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DOES USER CHARGES EXEMPTION AFFECT HEALTH CARE SEEKING? EVIDENCE FROM PORTUGAL

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To my Family, to which I owe any achievement,

To my Dad, who taught me to find the Good in any person and any situation,

To my Mom, the strongest and most caring woman I have met in my life,

To Siria, who guided and helped me in every important moment and decision,

To all my friends, for making my days special.

Abstract

Using Portuguese survey data, this work evaluates the impact of the exemption from user charges on public healthcare services utilization. Services considered are appointments in health centers, visits at emergency departments, and usage of any service when sick. Results suggest that the exemption has a positive effect on the demand of each service, and that the magnitude is bigger for less urgent types of care. In addition, the impact of the exemption is attenuated for individuals with chronic diseases and for older people.

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Introduction

The capacity of public health systems to help people in need is not infinite. This was made dramatically clear by the COVID-19 pandemic: due to the overcrowding of the health facilities, many services were interrupted and lots of patients were unable to receive the assistance they needed. In less extreme times, some health systems are plagued by long waiting lists and the substantial waiting times before receiving care or performing tests.[1]

Even in healthcare systems indirectly financed by taxes, the scarcity of resources – both human capital and means such as facilities, equipment, and medications - has led to the introduction of user charges. In these systems, if no payment has to be made at the moment of accessing care, there is the risk of moral hazard: users could use more services than they would if they were to pay themselves. User charges are the instrument devised to control service demand, trying to ensure that care is sought when needed, therefore allocating public resources to those who most need them.

However, to avoid that some categories refrain from using health services when needed, exemption from payment of fees is usually granted to people meeting certain criteria, as poor people, those with chronic conditions, and pregnant women. Indeed, these categories suffer the most severe consequences of the charges, as on the one hand they are likely to need assistance often (and so, pay more frequently), and on the other hand they might be the ones with the worse financial conditions, and could refrain from seeking assistance when needed to avoid other expenses.

The main questions this paper addresses are whether user exemptions have an impact on services utilization and, in that case, whether they increase demand for unnecessary care, acting against the rationale for which the charges were introduced in the first place.

Given how the exemption is assigned, we need to consider that just comparing those exempted with those who are not implies comparing people that would end up acting differently even in the absence of the exemption (selection bias issue). For this reason, the analysis includes relevant cofounders in order to isolate and precisely quantify the impact of the exemption.

To determine whether the exemption favours moral hazard, we use some indicators of necessity of care, which will allow to identify vulnerable individuals - people that, ceteris paribus, should be more inclined to seek assistance.

We find that the exemption increases services utilization for all types of care considered, especially those which are less urgent. At the same time, the more vulnerable and (theoretically) in need the people are, the smaller the effect of the exemption on their service utilisation. This suggests that, when care is needed, the exemption represents a weaker incentive because the decision to seek assistance is taken independently from

[1] For instance, in Italy during 2021 71% of the issues related to access to care were related to long waiting times (Rapporto Civico sulla Salute 2022, Cittadinanzattiva 2022).

the exemption status. On the contrary, for relatively healthier and less vulnerable individuals, we see a bigger effect, which points to the fact that the exoneration might favour unnecessary care.

The paper is structured as follows. First, we review the relevant literature relative to the impact of cost-sharing structures, insurances, exemption from associated costs, and introduction of fees on health services utilization. Next, we describe the Portuguese National Health System, with special attention devoted to user charges and to the functioning of the exemption from their payment. Next the data used in the analysis are described alongside the methodologies employed to estimate the impact of user charges exemption on access to the health care. The second part of the work presents the analysis and the results. In particular, we focus on the impact of exemptions on appointments in health centers (Study I) and visits to emergency departments (Study II), which we then compare (Study III); next we consider the effects of the exemption on any kind of services utilization for people that required assistance in response to sickness (Study IV) and propose two approaches to understand whether the exoneration assigned to minors is impactful (Study V). The last section concludes.

Literature review

Without any doubt, the first work to mention when it comes to the literature on medical care and cost sharing is the RAND Health Insurance Experiment (HIE).[2] This study paved the way for this strand of research and was regarded as a "*gold standard*" (Levy, Meltzer, 2007) in the academic literature on the effects of health insurance due to its influence on policy in the 1980s and 1990s.

This field experiment focused on how the utilization of health services, the quality of care, and people's health status are affected by cost-sharing arrangements. Families were randomly assigned to one of six types of health insurance plans, ranging from one granting free care to one with a high burden on the family itself. The results of the experiment highlight that spending for healthcare services decreases with cost-sharing: participants assigned to plans under which they had to pay more made fewer medical visits and were admitted to hospitals less frequently. Indeed, health insurance without co-payments was found to make more people use services, and each user would use more services (both outpatient and inpatient ones).[3] On the contrary, both the use of effective ("*appropriate or needed*") and less effective ("*inappropriate or unnecessary*") services were reduced by cost sharing. However, for most of the participants (the average American covered by employment-based insurance), the variation in use had negligible effect on health status. Instead, only those that were both sick and poor suffered the most from the detrimental effects of cost sharing.

A second experiment to mention is the Oregon Health Insurance Experiment. This consisted in a randomized controlled experiment design aimed at studying the effect of expanding public health insurance on health care use, health outcomes and well-being of low-income adults. It took place from 2008, when the state of Oregon selected names for the Medicaid program via lottery for low-income, uninsured individuals. The extended coverage resulted in a significantly higher number of outpatient visits, hospitalizations, drug prescriptions, emergency department visits, and an increase in compliance with recommended preventive care.[4]

The Qin et al. (2019) survey paper evaluated 17 studies from 12 low- and middle-income countries (LMIC). The findings suggest that a reduction in user charges improves health outcomes, especially of children and lower-income populations.[5] The higher access to healthcare is probably the reason behind this result. Indeed, in 12 of the 14 studies that reported healthcare use, people used more healthcare services following the reduction in user charges. Furthermore, 9 studies find both an increase in services utilization and improved health outcomes.

Ridde and Morestin (2011) performed a similar review for studies tackling the abolition of user charges in Africa. In 17 out of 20 papers, the effect of the abolition of fees on the usage of health service was the main

[2] The RAND HIE is the largest health policy study in the history of the United States. The fieldwork of the experiment dates back to 1976 and lasted for 6 years. 7700 people from 2750 families participated in the study.

[3] Inpatient services require hospitalization, meaning that the patient is required to stay in the health facility, while outpatient services do not.

[4] In addition, it declined exposure to substantial out-of-pocket medical expenses and medical debt, reduced depression and improved self-reported measures of mental and physical health.

[5] Changes in user changes policies comprise both removal of charges and reduction of charges.

focus. They showed a rise in visits in primary care after the abolition (from 17% in Madagascar to 80% in Uganda) and, more in general, higher service utilization. However, the effects were sometimes heterogenous, probably because of the different methodologies employed in the analyses.

Rice and Matsuoka (2004) reviewed the research on the impact of patient cost-sharing on services and medications utilization and the resulting impact on health status for people aged at least 65. Almost all of the 22 studies considered[6] suggested that increased cost-sharing causes a decline in both the service utilization and the health status of the individuals. Among the 15 studies that focused on the "*appropriate*" usage of services and medications, 12 showed that the use of prescription drugs and service usage declined because of cost-sharing.

Another study that focused on high-risk groups is Abdu et al. (2004). They investigated the impact of the exemption from user fees on service utilization and treatment seeking behaviour in Sudan for pregnant women and children under 5 years, in particular need of medical assistance to prevent progression of malaria.[7] They found that the exemption increases services utilization, promotes early diagnosis, and improves treatment-seeking behaviour. Moreover, the largest the exemption, the largest the changes during the period of observation.

In a paper from 2012, Prinja et al. studied the effect of the opposite phenomenon: the introduction of user charges in North India. They show that demand is influenced heavily by prices, with a strong effect on the hospitalization rate. They also noticed that, in districts with user charges, the share of rich people among inpatients was higher than in districts without user charges, where there was a higher share of poor people hospitalized. Moreover, the decline in hospital admission in the districts where fees were introduced, was significantly higher for women and among rural population. They concluded that the decline in healthcare usage due to user charges is inequitable from gender and income perspective and probably reflects lower paying capabilities. Finally, it was found that user charges implementation discourages preventive care service and delays medical care utilization at early stage of disease onset. However, they did not establish whether demand reduction was only for 'unnecessary' forms of care or whether 'necessary' care utilization also decreased.

Moving to studies closer to the present one, focusing on Portugal, Ramos and Almeida (2016) evaluated how the rise in direct costs impacted the demand for emergency services (ES). They studied the effect of the changes in co-payments introduced in 2012 (which we will discuss in a later section) through a difference-in-difference approach. They found that the increase in co-payments did not moderate the ES demand and utilization. According to the authors, the reason lies, rather than in the little or no elasticity of demand, in the nature of the co-payments in Portugal, which are fixed and not very high, and not paid by the low-income people, which are exempted.

[6] Among which, 16 were about cost-sharing for prescription drugs and the remaining 6 about medical services.
[7] In particular, the effect was assessed considering different levels of exemption (25%, 50% and 75%)

Quintal et al. (2016), assessed the impact of fees and the exemption on the use of paediatric care in Portugal. The results suggest that the behaviour of the payers and the exempted is not statistically different even at low income, and that there is no moderating effect of the user charges on this kind of service.[8] A possible explanation is that parents are less sensitive to the monetary cost when their children are involved.

[8] The authors expected to see that lower income impacts negatively on utilization if fees constitute a barrier to access to care, but this was not a consistent result, even in cases of preventive care, which is associated with higher price sensitivity.

The Portuguese Health System

The health system in Portugal is mainly organized around the National Health Service, NHS (*Serviço Nacional de Saúde*, SNS), whose funding derives for most part from governmental budget (around 9.5% of GDP in 2019, below the EU average of 9.9%), hence from taxes. This system coexists with different social health insurance schemes for certain professions (health subsystems) and voluntary private health insurance (VHI), which together cover 25% of the population as of 2017 (Country Health Profile 2021, OECD).

The NHS was established in 1979 and operates under the supervision of the Ministry of Health in order to assure the right to health protection, as prescribed by the Portuguese Constitution. It covers only Continental Portugal, but all Portuguese residents have access upon registration.[9] This must be made at the health centre of the person's area and allows him/her to receive the NHS Number and to benefit from the public healthcare system' assistance.[10] The NHS offers a wide range of healthcare services tendentiously free of charge for the users. The costs they incur in, called user charges (or in Portuguese *taxas moderadoras*),[11] are standardized and mainly serve to fight moral hazard, filtering unnecessary access to services and excessive consumption, rather than as a source of funding.[12]

Five regional health administrations (North, Central, Lisbon and Tagus Valley, Alentejo, and Algarve) are responsible for providing the services to the populations of their respective regions, while the decisions regarding policies, rules, standards, and the management of the financial, human, equipment and facility resources are competence of the Central Administration of the Health System (*Administraçao Central do Sistema de Saúde*, ACSS).

The services provided by the NHS are mainly delivered in:

- Health centers groups (A*groupamentos de Centros de Saúde*, ACES), responsible for providing primary health care to the local communities. In each group, several health centers are aggregated together. For each municipality there is at least one centre (and it might have extensions in its jurisdiction).
- Hospital establishments, which are mainly responsible for secondary health care. Most of them are now part of a hospital centre, grouping more hospitals in the same city or region.
- Local health units (*Unidades Locais de Saúde*, ULS), which pool together health centers and hospitals in the same city or region in a single unit and provide both primary and secondary health care.
- Private entities, with whom the SNS has conventions for complementary healthcare services.

[9] The regions of the Azores and Madeira have their own healthcare systems.
[10] The number has to be shown whenever a public medical service is used.
[11] But we will refer to them also as moderating fees or user fees.
[12] As explained in Quintal et. al (2016), payments made at the time of use imply that in deciding whether to seek care, associated costs are considered together with the benefits, making the consumer moderate the demand and allowing a reduction of unnecessary use of care.

The health subsystems provide healthcare to members of certain professions or organizations,[13] in parallel to the SNS. The financing for these types of schemes usually depends on its beneficiaries (through discounts in their salaries) or their employers. Among these subsystems, ADSE is the most important one, covering all public servants (more than 1.3 million beneficiaries) in the Public Administration.[14] The subsystems provide healthcare through public and private medical establishments, thanks to conventions between the subsystems and the services providers.[15]

For what concerns health insurances, subscription is usually voluntary. Insurance healthcare services are provided either through a direct scheme (services are provided by establishments with previous convention with the insurance network) or through a free scheme (services are provided by entities with no previous convention, hence the insured person pays in advance and is later reimbursed).

The share of Government spending in the health sector is almost 20 pp. lower than the EU average (61% the former and 80% the latter in 2019, Country Health Profile 2021, OECD) and has decreased by 5.6% from 2010 (following fiscal consolidation measures, more in the following Section).[16] Out-of-pocket payments have increased and are now the second source of revenue in the health system (30.5%, compared to the European average of 15.4%), with VHI accounting for 8.6% and continuously growing.

User charges in Portugal

User charges are the amounts of money charged to users when receiving specific health care services from the SNS.

In January 2012 a new regime regarding user fees in hospitals and primary care services (mainly emergency departments visits and outpatient services) came into force in the context of the international financial crisis, which hit the Portuguese economy hard. The revision did not entail a change in the purpose of these fees: it was explicitly reaffirmed in the preamble of the new law that they were meant to rationalize the use of the resources and control the expenditures, guiding towards an appropriate use of the health services,[17] and it was recognized the small role of such charges for the NHS funding (Barros, 2012).[18]

In the Memorandum of Understanding (MoU) signed by Portugal with the European Commission, the European Central Bank and the International Monetary Fund, the attention regarding user fees was given to two main aspects: their levels and the exemption rationale. In particular, it was explicitly required a revision of the existing exemption categories and an increase in fees for certain services (even though the basic structure of user charges in Portugal was in line with the MoU prescriptions).

[13] Hence, it is possible to distinguish between private and public subsystems, depending on whether the individual is a public servant or a member of a private company.

[14] Other public subsystems include the ADM for the Armed Forces, SAD/GNR for the National Republic Guard, the SAD/PSP for the Public Security Policy and the SSMJ for special professional groups. These are entirely financed by the State.

[15] In case of no previous conventions, the beneficiaries are reimbursed of the payment they advanced.

[16] Even though substantial additional funding was granted in response to the COVID pandemic in 2020 in order to allow additional hiring, bonus payments and procurement of equipment (medical and for personal protection).

[17] The rationale of user charges is indeed to improve allocative efficiency (Schokkaert, Van de Voorde, 2015).

[18] Indeed, moderating fees contribute only to a negligible part of the SNS income (between 1- 2%; Quintal, 2016).

