Effect of a cost-sharing variation on the utilization of GES insurance and private healthcare services

TESIS PARA OPTAR AL GRADO DE

Magister en Análisis económico

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Santiago, junio 2022

Abstract: Effect of a cost-sharing variation on the utilization of GES insurance and private healthcare services

Since 2006, the cost-sharing faced by the public insurer beneficiaries aged 60 years and over had decreased to zero for all "*Garantias Explicitas en Salud*" (Explicit Health Guarantees, GES) care and non-GES services provided within the public healthcare system. In this study, we analyze the effect of the cost-sharing variation on the utilization of public and private healthcare services utilization. Using the 2016-2019 FONASA beneficiary's database, the first-time utilization (aka activation) of the GES insurance database, and the private medical claim registry, through the implementation of a regression discontinuity design, we estimated the treatment effect of this policy. We found that the decrease in cost-sharing translates into a 3-percentage point increase in the GES insurance activation. If we restrict our analysis to the activation of chronic GES insurance, we found an increase of 5 percentage Regarding private healthcare services, our findings suggest that utilization of healthcare services through the MLE scheme is, for the most part, not responsive (by means of an increase in opportunity cost) to variations in cost-sharing for public healthcare services, except for hospitalization services, where we estimate a decrease of 11 percentage points in their utilization, although this estimate is significant only at a 10% of significance. Additionally, we found that treatment is heterogeneously distributed across different subgroups of the population.

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1 Policy Background and theorical framework

1.1 Chilean health system

The Chilean Health System consists of two subnetworks, one public and one private (Víctor Becerril-Montekio et al., 2011, Pablo Buris Poch et al., 2014). In general terms, the public sector is organized through the "*Fondo Nacional de Salud*" (National Healthcare Fund, FONASA), the public health insurer that provides coverage to around 80% of the Chilean population, and the national system of healthcare service providers (i.e., primary care, secondary care, tertiary care, etc.). The private sector, which serves the remaining 20%, is based on private health insurers (ISAPREs) and an extensive network of private service providers.

FONASA classifies its beneficiaries based on their income, defining four incremental brackets that account for their socio-economic situation (A, B, C, and D) (FONASA, 2022). Bracket A contains people with very limited financial resources, while higher-income individuals fall into bracket D. Although all of its beneficiaries have the right to receive care in the public healthcare network, the copayment that each group must contribute is different. Members of brackets A and B are not required to contribute at all, while 10% and 20% of the total cost of services provided must be shouldered by individuals in brackets C and D, respectively (FONASA, 2022).

Since its implementation in 2005, the "*Garantias Explicitas en Salud*" (Explicit Health Guarantees, GES) system has been recognized as the most significant reform to the Chilean healthcare system. In principle, the system brings together a multitude of health insurance policies that are directly linked to the detection and treatment of specific pathologies, of which there are 85 to date. Broadly speaking, the healthcare services provided by the public network can be divided into GES and non-GES care. Although the GES system only covers a limited number of pathologies, these are the most prevalent and burdensome in Chile and, as such, explain a considerable portion of the total volume of care provided in the public sector.

An important note here is that GES insurance does not affect the copayment contribution required of FONASA beneficiaries; rather, it confers timely access to a predefined set of health benefits (Superintendencia de Salud, 2022a). This is of major importance considering the long waiting lists that are currently such a feature of the Chilean healthcare system.

As a consequence of the significant volume of beneficiaries insured by FONASA, together with the limited capacity of public networks to provide adequate healthcare within a suitable time frame, the issue of waiting lists has become one of the most serious public health concerns in Chile (Jorge A. Acuna et al., 2022, V Rojas et al., 2018). Care provided within the GES system is not significantly affected by this problem, whereas all non-GES care is strongly affected.

In an attempt to address the problem, the Ministry of Health has promoted and reinforced the FONASA "Modalidad Libre Eleccion" (Free Choice Modality, MLE) scheme. This allows FONASA beneficiaries to buy healthcare services directly from private providers and thus avoid public system waiting lists (Superintendencia de Salud, 2022). The cost-sharing scheme offered by the MLE is different from that described earlier. Instead, the copayment required of beneficiaries depends on the scale of the service provider (outpatient care center, clinic, etc.), but in all cases, costs paid through the MLE scheme are higher than those associated with the public healthcare network.

Finally, although the care provided through the MLE can be considered a substitute for non-GES care, MLE care does not constitute a substitute for GES care. Because the healthcare system has a legal obligation to meet GES needs, it purchases care directly from the private sector if the public system is unable to supply the required services, and thus access to GES care through MLE is not an option.

1.2 Chilean healthcare subsidy for adults aged 60 years and over

As part of a drive to expand social security benefits for Chile's elderly population, since 2006 the cost-sharing faced by FONASA beneficiaries aged 60 years and over had decreased to zero for all GES and non-GES services provided within the public healthcare system (Biblioteca del Congreso Nacional de Chile, 2006). Although FONASA brackets A and B are not affected by the policy, brackets C and D benefit from a reduction in their cost-sharing burden from 10% and 20% to zero, respectively.

Since the MLE scheme is based on care provided within the private healthcare network, this modality remains unaffected by the policy. Nevertheless, as public care becomes free, the opportunity cost associated with the purchase of private healthcare services grows relative to that of public healthcare services. In this sense, a policy that in principle should not affect the MLE system could generate a variation in its use.

1.3 Theorical Framework: Health insurance and healthcare service consumption

The relationship between individual preferences and the constraints on access to them determines consumer incentives. In the healthcare market, wages and prices determine the feasible choices available. However, the price of healthcare services paid by individuals depends not only on the cost of the services themselves but also on the coverage that health insurers provide to their beneficiaries (Peter Zweifel and Willard G Manning, 2000). Being insured modifies the context and behavior of individuals with respect to healthcare and illness, not only because it affects the price paid for medical care, but also because it influences the individual's disposable income and the opportunity cost of time spent out of work due to illness, which is associated with the payment of sick leave (Peter Zweifel and Willard G Manning, 2000). The change in health behavior and healthcare consumption caused by insurance is referred to as moral hazard.

A review of the literature reveals two categories of moral hazard: “ex-ante” and “ex-post” (Peter Zweifel and Willard G Manning, 2000). Ex-ante moral hazard refers to a phenomenon whereby individuals, knowing that they will take out health insurance but prior to being insured, lose their incentives to exercise preventive behaviors, thus threatening their health stock (Isaac Ehrlich and Gary S. Becker, 1972). Ex-post moral hazard describes a situation in which insured individuals increase their demand for healthcare services due to decreases in the prices charged (J. A. Nyman, 2004, Peter Zweifel and Willard G Manning, 2000). Broadly speaking, the greater the “generosity” of the insurance—i.e., the lower the deductible or cost-sharing amount—the greater the amount of healthcare services demanded (Peter Zweifel and Willard G Manning, 2000).

1.3.1 The effect of cost-sharing on healthcare consumption

Cost-sharing policies in healthcare are applied to reduce the risk of moral hazard and improve the efficiency with which the healthcare system provides care, thus containing costs (Peter Zweifel and Willard G Manning, 2000). However, as the value of healthcare as seen by individuals is lower than the market price—due to cost-sharing—demand will increase from some individuals who perceive a lower value of care (i.e., individuals without a well-founded need to seek healthcare). In this sense, cost-sharing instruments may disincentivize demand from low-value individuals while affecting demand for care that is genuinely required, thereby having a negative effect on health outcomes (Katherine Baicker and Dana Goldman, 2011). Additionally, as suggested by the literature, changes to cost-sharing may be related to a heterogeneous effect distribution across subgroups, with a greater impact on vulnerable groups, thus reinforcing inequity in access to healthcare (Katherine Baicker and Dana Goldman, 2011, N. Johansson et al., 2019).

1.3.2 Experimental Evidence

The RAND Health Insurance Experiment was a controlled study in which families from various US states were assigned to 14 insurance plans. The study sought to gather information about how being insured affects demand for healthcare services, along with i) whether the demand response varies according to wage; ii) whether the price elasticity of demand is heterogeneous across different service types; and iii) whether variation in the consumption of healthcare services translates into an improvement or decline in health (W. G. Manning et al., 1987).

