



## Price elasticity of expenditure across health care services<sup>☆</sup>

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### ABSTRACT

Policymakers in countries around the world are faced with rising health care costs and are debating ways to reform health care to reduce expenditures. Estimates of price elasticity of expenditure are a key component for predicting expenditures under alternative policies. Using unique individual-level data compiled from administrative records from the Chilean private health insurance market, I estimate the price elasticity of expenditures across a variety of health care services. I find elasticities that range between zero for the most acute service (appendectomy) and  $-2.08$  for the most elective (psychologist visit). Moreover, the results show that at least one third of the elasticity is explained by the number of visits; the rest is explained by the intensity of each visit. Finally, I find that high-income individuals are five times more price sensitive than low-income individuals and that older individuals are less price-sensitive than young individuals.

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### 1. Introduction

U.S. policymakers are debating health care reform options to reduce the large and growing cost of medical care. The Medicare Modernization Act of 2003 and the Affordable Care Act of 2010 both attempt to address this issue, relying crucially on assumptions regarding consumer responsiveness to out-of-pocket costs. To evaluate the potential benefit of different health care reform options in reducing costs, policymakers need a better understanding of expenditure elasticity, i.e., the ways in which consumer demand for

health services changes in response to differences in out-of-pocket costs (referred to as “price” in this paper). Consumers hoping to limit their own out-of-pocket costs respond to price in two ways: by changing the frequency of service or by changing the quality of care to reduce per-visit costs. Understanding how individuals’ trade off frequency and quality is thus crucial for policymakers seeking to control costs.

Unfortunately, there is little empirical evidence on how consumers respond to differences in price and the ways in which this varies by type of health service (e.g., emergency room care, routine visits) and by individual characteristics (e.g., income, age, education, socioeconomic status). This lack of research is primarily due to the difficulty of identifying exogenous, or externally caused, variation in prices. In health insurance markets, individuals select their plans using information that they – and not the provider or insurer – possess about their health status. This “information asymmetry” can lead to selection bias in those individuals who expect to use more services than the average person or the ones that are risk-averse. Thus, any type of health event or shock that is related to the individual’s health status will therefore be correlated with the coin-urance rate of the chosen plan, creating an endogeneity problem that biases estimates for price elasticity.

Only a few studies have been able to identify sources of exogenous price variation in health care usage, and they have been able to

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do so only in limited settings. For example, using the RAND Health Insurance Experiment of the 1970s, Manning et al. (1987) randomized consumers into health insurance plans with varying levels of generosity. Kowalski (2009) and Eichner (1998) used health shocks to individuals with large families who shifted their coinsurance rates (i.e., the percentage of medical expenses, beyond the deductible, that must be covered by the patient) from a fixed amount to zero to estimate the impact of such a change on individual's total expenditures. In these papers, researchers focused on total expenditures but were not able to examine how sensitivity to price varied across different types of health services or different individual characteristics.

In the literature of price elasticity, this is the first paper, to my knowledge, that estimates elasticities in a context of a middle-income country, like Chile. Therefore this could be a good starting point for future research. Moreover, the estimates are comparable to the ones found in the literature for high-income countries, like the U.S.

In this study I use a unique and detailed data set to describe new evidence on how health care consumers respond to changes in the price of care. I describe the ways in which price elasticities vary both by type of health service and consumer demographics. This study uses individual-level census data from the Chilean private health insurance market. Several features of the Chilean data make it useful for understanding the price elasticity of health expenditures in the United States. First, the health care system in Chile incorporates several policy mechanisms currently under debate in the U.S., such as health insurance exchanges, individual mandates, and regulations on the private health insurance system (e.g., premiums based on community ratings and minimum levels of benefits). Second, as in the United States, the private insurance market is a significant part of health care system in Chile. Third, detailed information from five datasets is available concerning patient characteristics, family member characteristics, plan characteristics, and prices (e.g., claims and out-of-pocket expenditure by individual and health care service). I combine these data to construct a panel of plan choices, fees for services at service providers, coinsurance rates and insurer payment caps for all participants in private sector plans. The Chilean health care system is thus an interesting case to study on several levels, and access to the complete private-sector administrative records allows me to analyze the entire population insured under the private system. Finally, the coverage and richness of the data allow me to examine the heterogeneity of price responses, allowing for a richer understanding of consumer behavior in response to differences in price.

The paper is organized as follows. Section 2 provides a brief literature review. Section 3 presents background information on the health insurance system in Chile. Section 4 describes the econometric approach and instrumental variable strategy used in this study. Section 5 describes the data and sample selection. Section 6 outlines concerns with the approach. Section 7 shows the results of the main regressions across health care services for two main types of health services: urgent (acute) health care services and elective health care services, while Section 8 presents a deeper analysis of the price elasticity across age and income. Section 9 outlines the checks for robustness. Section 10 is the conclusion.

## 2. Literature review

Many researchers have tried to quantify the impact of information asymmetry, e.g., the differences between an individual's and a provider's knowledge of the individual's health status, on consumer welfare. Akerlof (1970) and Rothschild and Stiglitz (1976) were the first to formalize the idea of asymmetric information and its impact on insurance markets. Several studies (Einav et al., 2008;

Cohen and Einav, 2007; Finkelstein and Poterba, 2004; Lusting, 2007; Bajari et al., 2006) have examined the presence of asymmetric information in different markets, either testing for adverse selection or quantifying the implications of asymmetric information. Some researchers have attempted to measure moral hazard in insurance markets, e.g., an individual's tendency to take undue risks because he or she is not bearing the cost of those risks (Chiappori et al., 1998; Kaestner and Dave, 2006; Vera-Hernandez, 2003).

Other papers have explored price elasticity in health markets. Using data from the RAND Health Insurance Experiment of the 1970s, Manning et al. (1987) found a price elasticity of  $-0.2$ . Categorizing the sample as nonusers, users only of outpatient services, and users of both inpatient and outpatient services, they found that consumer use of medical services responds to changes in out-of-pocket costs. Furthermore, they found that cost-sharing affects primarily the number of medical visits, rather than the intensity of each of those visits, i.e., the price of each visit. They found similar results for use of outpatient services for both acute and chronic conditions.

The research to date has been unable to address the different types of reactions people have when faced with health shocks, such as car accidents, appendectomies, etc. Furthermore, they have not estimated price responsiveness for different types of health services or for individuals with different demographic backgrounds. Eichner (1998) estimated a basic relationship between total expenditure and out-of-pocket costs using the minimum-distance method.<sup>1</sup> To avoid the selection problem, he incorporated the idea that identical families face different marginal costs as their expenditure suddenly reaches the deductible. He found an elasticity of  $-0.7$ . Kowalski (2009) estimated the price elasticity of expenditure for medical care across groups with varying levels of medical expenditures. In her paper, she addressed three of the main problems present in this market: censoring at zero, the selection problem and the lack of variation across the distribution of expenditures. She used the differences in marginal prices between individuals who have an injured family member and individuals who do not as in Eichner (1998). She found price elasticities to be stable at  $-2.3$  across the 0.65–0.95 quantiles of the expenditure distribution. These two papers share the same limitations: They estimate price elasticity only over total expenditure, focus on subsamples of population, and focus on specific events or changes in price.

In this paper, I address both sets of issues. First, I explore the relationship between individual behavior and both type of health shock (and thus type of health service) and demographic background. Second, I draw on data regarding the entire population of Chileans insured in the private market,<sup>2</sup> not just one particular sub-population or one specific event.

Finally, to my knowledge there is no research on low and middle-income countries on price elasticity of expenditure. However, there are some papers that study income elasticity of health care spending. Musgrove (1983), Hitiris and Posnett (1992) and DiMatteo (2003), studied this elasticity for a group of countries, Latin American countries, OECD countries and US and Canada. All of them found similar results, with elasticities ranging from 1 to 1.5. Also, DiMatteo (2003) found that income elasticities are higher at low-income levels and lower at higher income levels.

<sup>1</sup> This method is described in Newey (1987).

<sup>2</sup> Several papers study the Chilean health insurance market. Some focus on policy (Ferreiro, 2000; Aedo and Sapelli, 1999), others focus on collusion (Agostini et al., 2004), and others study how public and private systems interact (Sapelli and Torche, 2001; Hoffer, 2006; Sanhueza and Ruiz-Tagle, 2002). Few of these papers give a detailed explanation of how the market works, and none of them study asymmetries of information or, in particular, the price elasticity of expenditure on medical care.

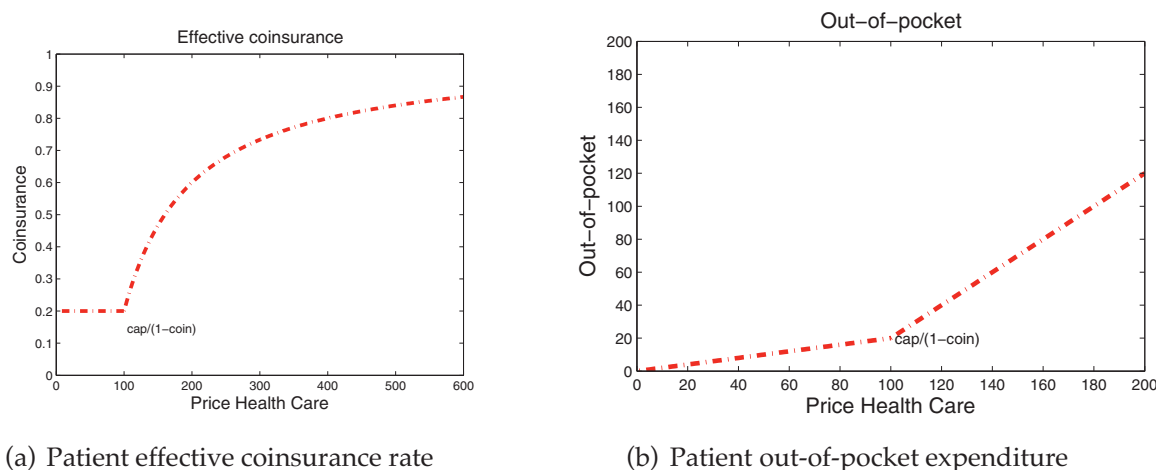


Fig. 1. Effective expenditure: (a) patient effective coinsurance rate and (b) patient out-of-pocket expenditure.

### 3. The health insurance system in Chile

Private<sup>3</sup> and public health insurance systems coexist in Chile.<sup>4</sup> The private system is composed of 13 firms, called Instituciones de Salud Previsional (ISAPREs), which serve approximately 2.5 million people (15% of the population). In 2007, there were 6914 individual and group plans available across all ISAPREs. The public sector is managed by the federal agency Fondo Nacional de Salud (FONASA), which provides insurance to more than 11 million people (70% of the population). The remaining 15% of the population is either enlisted in the Chilean Army or uninsured. Health insurance in Chile is mandatory for salaried workers and retirees. Individuals can switch from public to private insurance at any time. Those insured by a private provider may switch to another private provider once a year (similar to the U.S. system).