In response to the requirements of the MoU, a legislation setting the new levels of user charges together with norms of their yearly updates according to inflation, and new rules defining exemption groups was enacted. The newly set levels of user charges were among the highest in Europe. The value of the fees is defined annually by the Government, however the total amount due per episode of treatment cannot exceed the value of 40.00€.[19]

Such fees are to be paid when the user shows up to the consultation, is admitted to the emergency department, or when complementary diagnostic and therapeutic acts are conducted.[20] The health centres that integrate the SNS or which are in a contract with the SNS are required to provide all means for the effective collection of the fees, including cases of payment at a later time. In such cases, the entities must notify the user immediately when the fee is due. If the users do not pay, they are notified to proceed with the payment and in case they still do not comply, this might give rise to coercive payment.

Historically, exemptions were conceded to four categories of people: poor people, chronic patients, children and pregnant women, and individuals positively contributing to the society like blood donors and firemen. After 2012, the income threshold for the exemption related to poverty was raised, implying that a bigger proportion of the population can now benefit from the exemption. At the same time, exemptions for special groups and chronic patients were limited (for example, chronic patients receive exemption only when the care is related to their condition).

While there are many reasons that might make an individual eligible for receiving the exemption from the payment of user charges, it must be noted that the assignment of exemption is not automatic, and usually a request is needed to obtain it. Moreover, the procedures vary according to the situation. Here is a non-exhaustive list of people that are eligible for receiving the exemption:

- Pregnant and parturient (also in case of voluntary interruption of pregnancy), who are required to present an official medical certificate attesting their status.
- Minors (under 17 years and 365 days), who are required to show a legally valid civil identification document (until 2015 exemption was granted only to children up to and including 12 years of age).
- People with a degree of disability equal or above 60%, who are required to present a medical certificate that proves their degree of incapacity.
- People in a situation of economic insufficiency,[21] and their family members, who are required to apply via internet.
- Unemployed people regularly registered at an Employment Centre who receive an unemployment benefit not exceeding 1.5 times the social support index and who required to show the proof of the employment centre, their spouse and family members.

[19] The episode of treatment consists in a visit at a NHS facility, during which different tests can be performed. The total including also all the fees for the complementary diagnostic and therapeutic means cannot be above that threshold (Barros, 2012).

[20] In case consultation is carried out at home, the entity responsible for the collection establishes when the most appropriate time.

[21] Economic insufficiency arises whenever the household average monthly income is less 1.5 times the social support index (which changes yearly). The assessment of economic conditions is based on the information contained in the *Autoridade Tributária e Aduaneira* database and the elements reported by Social Security.

- Benevolent blood donors, as certified by a declaration issued by the Portuguese Institute of Blood and Transplantation (*Instituto Português do Sangue e da Transplantaçao*), proving two blood donations in the last 12 months. Alternatively, a declaration with more than 30 donations in the lifetime may be submitted.
- Living donors of cells, tissues, and organs, who are required to show a declaration by the Portuguese Institute of Blood and Transplantation.
- Firefighters, who only need to be included in the identification list of registered firefighters available in the National Register of Users (*Registro Nacional de Utentes*).
- Transplant patients, who are required to present a declaration issued by the competent services for the exercise of the transplantation activity.
- Military or ex-servicemen of the Armed Forces who, due to the provision of military services, are permanently disabled. They are required to present the identification card of the Disables of the Armed Forces (*Deficientes das Forças Armadas*).
- Asylum seekers or refugees and their immediate family, who are required to present valid documentation of asylum application.

In addition, for certain healthcare services, no fees are charged. Some examples are:

- Consultation and complementary acts prescribed in the context of degenerative neurological diseases, treatment of chronic pain, mental health, muscular dystrophies;
- Respiratory healthcare at home;
- Consultations and complementary acts necessary for donations of cells, blood, tissues, and organs;
- Programs for the treatment of chronic alcoholics and drug addicts;
- Vaccination provided for in the national vaccination program.
- Chemotherapy, radiotherapy, AIDS/HIC, diabetes.

From past literature to our research question

From the majority of the existing literature, we learn that like other normal goods and services, the demand for healthcare services is negatively related to prices. Whenever fees are imposed (reduced or removed), health services usage decreases (increases). This generally holds for the different types of services (visits in emergency departments, appointments, preventive care, outpatient, and inpatient, etc.) and for all individuals, even though the magnitude of the effect varies depending on the nature of the assistance required and on the category the individual belongs to (age groups or income). In the studies focusing on Portugal, however, it appears that the 2012 rise in co-payments did not cause a change in ES utilization and that, for children care, neither the exemption nor the fees were determinant in affecting demand for healthcare services.

In this paper, we will further analyse the effect of the exemption from moderating fees on the demand for health care services in Portugal. As explained before, some users incur in the payment of fees at the moment of receiving assistance, but some of them are exempted. In what follows, we will compare users belonging to these two groups, controlling as much as possible for confounding factors. Specifically, we focus on appointments in health centers (Study 1 and 3), visits to emergency departments (Study 2 and 3), and general assistance when the individual is sick (Study 4).

In particular, what we would like to understand is whether the impact of the exemption depends on the health situation of the user, i.e., whether the exemption favours necessary or unnecessary use of care, and whether the effect on one is bigger than the effect on the other in magnitude.

It must be noted that, due to data limitations, we are not able to determine whether the exemption leads to improvements in health status of the individuals or whether it helps to achieve particular health outcomes. Therefore, we will direct our attention only to the impact of exemptions on the demand of health services.

Data description

To conduct this study, we use data from six survey waves on access to health care in Portugal.[22] For the main analysis we use waves from 2019, 2020 and 2021, while for the descriptive statistics we also consider data from 2013, 2015 and 2017. This choice is due to the fact that the first four waves do not include some questions that are relevant in the main analysis.

Each wave surveyed approximately 1200 respondents, resulting in a repeated cross-section. Table 1 provides a description of the variables used in this analysis.

Table 1

Variable name	Description	Type	Number of obs.	Mean	Standard Deviation
app_centrosaude	Whether the respondent had an appointment in a health centre in the last 12 months	Binary	6318	0.54	0.50
times_urgency	Number of visits at emergency departments in the last 12 months	Count	7194	0.53	1.50
feltsick	Whether the respondent felt sick in the last 12 months	Binary	7572	0.36	0.48
help_health	Whether the respondent who felt sick in the last 12 months looked for help in the health system	Binary	2746	0.86	0.35
exempt	Whether the respondent is exempted from payment of user charges	Binary	7370	0.41	0.49
cronica	Whether the respondent has a chronic disease	Binary	5058	0.26	0.44
fam_doctor	Whether the respondent has a family doctor assigned	Binary	3795	0.91	0.29
health_state	Self-evaluation of one's own health state	Ordinal (1 to 5)	3795	2.26	0.84
insured	Whether the respondent has a private insurance	Binary	7567	0.16	0.63
cost_consulta_centrosaude	Cost of the last appointment at the health centre in euro	Continuous	3618	2.14	4.25
cost_urgency	Cost of the last visit at the emergency department in euro	Continuous	3084	3.95	8.27
cost_consulta	Cost of the last visit in euro	Continuous	1547	8.79	17.69
unidade_salute	Type of health unit the respondent is registered with	Binary	3437	0.67	0.72
confidence_urgencia	Trust in the care provided in the emergency departments	Ordinal (1 to 10)	4963	7.68	1.82
confidence_cds	Trust in the care provided in the health centers or family health units	Ordinal (1 to 10)	4987	7.90	1.72
impor_wait_time	Importance of waiting times when deciding whether to look for help in the health system	Ordinal (1 to 10)	5034	9.02	1.40
impor_distance	Importance of the distance from the health system facility when deciding whether to look for help in the health system	Ordinal (1 to 10)	5042	8.94	1.39
impor_trav_time	Importance of the time to get to closest health system facility when deciding whether to look for help in the health system	Ordinal (1 to 10)	5040	8.96	1.38
import_confidence	Importance of the confidence in the quality of the facility when deciding whether to look for help in the health system	Ordinal (1 to 10)	5029	9.30	1.13
import_costs	Importance of the costs the respondent has to pay when deciding whether to look for help in the health system	Ordinal (1 to 10)	5029	8.90	1.51

[22] The name of the survey is "Acesso a cuidados de saúde", a survey carried out under the Chair BPI | la Caixa in Health Economics.

nomeds	Whether the respondent did not buy all the meds needed for lack of money	Binary	7572	0.10	0.30
no_emg_cons	Whether the respondent did not go to an appointment or to the emergency departmentfor lack of money	Binary	7572	0.05	0.22
no_es_transp	Whether the respondent did not go to an emergency visit for the cost of transportation	Binary	7572	0.04	0.18
no_es_salary	Whether the respondent did not go to an emergency visit to avoid losing the salary that day	Binary	7572	0.05	0.22
generico	Whether the respondent asked for generic drugs because cheaper	Binary	7572	0.29	0.46
treated_well	Whether the respondent has been treated with dignity and professionality the last time they received assistance from a health professional	Binary	5058	0.75	0.43
cancelled	Whether the respondent cancelled a medical appointment in the last 3 months	Binary	2540	0.16	0.37
condicao_economica	Self-evaluation for the economic situation of observation's own family	Ordinal (1 to 4)	2540	2.68	0.77
edu_level	Education level of the observation	Ordinal (1 to 4)	7572	2.19	0.94
profession	Occupation of the individual	Nominal (6 possible values)	6733	//	//
region	Region where the observation lives	Nominal (7 possible values)	7572	//	//
age15_and_above	Number of people aged 15 or more living in the interviewed person's house	Count	7572	2.52	1.05
household_nr	Number of people living in the interviewed person's house	Count	7572	2.95	1.30
alchool_cons	Respondent classification according to their drinking habits	Ordinal (1 to 4)	4982	2.43	1.21
smoker	Respondent classification according to their smoking habits	Ordinal (1 to 4)	5026	2.99	1.33
age	Age of the respondent	Discrete	7572	45.79	18.11
age_groups	Age group of the respondent	Ordinal (1 to 5)	7572	2.48	1.08
female	Whether the respondent is female	Binary	7572	0.53	0.50
year	Year of the survey	Discrete	7572	//	//

Methodology

The dependent variables we deal with are binary, count and ordinal. For this reason, in the following subsections we are going to present the different models we employ: probit, tobit type I, zero-inflated negative binomial, and ordered probit (and logit).[23] Next, we motivate our approach in selecting specific variables as controls for the regressions and finally we illustrate how to solve the lack of the income variable for 2019 survey wave.

Probit model

When the dependent variable is a dummy, we are interested in modelling conditional probabilities, which corresponds to modelling conditional means:

$$E[y_i|x_i] = P(y_i = 1|x_i) = p(x_i)$$

where $p(x_i)$ is called response probability. With linear index models like probit, we employ non-linear functions to shape the response probability:

$$P(y_i = 1|x_i) = G(x_i\beta)$$

In most cases, $G(\cdot)$ is a cumulative distribution function (cdf) for a continuous random variable, transforming the linear index $x\beta$ into a real number bounded between 0 and 1. For the probit model, $G(\cdot)$ is the standard normal cdf Φ. The underlying assumption of this framework is that the dependent variable y_i is generated by a linear latent variable model where errors are normally distributed:

$$y_i^* = x_i\theta + e_i$$

$$e_i|x_i \sim N(0,1)$$

$$y_i = \begin{cases} 1 \; if \; y_i^* > 0 \\ 0 \; if \; y_i^* \leq 0 \end{cases}$$

where y_i^* is not observed. From the latent model, we derive the response probability:

$$P(y_i = 1|x_i) = P(y_i^* > 0|x_i) = P(x_i\theta + e_i > 0|x_i) = P(e_i > -x_i\theta|x_i)$$

So, recalling the assumption on the distribution of the error term, we find that:

$$P(y_i = 1|x_i) = 1 - \Phi(-x_i\theta) = \Phi(x_i\theta)$$

From here, it is possible to completely characterize the conditional distribution of y using a well-known cumulative distribution function. Indeed, since $P(y_i = 1|x_i) = \Phi(x_i\theta)$ and $P(y_i = 0|x_i) = 1 - \Phi(x_i\theta)$, we can write:

$$f(y|x;\, \theta) = [1 - \Phi(x\theta)]^{(1-y)}\Phi(x\theta)^y \; if \; y \in \{0,1\}$$

From here, we retrieve the log-likelihood function:

$$\mathcal{L} = (1 - y)\ln{(1 - \Phi(x\theta))} + y\ln{[\Phi(x\theta)]}$$

which we employ to retrieve the coefficients of interest by maximum likelihood estimation (MLE).

[23] Most of the regressions are also replicated with the OLS models as a robustness check. Results are shown in the appendix.

Given how the response probability is defined, the partial effect for x_j is then equal to:

$$\frac{\delta p(x)}{\delta x_j} = \theta_j \phi(x\theta)$$ [24]

Tobit Type I and Zero Inflated Negative Binomial models

Count variables in our dataset tend to be distributed with a huge mass at zero. Therefore, we employ two models, the tobit type I and the zero inflated negative binomial.

The tobit type I model assumes that the response variable is related to the latent one y^* and that, depending on the latter's values, it takes positive values but also a number of zeros if the value of y^* is below a certain threshold.[25] Besides, normality and homoskedasticity of the error term are assumed. The relation between y and y^* is defined in the following way:

$$y_i^* = x_i\beta + \mu_i$$

$$\mu_i | x_i \sim N(0, \sigma^2)$$

$$y_i = \begin{cases} 0 \ if \ y_i^* \leq 0 \\ y_i^* \ otherwise \end{cases}$$

In order to derive $E[y_i|x_i]$, we decompose this last expression and obtain:

$$E[y_i|x_i] = P(y_i > 0|x_i) * E[y_i|x_i, y_i > 0] + P(y_i = 0|x_i) * E[y_i|x_i, y_i = 0]$$

where the last element is clearly zero, so we are left with:

$$E[y_i|x_i] = P(y_i > 0|x_i) * E[y_i|x_i, y_i > 0]$$

For $P(y_i > 0|x_i)$, we employ the probit model (recalling the assumption on the distribution of μ) and write:

$$P(y_i > 0|x_i) = P(x_i\beta + \mu_i|x_i) = P\left(\frac{\mu_i}{\sigma} > -\frac{x_i\beta}{\sigma}|x_i\right) = \Phi\left(\frac{x_i\beta}{\sigma}\right)$$

while for $E[y_i|x_i, y_i > 0]$ we have:

$$E[y_i|x_i, y_i > 0] = x_i\beta + E[\mu_i|\mu_i > -x_i\beta] = x_i\beta + \sigma\lambda\left(\frac{x_i\beta}{\sigma}\right)$$ [26]

Hence, we can rewrite the equation for the unconditional expectation[27] for the whole sample as:

$$E[y|x] = \Phi\left(\frac{x\beta}{\sigma}\right)x\beta + \sigma\phi\left(\frac{x\beta}{\sigma}\right)$$

---

[24] Where $\phi(\cdot)$ is the standard normal probability density function (pdf).