The RAND experiment found that the number of outpatient visits and the probability of using healthcare services increase with lower cost-sharing, with rates highest when there is no cost-sharing and lowest when cost-sharing is high (around 95%). Regarding the response in subgroups with different salaries, it is reported that the higher the salary, the higher the probability of using any healthcare service. This effect is greater in those plans involving cost-sharing (W. G. Manning, J. P. Newhouse, N. Duan, E. B. Keeler, A. Leibowitz and M. S. Marquis, 1987). Regarding the price elasticity of demand, it is found that the price sensitivity of healthcare consumption ranges, depending on the nature of the attention received, between -0.1 and -0.2, meaning that a 10% increase in price translates into a reduction of 1 to 2% in utilization of each service. Finally, the RAND experiment recorded a statistically significant improvement in the health outcomes evaluated (blood pressure control, myopia, and oral health), but only for the lowest income subgroup (W. G. Manning, J. P. Newhouse, N. Duan, E. B. Keeler, A. Leibowitz and M. S. Marquis, 1987).

1.3.3 Quasi Experimental evidence

Chandra and colleagues evaluated the effect of an increase in cost-sharing on the low-income population of Massachusetts, analyzing the increase in copayments experienced by beneficiaries of the Commonwealth Care program, which covers the region's lowest-income individuals. During 2008, beneficiaries experienced an exogenous increase in cost-sharing, which was used by the authors to estimate the effect of cost-sharing on the utilization of healthcare services and the price elasticity of demand (Amitabh Chandra et al., 2014).

The authors used administrative information regarding Commonwealth Care beneficiaries, along with medical claims data one year before and one year after the cost-sharing changes. Analysis involved a generalized linear model with a log-link function to estimate the price elasticity of demand.

The authors found a total price elasticity of demand of -0.158, meaning that a 10% increase in price translates into a reduction in utilization of 1.58%. They also found some heterogeneity when evaluating elasticity for specific services—outpatient, emergency room, hospital, and laboratory—but these showed narrower ranges (-0.1 to -0.3). Finally, the reported results suggested that the price elasticity of demand is lower for less healthy individuals (chronic patients) compared to healthy individuals (Amitabh Chandra, Jonathan Gruber and Robin McKnight, 2014).

Johansson and colleagues evaluated the effect of an increase in cost-sharing on primary care and specialist consultations among the young adult population in Sweden (N. Johansson, N. Jakobsson and M. Svensson, 2019). At the age of 20 years, the copayment for primary care and specialist visits rises from zero to 10 euros. In addition, the authors evaluated the heterogeneity of cost-sharing policies by performing a subgroup analysis of sex and income.

The study took data from the regional registry of individuals in Sweden, which informs socio-demographic covariates for each individual, together with data on healthcare services provided as part of primary care. In particular, the authors employed a sharp regression discontinuity design (RDD), using age as the assignment variable and the number of visits per capita per year as the dependent variable (N. Johansson, N. Jakobsson and M. Svensson, 2019).

The authors reported that the introduction of copayment is associated with a 7-percentage point decrease in the number of visits per capita per year—a statistically significant effect (N. Johansson, N. Jakobsson and M. Svensson, 2019). In addition, the authors found a gradient effect when analyzing by income quintile, with the lowest-income individuals being the most susceptible to the increase in cost-sharing. Moreover, the authors reported notable differences in sensitivity to copayment increases between men and women, with a percentage point reduction of 9.2% and 3.5%, respectively (N. Johansson, N. Jakobsson and M. Svensson, 2019). No significant effect was found regarding visits to specialists, which the authors attributed to the greater severity of care.

In relation to the elderly population, two papers have evaluated the effect of a variation in cost-sharing on the utilization of healthcare services (Shigeoka et al.) and on medical expenditure (Fukushima et al.). Both studies addressed the sudden age-related drop in cost-sharing in Japan, which goes from 30% to 10% at the age of 70 (Kazuya Fukushima et al., 2016, Hitoshi Shigeoka, 2014).

The main differences between the two studies are the databases used. Shigeoka and colleagues used the National Patient Survey, which is a cross-sectional survey reporting on outpatient and inpatient care received during September, performing a sharp RDD using age as a running variable and the number of appointments or visits as the dependent variable. However, the National Patient Survey provides information about only a limited set of services, and Fukushima and colleagues instead used medical claim data, which reports information for all healthcare services provided, along with their associated cost. Fukushima and colleagues also applied an RDD with age as a running variable, but used medical expenditure as the dependent variable rather than counts.

Shigeoka and colleagues concluded that i) the decrease in cost-sharing leads to an increase in the utilization of healthcare services, with a price elasticity of demand of -0.2 for both inpatient and outpatient visits (Hitoshi Shigeoka, 2014); ii) the higher utilization of healthcare services does not translate into an improvement in health, at least for the evaluated outcomes of mortality and self-reported physical/mental health (Hitoshi Shigeoka, 2014); and iii) the reduction in cost-sharing causes a decrease in individuals' out-of-pocket spending, meaning that despite higher utilization of services, the price reduction has a strong effect on expenditure (Hitoshi Shigeoka, 2014).

For their part, Fukushima and colleagues found that the reduction in cost-sharing from 30% to 10% at age 70 is associated with an increase in medical expenses (mediated by an increase in demand), implying a price elasticity of demand of -0.16 (Kazuya Fukushima, Sou Mizuoka, Shunsuke Yamamoto and Toshiaki Iizuka, 2016). The authors found that responses to the change in copayment are heterogeneous in terms of the type of services, being higher for orthopedic and eye-related services

(Kazuya Fukushima, Sou Mizuoka, Shunsuke Yamamoto and Toshiaki Iizuka, 2016). In addition, the health status of each patient affects the use of resources, with those affected by the policy being healthy individuals and not the sick (Kazuya Fukushima, Sou Mizuoka, Shunsuke Yamamoto and Toshiaki Iizuka, 2016). Finally, the authors found no evidence that increased utilization of services translates into improvements in health (Kazuya Fukushima, Sou Mizuoka, Shunsuke Yamamoto and Toshiaki Iizuka, 2016).

2 Motivation and research question

As mentioned previously, cost-sharing policies are widely used to improve the efficiency of healthcare networks and contain spending given a limited health budget. Nonetheless, these policies have an important drawback: while they discourage excessive healthcare service utilization, they may also reduce access to necessary health, which could translate into poor health outcomes and costly health events in the future.

Despite the large body of literature addressing this issue, most of the experimental and quasi-experimental evidence is developed in the context of high-income countries. As such, it is fundamental that the effect of cost-sharing policies on the use of healthcare services be evaluated in a middle-income country such as Chile. Furthermore, ours is, to our knowledge, the first study to assess the effect of variation in cost-sharing in the context of a mixed healthcare system with multiple access scheme.

In the present work, we will analyze the effects of the change in cost-sharing at age 60 on the use of public and private healthcare services in Chile. Regarding public healthcare services, we will evaluate how the activation of GES insurance varies with the implementation of the policy of interest, while for private healthcare services, we will assess whether utilization changes after the 60^{th} birthday. In addition, we will conduct a subgroup analysis to assess heterogeneity in the way beneficiaries respond to this change in cost-sharing.

Based on what is described in the literature, we expect the use of GES insurance to increase as a result of the decrease in cost-sharing. By contrast, due to the increase in the opportunity cost associated with the purchase of healthcare services in the private sector, we expect a decrease in the use of private services. We hypothesize that the latter is mediated by a substitution effect: beneficiaries prefer to use public healthcare services—which become free of charge from 60 years onward—than to pay for private services through the MLE scheme.

As the beneficiaries of FONASA bracket D are those who experience the greatest variation in terms of cost-sharing, we will focus on this subgroup in the present work.

3 Methods

3.1 Data

We have combined three databases into our own: i) the FONASA beneficiary database, which contains individualized socio-demographic information for FONASA bracket D beneficiaries; ii) the GES database, which reports activation of the GES insurance; and iii) the MLE claim database, which records every instance of medical attention incurred in the private healthcare network. All databases have an identification variable that allows us to aggregate information at the individual level.