The public and private systems differ in many respects, including provider access, premiums, coinsurance structure, insurer payment caps, and exclusions. The public system premium is set at 7% of taxable income, independent of age, number of household members, or other demographic characteristics; in the private system, premiums vary depending on age, sex and various family characteristics. Private system premiums vary, but are set at a minimum of 7% of an individual's taxable income. Coinsurance rates under the public system range from 0% to 20%, depending on family characteristics; private system coinsurance rates range from 0% to 50%. All plans have two coinsurance rates: one for inpatient care and one for outpatient care. Every plan assigns an insurer payment cap to each health care service, and these caps apply to each visit. By law, the caps in each of the plans offered by the ISAPREs must be equal to or higher than the FONASA caps.<sup>5</sup> In the Chilean market, the coinsurance rates and the insurer payment caps remain constant across visits and payments do not accumulate over time. ISAPREs can exclude individuals from coverage based on pre-existing illnesses; however, once individuals are in the private system, they can remain as long they want. Moreover,

an ISAPRE can increase premiums only by 1.3 times the average increase in the other plans it offers.

Several factors in the Chilean private system may contribute to information asymmetry between the individual and health care providers or insurers. First, each individual's health status is known only to him or her (and not the provider), leading to selection bias, in that individuals with pre-existing conditions will tend to select plans with more-generous benefits.<sup>6</sup> Second, the mandatory 7% of income minimum premium may be a source of moral hazard, i.e., a tendency for the individual to use health services more frequently than the person might do otherwise to justify the relatively large cost of the insurance. Third, moral hazard may also result from the relationship between the ISAPREs and medical service suppliers (hospitals and/or physicians). Because the ISAPREs pay health service providers on a fee-for-service basis,<sup>7</sup> and providers may be tempted to increase the number of services they provide.

#### 3.1. Using the insurance

How much can an individual expect to pay for each health care service? For any particular service, a person pays her coinsurance rate. However, if the difference between the service's price and one minus the coinsurance rate is higher than the insurer payment cap, the insurance company will cover only the insurer payment cap for that service. In other words, after hitting the cap, the patient pays the rest. The basic formula of out-of-pocket expenditure is:

$$\text{fee} - \text{minimum}([\text{fee} \times (1 - \text{coinsurance})], \text{cap}),$$

where fee is the price of the health service, "minimum" denotes the lesser number between  $[\text{fee} \times (1 - \text{coinsurance})]$  and the insurer payment cap. For example, suppose the individual wants to visit a general physician. The coinsurance rate is 20%, and the insurer payment cap for general physician is \$90. If she decides to see Dr. X, who charges a fee of \$100 per visit, she will pay \$20. This is calculated by subtracting, the minimum value between \$80 (because  $\$80 = \$100 \times (1 - 20\%)$ ) and the insurer payment cap [\$90]), from the total charge of \$100. If she wants to see Dr. Y, who charges \$200 per visit, she will pay \$110. This is the fee (\$200) minus the cap (\$90), because in this case the insurer payment cap (\$90) is less than \$160 ( $\$160 = \$200 \times (1 - 20\%)$ ). Therefore, if the fee is greater

<sup>3</sup> The private insurance system was implemented in 1981.

<sup>4</sup> There is also complementary insurance is an issue that cannot be addressed in this paper because there is no information about it. However, the premium paid in complementary insurance represent only 12% of the total premium paid in health insurance in the private system. In terms of individuals covered, 2.5 million of individuals has complementary insurance (this number include all the population, 17 million).

<sup>5</sup> FONASA changes these caps once a year, generally in April. The ISAPREs must, in turn, update their caps based on the FONASA caps.

<sup>6</sup> Reporting the pre-existing illness alleviates the adverse selection problem.

<sup>7</sup> For new catastrophic insurance, ISAPREs compensate the providers based on health outcomes, not on services rendered.

**Table 1**  
Characteristics of the private health insurance market (December 2008).

	Market share	Total health expenditure (in millions)	No. of enrollees	Annual expenditure by enrollee
<b>Open ISAPREs</b>				
Colmena	15.10%	\$294.94	419,971	\$702.27
Cruz Blanca S.A.	20.33%	\$316.08	565,144	\$559.29
Vida Tres	4.88%	\$119.75	135,632	\$882.92
Ferrosalud	0.68%	\$7.59	18,862	\$402.54
Masvida S.A.	11.18%	\$153.91	310,968	\$494.93
Isapre Banmedica	20.82%	\$338.01	578,877	\$583.90
Consalud S.A.	22.93%	\$270.78	637,633	\$424.66
<b>Closed ISAPREs</b>				
San Lorenzo	0.18%	\$2.40	4987	\$481.42
Fusat Ltda.	1.25%	\$43.29	34,778	\$1244.73
Chuquicamata	1.34%	\$21.38	37,234	\$574.29
Rio Blanco	0.23%	\$13.19	6471	\$2038.25
Isapre Fundacion	0.93%	\$20.40	25,866	\$788.70
Cruz del Norte	0.14%	\$2.69	3973	\$676.75

All monetary values are in US dollars.

**Table 2**  
Descriptive statistics open ISAPREs plans.

	25 <sup>c</sup>	Median	75 <sup>c</sup>	95 <sup>c</sup>	Mean	Stdv
<b>Overall (individual and group plans)</b>						
Basic premium (in UF)	1.01	1.58	2.52	4.98	2.07	2.12
Outpatient coinsurance <sup>a</sup>	20%	20%	30%	30%	23.06%	8.86%
Inpatient coinsurance <sup>a</sup>	0%	10%	10%	40%	10.59%	13.68%
No. of enrollees <sup>b</sup>	1	4	14	206	59.8	397.73
<b>Individual plans</b>						
Basic premium (in UF)	1.11	1.7	2.79	5.7	2.33	2.39
Outpatient coinsurance <sup>a</sup>	20%	20%	30%	30%	21.79%	9.05%
Inpatient coinsurance <sup>a</sup>	0%	0%	10%	20%	6.81%	10.17%
No. of enrollees <sup>b</sup>	2	5	20	266	73.3	439.8

Note. UF=Unidad de Fomento (1 UF=\$42.41 as of January 2008). In the table, basic premium is not the final premium. The table includes plans that are not currently being sold but are still active for people who had enrolled before the plans discontinued.

<sup>a</sup> Cover number.

<sup>b</sup> There are thousands of plans with fewer than 10 were enrollees.

<sup>c</sup> Percentile.

**Table 3**  
Demographic characteristics of private insurance enrollees, 2007.

Characteristic	Representation
Male	64.12%
Work status	
Salaried worker	90.25%
Retiree	7.39%
Independent worker	2.36%
Lives in Santiago	58.9%
Individual plan <sup>a</sup>	73.84%

<sup>a</sup> Married plans (11.41%) and group plans (14.75%) are also available.

than the ratio between the insurer payment cap and one minus the coinsurance rate, the effective coinsurance rate is higher than the original 20%. Fig. 1a and b shows the effective coinsurance rate and the out-of-pocket expenditure for different general physician fees.

### 3.2. Characteristics of the market

As of December 2008, the private health insurance market included 13 ISAPREs, which are classified into two groups: closed (available only to workers in certain industries) and open (available to all workers). Closed ISAPRE firms are small and, combined, manage only 5% of the private market. Open ISAPREs are larger, with five covering more than 87% of individuals insured in the private market. For the purposes of this paper, I include only open ISAPREs in my analysis. Table 1 shows selected characteristics of the ISAPREs as of December 2008.

Among open ISAPREs, there are more than 40,000 plans; 33,981<sup>8</sup> are individual plans and the rest are group plans (e.g., some unions negotiate directly with the ISAPRE for identical coverage for all union members). Of individual plans, 3451 are available to the public.<sup>9</sup> For each plan, there is an average of 60 policy holders (73 for individual plans).

In Table 2, the basic premium is quoted in terms of an index value called the Unidad de Fomento (UF), which is adjusted daily by the Banco Central de Chile, based on the Consumer Price Index (IPC). Inclusion of the UF (as opposed to the peso) removes the effect of inflation from all my calculations. This basic premium is used to compute the total premium that a policyholder has to pay. Each plan's rates are divided into either outpatient or inpatient services. More than half the population has an outpatient coinsurance rate of 30% or less, and 10% of the population has an inpatient coinsurance rate of 10% or less.

#### 3.2.1. Summary statistics

Table 3 shows the characteristics of the private health insurance enrollees in 2007, the most recent year for which data are

<sup>8</sup> Anecdotal evidence (by talking with people in the industry) suggests that this huge number is driven by the restriction on the premium, the 7% of taxable income. Firms say that they have "to create" different plans with different levels of generosity that have to match the premiums.

<sup>9</sup> This number is from January 2008 data. The rest of the plans are still being used by people who do not want or cannot switch to other plans. In summary, these plans are not available for the public.

**Table 4**  
Descriptive statistics of private insurance enrollees, 2007.

	25 <sup>c</sup>	Median	75 <sup>c</sup>	95 <sup>c</sup>	Mean	Stdv	Public plan mean
Age (years)	33	41	51	66	42.78	12.74	44.3
No. of dependents <sup>a</sup>	0	1	2	4	1.06	1.30	0.7
Taxable income <sup>b</sup>	\$936	\$1532	\$2332	\$2385	\$1561	\$733	\$345
Premium <sup>b</sup>	\$88.8	\$138.4	\$186.2	\$343.9	\$156.6	\$107.7	\$24.15
Premium/income	7.2%	8.1%	10.7%	20.0%	10.3%	5.9%	7%

<sup>a</sup> Not including the account holder.

<sup>b</sup> Monthly. Many policy holders report the maximum taxable income that is set by law (60 UF).

<sup>c</sup> Percentile.

**Table 5**  
Health service usage in the private sector, 2007.

	25 <sup>b</sup>	Median	75 <sup>b</sup>	95 <sup>b</sup>	Mean	Stdv
Services fee	\$6.84	\$18.88	\$35.2	\$128.8	\$44.53	\$187.68
Out-of-pocket <sup>a</sup>	\$0.95	\$4.55	\$11.23	\$50.6	\$15.29	\$85.4
Total annual expenditure						
All families	\$39.3	\$146.3	\$401.3	\$1611.8	\$424.7	\$1249.4
Families spending >\$0	\$60.5	\$173.7	\$441.9	\$1716.5	\$464.6	\$1299.7
Individuals spending >\$0	\$23.7	\$69.3	\$188.8	\$825.3	\$226.9	\$870.0

<sup>a</sup> Includes all health services.