[25] The presence of these zeros in our dataset is not due to censored data (observability issue), but rather to the underlying process itself (e.g., the number of visits to the emergency room cannot be negative). Even if the resulting distribution from the two causes look alike, the underlying cause is conceptually different.

[26] Where λ represents the inverse Mills ratio:

$$\lambda(z) = \frac{\phi(z)}{\Phi(z)}$$

[27] Unconditional on *y*, but still conditional on *x*.

In order to estimate the model and retrieve the coefficients, we employ the maximum likelihood approach[28] defining the density of y_i as:

$$f(y_i|x_i,\beta) = \begin{cases} 1-\Phi\left(\frac{x_i\beta}{\sigma}\right), & y_i = 0 \\ \frac{1}{\sigma}\phi\left(\frac{y_i - x_i\beta}{\sigma}\right), & y_i > 0 \end{cases}$$

By employing the indicator function, we rewrite it as:

$$f(y_i|x_i,\beta) = \left\{1-\Phi\left(\frac{x_i\beta}{\sigma}\right)\right\}^{1[y_i=0]}\left[\frac{1}{\sigma}\phi\left(\frac{y_i - x_i\beta}{\sigma}\right)\right]^{1[y_i>0]}$$

From here (through the log-likelihood function for the entire sample), by MLE we retrieve the coefficients which we employ in the estimation of the average partial effects. For a generic x_j, we define the APE on $E[y|x,y>0]$ as:

$$\frac{\delta E[y|x,y>0]}{\delta x_j} = \beta_j\left\{1-\lambda\left(\frac{x\beta}{\sigma}\right)\left[\frac{x\beta}{\sigma}+\lambda\left(\frac{x\beta}{\sigma}\right)\right]\right\}$$

while for $P(y>0|x)$, the partial effect of x_j is computed as:

$$\frac{\delta P(y>0|x)}{\delta x_j} = \phi\left(\frac{x\beta}{\sigma}\right)\frac{\beta_j}{\sigma}$$

Therefore, the partial effect of x_j on $E[y|x]$ is given by:

$$\frac{\delta E[y|x]}{\delta x_j} = \frac{\delta P(y>0|x)}{\delta x_j} * E[y|x,y>0] + P(y>0|x) * \frac{\delta E[y|x,y>0]}{\delta x_j} =$$

$$= \Phi\left(\frac{x\beta}{\sigma}\right)\beta_j = P(y>0|x)\beta_j$$

This implies that the coefficient is scaled down by a factor equal to the probability of observing positive outcomes. When this probability is close to one, then the effect of the corner solution on the coefficient is small.

Alternatively, we employ a zero-inflated negative binomial model. Such model accounts for two zero generating processes. One generates zeros in the sense that the observation has a value of the outcome variable equal to 0 even if he/she possesses features that would normally make the variable assume positive values. The other, governed by the negative binomial distribution, generates counts, some of which might be zero. Hence, the response variable of two individuals with a value of zero might be identical but the processes leading to that outcome might be different. We will refer to the first observations as "certain zero", and these are the data that inflate the number of zeros and make it

[28] Note that in this case, employing an OLS model for $y > 0$ would yield an inconsistent estimator of β since we would estimate:

$$y_i = x\beta + e_i$$

omitting the term $\sigma\lambda\left(\frac{x\beta}{\sigma}\right)$ which is strongly correlated with $x\beta$. If we instead apply the OLS to all ys, we will get a biased estimator of β since the equation for $E[y|x]$ is not linear.

impossible to explain the number of individuals with a null value of the outcome variable in the same way as the number of individuals with a positive value.

Hence, in the zero-inflated negative binomial, two separate models are generated and combined: a logit model for the "certain zeros", predicting whether the observation would be in this group, and a negative binomial, predicting the counts for the observations that are not certain zeros. Hence, for each observation there are two possible cases: in one the count is surely zero, in the other counts spawn from the negative binomial model. We suppose that the first case occurs with probability π and the other with probability $1-\pi$, and from here it follows that the probability distribution of the zero-inflated negative binomial variable y is:

$$P(y_i = j) = \begin{cases} \pi_i + (1-\pi_i)g(y_i = 0)\ if\ j = 0 \\ (1-\pi_i)g(y_i)\ if\ j > 0 \end{cases}$$

where π_i is the logistic link function and $g(y_i)$ is the negative binomial distribution (both are defined in the appendix). The regression coefficients are once again estimated using MLE.

Ordered Probit model

Being ordered, the modelling of variables such as the frequency of emergency usage requires the application of an ordered probit model. This is a generalization of the probit model discussed above, employed in cases of ordinal dependent variables (i.e., a variable for which the relative ordering between the different values is significant). The assumption underpinning this model is the existence of a real-valued latent variable which we call again y^* and that is determined by:

$$y_i^* = x_i\beta + \epsilon_i$$

with the error term following the standard normal distribution conditioned on *x*. In this case, the response variable that we observe, y_i, gives information regarding the interval in which the latent variable falls:

$$y_i = \begin{cases} 1\ if\ {y_i}^* \leq \theta_1 \\ 2\ if\ \theta_1 < {y_i}^* \leq \theta_2 \\ 3\ if\ \theta_2 < {y_i}^* \leq \theta_3 \\ \vdots \\ K\ if\ \theta_{k-1} < {y_i}^* \end{cases}$$

Where $\theta_1, \theta_2, \cdots, \theta_{K-1}$ is a set of thresholds. If we then define $\theta_0 = -\infty$ and $\theta_K = \infty$, it follows that

$$y_i = k\ iff\ \theta_{k-1} < {y_i}^* \leq \theta_k$$

Hence, the conditional distribution of y_i can be written as:

$$P(y_i = j|x_i) = P\left(\theta_{j-1} < {y_i}^* \leq \theta_j \middle| x_i\right) = P\left(\theta_{j-1} < \beta x_i + \varepsilon \leq \theta_j \middle| x_i\right)$$
$$= \Phi\left(\theta_j - \beta x_i\right) - \Phi(\theta_{j-1} - \beta x_i)$$

Consequently, the log-likelihood for the sample is:

$$\mathcal{L}(y|x,\beta,\theta) = \sum_{i=1}^{N}\sum_{j=0}^{K} Z_{ij}\ln\left[\Phi\left(\theta_j - \beta x_i\right) - \Phi\left(\theta_{j-1} - \beta x_i\right)\right]$$

where Z_{ij} is the indicator variable that equals 1 if $y_i = j$ and 0 otherwise. As usual, the log-likelihood function will be the employed in the estimation of the parameters via MLE.[29]

Dealing with selection bias

The problem that we face in estimating the effect of the exoneration on service utilization is that individuals who do not have to pay moderating fees are not directly comparable to those who are not exempted. This results in a problem of selection bias, implying that there would have been differences between the averages of the potential outcomes for the group of exempted and not exempted people even if the formers ended up not receiving the exemption, i.e., participants and nonparticipants will differ in their choices to seek assistance even in the absence of treatment.

Indeed, by performing simple t-test for the differences in the averages of many variables between the treated and non-treated, it is possible to see that there exist imbalances in covariates that, on their turn, would affect the dependent variables of our studies. Just to mention some, those who suffer from chronic diseases and those who declare to be "poorer"[30] are more likely to be exempted from paying user charges (as we would expect, given how exemption is assigned). The presence of imbalances is consistent with the nature of the treatment: since it is not an experimental setting in which assignment is randomized across people, individual characteristics determine whether or not the person is eligible for the exemption.

To avoid obtaining estimates that are biased by selection bias, in the models presented above we aim at solving this issue by adding as controls the observable characteristics that influence exemption. As a robustness checks, in some of the studies we also compare the effect of the exemption obtained via regressions with the ones resulting from the STATA's average treatment effect estimation.

The estimation performed by the statistical software relies on the idea of matching: finding a large subgroup of nonparticipants within the sample with characteristics similar to those of the participants. Once this is done, a more adequate control group is available, and the difference in the outcome can be more properly attributed to the treatment. In particular, two types of matching will be employed: propensity-score matching and nearest-neighbour matching, and indeed both "*impute the missing potential outcome for each subject by using an average of the outcomes of similar subjects that*

[29] For the ordered logistic model, in the conditional distribution we will employ the logistic function in place of the standard normal cdf.

[30] Data regarding income are derived from answers to the question: "Thinking about your family's total monthly income, would you say your family is able to survive?". More about this topic later.

receive the other treatment level" (STATA documentation). The difference is that, for propensity score matching, subjects are regarded as similar on the basis of estimated treatment probabilities (known as propensity scores indeed), while for the nearest neighbour matching it is employed a weighted function of the covariates for each observation. For both approaches then, the treatment effect is obtained averaging the differences between the observed and the potential outcomes for each subject.

Chronic diseases and age as indicators of serious condition?

In order to understand the effect of the exemption on healthcare services utilization, and in particular to determine if it favours unnecessary use of care, we need to find an indicator of seriousness of individuals' condition which we can employ to determine whether or not care is indeed necessary. At the same time, it must be noted that necessity of care is not something totally objective,[31] so our indicator only aims at determining which individuals, given the information at our disposal, should be more propense to receive care.

The variable "*health_state*" captures the answers to the question "*Generally, how do you consider your health condition?*". It is a categorical variable taking values from 1 to 5, where 1 corresponds to "*Very good*", 2 to "*Good*", 3 to *"Reasonable*", 4 to "*Bad*", and 5 to "*Very bad*". However, several issues arise. First, this is a subjective and possibly imprecise self-assessment, even if it can be based on objective facts. Moreover, it is likely that individuals who under-estimate the seriousness of their condition will be less inclined to receive help from the healthcare service and vice-versa. Finally, there is a risk of reverse causality as the answer to the question might embody the care already received. For these reasons, we are not going to use this variable in our preferred models.[32]

The main variable we employ to take into account the health status of the individuals is the dummy "*cronica*", which takes a value of 1 if the individual is affected by (at least) one chronic disease which requires specific medication, and 0 otherwise. Among the conditions mentioned by the individuals undertaking the surveys, the most common are hypertension, diabetes, and arthrosis.

Although this is not the perfect indicator of the seriousness of an individual's condition, when plotting the health status categories for those afflicted by a chronic disease and those who are not, remarkable differences emerge.[33] Graph 1 in Table 2 shows that the distribution of those without chronic diseases

[31] An individual might feel the need of receiving help even if it is not so. However, the psychological relief of receiving help has to be accounted in the process. Unfortunately, we are not able to account for this factor.

[32] Nonetheless, in the appendix we present studies in which we use health status self-assessment, and we compare the results.

[33] Even if we do not to employ the variable "*health_state*" within our regressions for the relation it might have with service utilization (as previously explained), in this case it makes sense to look at it to retrieve information, because we are not looking at service use.

is centred around the "G*ood*" state (around 55% of the observations) and that in general 99% of the individuals falls within the 3 categories indicating good health. The situation for those with chronic disease is different: the distribution is now centred around the "*Reasonable*" state (around 60% of the respondents) and observations are almost normally distributed around it, with the tails corresponding to the extreme states counting for almost 3% of the total data. So, even if having a chronic disease does not imply *tout court* a bad health status, it is surely associated with a deterioration of the individual's health condition.

Together with "*cronica*", we include in the regressions "*age_groups*" to take into account individuals' age. As the health status generally worsens with age, it is reasonable to assume that older individuals are more vulnerable and consequently more in need of healthcare. The plot of "*health_state*" for the different age groups (Graph 2 in Table 2) confirms that health condition is inversely related to age.[34] It is straightforward to see that as we move towards elder individuals, health conditions worsen significantly. Even though the proportion of those who reported a "*Very bad*" state is never above 3.5%, the share of those in a "*Bad*" state goes from 0.35% in the younger group to around 32% in the older one. Therefore, as expected, older individuals are associated with worse health conditions.

In addition, as displayed in Graph 3 of Table 2, also the proportion of people suffering from chronic diseases increases with age (the average age for those with a chronic disease is around 59, while it is 41 for the others). Hence, in order to determine whether the exemption leads only those more in need, or those less in need, or both categories to recur more to the help of the healthcare system, we employ both indicators.

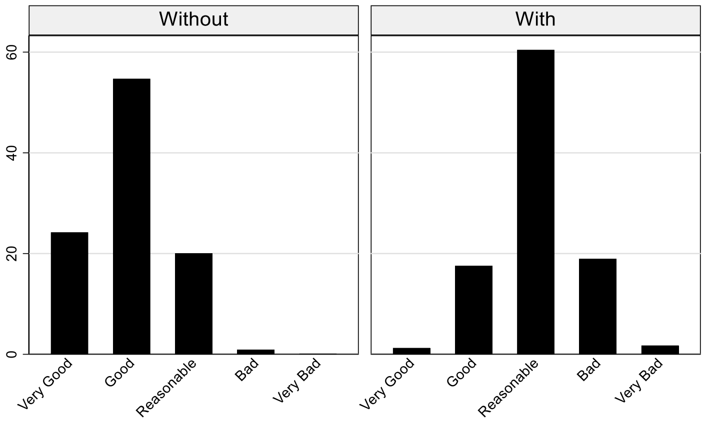
One final observation on the distribution of the exemption among the different age groups (Graph 4 in Table 2). The older the individuals, the more likely they are to receive the exemption from the payment of user charges.[35] At the same time, for the youngest respondents the proportion is never too small - especially if compared to the proportion of those affected by chronic disease:[36] in fact, it is never below 31% (for the group 30-44 years), while it reaches around 71% of the sample when considering the oldest category.

[34] Please note that the numerical value of the health status is higher for worse health conditions.

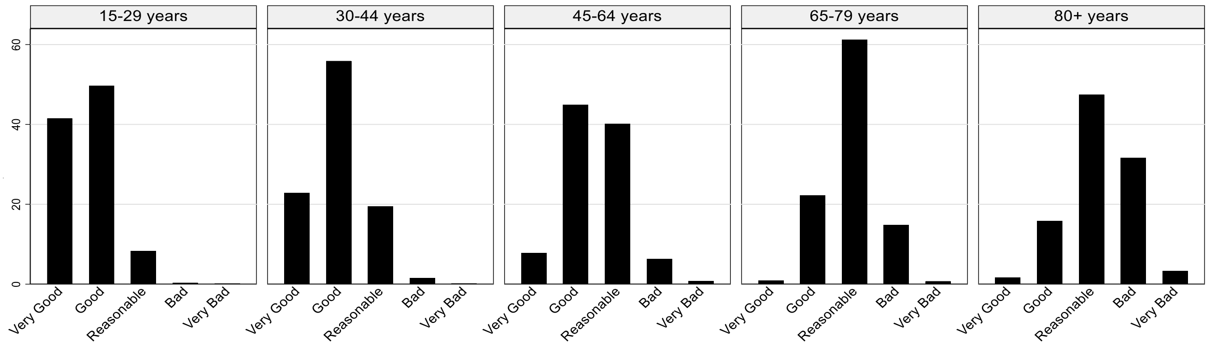
[35] Indeed, people in the oldest age groups are those that on average have the worst wealth situation, and as we have seen in Graph 3 of Table 2 are the ones more afflicted by chronic diseases.