From the FONASA beneficiary database we extracted information for all people born between 1954 and 1961 who were public insurance beneficiaries (specifically in the D bracket) during the years 2016-2019, thus yielding individuals aged between 55 and 65 years. For the base case analysis, we filtered the target population by those individuals with a chronological age ranging from 58 years and 1 month to 62 years and 1 month, which gives us a window of 24 months before and after the 60th birthday.

The GES database reports the first-time utilization, which we will refer to as activation, of GES insurance. Activation reflects the beginning of diagnostic and treatment processes aimed at relieving GES health problems. Although we do not have access to data relating to all GES care provided by the public healthcare network, activation provides us with an insight into healthcare service utilization.

It should be noted that we only record once the diagnosis of disease unless the disease is a repeatable event (Myocardial infarction for example). Regarding treatment, we only see the first time that treatment is indicated, even though this treatment is provided for a lifetime (chronic diseases).

As the GES system is linked to specific pathologies, individuals may experience multiple activations within a month (one for each pathology). Additionally, this insurance may provide diagnostic and/or treatment-related care, therefore some individuals may experience numerous activations within a specific GES health problem —the individual becomes diagnosed and then treated. From this follow, that the number of monthly GES insurance activation goes from zero (individuals who do not experience an activation) to n, with $n>0$.

The MLE claim database contains information about all the services provided within the private healthcare network, allowing us to fully investigate how resource utilization is affected by variation in cost-sharing.

Our final database contains 476,270 individuals who were FONASA bracket D beneficiaries between 2016 and 2019, with ages ranging from 58 to 62 years. Table 1 shows the descriptive statistics for the sample. It is worth mentioning that, as beneficiary information is expressed at the monthly level, following the merge, our database reports information on the monthly activation of GES insurance and utilization of private healthcare services. As mentioned before, we established a window of 24 months before and after the cut-off of 60 years and one month, with each month representing a specific age cell. Table 2 summarizes the baseline covariates for the individuals included in a set of selected age cells.

Table 1. Descriptive statistics for baseline covariates of the constructed data

	Mean	Standard deviation
Panel A: year 2016		
Total Number of observations	226,087	
Women (%)	42%	49%
Residence in a non-metropolitan area (%)	57%	49%
Pensioner (%)	6%	23%
Employed (%)	93%	25%
Self-employed (%)	1%	1%
Wage ($)	$493,592	$384,876
Panel B: year 2017		
Number of observations	224,024	
Women (%)	42%	49%
Residence in a non-metropolitan area (%)	56%	50%
Pensioner (%)	6%	23%
Dependent worker (%)	83%	37%
Independent worker (%)	1%	1%
Wage ($)	$517,295	$401,955
Panel C: year 2018		
Number of observations	278,385	
Women (%)	43%	49%
Residence in a non-metropolitan area (%)	57%	49%
Pensioner (%)	4%	19%
Dependent worker (%)	91%	28%
Independent worker (%)	1%	1%
Wage ($)	$519,150	$407,238
Panel D: year 2019		
Number of observations	287,850	
Women (%)	43%	50%
Residence in a non-metropolitan area (%)	57%	49%
Pensioner (%)	3%	17%
Dependent worker (%)	96%	20%
Independent worker (%)	1%	1%
Wage ($)	$555,017	$414,003

Monetary amounts ($) are in Chilean Pesos (CLP).

Table 2. Baseline covariates for selected age cells.

Age cell	-22	-16	-10	-4	-2	0	2	4	10	16	22	24
Number of individuals	195,158	185,756	183,681	174,798	175,950	175,004	171,825	168,695	163,236	155,294	149,011	147,682
Copayment (%)	0.20	0.20	0.20	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Women (%)	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.42	0.42	0.41	0.41	0.41
Residence in non-metropolitan area (%)	0.57	0.56	0.57	0.56	0.56	0.57	0.56	0.56	0.57	0.57	0.57	0.57
Pensioner (%)	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.05	0.06	0.07	0.08	0.09
Employed (%)	0.92	0.92	0.91	0.91	0.91	0.90	0.90	0.90	0.89	0.88	0.87	0.86
Self-employed (%)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Wage ($)	$539,891	$540,438	$539,397	$540,858	$540,716	$540,586	$541,694	$547,343	$556,323	$564,693	$562,873	$564,049

Monetary amounts ($) are in Chilean Pesos (CLP).

3.2 Empirical strategy

3.2.1 Regression discontinuity design framework

The RD design is a quasi-experimental method that makes use of the arbitrariness with which certain thresholds or cut-off points are defined to dictate qualification for the benefits provided by public policies (Joshua D Angrist and Jörn-Steffen Pischke, 2008, David S. Lee and Thomas Lemieux, 2010). In this sense, whether the treatment will be received or not is determined as a function of an observable assignment variable called the running variable. If the running variable exceeds the cut-off point, then individuals are treated.

Assuming that all factors affecting the outcome of interest vary continuously at the cut-off point, the expected value of the outcome for individuals located just below the cut-off point supposes an appropriate counterfactual for the treated individuals—just above the cut-off (David S. Lee and Thomas Lemieux, 2010). The average treatment effect is then estimated by the difference between the expected values just below and just above the cut-off point (David S. Lee and Thomas Lemieux, 2010).

The above implicitly states the identifying assumption underlying the RD design, which is that individuals do not have perfect control over the assignment variable; in other words, they cannot accurately manipulate the treatment assignment (David S. Lee and Thomas Lemieux, 2010). It is important to note that individuals can attempt to manipulate the treatment assignment, the only requirement being that they do not exhibit perfect control. If this assumption does not hold, then individuals above the threshold would be systematically distinct from those just below and, thus, individuals below the threshold would no longer be an appropriate counterfactual. In the event that individuals do not have perfect control over the assignment variable, the treatment assignment becomes as good as random, and therefore the individuals above and below the cut-off point are, on average, comparable (David S. Lee and Thomas Lemieux, 2010).

It is important to note that the treatment assignment can be a deterministic function of the running variable, in which case it is called a sharp RDD. If the treatment assignment is a probabilistic function of the running variable, it is called a fuzzy RDD (David S. Lee and Thomas Lemieux, 2010).

3.2.2 Specification

With the aim of estimating the causal effect of the cost-sharing policy at the 60th birthday, we focused on the age discontinuity in cost-sharing and opportunity cost with regard to the activation of GES insurance and the consumption of private healthcare services, respectively. As long as there is no evidence of perfect manipulation of the assignment variable and provided no other covariates display a discontinuity at the cut-off, we can attribute the discrete changes in the evaluated outcomes to the implementation of the policy (Joshua D Angrist and Jörn-Steffen Pischke, 2014, 2008, David S. Lee and Thomas Lemieux, 2010). In this sense, as has been reported by multiple studies, the use of age as an assignment variable has the advantage that it does not allow perfect manipulation (Olivier Bargain and Karina Doorley, 2011, Hsing-Wen Han et al., 2020, N. Johansson, N. Jakobsson and M. Svensson, 2019, Thomas Lemieux and Kevin Milligan, 2008, Anton Nilsson and Alexander Paul, 2018, Hitoshi Shigeoka, 2014). In any case, we will test the validity of this assumption formally. Regarding the second requirement, although there are many lifestyle and risk profile changes associated with aging and health care services consumption (Jorid Kalseth and Thomas Halvorsen, 2020, Irene Papanicolas et al., 2020), none of these are discrete around the threshold; rather, they are continuously changing.

As the copayment or the opportunity cost is a deterministic function of age, we applied a sharp RD design. The general form of our estimated regression is presented in Equation 1.

$$(1) \qquad Y_{i,a} = \beta D_{i,a} + f(a) + \gamma X_{i,a} + e_{i,a}$$

Here, $Y_{i,a}$ is the monthly number of GES insurance policies activated or the monthly number of private healthcare services utilized for individual i at age a; $D_{i,a}$ is a dummy that takes the value of 1 if individual i is over or equal to 60 years of age; $f(a)$ is a smooth function of age; $X_{i,a}$ is a vector of individual covariates (sex, area of residence, year of birth); and $e_{i,a}$ is an unobserved error component. The parameter of interest is β, which measures any deviation from the continuous relationship between age and outcome (i.e., the treatment effect).