<sup>b</sup> Percentile.

**Table 6**  
Expenditure data, by generosity and coinsurance rate, 2007.

	Total annual expenditure	Individual annual expenditure
<b>Generosity (UF)</b>		
4 ≤ x < 9	\$802	\$430
9 ≤ x < 11	\$953	\$517
11 ≤ x < 14	\$977	\$609
14 ≤ x < 19	\$1411	\$904
19 ≤ x	\$1513	\$1155
<b>Coinsurance inpatient–outpatient</b>		
0–0%	\$1310	\$828
20–0%	\$1061	\$615
30–10%	\$1039	\$626
30–30%	\$1173	\$641

Note. I calculated the measure of generosity by taking a simple average of insurer payment caps of the most popular health care services by plan that people used. Monetary values in dollars, except generosity.

available for the insured population. Most policyholders are male (64%) salaried workers (90%) who are enrolled in individual plans (73%) and live in Santiago.<sup>10</sup>

Further details are available in Table 4, which shows distributions of age, number of enrollees, and taxable income. Most enrollees are young: The average policy holder is 42 years old and has 1.06 dependents. Enrollees in the 75th percentile have an average of two dependents, which represents a typical married couple with 1 child. The table shows that the market is composed mainly of people in the upper-middle income bracket; the median income is close to four times the minimum wage.<sup>11</sup> The 95th percentile of enrollees pays a monthly premium of \$343.90, which represents a large family with an expensive plan. The average enrollee has a premium that is 8.1% of his taxable income, which is close to the 7% minimum. However, some policy holders pay more than this amount because they have larger families or desire better coverage.

Table 5 shows expenditure data for health care services used in 2007. Among all private-sector enrollees in 2007, 8.58% used no health service. Among those who used at least one health service, outpatient services constituted 91.16% of services used. 39.9% of health care users were males and more than 60% were females.

Table 6 shows annual expenditures on health care by generosity of the insurer, i.e., the average amount of insurer payment caps for the most popular health care services within each plan. As expected, health care service usage increases when plan generosity increases. As shown in the table, the plans are divided into four groups defined by similar inpatient–outpatient coinsurance rates, and there is no direct relationship between coinsurance rate and total medical expenditure.

## 4. Econometric estimation

### 4.1. Empirical approach

I based my empirical approach on a two-period utility model (see Appendix A). The structure of the Chilean system is an ideal environment for studying price elasticity across health care services because there are distinct insurer payment caps for each health care service. In the empirical model, I examine the impact of a measure of plan generosity on expenditure. In particular, I estimate the following regression for several health care services that are classified as either acute or elective care:

$$\log(h_{ist}^*) = X_{ist}^{p(i)} \beta + \epsilon_{ist} \quad (1)$$

where  $i$  is an individual,  $p(i)$  is the plan that individual  $i$  chose,  $s$  is health care service and  $t$  is time period. I assume that  $\log(h_{ist}^*)$  is the logarithm of the expenditure in health service  $s$ , by individual  $i$  in time period  $t$ .  $X_{ist}^{p(i)}$  are individual, plan and health services characteristics, including a measure of the expected coinsurance rate for health care service  $s$  at time  $t$  in plan  $p(i)$ ,  $\epsilon_{ist} = \nu \zeta_{ist} + \varepsilon_{ist}$ , where  $\varepsilon$  is drawn from a normal distribution and  $\zeta_{ist}$  is an unobserved shock (for the insurer and the econometrician). This could be either an acute or elective health shock, the latter of which is a shock related with the known, existing health status of individual  $i$ . Furthermore,  $\log(h_{ist})$  is the observed logarithm of the medical expenditure, which is described by the following equation as a typical corner solution model, together with Eq. (1) (Tobit model):

$$\log(h_{ist}) = \max\{0, \log(h_{ist}^*)\} \quad (2)$$

<sup>10</sup> More than half the population of Chile resides in the capital city of Santiago.

<sup>11</sup> The minimum wage in Chile is \$159,000 pesos (US\$300) per month.



4.2. Endogeneity

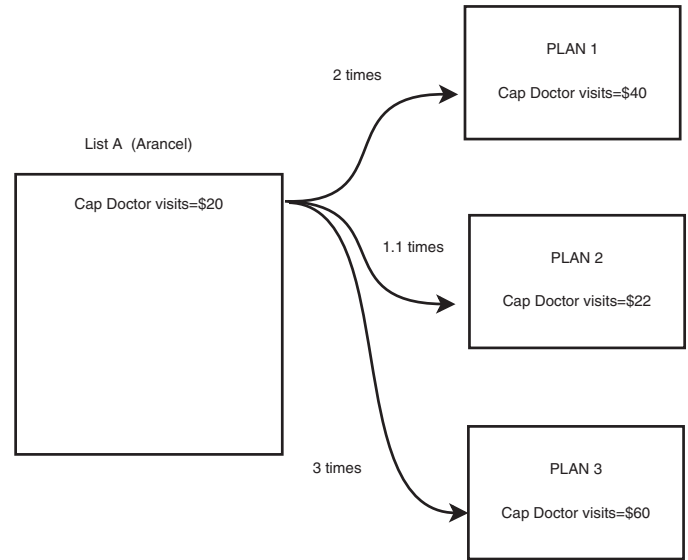
In this paper, I use instrumental-variables techniques to estimate price elasticity only for elective care. I assume that health shocks that do not result from known health status (e.g., a car accident, appendicitis) will not be correlated with the coinsurance rate. Therefore, endogeneity is not a concern for acute care health services because these are unforeseen conditions.

If the vector of plan characteristics  $X_{ist}^{p(i)}$  includes a measure of generosity, I would assume that the measure is not correlated with an acute health shock incorporated in  $\epsilon_{ist}$ , although it is correlated with non-acute (elective) shocks incorporated in  $\epsilon_{ist}$ . To estimate reliable coefficients from Eq. (1), I must first construct a correct measure of generosity that summarizes both the cap and the coinsurance rate because these two figures determine out-of-pocket expenditures. In previous studies this was not possible because price heterogeneity was not available. Second, I need instruments to address endogeneity.

4.2.1. Measure of plan generosity

In the Chilean private health insurance system, the two important prices in each plan are the coinsurance level and the insurer payment cap. When individuals choose their plans, they consider out-of-pocket expenditure as a combination of cap and coinsurance rate. The coinsurance rate is set for each plan (i.e., is unchanged across services within each plan), but caps differ across health care services. These two prices (coinsurance rate and cap) can be summarized into a single price for a health care service by calculating an *expected effective coinsurance rate* by plan and health care service.

I calculated the expected effective coinsurance rate for plan  $p$  and health care service  $s$  using provider fees (which vary) and out-of-pocket expenditure. For example, suppose that individuals in plan  $p_0$  can choose from four different psychologists. The psychologists charge \$100, \$120, \$120 and \$140 per session. Assume that for plan  $p_0$ , the cap for psychologist visits is \$90 and the coinsurance rate is 20%. The out-of-pocket expenditures for each of these prices in plan  $p_0$  are: \$20, \$30, \$30 and \$50, respectively,<sup>12</sup> and the effective coinsurance rates for psychologist visits in plan  $p_0$  are 20%, 25%, 25% and 35.7%, respectively. Thus, the effective expected coinsurance rate in plan  $p_0$  will be the average of the four effective coinsurance rates: 26.42%. For plan  $p_1$ , I observe that individuals go to different psychologists, who charge the same amount, \$100 per session. If plan  $p_1$  has a cap of \$90 and coinsurance rate of 30%, then the expected effective coinsurance rate for these psychologists in plan  $p_1$  is 30%. (Given the cap and coinsurance rate, the out-of-pocket expenditure is always \$30). To check the robustness of this calculation, I experimented with different ways of calculating the figure. I use this distribution instead of the distribution of fees in the market for health care services for two main reasons. First, if I use all the market prices, I'm assuming that the individual can go to any provider; however, there are geographical issues that make individuals go only to some providers. Second, I think this is the best proxy for the choice set that each individual has. On the other hand – for robustness checks purposes – I use the distribution of fees in the market for health care service  $s$ , which resembles the Currie and Gruber (1996) calculations of simulated instruments. I also use a uniform distribution of fees. Full details are in Section 7. The results using these other distributions are very similar in magnitude to the main results.



(a) Link between caps and arancel

Fig. 2. Arancel. Link between caps and arancel.

4.2.2. Instrument

I next turn to the instrument variable, which I assume is necessary only for elective care. The instrument will be defined by the exogenous cap change induced by the public insurer in April.

• Elective care

After speaking with several doctors, I developed a short list of health care services that could be classified as elective.<sup>13</sup> Then, I narrowed this list to the most popular services based on the number of users. The final list included three elective health care services: home visits, psychologist services and physical therapy evaluations, all of which provide a sufficient number of observations to support this analysis. Table 7 shows the distribution of cap changes for the three elective services I study in this paper.

The expected coinsurance rate is affected by the cap set by insurance providers. By law, private insurance companies must offer caps that are equal to or higher than public caps; these caps must be updated annually following the public insurer annual update. Each private insurance company has a unique<sup>14</sup> list of caps (the arancel) that is linked with its plans. Suppose that insurance company A has an arancel called **List A** and offers three plans: **Plan 1**, **Plan 2** and **Plan 3** (see Fig. 2). The cap for doctor visits in **Plan 1** is equal to 2 times the cap for doctor visits listed in the arancel of company A (**List A**). The cap for doctor visits in **Plan 2** is 1.1 times the cap for doctor visits found in **List A**. Finally, the cap for doctor visits in **Plan 3** is 3 times the cap for doctor visits. Thus, the caps for each health care service are linked to the cap that appears in the unique list of caps (arancel), which in this example is **List A**. Private insurance companies update each plan after public updates by changing the arancel, which is linked to every plan. From the point of view of each individual,

<sup>13</sup> Doctor visits, home visits, psychologist, psychiatric, physical therapy evaluations. I am not using doctor visits because for that code there are many different specialties that are impossible to separate. I did not choose psychiatric because is less popular than psychologist.