[36] When we calculate the share of exempted individuals for men and women younger than 45 (results not reported here here), we observe that more women tend to be exempted. One reason could pregnancy.

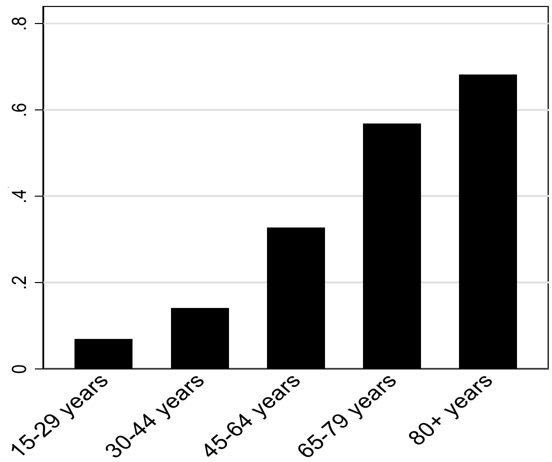
Table 2



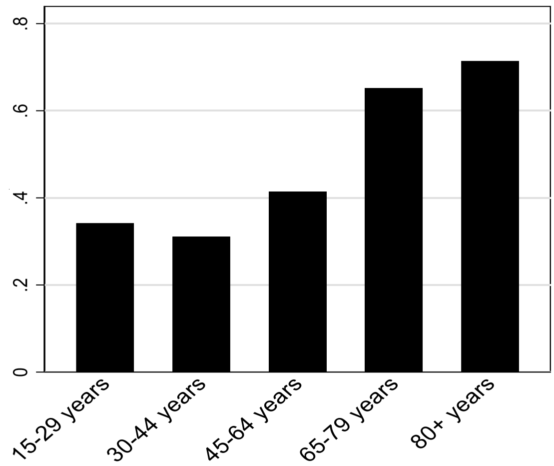
Graph 1 Distribution of health status by chronic condition.



Graph 2 Distribution of health status across age groups.



Graph 3 Distribution of chronic condition across age groups.



Graph 4 Distribution of exemption status across age groups.

The "income problem"

The dataset at our disposal contains income information in "*condicao_economica*", an ordinal variable whose values, referred to the family's economic situation, range from 1 to 4 and where 1 corresponds to "*difficult*", 2 to "*somewhat difficult*", 3 to "*somewhat easy*", and 4 to "*easy*". Unfortunately, this variable is only available in 2020 and 2021 for a total of 2540 observations. Restricting our sample to these two survey waves would mean to focus only on two very particular years, those of the COVID-19 pandemic.

To overcome this problem, we plan to estimate the economic condition of the 2019 respondents to later use it in the regression models. Given the nature of this variable, first we employ an ordered logit model on observations post-2020. The regression includes variable such as those relative to age, education, profession, gender, region, and presence of a private insurance, which allow us to predict the economic condition rather well. Next, we use the coefficient estimated in this first stage to estimate the individuals' probability of ending up in each of the four categories of "*condicao_economica*" for 2019.[37] Then, we assigned each person to the category for which the probability was the highest.[38]

This method allows to estimate the effect of the exemption using more data, hence with more precision, and to include a non-pandemic year in the sample. At the same time, one must be mindful that the prediction of the economic status for 2019 is far from perfect. Even when we compare the predictions of the ordered probit model for 2020 and 2021 with the actual "*condicao_economica*" ones, while the majority of individuals (61%) is allocated to the correct category, there is still some noise, as shown in Table 3.

Table 3

condicao_economica	condicao_generated				Total
	Difficult	*Somehow difficult*	*Somehow easy*	*Easy*	
Difficult	127	143	55	1	326
Somehow difficult	29	502	293	4	828
Somehow easy	4	206	826	40	1076
Easy	3	22	187	98	310
Total	163	873	1361	143	2540

It is worth mentioning that the results of the regressions when employing "*condicao_generated*" are similar to those obtained when using "*condicao_economica*" for 2020 and 2021. These results are shown in the appendix.

[37] This because in estimating the ordered logit model, we used some variables for which we have data only for 2019, 2020 and 2021. However, this is not a problem since, for the regressions we will perform later on, we will employ variables for which we have data limited to these same years as well.
[38] So, in the final version of "*condicao_generated*", the values for 2020-2021 are equal to those of "*condicao_economica*" and only those relative to 2019 are generated from the ordered logit model.

Study I: The impact on appointments in health centers

In this first study we focus on understanding the effect of the exemption on appointments in health centers. The main dependent variable is "*app_centrosaude*", a binary variable equal to 1 if respondents state they have had an appointment in a health centre in the last year and 0 otherwise.[39] Data for all years excluding 2013 are available, for a total of 6318 observations.

The distribution is pretty balanced, with 53.7% of individuals with at least one appointment in the previous year. However, the situation changes when we look at some specific segments of the sample, as Graph 1 of Table 4 shows: a higher proportion of exempted individuals (70%) tends to go to medical appointments with respect to non-exempted individuals (44%). Is this due to the fact that those exempted have poorer health, therefore are more in need of medical attention? Or are they induced to use the health system even in cases when it is not strictly necessary just because they do not have to pay for it? Or is it a mixture of both?

To dig deeper, we also consider the presence of chronic diseases in Graph 2 of Table 4. Let's consider people without chronic diseases first (left-hand side panels). Among those without an exemption, 35% had at least one medical appointment in the previous year. Among those exempted instead, the proportion increases considerably to 58%. Moving on to the people suffering from a chronic disease (right-hand side panels), we notice that the percentages of those who had at least one appointment are higher compared to their counterparts both exempted and non-exempted. Again, the figure is higher for those who are exempted (84%) than for those who are not (73%), even if the difference is not as big as the one for people who do not have chronic diseases (11 pp vs 23 pp).

Therefore, individuals with serious conditions recur to the health system more than the others even if by doing that they have to pay, while individuals not having chronic diseases might be particularly incentivized to do that by the exemption, even if the situation does not necessarily require care, suggesting that the impact of the exemption is smaller when people are more in need.

Incidentally, it is interesting to consider how the percentage of individuals with at least one medical appointment changes depending on the age group and the exemption status. As shown in Graph 3 of Table 4, older individuals are more likely to have at least an appointment, no matter the exemption status. However, we see that the variation between old and young observations is bigger in the upper panel: also in this case the graph suggests that the difference in service utilization between the more vulnerable (here represented by the old people) and the ones that should be healthier is bigger for

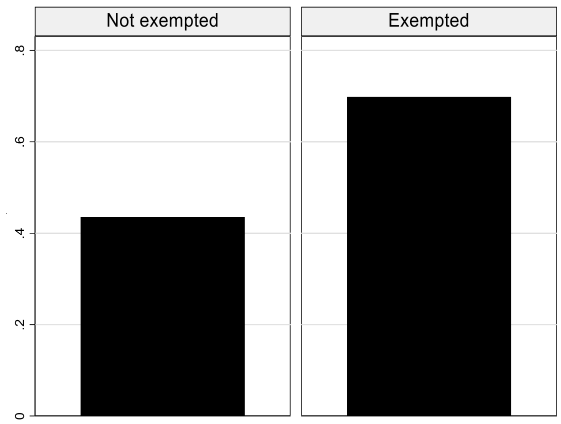
[39] The exact question is: "*Did you go to an appointment in a health centre in the last year?*"

non-exempted, signalling that being exonerated from payment of moderating fees impacts differently on the decision to seek assistance depending on the health status of the consumer.

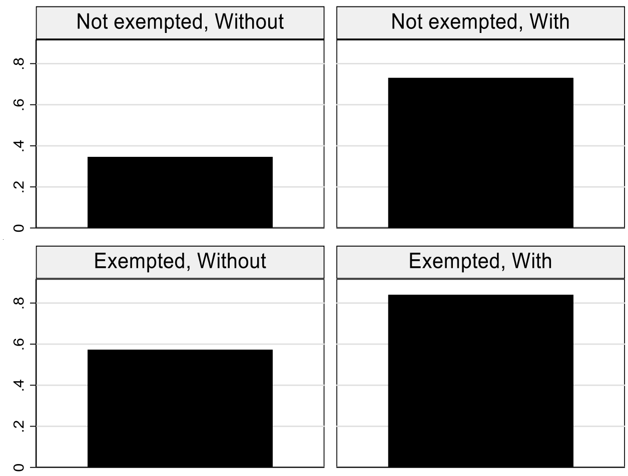
To make sure that the exemption has an effect on the amount the individuals have to pay for appointments, we look at the distribution of a proxy variable, "*cost_consulta_centrosaude*", which measures the amount paid in user charges for the last appointment of the individual in a health centre. In particular we are interested in checking that there exists a difference between exempted and non-exempted individuals. Already by a simple comparison of the means for the two groups (€0.36 and €3.96, respectively), we notice that this difference exists. This impression is confirmed when we look at the histograms in Graph 4 of Table 4.[40]

[40] We restrict the x-axis to costs below €30, which account for virtually the entire sample (99%). The presence of the mass at 5 for exempted individuals might be due to different reasons: wrong charging to the users, wrong reporting, or possess of the exemption at the moment of the survey but not at the time of the appointment. Still, the number of cases is rather small.

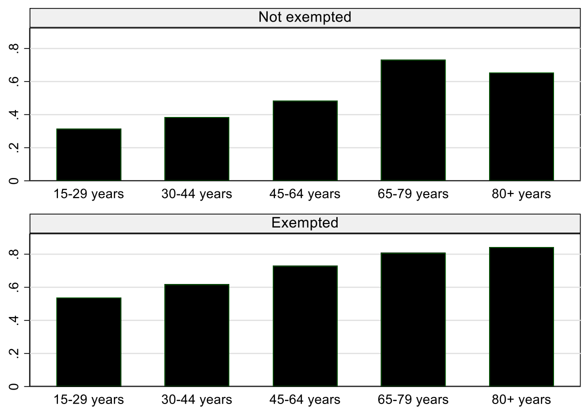
Table 4



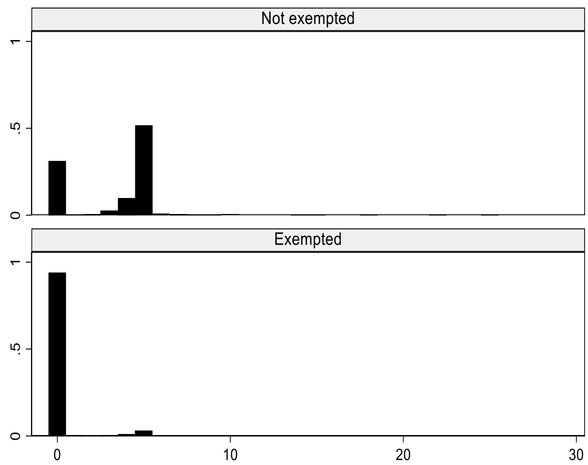
Graph 1 Proportion of people with at least one appointment in health centers by exemption status.



Graph 2 Proportion of people with at least one appointment in health centers by exemption status and chronic condition.



Graph 3 Proportion of people with at least one appointment in health centers by exemption status and across age groups.



Graph 4 Distribution of user charges for appointments in health centers by exemption status.

In order to better identify the causal effect of the exemption on our variable of interest, we estimate some econometric models including several controls, and use the probit framework as we are dealing with a binary variable.

In the first regression for this study, we will regress having had an appointment in a health centre on the age group and the presence of a chronic disease, both interacted with the presence of the exemption. By employing the interaction term on age and by subtracting the marginal effects for the individuals in the same age group, we are able to determine the effect of the exemption for individuals aged differently and see if it varies with age.

As control we use the gender, economic condition and education level of the respondent, the presence of a private insurance, whether the respondent has a family doctor, alcohol consumption habits, whether the respondent felt sick in the previous 12 months, and the year.

Results are shown in Column I of Table 5. First of all, it is worth noting that the vast majority of the coefficients is significant at the 1% or 5% level. Those not significant are the ones referred to the effect of the education, of the level of alcohol consumption and of the private insurance.

Concerning the effects on the response probability, the estimates provide interesting insights. Indeed, the coefficients linked to the age groups are telling us that, with respect to the benchmark category of non-exempted individuals aged between 15 and 29 years, all the other categories are more likely to go to a visit in a health centre, implying that both age and the exemption positively impact on our dependent variable.[41]

Moreover, as we expected, individuals affected by a chronic disease are more likely to have an appointment at health centers (increase of 0.212 in the response probability). However, in case the individual is both exempted and afflicted by a chronic disease, we detect an attenuation on the impact of the exoneration (interaction term's coefficient of -0.088). We rely on the logic assumption that it is mainly the exemption effect for chronic individuals with respect to non-chronic individuals that gets attenuated, rather than the effect of the chronic disease that gets attenuated for exempted individuals with respect to non-exempted individuals. It is hard to believe that for an exempted individual having a chronic disease has a smaller impact than not having a chronic disease when deciding to seek assistance.[42]

[41] It must be noted that the coefficients referred to the three oldest groups of exempted people are not statistically different from each other. This holds for all the five Columns of Table 5.

[42] In the appendix, we will perform two regressions keeping "*exempt*" at 0 and at 1 following the framework of the next study, and we see that in both cases the coefficient of "*cronica*" is positive and significant, while when we keep the values of "*cronica*" fixed we observe a big difference on the effect of "*exempt*" (as showed in the next paragraphs).