As the policy is implemented according to age, and age is a discrete variable, following the approach of several published works (Michael Anderson et al., 2012, David Card et al., 2009, N. Johansson, N. Jakobsson and M. Svensson, 2019, Thomas Lemieux and Kevin Milligan, 2008) we collapsed the individual data into each age cell. The work of Lee and Card (2008) proves that estimating the age cell regression with heteroskedasticity-consistent standard error (Robust SE) is equivalent to individual estimation with clustered standard errors (i.e., standard errors clustered by age). This approach is justified by the large size of our database (about 21 million observations), which makes it difficult to perform analysis due to RAM or CPU capacity limitations. In line with the above, we use the aggregated specification, as shown in Equation 2.

$$(2) \qquad Y_a = \beta D_a + f(a) + \gamma X_a + e_a$$

Here, Y_a is the monthly number of GES insurance policies activated or private healthcare services utilized at age cell a; D_a is a dummy that takes the value of 1 if age cell a is greater than or equal to 60 years; $f(a)$ is a smooth function of age; X_a is a vector of baseline covariates (sex, area of residence, year of birth) aggregated at age cell a; and e_a is an unobserved error component. Note that with this specification, the interpretation of the parameter of interest (β) is the same as in the individual specification. Because the dependent variable is in nature count per unit of time (number of activation of GES insurance or number of healthcare services utilization per month), we estimate our model using a Poisson regression with an exposure term defined as the total number of people in a given age cell.

To take advantage of our rich data set, we performed a more in-depth analysis of the outcomes. Activation of GES insurance was grouped according to underlying health problem (i.e., chronic disease, mental health, heart and brain disease, etc.). Private healthcare services were grouped in accordance with the nature of the services provided (i.e., physician visits, hospitalization services, etc.).

To assess the robustness of the treatment effect, we performed several sensitivity analyses. First of all, we included higher-order polynomials on the regression estimate. However, it is worth mentioning that polynomials of grades higher than 2 lead to noisy estimates (Andrew Gelman and Guido Imbens, 2019). Additionally, we assess the effect associated with an increase in the bin size (from monthly age cell to quarterly) and variation in the window size around the threshold. Furthermore, we estimate the regression without the baseline covariates and with a different type of regression model.

4 Results

In this section, we use an RDD approach that compares healthcare utilization before and after turning 60 years old to analyze the potential causal effect of the cost-sharing policy on utilization of public and private healthcare services.

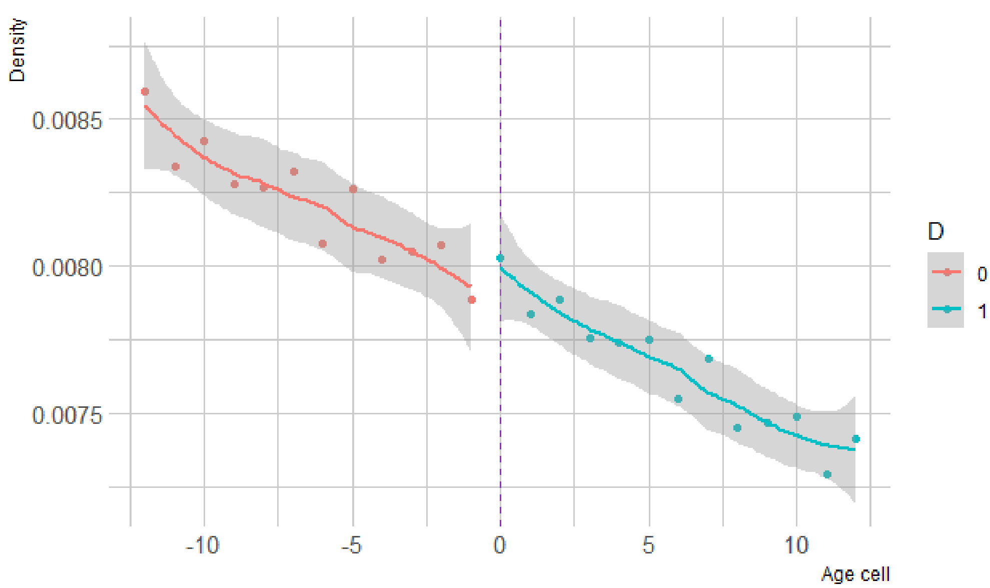
4.1 Assumption checks

In order to validate the approach and estimations used, we evaluate whether the assumption required to perform the RDD holds true. As stated previously, we will focus on two key assumptions: i) the treatment assignment mechanism behaves as intended, i.e., individuals are not able to perfectly manipulate the assignment variable (and therefore access to treatment); and ii) the cost-sharing policy shows no treatment effect over covariates collected prior to treatment (i.e., sex, wage, etc.). Both assumptions will be assessed using methods agreed on in the literature (graphically and formally).

The density of each age cell around the threshold is illustrated in Figure 1. As density runs smoothly over the age cell, no evidence was found regarding perfect manipulation of the assignment variable, which would be visible in the form of discontinuities if present. In addition, the relation between several prior covariates and the running variable is presented in Figure 2. As evidenced above, with the exception of cost-sharing for public healthcare services, which is expected to change at the 60th birthday, no prior covariate shows discontinuities or bumps around the threshold.

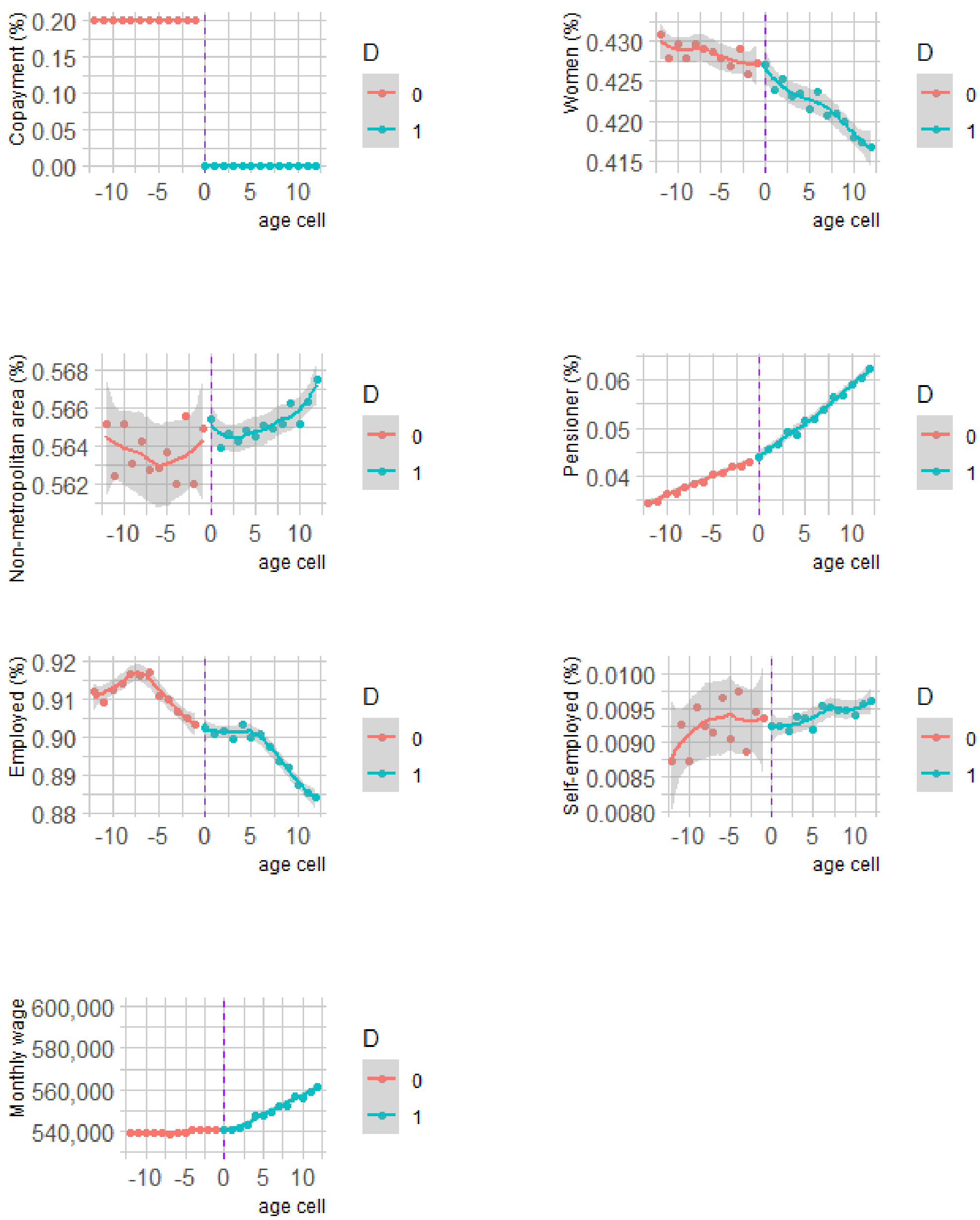
In line with these findings, when applying the manipulation density test proposed by Cattaneo and colleagues, the null hypothesis is not rejected (p-value near 1), so no evidence of manipulation is found. Also, the parametric approach presented in Table 3 shows that no significant treatment effect is estimated for age cell density and prior covariates when fitting a linear model, with an effect size near zero and a large p-value. Both results suggest that the assumption required to validate the RDD holds true, and are in tune with what is reported by published studies that evaluate the effect of age-related copayment policies on demand for healthcare services (Olivier Bargain and Karina Doorley, 2011, Hsing-Wen Han, Hsien-Ming Lien and Tzu-Ting Yang, 2020, N. Johansson, N. Jakobsson and M. Svensson, 2019, Thomas Lemieux and Kevin Milligan, 2008).