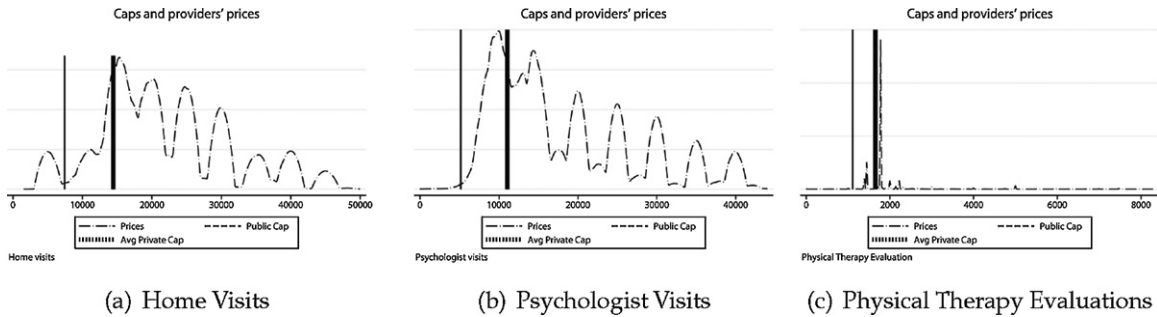
<sup>14</sup> In reality, the private insurance companies manage more than one list of caps. However, more than 90% of the plans are linked to lists that are updated each April.

<sup>12</sup> Remember that the formula is fee – minimum([fee × (1 – coinsurance)], cap).

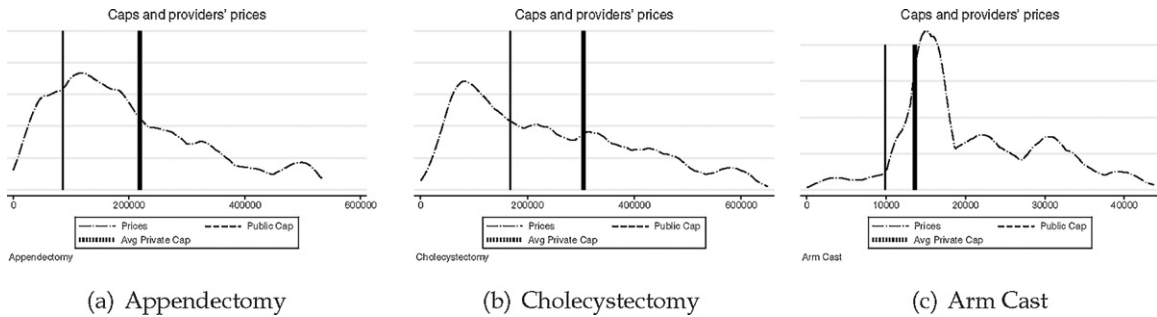
**Table 7**  
Change in the caps.

	25 <sup>a</sup>	Median	75 <sup>a</sup>	90 <sup>a</sup>	Mean
Home visits	0%	0.5%	1.67%	6.46%	1.55%
Psychologist	0%	0.41%	1.76%	4.25%	1.34%
Physical therapy evaluations	0%	0.06%	1.97%	7.7%	1.52%

<sup>a</sup> Percentile.



**Fig. 3.** Elective care: caps and providers fees. (a) Home visits; (b) Psychologist visits; and (c) Physical therapy evaluations.



**Fig. 4.** Acute care: caps and providers fees. (a) Appendectomy; (b) Cholecystectomy; and (c) Arm cast.

this change is an exogenous shock to prices, and therefore a very good instrument to use.<sup>15</sup>

I made estimates of elasticities using a Tobit regression with endogenous variables. The instrument is a dummy for time, to which I assign the value of 1 after April when the annual public change in caps induces the private-sector change in effective expected coinsurance rates. Because the change occurs in April, I divided the year into three periods: (1) January to April, (2) May to August and (3) September to December. I divided the year into three time periods so that I could (1) calculate coefficients using time periods of the same length and (2) analyze data from the entire year. I calculate total expenditure on health care services separately for each period. The control variables are number of dependents, age, gender, income, dummies for insurance companies, a dummy for residence in the capital city (Santiago) and dummies for winter time. These variables control for demographics that may affect an individual's decision of how much to spend on health care.

• Acute care

I assume that an acute health shock is randomly drawn from a distribution of shocks common to all individuals. The individual does not choose a health insurance plan assuming that he or she is likely to experience an acute care shock. Here, self-selection is produced only by the types of people, not by the distribution of

acute conditions. Formally, the unobservable health shock is not correlated with the expected coinsurance rates.

To address acute care, I selected three specific health care services: appendectomy, cholecystectomy (gallbladder removal) and arm cast.<sup>16</sup> Each of these is clearly an acute condition requiring sudden, unexpected services. As I did with elective care, I divide the year into three periods. I also use the same controls: age, gender, income, number of dependents, dummies for insurance company, dummy for winter time and a dummy for residence in Santiago. Figs. 3 and 4. show the distribution of fees for health care services I study in this paper. The cap of the public insurer and the average cap of the private insurance companies are marked by vertical lines.

**5. Data**

I used a unique data set that contains information on all individuals with private health insurance in Chile in 2007. The data include age and gender of all the insured, relation of the insured to the policyholder, wage of the policyholder, type of worker (policyholder), ISAPRE chosen, date of subscription to the plan, insurance premium, inpatient and outpatient coinsurance rates, fee of health care services, out-of-pocket expenditure for each individual and dependents, and type of provider. Furthermore, I used an additional data set that includes information on the characteristics of

<sup>15</sup> In a following section I address a reviewer's comment about possible anticipation issues.

<sup>16</sup> These are illnesses or conditions that cannot be explained due to medical history.

the plans offered, such as the list of caps for each plan<sup>17</sup> (aranceles), basic premium,<sup>18</sup> type of plan, and whether the plan is offered. These data sets are provided under confidentiality restrictions by the *Superintendencia de Salud*, the government agency that regulates the private health insurance market. I used the data on claims for each beneficiary during 2007 to estimate price elasticity across health care services. These data include an identification number for health care service used, the provider that offered this health care service, the fee that the provider charged for the health care service, the amount of money covered by the plan and the out-of-pocket expenditure paid. The detail of the data permits the estimation of price elasticity by individual health care services and for individuals with different backgrounds.

### 5.1. Sample selection

The sample is drawn from the entire private market, which covers more than 2.5 million people.<sup>19</sup> I included only individual plans from open ISAPREs (870,000 policyholders) in the estimation. For these individuals, the main selection criterion is a continuous enrollment restriction, common use in the literature.<sup>20</sup> Because the outcome of interest is expenditure across three time periods – with April playing a key role in the generation of the instrument – the final sample includes only policyholders who are enrolled for the entire year in the same plan (620,962 policyholders).<sup>21</sup> This sample is not representative of the Chilean population.

After cleaning the data and imposing the restriction of continuous enrollment, I limited the final sample to policyholders with plans that have available effective expected coinsurance rates. For some plans, there is no information available on these rates. Ultimately, the final sample includes 480,866 policy holders.<sup>22</sup> The differences between the initial sample (620,962) and the final sample (480,866) are not substantial: Average age is 48 and 44, respectively; average number of dependents is 0.88 and 1.06; the percentage of females is 48% and 48%; average premium is \$170 and \$150; average income is \$1560 and \$1547. I ran several tests to check for the similarities between these two samples. I cannot reject the hypothesis of equal average for female and income. For the rest of the variables, the test shows different averages among both groups. However, these differences seem to be small compared with the differences between the sample of private individuals and the Chilean population. All the results can be applied to populations with similar characteristics.

Because caps show up only when they are used,<sup>23</sup> there is a different sample size for each health care service. The samples are similar in terms of demographics: The mean age is around 42, the mean number of dependents is around 1.17, and the taxable income is a little different across samples. Even though the difference is small, I ran a specification using the smallest sample available for all the health care services without missing prices as a robustness

<sup>17</sup> There are missing caps for some health care services and some plans. Therefore the sample sizes are different across health care services.

<sup>18</sup> Remember that the total premium is calculated according age, gender and family size. To calculate the total premium, each plan has a basic premium and a table with numbers that multiplied the basic premium and which depend on age and gender.

<sup>19</sup> There are 1.2 million policyholders and 1.3 million dependents.

<sup>20</sup> I follow each individual during 2007.

<sup>21</sup> I impose this restriction to estimate the elasticities without including changes in the policy.

<sup>22</sup> This is the largest sample size; there are 321,017 individuals in the smallest.

<sup>23</sup> This is not a problem because there are thousands of plans.

**Table 8**

Average value of the expected coinsurance rate, 2007.

Coinsurance rate	Home visits	Psychologist	Physical therapy evaluations
Before annual change	43.14%	55.04%	49.01%
After annual change	41.60%	53.43%	47.32%

check. These results are similar using any of the sample size.<sup>24</sup> The main problem here is the attrition between the sample of 620,000 individuals and the 480,000. However, both samples are almost identical in terms of most demographic characteristics. Therefore, I think the results could be applied to whole sample.

## 6. Additional concerns

I have sought to address five potential concerns about the econometric approach. The first concern is related to the fact that health providers can update their fees when they see the regulatory change being realized. Thus, the instrument can move the expenditure by changing the fee of providers. Fig. 5 shows the distribution of fees for the health care services selected in each period of time, which are very similar. (I ran several Kolmogorov–Smirnov tests that reveal only small differences between the distributions.<sup>25</sup>) It seems, therefore, that the instrument is not moving the fee of the providers in a critical way. A second concern is that the estimations could be affected for some health care services due to seasonality (i.e., changing demand for health services at different times of year). Among the health care services analyzed, only expenditure on home visits presents a possible problem during the winter time. To test the impact of seasonality, I ran a regression using only two time periods: January–April and September–December.<sup>26</sup> The results are very similar across health care services.<sup>27</sup> A third concern is that individuals can anticipate the change in the caps, and can wait for the change and use the service after the change (for elective care). However, in Appendix C there are graphs showing the distribution of expenditure before and after the change; these graphs show no differences in the distributions (I ran several Kolmogorov–Smirnov tests that reveal no differences between the distributions.). Another concern is my choice of health care services to analyze. I use the most popular health care services – in terms of number of consumers – and those that can be easily categorized as either elective or acute care services. I considered only those health care services that involve a doctor visit.

Finally, there is a concern regarding whether the instrument has sufficient power. Table 8 shows the average value of the effective expected coinsurance rate for the health care services selected before the change and after the change. This average is calculated using the expected coinsurance rate of each plan. The change for home visits decreases from 43.14% to 41.60% (a –3.56% shift), for psychologist visits it decreases by –2.92%, and for physical therapy evaluations the change is –3.44%. These changes are large enough to differentiate between coinsurance rates before and after the annual change. Furthermore, the  $R^2$ s of the first stage for elective health care services are higher than 0.13 and the F statistics are larger than 10.

<sup>24</sup> The elasticities for expenditure on home visits, psychologist visits and physical therapy evaluations are very similar (as are the results for appendectomies, cholecystectomies and arm casts).

<sup>25</sup> Some differences are not significant. There is one time period for physical therapy evaluations in which the differences are large.

<sup>26</sup> In Chile, winter lasts from May through August.

<sup>27</sup> I discuss the results in Section 8.



