{1,r},...,\eta_2^{K,r},\eta_3^{1,r},...,\eta_3^{c_3-1,r},\eta_3^{c_3+1,r},...,\eta_3^{K,r}\right)<0$

Calculate the simulated probability as

$$P^r = P\left(\tilde{V}_1^1<0\right)\times\Pi_{K>1,K\neq c_1}Pr\left(\tilde{V}_1^K<0\right)\times\Pi_{K,K\neq c_2}Pr\left(\tilde{V}_2^K<0\right)\Pi_{,K\neq c_3}Pr\left(\tilde{V}_3^K<0\right)$$

and

$$P_{GHK}=\frac{1}{R}\sum P^r$$

9.4.1 Σ_K and Γ_K

The first variance I am concerned about is the following:

$$\Sigma\left(s\right)=cov\begin{pmatrix}u_1^1\\\vdots\\u_1^K\\u_2^1\\\vdots\\u_2^K\\u_2^{GR_2}\\u_3^1\\\vdots\\u_3^K\\u_3^{GR_2}\end{pmatrix}=\begin{pmatrix}\Sigma_{11}\\\Sigma_{21}\\\Sigma_1^{GR_2} & \Sigma_2^{GR_2} & \Sigma^{GR_2,GR_2}\\\Sigma_{31} & \Sigma_{32} & \Sigma_{33}\\\Sigma_2^{GR_3} & \Sigma_2^{GR_3} & \Sigma^{GR_3,GR_2} & \Sigma^{GR_3,GR_2} & \Sigma^{GR_3,GR_3}\end{pmatrix}$$

The matrix $\Sigma\left(s\right)$ depends on the chosen sequence s, as each sequence defines the company to which the guaranteed renewable plan en each period belongs to and the corresponding covariances. To normalize the utility of each period, I take differences

with respect to alternative K, resulting in vector $\tilde{u}$ and covariance matrix

$$cov\left(\tilde{u}\right) = \Sigma_K\left(s\right) = \begin{pmatrix} \tilde{\Sigma}_{11} & & & & & \\ \tilde{\Sigma}_{21} & & & & & \\ \tilde{\Sigma}_1^{GR_2}\left(s\right) & \tilde{\Sigma}_2^{GR_2}\left(s\right) & \tilde{\Sigma}^{GR_2,GR_2}\left(s\right) & & & \\ \tilde{\Sigma}_{31} & \tilde{\Sigma}_{32} & \tilde{\Sigma}_{33} & & & \\ \tilde{\Sigma}_2^{GR_3}\left(s\right) & \tilde{\Sigma}_2^{GR_3}\left(s\right) & \tilde{\Sigma}^{GR_3,GR_2}\left(s\right) & \tilde{\Sigma}^{GR_3,GR_2}\left(s\right) & \tilde{\Sigma}^{GR_3,GR_3}\left(s\right) \end{pmatrix}$$

Similarly, we define $\tilde{\alpha}_k = \alpha_K - \alpha_K$, and the corresponding covariance

$$cov\left(\tilde{\alpha}\right) = \Sigma_K\left(s\right) = \begin{pmatrix} \tilde{\Gamma}_{11} & & & & & \\ \tilde{\Gamma}_{21} & & & & & \\ \Gamma_1^{GR_2}\left(s\right) & \tilde{\Gamma}_2^{GR_2}\left(s\right) & \tilde{\Gamma}^{GR_2,GR_2}\left(s\right) & & & \\ \tilde{\Sigma}_{31} & \tilde{\Gamma}_{32} & \tilde{\Gamma}_{33} & & & \\ \tilde{\Gamma}_2^{GR_3}\left(s\right) & \tilde{\Gamma}_2^{GR_3}\left(s\right) & \tilde{\Gamma}^{GR_3,GR_2}\left(s\right) & \tilde{\Gamma}^{GR_3,GR_2}\left(s\right) & \tilde{\Gamma}^{GR_3,GR_3}\left(s\right) \end{pmatrix}$$

To set the scale and level of the utility, I normalize $var\left(u_t^K\right) = 1$, and $\sigma_K = \sigma_{K-1} = 0$, which leads to $Var\left(\epsilon_K^t\right) = Var\left(\epsilon_{K-1}^t\right) = 1$.

9.4.2 Cohort 0

I observe individuals from cohort 0 for 2009, 2010, and 2011. In all these periods they have access to the GR plan as well as the spot plans. The correlation of errors across alternatives in 2009 depends on the entire choice path since individuals entered the market, which unfortunately I do not observe. However, the GHK algorithm makes evident that the choice in 2009 provides enough information about the correlation of errors to estimate the choices in the following years.

Therefore, for cohort 0 I perform a "conditional" GHK estimation, taking their choice in 2009 as given and calculating the likelihood of their choice in 2010 and 2011 given their observed choice in 2009.

Note that cohort 0 in 2009 is comprised by individuals that either stayed in the their contract or switched within their company between 2008 and 2009. Since I cannot observe the GR contract for individuals that switched (and thus cannot construct the menu available to them in 2009), I restrict the sample of cohort 0 only to those that did not switch plans between 2009 and 2010, and thus picked the GR contract in 2009. I identify which are the ones that did not switch based on the tenure of their plans.

- For the sample defined above, I construct the variance-covariance $\Omega\left(k_0, k_1, k_2\right)$ considering the choice in 2009, 2010, and 2011, and the corresponding Cholesky decomposition $L\left(k_0, k_1, k_2\right)$.

- Draw the error terms for each option in 2009 consistent with k_0

- Draw the error terms for each option in 2010 and 2011 consistent with k_1 and k_2

- Calculate the simulated conditional probability, given the choice in 2009, as

$$P^r|c_1 = \Pi_{K \neq c_2} Pr\left(\tilde{V}_2^K < 0\right) \Pi_{K \neq c_3} Pr\left(\tilde{V}_3^K < 0\right)$$

And therefore

$$P_{GHK}|c_1 = \frac{1}{R} \sum P^r|c_1$$

9.5 Average cost curves with preference heterogeneity

Here I provide a simple proof that preference heterogeneity decreases the average cost curve at any price. Assume that there are two preferences, $u_1(h, \epsilon)$ and $u_2(h, \epsilon)$ that generate the same demand curve but such that u_1 entails a entails a higher degree of preference heterogeneity (and normalize $u_1(0,0) = u_2(0,0) = 0$). Under my definition, this means that $\partial u_1/\partial \epsilon > \partial u_2/\partial \epsilon \geq 0$.

For a given preference $r = 1, 2$ I define $u_r(h_r^*, \epsilon) - P \equiv 0$. It follows that $h_2^* > h_1^*$ (both are assumed to exist). Let $f()$ be the marginal distribution of ϵ with corresponding cdf $F()$. The average cost at price P is given by

$$AC\left(P\right) = \int_{-\infty}^{\infty} E_h(h|h > h^*(\epsilon, P)) f(\epsilon) d\epsilon \tag{15}$$

which is increasing in h^*.