Figure 1. Running variable density around the 60th birthday threshold.



Note: Density is defined as the ratio between the number of individuals within a specific age cell and total size of the sample (4726,270). D: is a dummy that takes the value of 1 if age cell a is greater than or equal to 60 years.

Figure 2. Relationship among several covariates and the age cells.



Note: Each bin represents the expected value of the measured outcome for each age cell. Monthly wage is expressed in Chilean pesos (4). D: is a dummy that takes the value of 1 if age cell a is greater than or equal to 60 years

Table 3. Effect of the cost-sharing policy over the running variable and prior covariates.

Dependent variable	Estimate coefficient Threshold (*D*)	Robust SE	p-value
Running variable density	3.8E-05	4.7E-05	0.42
Women (%)	7.1E-04	1.4E-03	0.62
Pensioner (%)	-1.9E-03	2.7E-03	0.48
Non-metropolitan area (%)	-1.3E-04	1.2E-03	0.91
Dependent worker (%)	-5.1E-04	2.1E-03	0.80
Independent worker (%)	-6.0E-05	1.5E-04	0.68
Monthly wage ($)	$2,098	$3,649	0.57

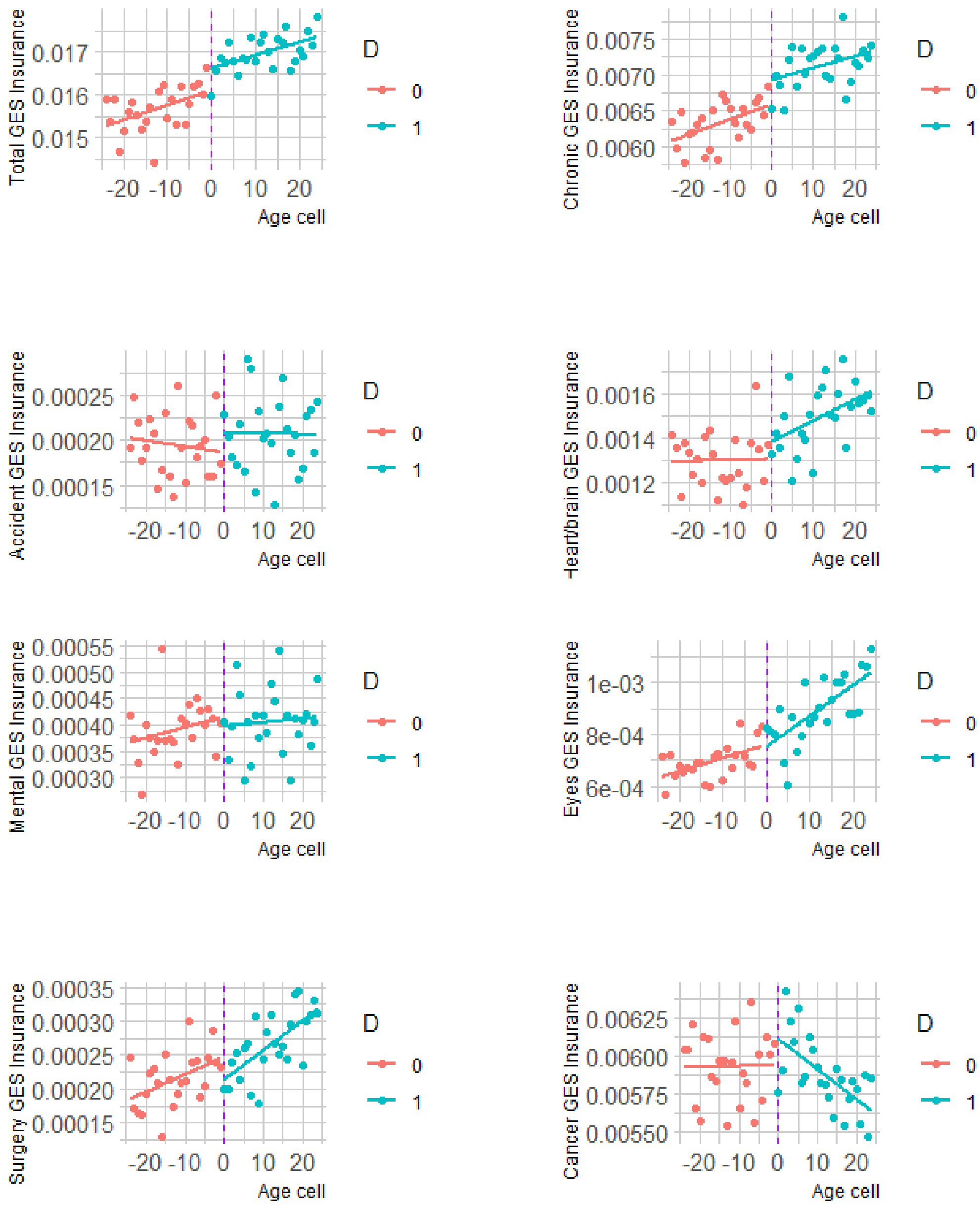
Monetary amounts ($) are in Chilean Pesos (CLP).

4.2 Activation of GES health insurance

In order to examine the effect of the decrease in cost-sharing on utilization of public healthcare, we begin our analysis by looking for any discontinuity in the activation of GES insurance around the 60th birthday. Figure 3 shows the number of GES insurance policies activated per age cell per month for the total number of pathologies (and their disaggregation by health problem) around the threshold. In most cases, we observe an increase in insurance policy utilization after the 60th birthday, particularly those relating to chronic disease. In line with these findings, Table 4 reports a statistically significant increase in the rate of GES insurance utilization, but only for the aggregated data and chronic services. Specifically, we found incidence rate ratios (IRR) of 1.03 and 1.05, which inform causal effects of a 3 and 5 percentage point increase for activation of GES insurance and chronic GES insurance, respectively. In practice, this means that the number of diagnoses and treatments associated with GES health problems provided by the public healthcare network has increased due to the change in cost-sharing.

As we have not been able to access GES medical claims data, we do not know the out-of-pocket expenditure of the individual and, therefore, cannot estimate the price elasticity of demand. In this context, we estimated a "generosity" elasticity of demand, which informs how the activation of GES insurance varies according to the percentual variation on the cost-sharing. This index was calculated as the ratio between the percentage point increase on GES insurance activation and the change in the cost-sharing (20%). We found an elasticity of -0.16 and -0.26, which means that a 10% increase in cost-sharing translates into a reduction in first-time use of GES insurance of 1.6% and 2.6% for activation of GES insurance and activation of chronic GES insurance, respectively.

Figure 3. Cost-sharing policy effect on the monthly per-age cell activation of GES insurance.