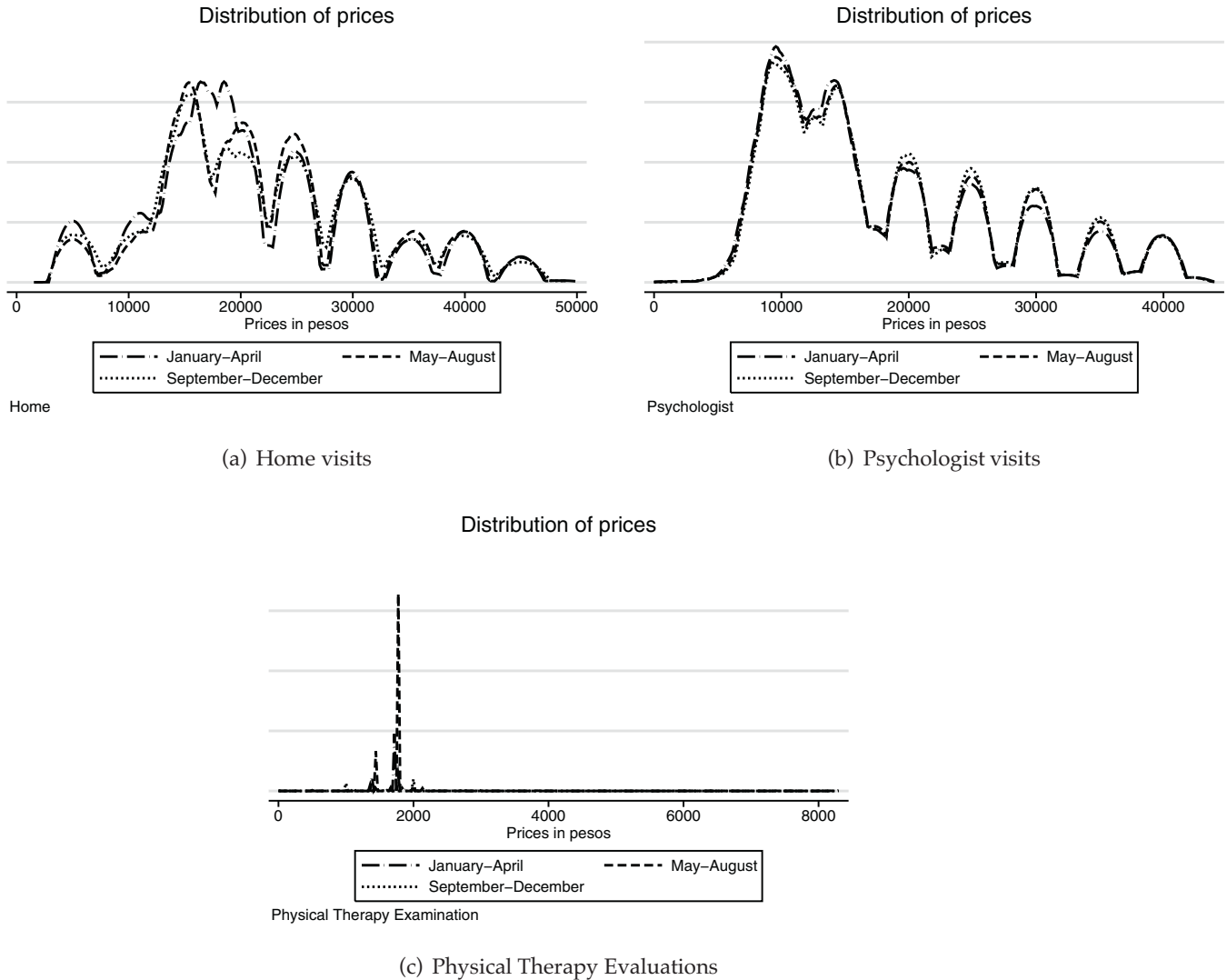


Fig. 5. Distribution of fees by time period: (a) home visits, (b) psychologist visits, and (c) physical therapy evaluations.

7. Results

7.1. Elective care

Table 9 shows elasticities for elective care. The estimates were calculated by using Eqs. (1) and (2). The top half shows the first stage of the two-step estimation. The second half shows the estimation derived from maximum likelihood. Findings for elective services show some sensitivity to price among consumers. Elasticities associated with the expected coinsurance rate range from  $-2.08$  to  $-0.32$ .<sup>28</sup> The elasticities for expenditure on home visits and psychologist visits are similar to each other and can be interpreted as evidence of moral hazard, i.e., individuals reacting to out-of-pocket prices.<sup>29,30</sup> For the other variables, the coefficients

have the expected sign, except for the coefficient on wage for home visits which is negative. This could be caused by the fact that low-income individuals are older than high-income individuals in this market; therefore this could be driving the results because older individuals used more home visits than younger ones. However, there is not a clear explanation for this result.

If we look at the magnitude of the elasticity in terms of expenditure for psychologist visits, for example, we find that the estimates imply that if the expected effective coinsurance rate for psychologist visits falls by one standard deviation (from 55.71% to 39.69%), expenditure will increase from \$153.56 to \$245.13 per period. If the expected effective coinsurance rate decreases by 10% (from 55.71% to 50.13%), total expenditure increases 20% (from \$153.56 to \$185.51).

Now, if we look at the effect in terms of the distribution of costs, the observed elasticity implies that if the expected coinsurance rate

<sup>28</sup> These findings are in line with Kowalski (2009) and Eichner (1998).  
<sup>29</sup> Even though I did not use doctor visits in the paper, the estimated elasticity for doctor visits is  $-1.014$ , almost half of the home visits elasticity.  
<sup>30</sup> The results for exogenous Tobit are smaller in absolute value, indicating that adverse selection is not present in this market (advantageous selection). This is

plausible given the possibility of cream skimming from the private to the public system. In one recent national survey, more than 85% of the individuals in this market reported being in good, very good or excellent health.

**Table 9**  
Price elasticities for elective care services (IV Tobit regressions).

Endogenous variable: total medical expenditure			
	Home visits	Psychologist	Physical therapy evaluations
<b>First stage</b>			
Instrument	−0.070 (0.0006)	−0.075 (0.0006)	−0.125 (0.0006)
R <sup>2</sup>	0.1535	0.2449	0.1135
Number obs.	1,300,357	1,442,600	1,140,343
Mean expenditure	\$65.92	\$153.56	\$11.75
Std. Dev. expenditure	\$80.51	\$264.59	\$17.65
<b>Second stage elasticities</b>			
Coinsurance	−1.886*** (0.118)	−2.081*** (0.083)	−0.321*** (0.029)
Wage	−0.068*** (0.019)	0.149*** (0.007)	0.044*** (0.002)
Mean coinsurance	48.4%	55.71%	50.54%
Std. Dev. coinsurance	16.89%	16.02%	20.62%

Standard errors are in parentheses.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

for home visits increased by one standard deviation (moving the rate to 65.29% from 48.4%), an individual in the 95th percentile of the distribution of expenditure would spend \$48.83 per period (a savings of \$94.04), which would place him or her in the 50th percentile of expenditure distribution. I find similar results for psychology services – an individual in the 95th percentile reduces expenditures to match those found in the 75th percentile when the coinsurance rate increases by one standard deviation.

Therefore, the results show that individuals react to the generosity of plans (i.e., by taking undue risks because they do not bear the full cost of the plan – moral hazard), taking into consideration selection issues. Thus, this finding suggests that policies that increase coinsurance rates for elective care could reduce health care costs. However, a deeper analysis is needed to account for possible welfare effects due to these policy changes.

## 7.2. Acute care

For this paper, I looked at three types of acute care services: appendectomy, cholecystectomy (gall bladder removal) and arm cast setting. The elasticities for these three acute services are low (see Table 10).<sup>31</sup> These results are consistent with the idea that individuals facing urgent or semi-urgent health needs are less responsive to price. For example, if the expected coinsurance rate for appendectomy declines one standard deviation – from 32% to 8.58%; expenditures increase 3.2%, from \$684.97 to \$707.52. Arm cast data are not quite the same because setting a cast is much less expensive than the other services. Therefore when individuals face these types of health shocks do not show moral hazard.

The literature on price elasticity from the 90s, 80s and 70s shows similar results to the ones presented by Manning et al. (1987), which in turn are quite different from the results in Eichner (1998) and Kowalski (2009). Unfortunately, Manning et al. (1987) and other papers in this literature, which are summarized in Zweifel and Manning (2000), use data from 30 or 40 years ago, making direct comparisons with current estimates difficult. Eichner (1998) uses more recent data to estimate price elasticity, but only report results for total expenditures. Kowalski (2009) on the other hand uses recent data and presents estimates both for total expenditures and specifically for outpatient expenditures. Since outpatient expenditures are more likely to be composed of elective

procedures this allows for a reasonable comparison with the results in this paper. Interestingly although individuals in Chile and in the U.S. are different on several dimensions, the results from this paper are quite comparable to the ones found in Kowalski (2009) and both point to the fact that individuals facing these elective services are very elastic. Kowalski (2009) find an elasticity of −2.3 for total costs and an elasticity between −2.04 (for the 65 quantile) to −2.13 (for the 95 quantile) just for outpatient expenditure.

## 8. Other analysis

In this section, I present a deeper analysis of the paper's main price elasticity estimates. The results highlight the importance of demographic variables in explaining variation in price responsiveness (see full results in Appendix B).

### 8.1. Number of visits

Consumers respond to price either in two ways: by changing the frequency of service consumption or changing the quality of care to reduce per visit costs. Understanding how individuals substitute frequency and quality is crucial for policymakers seeking to control costs and at the same time maintaining quality of care. In this section I examine the price elasticity for the number of visits across services.<sup>32</sup> This regression is similar to Eqs. (1) and (2), but instead of using total expenditure on the left hand side, I use number of visits.

Overall, the results show that at least one third of the elasticity is explained by the number of visits, whereas the rest is due to the intensity of each visit. The elasticity for frequency of home visit is −0.490, which is almost one third the elasticity of total expenditures on home visits. For psychologist visit, the elasticity for the number of visits is −0.78, 40% of the price elasticity for total expenditure.<sup>33</sup> Finally, the elasticity is −0.204 for physical therapy evaluations, which explains more than 60% of the price elasticity over total expenditure. This estimate can be explained by the fact that the number of visits is skewed toward 1 for physical therapy evaluations because of the nature of the visit (i.e., it is only a preliminary evaluation).

<sup>32</sup> As we know,  $\log(\text{total expenditure}) = \log(N^* (1/N) \sum_i \text{prices}_i)$ , where  $N$  is the number of visits and  $\text{prices}_i$  are the prices of each visit. I can separate the effect over total expenditure into two parts: the  $\log(N)$  and  $\log(\text{avg.price})$ .