Table 5

Regression of *app_centrosaude*					
Variables	Coefficients (marginal effects)				
	Column I	Column II *cronica = 0*	Column III *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
age_groups_exempted:					
30-44 not exempted	.061**	.049*	.209**	.055*	.063
45-64 not exempted	.088***	.082***	.145	.087***	.057
65-79 not exempted	.229***	.226***	.256**	.287***	.125*
80+ not exempted	.031	.062	.125	.09	-.072
15-29 exempted	.182***	.197***	.052	.193***	.13*
30-44 exempted	.229***	.244***	.148	.233***	.189***
45-64 exempted	.293***	.275***	.249**	.312***	.208***
65-79 exempted	.303***	.285***	.274***	.328***	.218***
80+ exempted	.279***	.27**	.256**	.342***	.208**
cronica	.212***	//	//	.319***	.085**
cronica_exempted	-.088**	//	//	-.121**	-.068
condicao_generated:					
somehow difficult	-.057**	-.033	-.086***	-.024	-.081***
somehow easy	-.096***	-.073**	-.112***	-.07*	-.106***
easy	-.134***	-.137***	-.074	-.109**	-.166**
insured	-.031	-.042	-.006	-.008	-.073**
female	.071***	.096***	.009	.085***	.026
fam_doctor	.239***	.225***	.285***	.26***	.204***
feltsick	.204***	.287***	.054**	//	//
alcohol_cons:					
medium drinker	.006	-.001	.025	.011	-.008
light drinker	.042*	.051*	.026	.067**	-.07
not drinker	.031	.036	.024	.053**	-.006
edu_level:					
Basico	-.029	-.028	-.023	-.022	-.041
Secundario	-.011	-.01	-.008	-.013	-.01
Superior	-.036	-.027	-.074	-.032	-.041
year:					
2020	-.088***	-.098***	-.055**	-.093***	-.06**
2021	-.125***	-.109***	-.151***	-.113***	-.139***
R^2	.2191	.1599	.1397	.1576	.1378
Number of obs:	3457	2476	981	2371	1086
Significance levels	10% = *		5% = **		1% = ***

To consider the results under a different perspective, consider Table 6. Here we consider the effect of the exemption for four groups of people (with/without the exemption, with/without the chronic disease) and in different age groups – all other variables being equal.

Table 6

Effect on the expected response probability	Group 1 (15-29)	Group 2 (30-44)	Group 3 (45-64)	Group 4 (65-80)	Group 5 (80+)
No exemption, no chronic disease	0	+.06	+.09	+.23	//
Exemption and no chronic disease	+.18	+.23	+.29	+.30	+.28
Difference	+.18	+.17	+.20	+.07	//
No exemption, with chronic disease	+.21	+.27	+.30	+.44	//
Exemption and with chronic disease	+.31	+.35	+.42	+.43	+.40
Difference	+.10	+.08	+.12	-.01	//

As stated above, the results suggest that older individuals are more likely to recur to the help of the health system, and that the exemption also has a positive effect for every age group. Indeed, the coefficients of each of the age groups for exempted individuals are almost always higher than the coefficients for the respective age group of non-exempted individuals.

Two more interesting takeaways can be drawn from Table 6. First, the difference between those exempted and those who are not is always bigger for individuals not afflicted by chronic disease, for any age group (when we look at the *Difference* rows for the same age groups). Second, the difference of the effects of the exemption for the individuals in the same age group gets smaller when we consider the oldest age group (the representative one at least, the 65-80 group), both for people afflicted by chronic disease and those who are not (going from the left to the right in the same *Difference* row).

These results suggest that for more vulnerable individuals the effect of the exemption on appointments in health service is attenuated. Possibly, for the most vulnerable ones - in this case, the oldest and/or those with chronic diseases - whether they have to pay for the service represent a less impactful incentive. On the contrary, for the other groups (the youngest or those without chronic diseases), the exemption leads to larger effect on the response probability.

All in all, these findings suggest that the exemption leads to more services utilization in general, but that the intensity of this effect is attenuated when we look at the individuals more in need of help, either because they are older or because they suffer from a chronic disease (recall that the sign of the interaction term is negative).

Moving on to the control variables, it is worth mentioning the negative effect that wealth has on appointments in health centers (moreover, the effect is increasing in absolute value as wealth increases). This is probably due to the fact that these individuals might recur to private assistance.[43]

Regarding the presence of a family doctor, this causes a strong increase in the expected response probability (+.25). Similarly, being a woman is associated with higher probability of attending to a visit in health centre. Unexpectedly, also the effect of the variable "*feltsick*" is strongly positive, implying that those who felt sick in the year in which the survey was taken are more likely to have had an appointment in a health centre. The reasons can be multiple: for example, an appointment could have been the answer to that case in which the person felt sick or an individual who felt sick might have worse health conditions, requiring more (or more often) assistance.

[43] Recall that the dependent variable only refers to appointments in public health centers.

Finally, the negative effects related to the years 2020 and 2021 might be an indicator of the effects that COVID pandemic has had on services utilization (either disruption of services and/or people's fear of catching the virus).

In Columns II and III of Table 5 we study the effect of the exemption separately for observations without and with chronic disease respectively.[44] Before commenting the results, it is interesting to notice in Table 7 how the ratio of the proportions of those who had a visit to those with the exemption is similar between individuals with and without chronic diseases (1.21 for chronic group, 1,26 for the other).

Table 7

	app_centrosaude	*exempted*	Ratio
No chronic disease	0.412	0.327	1.26
With chronic disease	0.802	0.662	1.21

For those not afflicted by a chronic disease, we see that the coefficients of the categories of "*age_groups_exempted*" are comparable to those of Column I, hence we can state that older groups are associated with higher service utilization and that the exemption makes individuals seek more assistance for any age group considered. However, we notice again that the effect of the exemption gets smaller for the fourth age group (indeed, the differences of the coefficients for those exempted and those not in the same age groups are respectively: .197, .195, .193 and .059).[45] When we look at the same coefficients for those with a chronic disease instead, we notice that for many categories the estimates are not significant. For those that are significant, it seems that the trend related to higher utilization as age increases and for those exempted persists (although we cannot infer anything regarding the differences of the effect of the exemption for the different age groups).

By looking at the other coefficients, we see again that wealth is negatively related to service utilization, while the presence of a family doctor strongly (and positively) impacts on the response probability, both effects existing whether or not the individual has a chronic disease. A substantial difference exists for the impact of the variable "*feltsick*". Indeed, the effect in Column II is .287, more than five times the one in Column III, .054. This might be due to the fact that individuals with a chronic disease might feel sick in the context of their condition, and they might be used to it and know how to deal with the sickness. This might imply a smaller impact of this variable for those in Column III. On the contrary, individuals with no particular health conditions might be alarmed when feeling sick and react to this by seeking help. Another difference is the one related to gender. Indeed, among those without a chronic disease, being a woman implies higher service utilization, while the effect is

[44] Obviously, in this case we will miss the coefficients referred to "*cronica*" and "*cronica_exempted*"

[45] Again, the fifth group's coefficient is not significant probably because of lack of observations, so we are unable to determine the difference in the effect.

not significant for those with the disease. Finally, in both regressions we see the negative impact of the years 2020, 2021, probably due to the impact of the COVID pandemic.

Columns IV and V of Table 5 complete this first analysis. Here the constraint is on the variable "*feltsick*". From Column IV we can see that for what concerns the impact of age and the one of the exemption, we are in a situation similar to the one of Column I and II. Indeed, as we move towards older age groups, the effect on the response probability increases (both for exempted and non-exempted observations). Moreover, if we compare the individuals from the same age group, being exempted is associated with higher service utilization. For what concerns individuals that felt sick, we do not detect significance for the coefficients of the age groups among the non-exempted, but we do notice effects for those exempted. Again, these are increasing with age. For those of Column IV, we find again that the magnitude of the exemption's effect is much smaller for older individuals.

Regarding the presence of chronic diseases, we see the same effect that we have observed in Columns II and III regarding the variable "*feltsick*": for those that did not feel sick, the impact of the chronic disease is much stronger with respect to the effect on those that felt sick. A plausible reason is that the formers might have looked for assistance for an event related to their chronic condition, which then has a strong impact. For the latter instead, the fact of feeling sick could already be a major determinant of demand, and in that occurrence the presence of a chronic disease is less impactful.[46]

Regarding the interaction term "*cronica_exempted*", we notice that it is significant just in column IV, implying an attenuation of the exemption effect for individuals afflicted by chronic disease, but only in case in which the observation did not feel sick. On the contrary, in column V the estimate is not significant.

By looking at the other coefficients, we notice a difference in the variable "*insured*": for those that felt sick, having a private insurance impacted negatively on their probability to seek assistance, while for those that did not feel sick, the effect is not significant. We might explain this by assuming that some individuals feeling sick and with a private insurance might have opted for private care. Other differences can be found in the effect of the gender of the person, in the same fashion of the study where we constrained for "*cronica*". Again, we detect a negative effect of wealth and COVID years, both for people that felt sick and for those who did not.

In a second analysis we consider only chronic disease as indicator of necessity to care, hence we employ as regressors "*exempt*", "*age_group*", "*condicao_economica*", "*cronica*", "*insured*", "*edu_level*", "*fam_doctor*", "*cronica_exempted*", "*female*", "*feltsick*", "*treated_well*", "*alcohol_cons*" and "*year*". Table 8 stores the results. As before, Column I is referred to the complete

[46] Those that felt sick, when deciding to seek help, might be less influenced by the presence of a chronic diseases because everyone in this group already has a "reason" to seek assistance, contrary to what happens to the others. For them in fact, we can expect a bigger difference between chronic patients and non-chronic patients, reflected by a higher coefficient.

regression, while in Columns II and III we constrained "*cronica*" and in Columns IV and V on "*feltsick*".

Looking at the Column I in Table 8, and focusing first on the significance of the coefficients, we notice that those referred to the "*exempt*", "*cronica*", "*cronica_exempted*", "*fam_doctor*", "*feltsick*", and "*year*" are all significant at the 1% level. For the ordinal variables, except for "*edu_level*" and "*alcohol_cons*", most of the times significance at the 1% is reached, too.

Regarding the impact of each of the regressors on the response probability, chronic disease and exemption increase the likelihood of a visit in health centers (respectively, they cause an increase in the expected response probability of .217 and .164), but when these two features are present in the same individual, the probability is attenuated (by -.095). At the bottom of the Table in Column I, we see the estimation of the ATE of the exemption computed through the two matching methods, nearest neighbour and propensity score, and we notice that the result we get from the regression is very close to these two values (in particular the one obtained through the propensity score method), suggesting that the previous estimate is precise.

Table 8

Regression of *app_centrosaude*					
Variables	Coefficients				
	Column I	Column II *cronica = 0*	Column III *cronica = 1*	Column IV *feltsick = 0*	Column V *feltsick = 1*
exempt	.164***	.173***	.05*	.175***	.125***
cronica	.217***	//	//	.326***	.076**
cronica_exempted	-.095***	//	//	-.131**	-.055
age_groups:					
30-44	.054**	.048**	.152**	.05*	.061
45-64	.094***	.08***	.174***	.097***	.063
65-79	.152***	.144***	.225***	.177***	.092**
80+	.08	.075	.183**	.126	.048
condicao_generated:					
somehow difficult	-.057**	-.034	-.086**	-.029	-.079***
somehow easy	-.97***	-.073**	-0112**	-.074**	-.099***
easy	-.135***	-.135***	-.077	-.11**	-.173***
insured	-.032	-.042	-.008	-.01	-.073**
female	.07***	.096***	.005	.084***	.025
fam_doctor	.24***	.224***	.286***	.26***	.206***
feltsick	.205***	.289***	.054**	//	//
treated_well	.006	.007	-.015	.023	-.064**
alcohol_cons:					
medium drinker	.006	-.003	.025	.01	-.006
light drinker	.042*	.052*	.03	.067**	.006
not drinker	.031	.035	.026	.052*	-.003
edu_level:					
Basico	-.029	-.024	-.03	-.02	-.045
Secundario	-.012	-.007	-.012	-.011	-.017
Superior	-.037	-.026	-.085	-.031	-.051
year:					
2020	-.09***	-.101***	-.054**	-.097***	-.058**
2021	-.127***	-.112***	-.152***	-.117***	-.141***
R^2	.2179	.1587	.1346	.1560	.1403
Number of observations:	3457	2476	981	2371	1086
Significance levels	10% = *		5% = **		1% = ***
ATE – nearest neighbour[47]	.202***	.202***	.033	.221***	.107***
ATE – propensity score[48]	.163***	.197***	.051	.189***	.08***

In addition to this, as in the previous model, we see that as individuals belong to different age groups the response probability is differently affected, with the peak reached for individuals in the range 65-79 years (.152 increase in the response probability). For the oldest group (more than 80 years) the coefficient is again not significant probably because of the small number of observations employed in the regressions. For the other regressors the implications are similar too: wealth is inversely correlated with appointments in health centers, the presence of a family doctor has a strong, positive effect, as the fact of the individual feeling sick in the year of the survey and the gender of individual

[47] For this method, we are required to specify the variables in the outcome model, so we employ the same used in the probit.
[48] For this method, we are required to provide the variables that predict treatment assignment in the treatment model, so we employ "*cronica*", "*profession*", "*female*", "*condicao_generated*", "*insured*", "*feltsick*", and "*age_groups*".

(being a women is associated with higher likelihood of seeking assistance). Finally, we find again that drinking habits have no significant effect on services utilization and that COVID years negatively impacted on the choice to seek assistance in the health system under the form of appointments in health centers.

The results of this regression suggest that the exemption leads to higher services utilization in the same way as suffering from a chronic disease. However, the effect of both characteristics together (hence of the interaction term) is negative. This suggests that the effect of the exemption alone is stronger for individuals not affected by chronic disease, while for those afflicted the effect of the exemption alone is attenuated.

To double check these results, we run the regressions whose results are in Columns II and III. From the coefficients we notice that for the regression which involves only individuals affected by chronic disease, the coefficient of "*exempt*" is significant at the 10% while, in the other regression, it is significant at the 1% level. Moreover, there is a strong difference is in the magnitude of the effect of the exemption on the response probability in the two cases: for individuals not afflicted it amounts to .17, more than 3 times the impact on afflicted individuals (.05). When looking at the results obtained through the ATE estimates, we see that the effects computed in this way are slightly higher in Column II, and similar (but not significant) in Column III.

For the other coefficients, we notice results similar to those of Table 5 in Columns II and III. So, age is positively related to service utilization even though for individuals with the chronic disease each age group has a bigger impact on services utilization with respect to the same age group for those not afflicted. The effect of "*feltsick*" is much bigger (almost six times) for those without the disease.[49] Again, we notice the negative effect that wealth of the family has on the variable of interest, for both chronic and non-chronic individuals, as if richer individuals are less likely to have appointments in health centers than the others (they might recur to private care). Finally, COVID years (2020 and 2021) negatively impacted on probability to seek assistance in the form of appointments in health centers for both people afflicted and not afflicted by chronic diseases.

In Column IV and V, we constrain for "*feltsick*", so we study the impact on the probability of having (at least) one appointment in a health centre for individuals that did not feel sick and that did feel sick. In both cases we see that the exemption positively impacts on the response probability, although the

[49] Again, this might be due to the fact that chronic patients are more "used" to sickness. Hence, when they feel bad, they might know what to do, without looking for external help. On the contrary, for non-chronic patients, feeling sick is a strong driver to look for assistance. An alternative explanation is that, for the group of not afflicted, in terms of service utilization there is a significance difference between those that felt sick and those who did not, because the formers might have sought assistance in the circumstance in which they felt sick, implying a substantial coefficient for "*feltsick*". In the group of people with a chronic disease instead, such a difference might be less relevant because they tend to require assistance in any case.

effect is stronger in Column IV (.175 vs .125).[50] The coefficients resulting from the ATE estimation are once again similar, both higher in the case of individuals that did not feel sick, and both smaller in the other case.