Note: Each bin represents the aggregated rate of monthly GES insurance activation for each agecell. This was estimated as the ratio between total number of GES activation and the total number of individual within a specific age cells. D: is a dummy that takes the value of 1 if age cell a is greater than or equal to 60 years.

Table 4. The estimated effect of cost-sharing policy on the first-time utilization of GES insurance

GES Insurance	Rate ratio (% increase in utilization)	Effect size Threshold	Robust SE	p-value
Total GES insurance	1.032	0.03	0.01	0.03
Chronic GES insurance	1.051	0.05	0.02	0.01
Accident GES insurance	1.119	0.11	0.10	0.28
Heart/brain GES insurance	1.064	0.06	0.05	0.20
Mental GES insurance	1.064	0.06	0.05	0.20
Eyes GES insurance	1.001	0.00	0.05	0.98
Surgical GES insurance	0.872	-0.14	0.09	0.14
Cancer GES insurance	1.030	0.03	0.02	0.17

To prove the robustness of our result, in Table 5 we present the sensitivity analysis for the non-incorporation of baseline socio-demographic covariates in our Poisson model, the nature of the model fitted, a greater age cell size (quarterly and semesterly), the length of the window around the threshold (1 to 4 years), and the estimation results when fitting by higher-order polynomials. It should be noted that this analysis was carried out only for the aggregated data and for chronic GES insurance.

With regard to the inclusion (or not) of baseline covariates, the results presented in Table 5 suggest that covariate adjustment displays a marginal effect over the effect size and standard error. The same can be said of the nature of the fitted model: when we estimate our model with a negative binomial regression, little effect is found. In accordance with expectations, we found a small increase in the effect size for most age cell size scenarios—which may be related to the fact that a monthly consumption window is very small in terms of reflecting patterns of individuals' healthcare consumption—and an increase in the standard error. Regarding the size of the window around the threshold, we observe a decrease in effect size and a loss of significance if we restrict the analysis to a window of ±12 months around the 60th birthday; by contrast, with a larger window, our results increase in effect size and significance. Finally, when we modeled the treatment effect by higher-order polynomial, we found that the effect size is lost for a polynomial of order greater than 2.

Table 5. Robustness analysis of cost-sharing policy effect on activation of GES insurance.

	Rate ratio (% increase in utilization)	Effect size Threshold	Robust SE	p-value
Panel A: All public healthcare services				
Base Case estimate	1.032	0.03	0.01	0.03
Without socio-demographic covariates	1.032	0.032	0.015	0.039
Negative binomial model	1.035	0.035	0.015	0.017
Bin size:				
Trimester	1.034	0.034	0.017	0.049
Semester	1.033	0.032	0.023	0.157
Window size around the threshold:				
±12 months around the threshold	1.014	0.014	0.020	0.487
±36 months around the threshold	1.028	0.028	0.012	0.018
±48 months around the threshold	1.037	0.036	0.010	0.001
Higher-order polynomial:				
Quadratic	1.030	0.030	0.014	0.037
Cubic	1.008	0.008	0.019	0.665
Quarter (grade forth)	1.012	0.012	0.019	0.526
Panel B: Chronic healthcare services				
Base Case estimate	1.051	0.05	0.02	0.01
Without socio-demographic covariates	1.051	0.050	0.023	0.032
Negative binomial model	1.053	0.051	0.019	0.008
Bin size:				
Trimester	1.054	0.053	0.021	0.012
Semester	1.051	0.050	0.025	0.048
Window size around the threshold:				
±12 months around the threshold	1.031	0.031	0.027	0.249
±36 months around the threshold	1.054	0.052	0.016	0.001
±48 months around the threshold	1.064	0.062	0.014	0.000
Higher-order polynomial:				
Quadratic	1.052	0.051	0.019	0.009
Cubic	1.021	0.021	0.026	0.423
Quarter (grade forth)	1.027	0.026	0.026	0.315

Finally, we report the heterogeneity analysis in Table 6. We observe that the treatment effect is lost when we restrict the analysis to the subgroups of females and individuals living in the metropolitan area; by contrast, the treatment effect increases in size and significance if we include males and individuals living in non-metropolitan areas in the analysis.

Table 6. Heterogeneity analysis of the effect policy on the GES insurance activation.

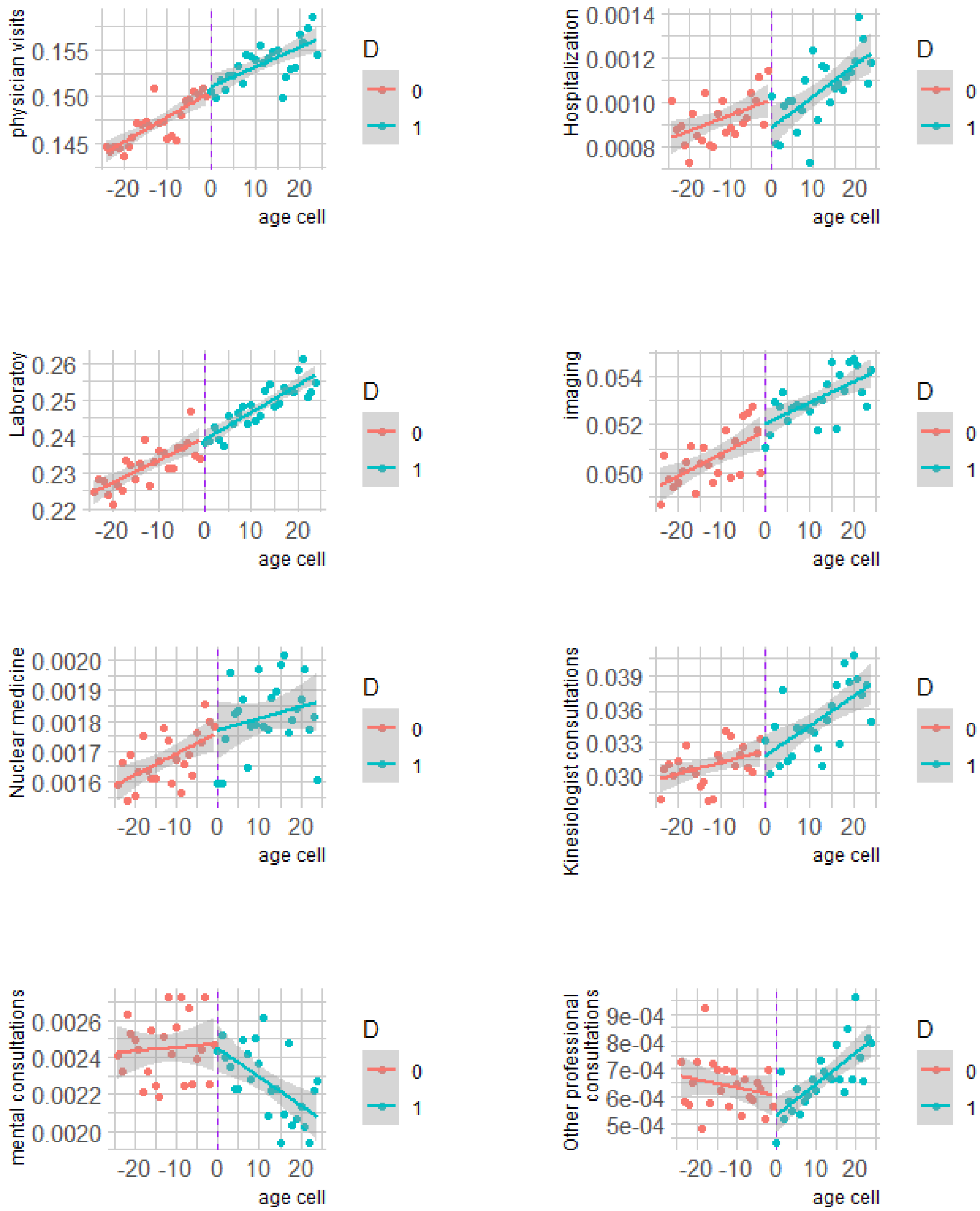
Subgroup analysis	Rate ratio (Increase in utilization %)	Effect size Threshold	Robust SE	p-value
Panel A: Female				
Total GES insurance	1.02	0.02	0.02	0.26
Chronic GES insurance	1.02	0.02	0.03	0.35
Panel B: Male				
Total GES insurance	1.05	0.05	0.02	0.01
Chronic GES insurance	1.08	0.07	0.03	0.01
Panel C: Non-metropolitan area				
Total GES insurance	1.05	0.05	0.02	0.01
Chronic GES insurance	1.07	0.07	0.03	0.01
Panel D: Metropolitan area				
Total GES insurance	1.01	0.01	0.02	0.54
Chronic GES insurance	1.03	0.03	0.03	0.28