<sup>33</sup> The elasticity for doctor visits is −0.936, explaining more than 90%.

<sup>31</sup> These mirror the Manning et al. (1987) results.

**Table 10**  
Price elasticities for acute care services (Tobit regressions).

Endogenous variable: total medical expenditure			
	Appendectomy	Cholecystectomy [gallbladder removal]	Arm cast
Number obs.	586,696	520,282	803,231
Mean expenditure	\$684.97	\$1019.34	\$51.93
Std. Dev. expenditure	\$473.49	\$570.05	\$29.94
<b>Elasticities</b>			
Coinsurance	−0.045 <sup>***</sup> (0.011)	−0.07 <sup>**</sup> (0.009)	−0.028 <sup>***</sup> (0.010)
Wage	0.124 <sup>***</sup> (0.025)	0.130 <sup>***</sup> (0.020)	−0.008 (0.011)
Mean coinsurance	32.00%	22.96%	42.22%
Std. Dev. coinsurance	23.42%	19.63%	16.90%

Standard errors are in parentheses.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

## 8.2. Distribution of demographics

Two of the most important demographic variables are income and age.

### 8.2.1. Income

I separated the sample into four groups based on income. The result (Table 14 in Appendix B) show that higher-income individuals have greater responsiveness to price than do low-income individuals.<sup>34</sup> For example, the highest-income patrons of psychologist services have an elasticity that is more than five times that of the lowest-income quartile (−1.108 vs −6.20). For physical therapy evaluations, the differences are smaller, high-income individuals are almost three times more responsive to price than are low-income individuals. For home visits, the results are two times higher. One possible explanation is that high-income individuals are better able to calculate out-of-pocket expenditures and search across health providers. In Chile, income and education are correlated (although all private enrollees generally hold at least secondary education<sup>35</sup>). Using the EPS 2006 (Social Protection Survey – 17,000 heads of household), a random panel for Chile, I calculated the correlation between a measure of literacy and income categories. The correlation was positive, which means that if income increases, people make fewer mistakes regarding (or better understand) financial literacy and simple calculations. These findings are supported by previous studies, in particular Hastings and Tejada-Ashton (2008), who showed that financial literacy is associated with greater price sensitivity.

Another possible explanation of this income-based heterogeneity is related to the variety of available fee structures. High-income individuals can easily move between expensive and average priced medical services. However, low-income individuals are constrained in their ability to substitute between fees – they already subscribe to the least-expensive services. This limitation implies that low-income individuals can respond only by forgoing medical care.

To test for this, I ran a regression by income group, using as an endogenous variable the number of visits. I did this to better understand how individuals substitute medical care, whether through reduced frequency or reduced quality (see Table 15 in Appendix B). Comparing these results with the price elasticity of total expenditure by income (see Table 14 in Appendix B), we see that the

relative importance of the number of visits over the total elasticity decreases with income level. For psychologist, the frequency explains 74% of the elasticity of total expenditure at the first quartile of income, then 46% at the second, 32% at the third and finally 17% at the fourth quartile of income. For physical therapy evaluations and home visits the pattern is similar (see Table 16 in Appendix B). This means that for low-income individuals, the price elasticity for the number of visits explains a higher percentage of the price elasticity of total expenditure than it does for high-income individuals. This evidence shows that low-income individuals forgo medical care more often than do high-income individuals.

### 8.2.2. Age

A second specification takes age into account. I separated the sample into five groups based on age. For the first quintile age group (average age of 27 years), price elasticity is the highest for psychologist visits and physical therapy evaluations, but not for home visits. The oldest quintile – with an average age of 62 years – is the least sensitive to changes in price. For both psychologist visits and physical exams, this group has a price elasticity that is less than one quarter that of any younger group. The age specification results are not conclusive for home visits. For each age group, price elasticity does not move in a set direction. The third quintile (with an average age of 40 years) has the highest elasticity (−2.355), and the youngest quintile has the lowest price elasticity. The fourth quintile has lower elasticity than the second and third quintiles (see Table 17 in Appendix B).

These results suggest that older consumers may be less responsive to price because they have difficulty computing expected expenditures or they have less information on health alternatives. On the other hand, they may have strong preferences for their providers or believe that switching costs across doctors are high. Support for the former stems from Salthouse (1996), who showed that performance in some cognitive tasks (test of limited time and simultaneity mechanisms) declines after age 60; also, this is consistent with Agarwal et al. (2007), who showed that older consumers pay higher fees and face higher interest rates than do middle-aged consumers in a variety of contexts. These two explanations, however, have very different policy implications. It is therefore necessary to conduct a deeper analysis that provides stronger conclusions.

Table 18 (in Appendix B) shows the price elasticity over number of visits. The fraction of the elasticity explained by the frequency is stable across age for each health care service. For home visits, the frequency explains an average of 25% (between 22% and 30%) of the elasticity of total expenditure; for psychologist services, it explains an average of 35%; and for physical therapy evaluations it explains

<sup>34</sup> “Low-income” with respect to the distribution of income in the private sector.

<sup>35</sup> Low-income individuals in this market are similar to blue-collar individuals here in the U.S. in terms of wage and education.

**Table 11**  
Elasticities across studied services (IV Tobit and Tobit regressions).

Endogenous variable: total medical expenditure						
	Home visits	Psychologist	Physical therapy evaluation	Appendectomy	Cholecystectomy [gallbladder removal]	Arm cast
Coinsurance	−1.750*** (0.3133)	−2.490*** (0.3443)	−0.703*** (0.2026)	0.003 (0.0326)	−0.009 (0.022)	−0.095** (0.040)

Standard errors are in parentheses.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

**Table 12**  
Elasticities across studied services (IV Tobit and Tobit regressions).

Endogenous variable: total medical expenditure						
	Home visits	Psychologist	Physical therapy evaluation	Appendectomy	Cholecystectomy [gallbladder removal]	Arm cast
Coinsurance	−1.86*** (0.1182)	−2.063*** (0.083)	−0.321*** (0.029)	−0.046*** (0.0133)	−0.07*** (0.0117)	−0.036*** (0.012)

Standard errors are in parentheses.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

an average of 66%. This evidence suggests that older and younger consumers are equally willing to switch providers. Thus, I cannot conclude that older consumers stay with their doctors more than younger consumers.

## 9. Robustness checks

For robustness checks, I ran additional regressions using different samples and controls to check the previous results.

### 9.1. Plan fixed effects

Of the more than 40,000 thousand plans in the Chilean system, only 1100 have 100 or more policyholders. Thus, I drew a random sample of 25% of the population restricted to these plans, for a sample size of 238,894 policy holders. Then I ran a regression using plan fixed effects and another using insurance company fixed effects, as in the main regression. The results were similar in both regressions.

For elective care, the elasticities are −1.57 for home visits, −1.84 for psychologist visits and −0.25 for physical therapy evaluations. None of the coefficients are significant. The results for acute care are similar, but also not significant.

### 9.2. Distribution of prices in the market

I calculated the expected coinsurance rate using only the fees faced by individuals within a plan. To ensure that the results are not driven by the distribution of fees used to calculate the expected effective coinsurance rate, I used the whole distribution of fees for each health care service. For that purpose I looked for the distribution of fees in the market for each health care service, then using the caps and the coinsurance rates for each plan/health care service, I re-calculated the effective expected coinsurance rate. The results (see Table 11) are similar to the ones using the distribution of fees for individuals within a plan.

### 9.3. Two time periods

To address the seasonality problem, I ran a regression using only two time periods, dropping the winter time period (see Table 12).

The estimates are similar to the main results of the paper. However, it is not possible to identify a possible seasonality effect.

## 9.4. Yearly expenditure

As discussed previously, one of the key assumptions of this paper is that individuals self-select into plans only according to health status at the moment of selection. Therefore, for acute care, it is not necessary to use instruments, and the natural regression uses total expenditure by year.<sup>36</sup> The results for the price elasticity over annual expenditure are similar to the ones found in the main regression. For appendectomy, the elasticity is −0.071, for cholecystectomy the elasticity is −0.098 and for arm cast the elasticity is −0.064. These results show that the setting of three periods does not drive the results of the estimates.

## 10. Conclusions

By using detailed and previously unavailable administrative data from Chile, this paper presents new empirical evidence on how health care consumers respond to prices. The analysis takes advantage of unique institutional features of the Chilean system to resolve identification biases that limited previous research on the price elasticity for health care.

I found that consumer response varies by type of health service. Specifically, individuals are more sensitive in their demand for elective care (home visits, psychologist and physical therapy evaluations) than for acute care (appendectomy, cholecystectomy [gallbladder removal] and arm casts). The estimated demand elasticities for elective health care are −1.88, −2.08 and −0.32, respectively, whereas the demand elasticities for acute health care are close to zero. The results on elective care are comparable to the ones found by Kowalski (2009) for a U.S. population. I also estimated the price elasticity for the number of visits. I found that almost one-third of the elasticity for expenditure on home care is explained by the number of visits (extensivity) and two-thirds by the intensity (the price of the health service) of each visit. For psychologist visits, the number of visits explained 40% of the elasticity; for

<sup>36</sup> “Natural” in this context means that all the literature based the estimates on yearly total expenditure.

physical therapy evaluations, the number of visits explained 60% of the elasticity.

Given the richness of the data, I extended my analysis to examine how demographic factors affect price elasticity. I found that price sensitivity increases with income and decreases with age. The results for high-income people may be due to the fact that high-income individuals are better at calculating complicated out-of-pocket expenditures because they are more educated. On the other hand, it is possible that this income-based heterogeneity is related to the variety of available pricing structures, with high-income individuals able to more easily move from one physician to another than low-income individuals. These results reveal heterogeneity in price responsiveness based on types of services and demographics. Several robustness checks, using two time periods and alternative distributions for prices, support these main findings.

One of the main concerns in the U.S. health care reform debate is the challenge of predicting and controlling health care costs. This paper addresses these points by quantifying expenditure elasticity and revealing how it varies. Policymakers can use this paper's results, for example, to understand how coinsurance rates or other features of the insurance plan might vary based on the type of service or demographic characteristics of the consumer. These design measures would allow policymakers to mitigate consumers' tendency to overuse unneeded care and would reduce average health care expenditures, regardless of whether instituted by private or (if established) a public insurance provider.

Although this paper provides a deeper understanding of consumer behavior in health markets, there remain unresolved questions for future research. I do not address preventive care, which may have important policymaking implications. For example, we do not know how consumers respond to changes in the price of preventive care and to what extent they will use free (subsidized) preventive care services. Understanding this topic may prove useful to further controlling future health care expenditures. In future research, I plan to study the impact of preventive care on future medical expenditure.