Regarding the variable "*age_groups*" instead, we notice that it is a significant determinant especially for those that did not feel sick, with the magnitude of the impact increasing as we move towards the older age groups. Again, wealth and years 2020-2021 impact negatively on service utilization irrespective of whether the individual felt sick or not, while individuals with a family doctor assigned are more likely to attend to a visit in health centers.

Regarding "*cronica*", we see a similar effect of Table 5: for those that did not feel sick, having a chronic disease causes a strong impact, much bigger than the one for those that felt sick. Once more, we assume that this happens because the formers might have looked for assistance for an event related to their chronic condition, while for the latter assistance might have been needed independently from their chronic condition, which is then less impactful.

The coefficients of "*cronica_exempted*" for the two regressions have similar implication to those of Column IV and V in Table 5. Indeed, in Column IV the impact of the interaction term again is negative and significant, while in the last Column we cannot reject the hypothesis that the same coefficient is 0. This suggests that for individuals that did not feel sick in the previous year, there is an attenuation of the exemption effect for those suffering from chronic disease (in the same fashion as Column IV of Table 5). However, this does not happen for individuals that felt sick.

We conclude the comparison by noticing that drinking habits have a slightly significant effect only for the observations studied in Column IV and not for those of Column V, probably because for the formers, being a not-drinker or a light drinker is associated to higher self-care and hence more regular controls. For those that felt sick instead, the alcohol consumption did not play a role in the decision to seek assistance.

From the studies conducted, it seems that exemption from user fees has a positive effect on primary care utilization (increase of .164 in the expected probability of having at least one appointment in public health centers), but that this is stronger when the individual is less vulnerable (no chronic disease or younger), pointing to the fact that the exemption might lead to higher unnecessary use of care. On the contrary, when care is more needed (older individuals or individuals suffering from chronic disease), the effect of the exemption is attenuated, implying that these individuals are influenced by other factors when deciding whether to require assistance.

[50] Maybe this is due to the fact that people use primary care on a routine basis, and that sickness might have induced them to resort to different types of services.

Study II: The impact on visits to emergency departments at public hospitals

In order to study the effect of the exemption on the number of visits in emergency departments, we employ as dependent variable "*times_urgency*", which contains information about the number of times the respondents state to have been at the emergency departments in a public hospital in the last year. The variable is present in every survey wave, from 2013 until 2021 and includes 7194 observations. Its distribution is shown in Graph 1 in Table 9. As a huge mass of the distribution - almost 74% - piles up at zero, a tobit type I and a zero-inflated negative binomial model will be used for the analysis.

In Graph 2 the differences in the distributions of the number of visits to the emergency departments between the people with and without the exemption are displayed. These charts suggest that among those exempted (right-hand side panel), the percentage of respondents who have never been to the emergency department over the last year (66%) is considerably lower than among the not exempted (left-hand side panel, around 80%). The difference may be due to the fact that those who are granted the exemption are more inclined to need help from the health care system as they tend to be sick more often, as previously discussed. An alternative (and complementary) explanation is that those exempted might opt to turn to the emergency departments more often than those not exempted because they do not have to pay for it, even if the gravity of the situation does not require it.

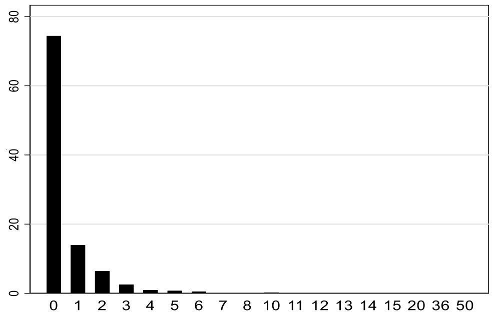
Next, we plot the distribution of "*times_urgency*" for those without and with a chronic disease (left- and right-hand side panel of Graph 3 Table 9 respectively). As expected, respondents with a chronic disease tend to use the emergency departments more often.

Finally, Graph 4 in Table 9 shows the distribution of the outcome variable considering both the presence of the exemption and of some chronic disease. When we consider individuals with a chronic disease (last two panels), the distribution is almost the same if we compare those possessing of the exemption with those who do not.[51] On the contrary, when we look at the proportions of those without chronic disease (first two panels), this difference is clearer, with more people turning to the emergency departments then they have the exemption.

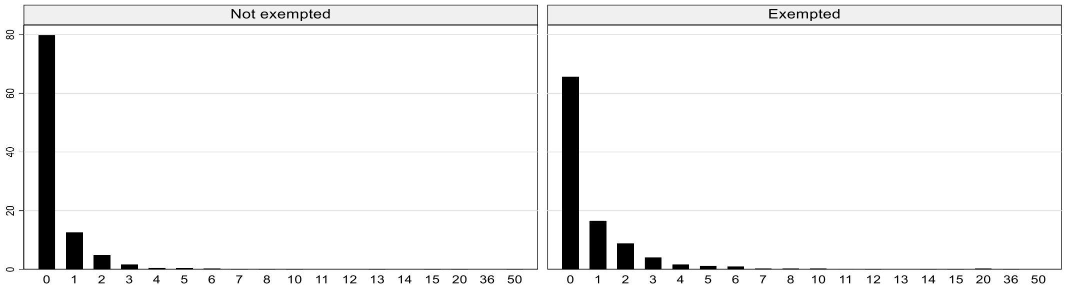
[51] For those with the exemption, 59% of the sample has never been in the emergency departments in the previous year, while for those without the exemption this proportion is 62%. Around 18% of those exempted went to the emergency departments exactly once, while the share for the other group is 20%.

Before estimating the econometric model, it is worth considering the distribution of the costs incurred by the users for their last emergency department visits in the previous year. We will employ the variable “*cost_urgency*” for this purpose. Graph 5 in Table 9 plots the distribution for those exempted and those not exempted. In line with our expectation, the cost for those with the exemption is indeed zero for the vast majority of the observations. Only 6% of them pay a positive amount, while the share is 47% for the non-exempted ones.

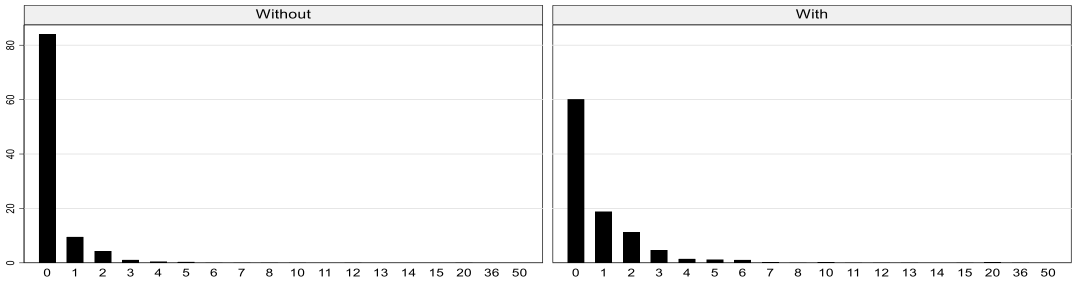
Table 9



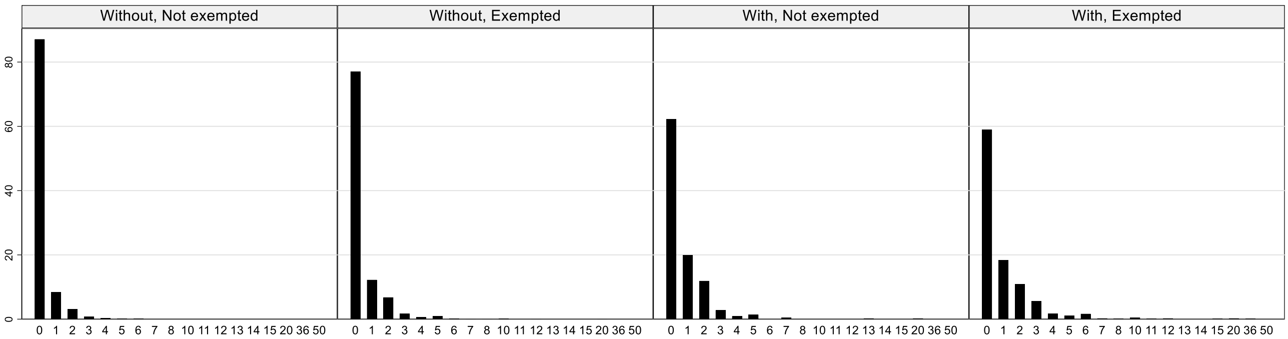
Graph 1 Distribution of the number of visits at emergency departments



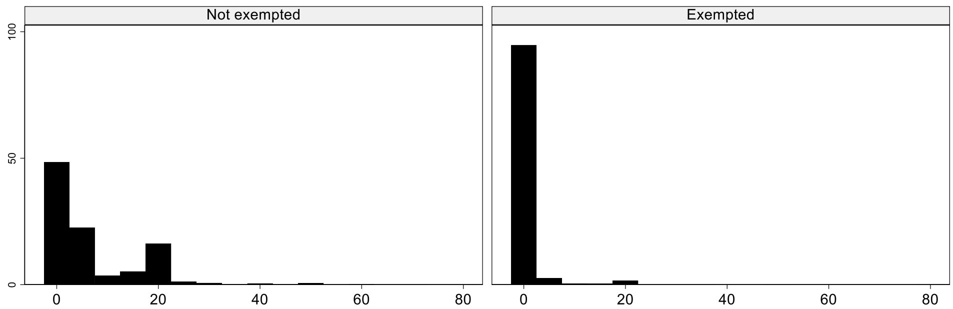
Graph 2 Distribution of the number of visits at emergency departments by exemption status



Graph 3 Distribution of the number of visits at emergency departments by chronic condition



Graph 4 Distribution of the number of visits at emergency departments by exemption status and chronic condition



Graph 5 User charges distribution by exemption status

The first model we employ is the tobit type I. We regress the number of visits to emergency departments in the last year on the presence of the exemption ("*exempt*"), the presence of a chronic disease ("*cronica*") and their interaction ("*cronica_exempted*"). We control for the patients' gender ("*female*") education level ("*edu_level*"), their age group ("*age_groups*"), economic conditions ("*condicao_generated*"), whether they have an health insurance ("*insured*"), whether they have been assigned a family doctor ("*fam_doctor*"), whether they were treated well the last time they received assistance ("*treated_well*"), whether they felt sick in the year the survey was taken ("*feltsick*"), their drinking habits ("*alchool_cons*") and the year in which the survey was taken ("*year*").

The results (Column I of Table 10) confirm what we have observed via visual inspection. Being exempted has a positive effect on the number of times the individual goes to the emergency department (.996 more visits). The coefficient is significant at the 1% significance level. Likewise, having a chronic disease positively impacts on the number of visits in emergency departments (1.444 more visits). At the same time, the coefficient on the interaction term is negative and statistically significant as well: for those who are afflicted by a chronic disease, the effect of the exemption gets attenuated (.735 less visits).

We now turn to the other coefficients. Having a private insurance is positively and significantly linked to the number of visits, meaning that insured individuals tend to visit the emergency departments more often than non-insured individuals. While education does not seem to have an impact, wealthier individuals tend to visit the emergency departments in public hospitals less often, similarly to what we observed in the study of appointments in health centers.[52] Weirdly, the coefficients referred to the age groups are all negative and decreasing, implying that age has a negative effect on secondary care. This might be due to the fact that older people prefer less demanding type of assistance, and do not opt that often for visits at emergency departments. An interesting result is the one referred to the "*fam_doctor*" regressor: it implies that having a doctor assigned has no impact on the number of visits at the emergency departments, similarly to what happens with the gender of the individual. Instead, as expected, whether the individual felt sick in the year in which the survey was taken has a strong impact on the dependent variable (2.681 more visits). Alcoholic consumption, and whether the patient was treated well in the past seem not to play a role here.

Finally, looking at the coefficients referred to the year, we see that only the one relative to 2020 is negative and significant, reflecting probably the impact that the COVID pandemic had on people's choice to seek help. In fact, with respect to 2019 (last year prior to the outbreak of the pandemic),

[52] It is interesting to notice that, not only the coefficients referred to the different income categories are negative, but that their negative impact grows when moving towards the richest bands. Again, the reason might be that wealthier individuals prefer to recur to private healthcare.

2020 is associated with a negative effect (-.798). 2021's effect instead is not significant: this is probably because on one side services' offer returned to levels similar to those pre-pandemic, and on the other people started to go back to normality thanks to the increased awareness and the developments of the research against the virus (vaccines mainly).[53]

As we did in the previous study, we further run two different regressions considering separately the individuals with chronic disease and those without and we obtain similar results (Columns II and III in Table 10). We notice that when we study only individuals with chronic disease the coefficient of "*exempt*" is not significant (recall that for appointments in health centers it was significant at the 10% level and much smaller in magnitude with respect to the coefficients for those without the disease). On the contrary, when the regression is estimated only for individuals not afflicted by any chronic disease, the coefficient is highly significant and positive.

These results point to the fact that for individuals affected by chronic diseases the impact of the exemption on services utilization is attenuated (in this case, null), even when we look at visits in emergency departments. For healthier individuals, we have a different situation, and those exempted tend to benefit from the help of the health system more than those who are not exempted (with respect to those in worse health condition). This might be an indicator that the exemption pushes individuals less in need of healthcare support to go to the hospital.[54]

Relative to the other coefficients, we see that, as in Column I, age has a negative effect on ES, whether or not the person had a chronic disease. Wealth instead has a negative impact only for those without a chronic condition. Moreover, just for them, having a private insurance and having been treated well by the healthcare personnel in the past has a positive effect. Lastly, both COVID years had a negative effect on in Column III, while in Column II only 2020's coefficient is significant.

Finally, in Columns IV and V we run two regressions separately for individuals that did not feel sick and for those who did, respectively. We see that in both cases, the exemption has a positive and significant effect, and as for the study on "*app_centrosaude*", the magnitude is higher for those who did not feel sick. For both categories, age has a negative effect that increases in absolute value as we look at the elder groups. Similarly, having a chronic disease has a positive impact on service utilization for both type of observations, even though in Column IV we see that the coefficient is almost double the one of Column V.[55]

[53] Indeed, by the end of August 2021, 74% of the Portuguese population had received two doses (or equivalent) of a COVID-19 vaccine (Country Health Profile 2021, OECD).

[54] Where less in need refers to the absence of chronic disease.

[55] We recur to the explanations given in the previous study to justify this result.