4.3 Private healthcare service utilization

With the aim of analyzing the effect of the policy on the utilization of healthcare services provided through the MLE scheme, we begin our analysis by studying the relationship between utilization of private healthcare services and the running variable. Figure 4 illustrates the utilization per age cell per month for all of the private healthcare services around the threshold. At first glance, and with the exception of hospitalization services, we found no evidence of discontinuities around the threshold. When formally testing the policy effect by the estimation of our Poisson model we found a negative effect on healthcare consumption at the 60th birthday for hospitalization, mental health consultation, laboratory testing, and consultations with kinesiologists and other healthcare professionals (Table 7). Instead, we found a positive effect on total services, physician visits, imaging, and nuclear medicine. It is worth mentioning that besides hospitalization services, where we reported an IRR of 0.89, significant at a 10%, which expresses an 11-percentage point decrease in hospitalization service utilization, most of the effect sizes are not statistically significant.

In practical terms, these results suggest that utilization of healthcare services through the MLE scheme is, for the most part, not responsive (by means of an increase in opportunity cost) to variations in cost-sharing for public healthcare services.

Figure 4. Cost-sharing policy effect over monthly per-age cell utilization of private healthcare services.



Note: Each bin represents the aggregated rate of monthly utilization of private healthcare for each age cell. This was estimated as the ratio between total number healthcare utilization and the total number of individuals within a specific age cells. D: is a dummy that takes the value of 1 if age cell a is greater than or equal to 60 years.

Table 7. Estimated effect of the cost-sharing policy on private healthcare service utilization.

Private healthcare services	Rate ratio (reduction in demand %)	Effect size Threshold	Robust SE	p-value
Total private healthcare	1.00	0.000	0.008	0.995
Physician visits	1.00	0.004	0.007	0.632
Hospitalizations	0.89	-0.122	0.071	0.087
Laboratory test	1.00	-0.003	0.011	0.820
Images	1.01	0.005	0.011	0.633
Nuclear Medicine	1.00	0.001	0.036	0.982
Kinesiologist consultations	0.99	-0.010	0.035	0.765
Mental consultations	0.99	-0.008	0.051	0.870
Other healthcare professional consultations	0.90	-0.110	0.084	0.191
Other procedures	1.00	-0.001	0.016	0.946

Concerning the robustness check, in Table 8 we present the sensitivity analysis for private healthcare utilization. Given that only hospitalization services seem to be affected by the cost-sharing policy, we restrict our analysis to this single outcome. According to the results obtained when we estimate the model without baseline covariates, little effect is found in terms of both size effect and Robust SE. This also seems the case when the model is estimated with a binomial regression model, although for this analysis the effect size becomes almost significant at 5% significance. Regarding age cell size, our results suggest that the policy effect decreases when larger windows are used (smaller treatment effect and loss of significance at 10%). Concerning the size of the window around the threshold, a variation in the effect size is observed, along with a drop in significance if we restrict the analysis to different window sizes. Finally, when we modeled the treatment effect by higher-order polynomial, we found that the effect size becomes higher and significant at 5%.

Table 8. Robustness analysis of the effect of cost-sharing policy on private healthcare service consumption.

	Rate ratio (reduction in utilization %)	Effect size Threshold	Robust SE	p-value
Hospitalizations services				
Base Case estimate	0.89	-0.122	0.071	0.087
Without socio-demographic covariates	0.885	-0.122	0.068	0.073
Negative binomial model	0.876	-0.132	0.070	0.057
Bin size:				
Trimester	0.904	-0.101	0.076	0.183
Semester	0.916	-0.088	0.078	0.260
Window around the threshold:				
±12 months around the threshold	0.836	-0.179	0.116	0.122
±36 months around the threshold	0.974	-0.026	0.055	0.633
±48 months around the threshold	0.976	-0.024	0.045	0.584
Higher-order polynomial:				
Quadratic (grade =2)	0.870	-0.140	0.071	0.048
Cubic (grade =3)	0.816	-0.203	0.102	0.047
Quarter (grade =4)	0.816	-0.204	0.106	0.055

Lastly, we report the heterogeneity analysis for the utilization of private healthcare services in Table 9. The treatment effect is lost when we restrict the analysis to sex subgroups (female or male), whereas when we evaluate the treatment effect by area of residence, we find that individuals living in non-metropolitan areas display a higher treatment effect (significant at 1%).

Table 9. Heterogeneity analysis of private healthcare service consumption.

Subgroup Analysis	Rate ratio (reduction in demand %)	Effect size Threshold	Robust SE	p-value
Panel A: Women				
Hospitalizations	0.875	-0.134	0.108	0.216
Panel B: Men				
Hospitalizations	0.896	-0.110	0.091	0.228
Panel C: Non-Metropolitan area				
Hospitalizations	0.742	-0.298	0.110	0.006
Panel D: Metropolitan area				
Hospitalizations	1.075	0.072	0.080	0.368

5 Discussion

In the present article we applied an RD design that focuses on the age discontinuity in cost-sharing at the 60th birthday in order to estimate the effect of a decrease in copayment on the activation of GES insurance and utilization of private healthcare services. Given that the assumptions required to implement the RDD are met, that no evidence of perfect manipulation of the assignment variable was found, and that no discontinuities around the threshold for baseline covariates was detected, our results do indeed provide estimates of the causal effect of the policy.

5.1 Activation of GES health insurance

According to our results, the change in cost-sharing leads to a significant increase in the activation of GES insurance. Specifically, we estimate that the change in cost-sharing causes an increase of 3 percentage points in the activation of GES insurance – with an elasticity of -0.16. When analyzing the result according to pathology type, we find that application of the policy causes an increase of 5 percentage points in the activation of chronic GES insurance, which implies an elasticity of -0.26. In practical terms, these findings show that following the implementation of the policy, the number of new GES diagnoses and first-time treatments provided increased. As chronic disease is the only category that reports a significant effect, we suspect that the overall effect found is strongly influenced by chronic health problems.

These results are consistent with the nature and complexity of each health problem evaluated. Chronic health problems, due to their long development period, tend to go unnoticed by individuals, with treatment thus being delayed. In contrast, acute events, such as heart attacks, strokes, or heart and brain disease, which involve major bleeding and thromboembolic events, should be less sensitive to copayment changes. The same can be said for more complex diseases such as cancer, and for more debilitating issues such as ocular diseases, diseases requiring surgical intervention, and mental diseases. It is worth mentioning that we found a non-significant negative effect for services relating to problems requiring surgical intervention, a result that we suspect may be due to the fact that only a few observations are available for these services, making it a sample feature.

Regarding mental health issues, we can also assert that in a context of financing restrictions—the Chilean healthcare budget allocated to mental health is low even compared to other middle-income countries (Alberto Minoletti et al., 2012, Pedro Retamal C et al., 2016)—and organizational failures (Alice Blukacz et al., 2020), the healthcare system does not have the capacity to meet increasing demand, a reality that is true even regarding GES care.

Table 5 shows that our estimations are not sufficiently robust to shrink the size of the window to 1 year, to increase the age cell size to 1 semester, or to conduct estimations with a higher-order polynomial. Concerning the first two analyses, although both estimations report a positive treatment effect—with some variation regarding effect size—these results are consistent with the loss of statistical power due to the decreased number of observations. Regarding the use of higher-order polynomials for robust analysis (cubic and quartic specification), although they are routinely reported in studies that apply the RD design, this method leads to noisy estimates and therefore should not be used (Andrew Gelman and Guido Imbens, 2019).