Some of the paper's results need to be explored further. Specifically, understanding what drives the low levels of price responsiveness among older individuals is of the utmost importance in both academic and policymaking arenas. Is it that this population is not well informed of the pricing structure, or is it that they cannot understand the calculations involved in pricing? A formal experiment may help illuminate this topic by examining how new information alters consumer behavior for older consumers.

On a final note, the results of this study are applicable to this particular population, which is younger, healthier and richer than the Chilean population as a whole. Therefore, we need to exercise care in applying the results to other samples. Nonetheless, the findings provide a starting point for moving in that direction.

## Appendix A. Model

This is a model of endogenous consumer demand for health insurance and health care use. Individuals have private information about their health status at the time of making the decision of which health insurance plan to purchase. The asymmetric information arises because (1) the insurance companies know the distribution of types but not the specific individual type and (2) they use prices of health care services to calculate the amount of money covered and not actual health status.

### A.1. Timing

There are two time periods in the model. In the first period the individual draws a health status  $\theta_i$  (or type), which is private

information, from a distribution  $F(\cdot)$  that is common knowledge. Also, she has to choose which health insurance plan to purchase, which translates into a choice of premium and coinsurance function. In the second period, the individual faces one of two types of health shocks that I assume are independent: one of which is drawn from a distribution that depends on the type  $\theta_i$  and another that is drawn from a distribution of commonly experienced health shocks. After the shock is realized, and conditional on the plan's characteristics, the individual must choose the level of health care use to address that shock.

### A.2. First period

In the first period, given the type or health status, the individual has to choose which health insurance plan to purchase. The individual chooses a plan from  $J$  plans available at that moment. She maximizes the expected utility, which takes into consideration that with probability  $1 - \lambda$  the shock in the second period is  $\theta = \theta_i + \psi$ , where  $\psi$  comes from a  $N(0, \sigma_\psi)$  and with probability  $\lambda$  the shock is  $\omega$  and comes from the common distribution  $W(\omega)$ . The decision is based on private information and therefore yields selection problems. She self-selects into a plan that maximizes her utility of future use of health services given her type.

### A.3. Second period

In the second period, the individual receives a penalty health shock  $\theta$ , then, conditional on the choice of plan made in the first period, she has to choose the level of treatment for that particular shock. However, she can receive a penalty health shock  $\omega$  that is drawn from a distribution  $W(\omega)$ , which is common to everyone. In other words, in the second period the shock is already realized; therefore, the individual knows which health care service to use, but she needs to solve the optimization problem of how much to use.

The utility of one period is  $u(c, H(h_i) - \text{shock})$ , where  $c$  is consumption of goods other than health,  $h_i$  is how much to use of health care service  $i$ ,  $H(\cdot)$  is a concave smooth function that transform health use into health status, and  $\text{shock}$  is the health shock (which is either  $\theta$  or  $\omega$ ). The utility is increasing and concave in both arguments; also,  $\partial^2 u / \partial c \partial s > 0$ , is true, which essentially means that with better health status or more consumption, an individual feels better.

### A.4. Solving the model

To see what dynamic problem the individual will solve, I use backward induction. In the second period the individual knows the plan's characteristics and the shock  $\theta$  or the shock  $\omega$ , so she has to decide what level of health care maximizes her utility subjected to budgetary constraints. Assuming that the shock received is  $\theta$ ,<sup>37</sup> the individual solves,

$$\max_h u(c, H(h) - \theta) \quad (3)$$

$$\text{s.t. } c = y - p - h * \text{coin}(h)$$

where  $y$  is income,  $p$  is premium and  $\text{coin}$  is coinsurance.

<sup>37</sup> It is easy to see that the first order condition and the solution does not depend upon the shock because is already realized, the only thing that changes is the health care service that the individual uses. However, after the shock is realized, the individual knows which health care service to use.



The first order condition is:

$$-u_1(c, h - \theta) * (\text{coin}(h) + h * \text{coin}'(h)) + u_2(c, h - \theta) * H'(h) = 0 \quad (4)$$

therefore,

$$\frac{\text{coin}(h) + h * \text{coin}'(h)}{H'(h)} = \frac{u_2(c, h - \theta)}{u_1(c, h - \theta)} \quad (5)$$

then the solution is a function of income, premium, coinsurance, the derivative of the coinsurance, the health shock and the derivative of  $H$ ,  $h^* = h(y - p, \text{coin}, \text{coin}', \theta, H')$ .<sup>38</sup> If the shock is  $\omega$ , the individual's solution is  $h^* = h(y - p, \text{coin}, \text{coin}', \omega, H')$ .

Now, in the first period, the individual knows that with probability  $1 - \lambda$  the shock that she will face is  $\theta = \theta_i + \psi$  and with probability  $\lambda$  the shock will be  $\omega$ . She has to maximize the expected utility solving the following problem,

$$\max_j (1 - \lambda)E_{\theta_i, \psi}[u(y - p_j - h_1 * \text{coin}_j(h_1), H(h_1) - \theta)] + \lambda E_{\omega}[u(y - p_j - h_2 * \text{coin}_j(h_2), H(h_2) - \omega)] \quad (6)$$

where the maximization is over the set of health insurance plans  $J$ .

This model allows for selection and moral hazard effects. There is private information on the health status and each individual will self-select into a plan that will give her the highest utility. Moreover, given the fact that the coinsurance level does not depend upon  $\theta$  or  $\omega$  and depend only on the level of health care usage,  $h_i$ , it creates a moral hazard problem.

#### A.5. Comparing health shocks

There are two big differences between  $\theta$  and  $\omega$ ; they are independent shocks, and  $\theta$  depends upon the type of the individual and  $\omega$  is the same across individuals. These two types of shock can be seen everyday in the real world. I assume that  $\omega$  shocks are random, for example a broken leg<sup>39</sup> or an appendectomy. Then, it is not surprising to think that those events were irrelevant at the moment of making a decision of which health insurance plan to purchase. However, it is easy to think that someone that has parents or relatives with history of some type of illness wants to be insured for those possible events.

Then the problem of selection appears only for the shock,  $\theta$ , that is related to the type  $\theta_i$  and not over the shock,  $\omega$ , that is independent of the type. Therefore, I use two different approaches, one for health care services related to  $\omega$ , which means health care services that are random events; and other for health care services related with the type of the individuals.

The model allows for both shocks to happen, however the random shock across individuals is not likely to happen often, because  $\lambda$  is very small. The optimization problem of the individual will be equivalent that a problem without the shock  $\omega$ , therefore the choice of the plan will be not related to the shock  $\omega$ . The intuition behind this proof is that the shock  $\omega$  has a small probability to happen, and the differences in expected utility of these events are bounded across plans.<sup>40</sup>

#### A.6. Sketch of proof

The following assumptions help us to prove that  $\omega$  is not used when choosing a plan.

**Assumption A.1.** There  $\exists \varepsilon > 0$  such that,

$$E_{G(\theta|s_0)}[u(\text{plan}_j)] - E_{G(\theta|s_0)}[u(\text{plan}_k)] > \varepsilon \quad (7)$$

where  $j$  is the best plan and  $k$  is the second best for individual  $i$

This assumption is just pointed out that there is no tie when individual  $i$  is choosing a plan.

**Assumption A.2.** The difference  $E_{K(\omega)}[u(\text{plan}_k)] - E_{K(\omega)}[u(\text{plan}_j)]$  is bounded  $\forall k$ , so a finite constant  $M$  exists, such that,  $|E_{K(\omega)}[u(\text{plan}_k)] - E_{K(\omega)}[u(\text{plan}_j)]| < M$

This is true in the Chilean case. The regulation obligates to the *Isapres* give at least the same coverage than the public insurer. Also, people can go to the public insurer if there is something urgent.

**Assumption A.3.**  $\lambda$  (the probability of facing the common health shock) is small enough such that satisfies  $\lambda < \varepsilon/(\varepsilon + M)$

In order to prove that the acute shock does not affect the decision of which plan to choose, I assume there are two scenarios. The first scenario is a world with only one shock, the one related to the individual's type. The second scenario is the one with both shocks to happen.

For the first scenario, I assume the individual in the first period chose plan  $j$ . Therefore,

$$E_{G(\theta|s_0)}[u(y - p_j - h * \text{coin}_j(h), h - \theta)] > E_{G(\theta|s_0)}[u(y - p_k - h * \text{coin}_k(h), h - \theta)] \quad (8)$$

$\forall k$ , with  $k \neq j$ .

Then I need to prove that under the second scenario, individual  $i$  chooses the same plan  $j$ . Then, I need to prove the following inequality is satisfied  $\forall k, k \neq j$ :

$$(1 - \lambda)E_{G(\theta|s_0)}[u(y - p_j - h_1 * \text{coin}_j(h_1), h_1 - \theta)] + \lambda E_{K(\omega)}[u(y - p_j - h_2 * \text{coin}_j(h_2), h_2 - \omega)] > (1 - \lambda)E_{G(\theta|s_0)}[u(y - p_k - h_1 * \text{coin}_k(h_1), h_1 - \theta)] + \lambda E_{K(\omega)}[u(y - p_k - h_2 * \text{coin}_k(h_2), h_2 - \omega)] \quad (9)$$

which is the same that,

$$(1 - \lambda)\{E_{G(\theta|s_0)}[u(\text{plan}_j)] - E_{G(\theta|s_0)}[u(\text{plan}_k)]\} > \lambda\{E_{K(\omega)}[u(\text{plan}_k)] - E_{K(\omega)}[u(\text{plan}_j)]\} \quad (10)$$

Hence, given **Assumption A.2**, it is enough to prove that,

$$E_{G(\theta|s_0)}[u(\text{plan}_j)] - E_{G(\theta|s_0)}[u(\text{plan}_k)] > \frac{\lambda}{1 - \lambda} M$$

Using **Assumption A.3**, I have

$$\frac{\lambda}{1 - \lambda} M < \frac{\varepsilon/(\varepsilon + M)}{1 - (\varepsilon/(\varepsilon + M))} M = \varepsilon \quad (11)$$

then,

$$E_{G(\theta|s_0)}[u(\text{plan}_j)] - E_{G(\theta|s_0)}[u(\text{plan}_k)] > \varepsilon > \frac{\lambda}{1 - \lambda} M \quad (12)$$

which proves that the individual chooses the same plan regarding the new negative shock. Moreover, if  $\lambda$  goes to 0, it is straightforward to show that the inequality is satisfied, given the fact that  $M$  is finite. This is true  $\forall k$ , because  $\varepsilon$  is the smallest difference between the best option and the second best option.

#### Appendix B. Other analysis

In this appendix, I present tables and other analysis of the price elasticity estimates, by number of visits, income quartile, age quintile, region and duration.

<sup>38</sup> The derivative is not well defined when the minimum is the same, in the case of the Chilena coinsurance function.