Table 10

Regression of *times_urgency*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
exempt	.996***	.901***	.259	1.194***	.81***
cronica	1.444***	//	//	2.275***	1.147***
cronica_exempted	-.735**	//	//	-1.613***	-.366
age_groups:					
30-44	-.262	-.165	-.726	-.176	-.568*
45-64	-.878***	-.860***	-.914*	-.916***	-1.101***
65-79	-1.354***	-1.044***	-1.572***	-1.420***	-1.611***
80+	-1.914***	-1.54**	-2.125***	-2.410**	-2***
condicao_generated:					
somehow difficult	-.161**	-.071	-.307	-.440	-.034
somehow easy	-.746***	-.743***	-.439	-1.263***	-.364
easy	-1.147***	-1.17***	-.585	-1.964***	-.577
insured	.379**	.571***	.033	.95***	-.145
female	.196		.265	.295	-.05
fam_doctor	-.047	.114	-.754	.199	-.165
feltsick	2.681***	2.571***	2.66***	//	//
treated_well	.146	.557***	-.548*	-.003	.256
alcohol_cons:					
medium drinker	.026	-.082	.225	.241	-.185
light drinker	.363*	.64***	.018	.982***	-.08
not drinker	.11	-.181	.505	.144	.108
edu_level:					
Basico	-.167	-.038	-.364	-.109	-.318
Secundario	-.044	.178	-.001	-.03	-.04
Superior	-.016	.001	.128	-.357	.160
year:					
2020	-.798***	-.78***	-.904***	-1.111***	-.653***
2021	-.202	.074	-.705**	.18	-.62***
cons:	-2.778***	-3.27***	.01	-3.653***	.663
R^2	.1202	.1229	.0682	.0534	.0272
Number of obs:	3404	2441	963	2333	1071
Left-censored	2624	2038	586	2083	541
Significance levels	10% = *		5% = **		1% = ***

Again, we observe that the interaction term between "*cronica*" and "*exempt*" is significant (and negative) only for those that did not feel sick, implying that for them, the effect of the exemption on the number of visits at emergency departments is attenuated by the presence of a chronic disease. As suggested previously, the reason might be that, when we consider people in "normal" circumstances, i.e., that did not feel sick, chronic patients require assistance regardless of the exemption, due to their permanent condition, and this makes the impact of the exemption attenuated for them compared to the effect on those without the chronic disease, who are particularly incentivized by the exoneration (in particular, in this case, the effect in Column V is not only neglected but also inverted).[56] For those

[56] Indeed, from the coefficients we learn that an individual having only the chronic disease has more expected visits at emergency departments than the same individual (so with all other covariates equal) with the chronic disease and the exemption.

that felt sick instead, we see no significant effect from the interaction maybe because when individuals feel sick, having or not a chronic disease plays a less important role than otherwise and makes people equally incentivized by the exoneration from fees, removing the attenuation effect. For the remaining coefficients, we notice a positive impact due to private insurance for individuals that did not feel sick, who, however, are negatively affected by wealth in their choice to seek assistance in emergency departments at public hospitals. Finally, regarding the impact of the year, we have similar effects of Column II and III (for columns IV and V respectively).

Now we turn to the zero-inflated negative binomial model. In this case we assume that the zero counts are generated by two processes: one regarding those who would look for assistance if needed and the other, generating "certain zeros", involving those not willing to look for help even if the circumstances would be suggesting differently (people without confidence or scared by the type of care provided in ES, people with bad experiences in emergency departments, people living too far away, people in possess of a private insurance and consequently relying on private institutions to receive assistance, etc.).

We will run two different regressions, one in which we specify the variables for the logistic model underpinning the generation of "certain zeros",[57] and the other in which we leave constant inflation (inflation on a mass point), hence without providing any explanatory variable. Regarding the variables employed for the remaining counts (the ones deriving from the negative binomial) we use the same variables of the tobit model.

From the results, stored in Table 11, we notice that for individuals not in the "certain zero" group, significance in both regressions is not achieved only for the regressors relative to "*edu_level*", "*alcohol_cons*", and "*fam_doctor*", while differences between the two are to be found in the coefficients of "*insured*" and "*treated_well*" that are significant respectively only in the first (the one with explanatory variables) and only in the second regression.

To retrieve the expected change in the visits to emergency departments associated to changes in the regressors, we need to recall that each coefficient represents the expected change in the logarithm of the dependent variable for a unitary change in the relative independent variable:

$$coeff. = E[\triangle \ln(y)] = E\left[\ln\left(\frac{y_1}{y_0}\right)\right]$$ [58]

To have a better understanding of how *y* is affected by a change in one of the regressors, we employ the logarithms properties, and we have that:

[57] These are "*generico*", "*insured*", "*distance_to_urgency*", "*time_to_urgency*", "*treated_well*", and "*import_confidence*".

[58] y_1 and y_0 are the values of the dependent variable for two identical individuals for which the only difference is a unitary change in the covariate "*coeff.*" is referred to.

$$e^{coeff} = \frac{E[y_1]}{E[y_0]}$$

So, when we look at the incident-rate ratios (IRR, the terms e^{coeff}) we have the ratios of the expected values of the dependent variable computed keeping all the covariates equal and unitarily changing only the regressor relative to the coefficient taken in consideration. If the ratio is bigger than 1, it means that the regressor positively impacts on "*times_urgency*", and vice versa if it is smaller than 1. Hence, the IRRs (from both regressions) relative to "*exempt*" suggest that for two individuals having all the same characteristics except for the exemption status, the one exempted has around 100% more visits at emergency departments than the other.[59] The effect of the chronic disease is similar in magnitude, but even in this case when these two characteristics are present together, the effect of the exemption is attenuated. Indeed, with respect to individuals for which the value of the intersection is 0, those with a value of 1 have 40% less visits.

Again, the effect of the age and wealth is negative and increasing in magnitude as we move towards the oldest and the richest. Two final remarks regard the massive impact related to the variable "*feltsick*" and the effect of COVID years. For the first, we see that the expected difference in visits at emergency departments between those that felt sick and those who did not (with all the other covariates kept constant) is around 300%, hence a 4-times increase. Regarding the variable "*years*" instead, we see that 2020 is associated with a 40% expected decrease, while 2021 utilization is comparable with 2019. The reason might be again that in the second year of the pandemic, increased awareness, and new means to fight the virus, together with an increased offer of healthcare services brough back the situation to normality, at least for the ES.

[59] The IRR is indeed close to 2, implying that the expected value of y for the individual with the exemption is almost double the one of the individual without. The average value of "*times_urgency*" for the years we are considering is .42, and for the same period the mean value for those exempted is .62 and for those not exempted .28.

Table 11

Regression of *times_urgency*				
Variables	Coefficients		Incident-rate ratios	
	Column I With explanatory var.	*Column II* Constant inflation	*Column III* With explanatory var.	*Column IV* Constant inflation
exempt	.7***	.627***	2.014***	1.872***
cronica	.732***	.859***	2.08***	2.361***
cronica_exempted	-.512***	-.412**	.6***	.662**
age_groups:				
30-44	-.211	-.199	.81	.819
45-64	-.563***	-.583***	.569***	.558***
65-79	-.702***	-.818***	.495***	.441***
80+	-1.006***	-1.035**	.365***	.355***
condicao_generated:				
somehow difficult	-.102	-.045	.903	.956
somehow easy	-.568***	-.401***	.567***	.669***
easy	-.669***	-.684***	.512***	.505***
insured	.337**	.18	1.401**	1.12
female	.17*	.18***	1.184*	1.197**
fam_doctor	-.085	-.18	1.089	.836
feltsick	1.559***	1.416***	4.855***	4.12***
treated_well	.048	.067***	1.049	1.069
alcohol_cons:				
medium drinker	-.057	-.014	.945	.985
light drinker	.196	.25**	1.217	1.283**
not drinker	.045	-.088	1.046	1.092
edu_level:				
Basico	-.096	-.122	.909	.885
Secundario	-.062	.002	1.065	1.002
Superior	-.021	-.173	.979	.841
year:				
2020	-.448***	-.414***	.639***	.661***
2021	-.004	-.079	.996	.924
cons:	-1.662***	-1.411***	.19***	.244***
R^2	//	//		
Number of obs:	2865	3404		
Left-censored	2209	2624		
Significance levels	10% = *	5% = **		1% = ***

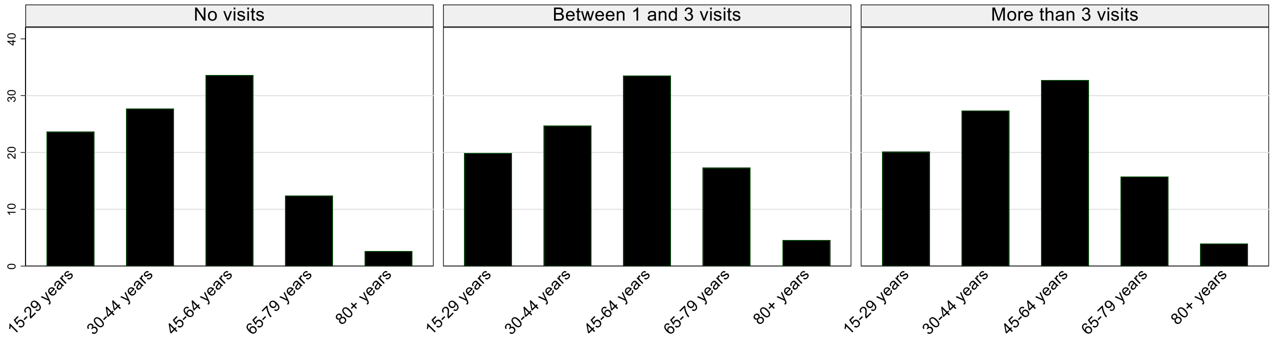
Since the dependent variable contains a lot of information, we can transform it to study it in different ways and employing other techniques. The first transformation we can perform consists in creating a new variable, named "*urgencia_grouped*", that takes 3 possible values:

- 0 if "*times_urgency*" is 0.
- 1 if "*times_urgency*" is between 1 and 3 (included).
- 2 otherwise (those with at least 4 visits at the urgency are considered to be intensive users).

The newly obtained variable is distributed as the upper part of Table 12 describes.

Table 12

urgencia_grouped:	Observations	Percentage
0	5352	7.68%
1	1643	21.7%
2	577	7.62%
Total	7572	100%



Graph 1 Age groups distribution by number of visits at emergency departments

A nice feature of "*urgencia_grouped*" is the fact that, across its categories, the proportions of individuals belonging to the different age groups is comparable, as shown in Graph 1 in Table 12. Hence, across the 3 different sub-groups we have similar individuals under this point of view.

The model we are going to employ to study this newly obtained variable is the ordered probit, because the values that the dependent variable takes are not to be considered as numerical values, but as indicators of different categories. We obtain the estimates stored in Table 13 for the causal effects of the regressors for the distinct categories.

By looking at the coefficients, we see that the effect of the exemption is different across the 3 categories not only in the magnitude but also in the direction.[60] With respect to non-exempted individuals, those exempted are .094 less likely to have 0 visits at the emergency rooms, .07 more likely to have from 1 to 3 visits and .024 more likely to have more than 3 visits. These figures obviously imply a positive relation between exemption and visits at emergency departments. The difference in the effect between group 1 and group 2 might be due to the fact that individuals that visit more than 3 times in one year emergency departments are likely to have poor health, which induces them to seek for assistance even if not in possess of the exemption (still, although small, exemption has an effect significant at any level).

The coefficients indicating whether the individual suffers from chronic diseases have the sign we would expect, too. Indeed, with respect to individuals without chronic diseases, those afflicted are .13 less likely to be in the first category of "*urgency_grouped*" (0 visits), .096 more likely to be in the second and .032 more likely to be in the third (all coefficients significant at any level).

[60] Indeed, the three categories are mutually exclusive, and by definition the sum of the coefficients has to return 0.

Table 13

Regression of *urgencia_grouped*			
Variables	Coefficients		
	Column I $times\_urgencia = 0$	Column II $0 < times\_urgencia \leq 3$	Column III $times\_urgencia > 3$
exempt	-.094***	.07***	.024***
cronica	-.127***	.095***	.032***
cronica_exempted	.07***	-.052**	-.018**
age_groups:			
30-44	.015	-.01	-.005
45-64	.067***	-.048***	-.02***
65-79	.113***	-.082***	-.03***
80+	.152***	-.113***	-.038***
condicao_generated:			
somehow difficult	.001	-.001	0
somehow easy	.07***	-.053***	-.017***
easy	.105***	-.081***	-.024***
insured	-.047***	.035***	.012**
female	.006	-.005	-.002
treated_well	.008	-.006	-.002
fam_doctor	.009	-.006	-.002
feltsick	-.243***	.181***	.062***
alcohol_cons:			
medium drinker	-.006	.004	.002
light drinker	-.042**	.031**	.01**
not drinker	-.024	.018	.006
edu_level:			
Basico	.026	-.02	-.007
Secundario	.006	-.005	-.002
Superior	.014	-.011	-.004
year:			
2020	.027*	-.02*	-.007*
2021	-.003	.002	.001
R^2		.1414	
Number of obs:		3457	
Significance levels	10% = *	5% = **	1% = ***

For what concerns the interaction term between the two coefficients just described, the results are in line with what we have seen until now. Indeed, in addition to the individual effects of these two covariates, the interaction implies that individual exempted and with chronic conditions are .07 more likely to be in category 0 of the "*urgencia_grouped*" variable, .05 less likely to be in category 1, and .02 less likely to be in category 2. Again, the interaction term does not add to the individual effects of its components but attenuates their effect, going in the opposite direction.

Regarding the other coefficients we notice again, for the vast majority, the difference in the impact between the second and the third category, which we can ascribe, as mentioned above, to the fact that heavy users are probably in need of constant and regular care, and the characteristics represented by the regressors might not play a role in the decisional process regarding whether to seek assistance.

Study III: Impact on emergency departments and on appointments in health centers, a comparison

A second transformation of "*times_urgency*" allows us to obtain a dummy variable. Once this is done, we can employ once again a probit model and make comparisons with the results of the study on appointments in health centers. Hence, we create a new variable "*urgencia_dummy*" which takes value 0 if "*times_urgency*" is 0 and value 1 otherwise (so, the newly created binary variable just carries information on whether or not the observation visited emergency departments in the year of the survey). Then we just regress this on the same regressors employed in the studies on "*app_centrosaude*", and we compare the results relative to the average partial effects to check the differences between the two cases.

The first thing we notice from Table 14 is that the estimates of the coefficients referred to "*exempt*", "*cronica*" and "*cronica_exempted*" are all significant at the 1% level. However, the effect of each of these regressors is stronger for "app_*centrosaude*" (.164, .217 and -.095 against respectively .095, .143 and -.088). Notwithstanding this, what we learn from these two studies is that whether the assistance required from the health system consists in visits to the emergency departments or in appointments to the health centers, individuals who are afflicted by chronic diseases or exempted from payment of user fees are more likely to look for help, but that the two effects do not sum in cases of individuals with both a chronic condition and the exemption. What we conclude then, is that the effect of the exemption on the choice to look for help is attenuated in cases of individuals with poorer health. Regarding the impact of the exemption, we see at the bottom of the Table that the outcomes of the ATE estimation are similar (although smaller) to the result of the regression, and also in this case smaller than those referred to the appointments in health centers.