Our heterogeneity analysis reports that men are more sensitive to changes in copayment, the same can be said for individuals that lives outside of the metropolitan area. This result is in tune with what is reported by Shigeoka and colleagues, who identified men as a group more sensitive to variations in copayment (Hitoshi Shigeoka, 2014). Nevertheless, as the outcomes assessed in this study, activation of GES insurance, differ greatly from the outcomes evaluated by Shigeoka, care should be taken regarding comparisons.

A plausible mechanism to explain the difference found between men and women is related to the fact that women are more involved with the healthcare system in general. According to information reported by FONASA, women aged 15-59 years exhibit higher utilization of healthcare services than their male counterparts (FONASA, 2021). Given that the GES data reports new diagnostic cases and the first indication for treatment, it would be consistent to consider that greater use of healthcare services reduces the probability of a late diagnosis or a delayed start of treatment, which is precisely the information to which we have access. Further information in needed regarding the mechanism that underlies this heterogeneity among individuals living inside and outside the metropolitan area.

Finally, although we have not measured the effect of the policy directly on healthcare utilization, our findings are in line with the notion that an increase in healthcare utilization will undoubtedly translate into more diagnoses and treatments provided, which is exactly what we are perceiving. Nevertheless, due to differences between the dependent variables studied, it is difficult to make direct comparisons between what is reported in the literature and our results.

5.2 Private healthcare service utilization

Regarding our results relating to private healthcare utilization, Table 7 shows that the estimates are less consistent than those obtained for public healthcare services. Almost all the outcomes evaluated show a marginal size effect and a large p-value with a changing effect direction, the exception being hospitalization services (at 10% of significance, at least). Regarding hospitalization services, we estimate a decrease of 11 percentage points in utilization due to the implementation of the policy (IRR=0.89).

These results can be explained by the peculiarities of the MLE scheme and the Chilean healthcare system. The modality was introduced as an alternative—in exchange for a higher copayment—to the long waiting lists that blight the non-GES care provided by the public network. In this sense, the FONASA beneficiaries who make use of this scheme are probably those who are less sensitive to the effects of cost-sharing. Additionally, most of the private consultations with healthcare professionals (physicians, nurses, kinesiologists, etc.), laboratory exams, and imaging are relatively cheap compared to the alternative of receiving care in the public system, which demands a lower copayment but suffers from longer waiting lists and the inability to choose a consulting professional. On the other hand, hospitalization is one of the most expensive services, and it is reasonable, therefore, that this type of service reports the greatest effect size.

Robustness checks for private healthcare consumption show that the results are not robust to window size around the threshold and age-cell size. Specifically, we found that as size increases, treatment effect decreases, and significance is lost. By analyzing window size, we observe that under a 1-year window we achieve the largest effect size (18 percentage point decrease in demand for services) but we lack the statistical power to find significant results. For larger windows, the effect size becomes almost null, and we lose significance. We believe that these results are driven by two forces: as we consider observations further from the cut-off (60^{th} birthday), the estimates become more biased toward remote observation. As such, although the treatment effect is diluted, restricting the window size does not provide us with sufficient statistical power to achieve significance. This trade-off has been acknowledged extensively in the literature (David S. Lee and Thomas Lemieux, 2010). Age cell size is also affected by the loss of statistical power and the inclusion of observations that are more remote from the threshold.

A plausible explanation of these results is that the increase in public healthcare utilization produces an additional load on a system whose networks are already overburdened. As such, even if individuals initially substitute care provided through the MLE scheme for that offered by the public network, the fact that the public sector is unable to meet this new demand due to waiting list issues mean that it will eventually return to the private sector.

Finally, our heterogeneity analysis reports that individuals living outside the metropolitan area are more sensitive to changes in copayment associated to public health services. One could hypothesize that, just as we find an increase in the utilization of GES care (measured as activation of GES insurance) non-GES care is similarly affected. Then, the non-GES care increases to detriment of private services because individuals substitute MLE care for public care. Although the reasons why this effect is not observed in the metropolitan area remain unknown.

5.3 Limitations

In general terms, one of the main limitations of the present paper is that we cannot fully analyze the effect of the cost-sharing policy on the utilization of public healthcare services. Our analysis is restricted to GES care and does not cover non-GES services. Notwithstanding the above, GES care represents an appropriate subject of study, as this type of care is almost completely unaffected by Chile's waiting-list problems and, as such, the effect of the policy can be measured with certainty.

A second limitation is that we lack access to medical claim data for the public sector, leaving us unable to identify all the GES services provided by the public healthcare network. Because of this, we cannot estimate the causal effect of the change in cost-sharing over healthcare service utilization. Even though the activation of GES guarantees us an insight of utilization, this "aggregated" data may hide the true variability and heterogeneity related to the utilization of healthcare services.

Another limitation of this work is that we only evaluate the effect of the policy in a rather specific subgroup of the population, FONASA D individuals around 60 years of age, leaving aside FONASA C beneficiaries. Further research should be conducted to determine the effect of cost-sharing reduction on FONASA C individuals, and the possible presence of a gradient effect between both brackets (the cost-sharing reduction is higher for the D bracket).

Lastly, we did not evaluate the treatment effect using a non-parametric approach. Although there are differences in terms of how to implement a non-parametric approach when the running variable is discrete, non-parametric estimation remains the gold standard in the RD setting (Brigham R Frandsen, 2017, David S. Lee and Thomas Lemieux, 2010).

5.4 Relevance of the findings

In October 2019, Chile experienced the most important civic and political crisis since the return of democracy. Initially carried out by high school students, as a response to the increase of 30$ pesos increase in the tariff on the public transport, after a few days the situation go out of control. On the 18th of October, under the motto "'It's not 30 pesos, it's 30 years", the "Estallido Social" (Social Outbreak) happened against the 30 years of inequalities and injustices produced by the Chilean model (Martín Arias-Loyola, 2021).

In this sense, the government of Gabriel Boric, who assumed the presidency on the 11th on March, has the responsibility to promote reforms that establish a welfare state that addresses the inequities produced by the 30 years of neoliberal model. Without going any further, during his first Public account, the new mandatory emphasized his support and commitment to measures aimed at resolving the discontent of the population, among them, the end of copayment for health services (Minsal, 2022).

How will the cessation of co-payment affect utilization or demand for health services? and if the demand increases, will the health system be able to respond to this increase? Both questions must be answered for the implementation of an adequate and efficient policy. In this context, the findings of our study become relevant. To our knowledge, this is the first study that assess the effect of a reduction in cost-sharing over the demand of healthcare. Even though our analysis is restricted to population around 60 years, and the literature shows heterogeneity in the elasticity among age groups, we hope that this work will serve as a starting point to expand the study of this topic in Chile.

6 Conclusions

According to our results, we estimate that the reduction in cost-sharing causes an increase of 3 percentage points in the activation of GES insurance. When analyzing the result according to pathology type, we find that the application of the policy causes an increase of 5 percentage points in the activation of chronic GES insurance. These results indicate that following the implementation of the policy, the number of new GES diagnoses and first-time treatments provided increased.

Regarding our results relating to private healthcare utilization, we have found that almost all the outcomes evaluated are not sensitive to the decrease in cost-sharing experienced by public healthcare services. The only healthcare services that report a significant treatment effect (at a 10% of significance) are the hospitalization healthcare services, where we estimate a decrease of 11 percentage points in the utilization due to the implementation of the policy.

Regarding the heterogeneity in the demand response to cost-sharing variation, both results, GES activation and private healthcare utilization vary by subgroup. For the GES insurance activation, we found that the treatment effect is restricted to men and individuals living outside of the metropolitan area, being the latter also true for private healthcare services utilization. We suspect that gender differences may be a consequence of the unequal patterns of health care utilization between Chilean men and women. Concerning the geographical heterogeneity, the reasons for this phenomenon remain unknown.

Future research should focus on three main issues. First, to measure the effect of the variation in cost-sharing on the actual utilization of healthcare services, and to estimate a price-demand elasticity for all services provided within the public health network. Secondly, it is important to analyze how the demand induced by a variation in cost-sharing affects the waiting list (does the waiting list problem worsen?) and vice versa. At last, research on different populations is needed to reveal the heterogeneity of the demand response to variation in cost-sharing and the underlaying mechanism.

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