<sup>39</sup> I'm not taking into consideration people that is more riskier, like a formula one pilot, or a professional soccer player.

<sup>40</sup> Everyone at least can have public insurance.

**Table 13**  
Elasticities for elective care (IV Tobit regressions).

Endogenous variable: number of visits			
	Home visits	Psychologist	Physical therapy evaluations
Coinurance rate	−0.490*** (0.042)	−0.780** (0.024)	−0.204*** (0.0158)

Standard errors are in parentheses.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

**Table 14**  
Elasticities for elective care, by income (IV Tobit regressions).

Endogenous variable: total medical expenditure			
Income quartile	Home visits	Psychologist	Physical therapy evaluations
First	−1.303*** (0.221)	−1.108*** (0.214)	−0.271*** (0.077)
Second	−0.913*** (0.165)	−1.325*** (0.143)	−0.175*** (0.005)
Third	−2.642*** (0.217)	−2.390** (0.139)	−0.500*** (0.048)
Fourth	<sup>a</sup>	−6.202*** (0.304)	−0.624*** (0.067)

Standard errors are in parentheses.

<sup>a</sup> Results are unavailable.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

**Table 15**  
Elasticities for elective care, by income (IV Tobit regressions).

Endogenous variable: number of visits			
Income quartile	Home visits	Psychologist	Physical therapy evaluations
First	−0.421*** (0.025)	−0.823*** (0.041)	−0.264*** (0.020)
Second	−0.367*** (0.020)	−0.616*** (0.014)	−0.167*** (0.015)
Third	−0.698*** (0.015)	−0.779** (0.011)	−0.381*** (0.012)
Fourth	<sup>a</sup>	−1.066*** (0.013)	−0.260*** (0.029)

Standard errors are in parentheses.

<sup>a</sup> Results are unavailable.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

### B.1. Number of visits

Table 13 shows the main results of the regression between number of visits and the dependent variables.

### B.2. Distribution of demographics

#### B.2.1. Income

The following tables show details of the main analysis by income quartile. Table 14 shows the results of the main regression, Table 15 shows the elasticity on the number of visits and finally Table 16 shows the fraction of the elasticity explained by the number of visits.

#### B.2.2. Age

Tables 17 and 18 show the elasticity on the number of visits and the elasticity over all expenditure, as in the main regression, by age quintile.

#### B.2.3. Region

In a third specification, I examined how location affects the results. Chile is divided in 15 regions, which have different patterns of weathers that can impact how individuals behave. I divided the country in three zones, the north (I, II, III, IV and XV regions), the center (Santiago, V and VI regions) and the south (VII, VIII, IX, X, XI, XII, XIV regions). Table 17 shows the elasticities. As I expected, the results for home visits and physical therapy are driven by the

**Table 16**  
Ratio of price elasticity for number of visits and price elasticity for total expenditure, by income.

Income quartile	Home visits	Psychologist	Physical therapy evaluations
First	32%	74%	97%
Second	40%	46%	95%
Third	26%	32%	76%
Fourth	<sup>a</sup>	17%	41%

<sup>a</sup> Results are unavailable.

**Table 17**  
Elasticities for elective care, by age (IV Tobit regressions).

Endogenous variable: total medical expenditure			
	Home visits	Psychologist	Physical therapy evaluations
<b>Age quintile</b>			
First	–1.071*** (0.342)	–4.996*** (0.730)	–0.847*** (0.190)
Second	–1.919*** (0.335)	–2.356*** (0.228)	–0.511*** (0.091)
Third	–2.355*** (0.281)	–2.324** (0.160)	–0.375*** (0.066)
Fourth	–1.681*** (0.223)	–1.922*** (0.133)	–0.201*** (0.049)
Fifth	<sup>a</sup>	–1.131*** (0.138)	–0.198*** (0.040)

Standard errors are in parentheses.

<sup>a</sup> Results are unavailable.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

**Table 18**  
Elasticities for elective care, by age (IV Tobit regressions).

Endogenous variable: number of visits			
	Home visits	Psychologist	Physical therapy evaluations
<b>Age quintile</b>			
First	–0.389*** (0.032)	–1.774*** (0.255)	–0.779*** (0.152)
Second	–0.596*** (0.024)	–0.964*** (0.017)	–0.469*** (0.017)
Third	–0.644*** (0.017)	–0.876** (0.011)	–0.320*** (0.012)
Fourth	–0.598*** (0.018)	–0.703*** (0.013)	–0.190*** (0.012)
Fifth	<sup>a</sup>	–0.397*** (0.013)	–0.138*** (0.010)

Standard errors are in parentheses.

<sup>a</sup> Results are unavailable.

\* 10% of significance.

\*\* 5% of significance.

\*\*\* 1% of significance.

center, which contains more than 50% of the population. However, we can see marked differences across the different zones for all the services. These differences might be due to weather conditions, price conditions, or demographic conditions.

In particular, the results for psychologist visits show that individuals living in the capital city are much more elastic than ones living at the extremes of the country. This result can be explained by the fact that there is more competition for this particular service in the capital city than in the extreme zones of the country and therefore it is easier for consumers to find different prices. Also, this difference could be explained by the fact that psychologists are used more often in the capital city than in the rest of the country. Another surprising result is the one for home visits in the south zone; it seems that this result could be biased due to weather conditions in the south of the country, given the fact that prices and expenditure are very similar across both the south and north zones.

#### B.2.4. Duration

In a fourth specification, I examined the duration (time spent) in a health plan. Using the distribution of durations, I found an inverted U-shaped pattern for price elasticity. The groups with the longest and shortest duration have the lowest elasticity estimates. Both elasticities are approximately one-third of the elasticity for duration groups between the shortest and longest. For example, expenditures for psychologist services have an elasticity of –3.699 for the middle duration group, whereas the longest duration group has an elasticity of –1.34. These results may suggest that individuals with high duration are accustomed to their physicians or know exactly where to purchase health care services but do not want to switch to a new physician (or new prices). For

**Table 19**  
Generosity within Isapres.

Plan generosity (Measure as average cap across plan)		
Isapre	Mean	Standard deviation
67	0.44853915	0.21656148
78	0.37734698	0.19966665
80	0.40663482	0.21144491
88	0.37544051	0.2388174
99	0.4302483	0.21466503
107	0.40338717	0.22431313

individuals with less time in the plan, however, the reasons for staying are not clear.

### Appendix C. Some concerns

#### C.1. Plans' generosity

As you can see in Table 19, the Isapres offer several plans with different degrees of generosity.

#### C.2. Anticipating behavior

As is mentioned in the document, it is possible that individuals anticipate the change in the coinsurance rate and then they act accordingly, postponing expenditures. However, as is shown in Fig. 6, the distribution of expenditure one month before and one month after the update in prices does not change at all. Moreover, I ran Kolmogorov–Smirnov test that show equal distribution for expenditures.

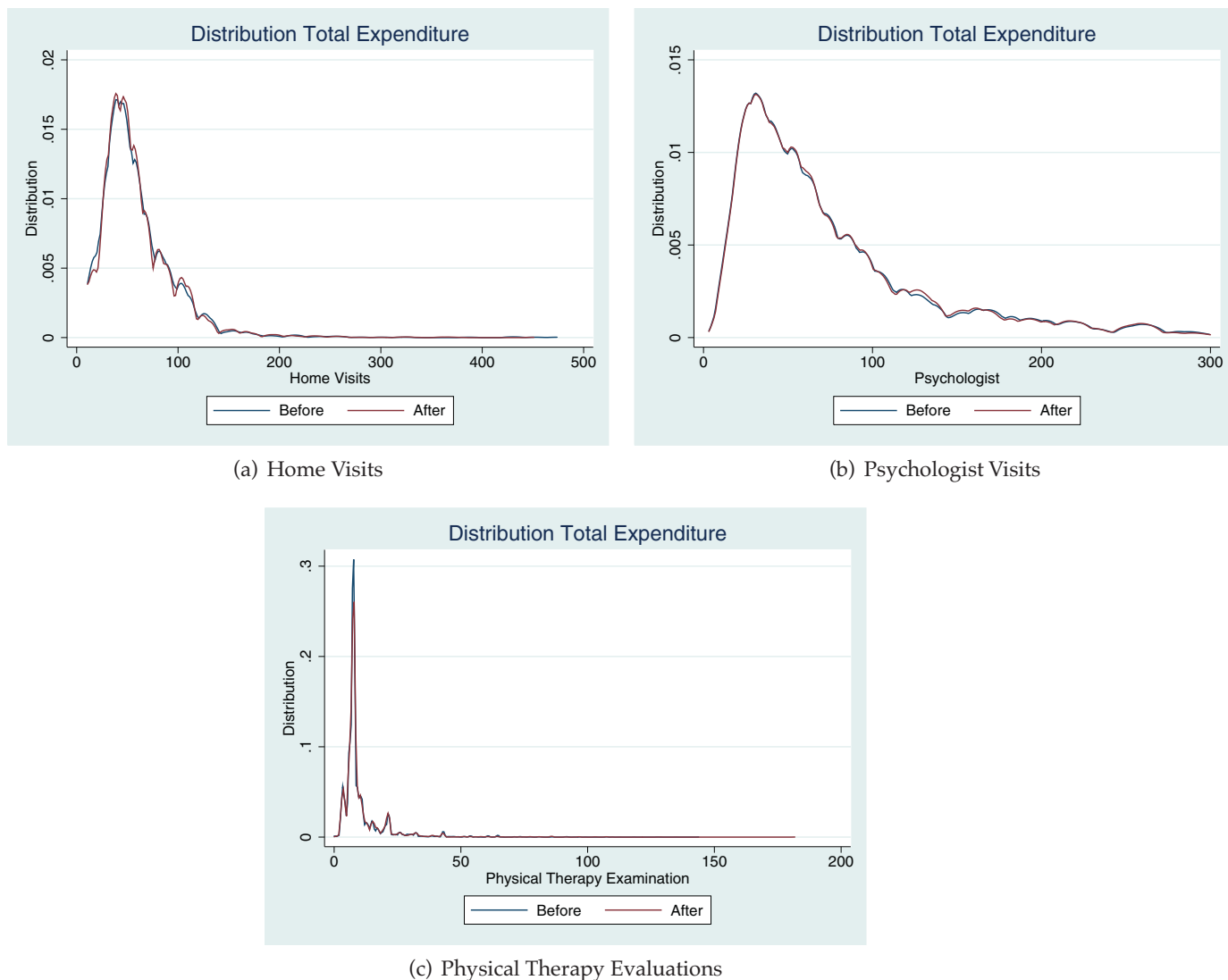


Fig. 6. Elective care: distribution of total expenditure. (a) Home visits; (b) Psychologist visits; and (c) Physical therapy evaluations.

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