Regarding the other regressors, it is interesting to notice the sign difference in the coefficients referred to the age groups. Indeed, if for appointments in health centers these are all positive (with significance not reached only for the last group), for visits at emergency departments we observe the opposite (with significance not reached only for the first group). The reason might be due to the fact that older individuals are less prone to visit emergency departments because they might prefer to opt for less demanding therapies (as if it is not worth anymore to visit emergency departments when you are older).

Table 14

Dependent Variables	*urgencia_dummy*	*app_centrosaude*
Variables	Coefficients	
	Column I	*Column II*
exempt	.095***	.164***
cronica	.143***	.217***
cronica_exempted	-.088***	-.095***
age_groups:		
30-44	-.015	.054**
45-64	-.07***	.094***
65-79	-.119***	.152***
80+	-.165***	.08
condicao_generated:		
somehow difficult	-.008	-.057**
somehow easy	-.072***	-.97***
easy	-.113***	-.135***
insured	.05**	-.032
female	-.005	.07***
fam_doctor	-.002	.24***
feltsick	.266***	.205***
treated_well	.003	.006
alcohol_cons:		
medium drinker	.008	.006
light drinker	.039*	.042*
not drinker	.014	.031
edu_level:		
Basico	-.023	-.029
Secundario	-.002	-.012
Superior	-.002	-.037
year:		
2020	-.045***	-.09***
2021	-.007	-.127***
R^2	.1834	.2179
Number of obs:	3457	3457
Significance levels	10% = * 5% = **	1% = ***
ATE – nearest neighbour	.07***	.202***
ATE – propensity	.066***	.163***

Other differences worth mentioning regard "*insured*", "*fam_doctor*", "*female*" and "*year*". Indeed, we observe that being insured increases the likelihood of visiting emergency departments, while for appointments in health centers the effect is not significant. On the contrary, having a family doctor assigned increases the likelihood of having health centers appointments, while it does not have an effect on visits at emergency departments. This point to the fact that family doctors induce individuals to look for assistance in the form of appointments in health centers but that they are not influent when it comes to visits at emergency departments. Regarding the gender, the results suggest that it is not impactful in the choice to seek assistance in the form of ES, but that being a woman positively affects appointments in health centers. The year in which the observation was interviewed matters too. Indeed, we notice that 2020 is associated with a negative effect on utilization of both services, but that 2021 has an impact only on appointments in health centers. A possible explanation might be that in 2021 the developments in the research and higher awareness of the COVID infection, together with a service offer returned to pre-pandemic values, brought people back to "normal" behaviour when it comes to more urgent care as the one provided in emergency departments, but that when it comes to appointments in health centers people might still be reluctant, scared by the virus.[61]

Finally, whether the individual felt sick in the year in which the survey was taken plays an important role in both circumstances (increasing by .266 and .205 the probability of visits in emergency rooms and appointments in health centers, respectively).

After this analysis, we perform other two comparisons by constraining first the variable "*cronica*" and then the variable "*feltsick*", respectively in Table 15 and Table 16.

The first thing we notice in Table 15 is that the impact of the exemption on "*urgencia_dummy*" is significant only for individuals without a chronic disease. Similarly, in the regression on "*app_centrosaude*" we found that the exemption's coefficient for those suffering from a chronic disease is significant only at the 10% level and that it is much smaller in magnitude than the coefficient for those without the disease. Hence, these results suggest that the exemption leads to higher services utilization mainly those with better health. The fact that in both Table 14 and Table 15 the coefficients of "*exempt*" are smaller in magnitude for "*urgencia_dummy*", might suggest that the exemption plays a more important role for less urgent care.[62] This finding is confirmed by the outcomes of the ATE estimations at the bottom of the Table. Indeed, we see that the estimated effects of the exemption are close to the results of Column I and II, and by comparing the results with those of Column III and IV we see that the magnitude of the impact on appointments in health centers is bigger.

Again, we notice the difference in the signs of the coefficients of "*age_groups*" between the first two and the last two columns, while if we focus on the effect on "*urgencia_dummy*" alone, we see that the negative impact of age is stronger for those afflicted by a chronic disease. The other relevant coefficients to comment are the ones relative to "*feltsick*", that are both positive and significant, implying that feeling sick increases the probability of visits in emergency departments regardless of the chronic condition of the individual, those referred to the wealth of the individual, which entail a negative effect only for not afflicted people, the ones of "*insured*", which suggest that having a private insurance increases the probability of having visits at emergency departments, but only for people not

[61] Assistance in emergency departments usually is related to more serious conditions and urgent care, so it is reasonable that this was service went back to "normal" before appointments in health centers.

[62] This might be so because appointments in health centers are in part related to a sort of preventive and "routine" care, which is more "apt" to be influenced by incentives, like the exemption. On the contrary, visits in emergency departments are something more related to curative and urgent assistance, and when needed, exoneration from payment of charges might play a less important role. Hence, the results suggest that demand for appointments in health centers is more elastic with respect to the demand for ES.

suffering from a chronic disease, and those referred to the year of the survey, which imply that COVID years impacted negatively on ES utilization (with respect to 2019), and specially for people with a chronic condition. Hence, with respect to the study of "*app_centrosaude*", we miss the consistent effect associated to the presence of a family doctor, which does not play a role neither for people not afflicted nor for those afflicted, and we do not detect any impact related to the gender of the user, which instead played a role in appointments in health centers for people without chronic diseases. What these results suggest, is that for people with a serious condition, few variables have an impact on the choice to seek assistance in the form of ES, probably because the chronic disease they have is a strong determinant of demand by itself. In column I instead, since we consider only people with no chronic disease, the demand for the service is influenced by more factors.

Table 15

Dependent Variable	*urgencia_dummy*		*app_centrosaude*	
Variables	Coefficients			
	Column I *cronica = 0*	*Column II* *cronica = 1*	*Column III* *cronica = 0*	*Column IV* *cronica = 1*
exempt	.077***	.016	.173***	.05*
age_groups:				
30-44	-.003	-.153**	.048**	.152**
45-64	-.052***	-.209***	.08***	.174***
65-79	-.073**	-.293***	.144***	.225***
80+	-.101**	-.369***	.075	.183**
condicao_generated:				
somehow difficult	.01	-.036	-.034	-.086**
somehow easy	-.065**	-.068	-.073**	-0112**
easy	-.108***	-.073	-.135***	-.077
insured	.066***	.001	-.042	-.008
female	-.004	-.02	.096***	.005
fam_doctor	.006	-.055	.224***	.286***
feltsick	.24***	.319***	.289***	.054**
treated_well	.029*	-.071*	.007	-.015
alcohol_cons:				
medium drinker	-.007	.067	-.003	.025
light drinker	.055**	.027	.052*	.03
not drinker	-.01	.078*	.035	.026
edu_level:				
Basico	-.032	-.046	-.024	-.03
Secundario	-.001	.01	-.007	-.012
Superior	-.012	.037	-.026	-.085
year:				
2020	-.035**	-.089**	-.101***	-.054**
2021	.02	-.082**	-.112***	-.152***
R^2	.1645	.1342	.1587	.1346
Number of obs:	2476	981	2476	981
Significance levels	10% = *	5% = **		1% = ***
ATE – nearest neighbour	.068***	.025	.202***	.033
ATE - propensity	.076***	.026	.197***	.051

In Table 16 we see for the first time that the effect of the exemption is stronger for individuals in a "condition of need": the coefficient relative to individuals that felt sick is higher than the coefficients for those who did not. A possible explanation might be that having felt sick, individuals might have been more inclined to seek "*intensive*" care represented by ES, and since these are the most expensive services,[63] exoneration from fees plays a bigger role. We also observe that the exemption coefficient is bigger in Column II than in Column IV, i.e., the exemption effect on the probability of having at least one appointment in health centers for individuals that felt sick. ATE estimates confirm this finding, even though the results obtained through this estimation are smaller in both cases (in particular in Column II).

The coefficient of "*cronica*" is positive and significant in both columns, however the interaction is significant, and again negative, only for those who did not feel sick, as in the case of "*app_centrosaude*". So, for people in "normal" circumstances, i.e., that did not feel sick, the exemption effect on ES utilization is attenuated when the person is also afflicted by a chronic disease. For people that felt sick instead, we observe no such an effect. This might be because in the second case, given that the sample includes only individuals that felt sick, there is no room for an attenuation to kick in. In other words, in the particular subsample we are analysing in Column II, the effect of the exemption exists and is equal across chronic and non-chronic observations because we are focusing on people for which care is likely to be necessary. In Column I instead, where we are studying a subsample of observations among whom some are more in need and others less in need of medical care, we observe a different situation: we detect the presence of an attenuation on the effect of the exoneration from fees that applies only to individuals that are more in need of care because suffering from a chronic disease, which suggests once again that the exemption increases services utilization especially for individuals less in need of it.

Concerning the other coefficients, we notice that higher age is associated with lower probability of visits at emergency departments, especially for those who felt sick (older individuals might be less willing to undergo "*intensive*" care, especially if they felt sick). Similarly, income is negatively associated with ES utilization, but only for those who did not feel sick (while in the study on appointments in health centers, we saw that wealth impacted negatively in both cases). Finally, we notice the positive impact that having a private insurance has, but only in Column I, and, on the contrary, the negative effect of year (slightly significant in 2020 for both, and significant at 5% for the regression in Column II).

[63] Data available on https://www.chlc.min-saude.pt/taxas-moderadoras/taxas-moderadoras-e-tabelas-de-precos/. Accessed on August 9, 2022.

Table 16

Dependent Variable	*urgencia_dummy*		*app_centrosaude*	
Variables	Coefficients			
	Column I *feltsick = 0*	*Column II* *feltsick = 1*	*Column III* *feltsick = 0*	*Column IV* *feltsick = 1*
exempt	.068***	.142***	.175***	.125***
cronica	.141***	.182***	.326***	.076**
cronica_exempted	-.101***	-.092	-.131**	-.055
age_groups:				
30-44	.007	-.114**	.05*	.061
45-64	-.039*	-.177***	.097***	.063
65-79	-.062**	-.278***	.177***	.092**
80+	-.079**	-.36***	.126	.048
condicao_generated:				
somehow difficult	-.026	.014	-.029	-.079***
somehow easy	-.079***	-.058	-.074**	-.099***
easy	-.11***	-.127*	-.11**	-.173***
insured	.064***	-.017	-.01	-.073**
edu_level:				
Basico	-.011	-.06	-.02	-.045
Secundario	-.006	-.002	-.011	-.017
Superior	-.032	.069	-.031	-.051
female	.009	-.054	.084***	.025
fam_doctor	.023	-.069	.26***	.206***
treated_well	-.014	.044	.023	-.064**
alcohol_cons:				
medium drinker	.014	-.014	.01	-.006
light drinker	.062***	-.008	.067**	.006
not drinker	.017	-.006	.052*	-.003
year:				
2020	-.029*	-.073*	-.097***	-.058**
2021	.024	-.082**	-.117***	-.141***
R^2	.0622	.0504	.1560	.1403
Number of obs:	2371	1086	2371	1086
Significance levels	10% = *	5% = **		1% = ***
ATE – nearest neighbour	.046***	.119***	.221***	.107***
ATE – propensity score	.058***	.081**	.189***	.08***

A further comparison that we perform is made by employing the variable "*age_groups_exempted*" in the same fashion as we did for the analysis of Table 5. The results are stored in Table 17.

Table 17

Dependent Variable	*urgencia_dummy*	*app_centrosaude*
Variables	Coefficients	
	Column I	*Column II*
age_groups_exempted:		
30-44 not exempted	-.020	.061**
45-64 not exempted	-.054**	.088***
65-79 not exempted	-.074**	.229***
80+ not exempted	-.137***	.031
15-29 exempted	.118***	.182***
30-44 exempted	.116***	.229***
45-64 exempted	.02	.293***
65-79 exempted	-.046	.303***
80+ exempted	-.088**	.279***
cronica	.132***	.212***
cronica_exempted	-.067**	-.088**
condicao_generated:		
somehow difficult	-.009	-.057**
somehow easy	-.072***	-.096***
Easy	-.113***	-.134***
insured	.049**	-.031
female	-.006	.071***
fam_doctor	-.002	.239***
feltsick	.265***	.204***
alcohol_cons:		
medium drinker	.009	.006
light drinker	.038*	.042*
not drinker	.015	.031
edu_level:		
Basico	-.026	-.029
Secundario	-.003	-.011
Superior	-.003	-.036
year:		
2020	-.044***	-.088***
2021	-.006	-.125***
R^2	.1845	.2191
Number of obs:	3457	3457
Significance levels	10% = * 5% = **	1% = ***

Looking at the variable "*age_groups_exempted*", we notice that, although some of the estimates are not significant for all the categories, it is possible to identify two trends: the exemption is generally associated with higher ES utilization, but its impact is bigger for the non-chronic individuals and decreases as we move towards the older age groups. Table 18 shows such patterns more clearly.

Table 18

Effect on the expected response probability	Group 1 (15-29)	Group 2 (30-44)	Group 3 (45-64)	Group 4 (65-80)	Group 5 (80+)
No exemption, no chronic disease	0	0	-.05	-.07	-.14
Exemption and no chronic disease	+.12	+.12	0	0	-.09
Difference	+.12	+.12	+.05	+.07	+.05
No exemption, with chronic disease	+.13	+.13	+.08	+.06	-.01
Exemption and with chronic disease	+.18	+.18	+.06	+.06	-.03
Difference	+.05	+.05	-.02	0	-.02

For all the other coefficients, what has been told in the previous comparison holds: the negative relation of wealth and service utilization, the positive effect of feeling sick, the fact that having a family doctor impacts only on appointments in health service contrary to what happens in case of possessing a private insurance.

Study IV: The impact on the choice to look for help when feeling sick

For this fourth and last study, we will focus on the dummy variable "*help_health*", which collects the answers to the question "*Regarding the last time that you felt sick, did you look for help in the health system?*", posed to individuals who stated that they felt sick in the preceding year, i.e., this is a follow-up question for individuals with values of "*feltsick*" equal to 1. These are 2746 out of 7572, and among them, 2367 looked for help in the health system in that occurrence.

Given the information embodied in the variable, this is a more general analysis with respect to the previous ones, because it focuses on the effect of the exemption on any kind of health service (the question of the survey says "help from the health system" but it does not specify whether it regards visit to emergency departments or appointments in health centers, or other services). At the same time, this is a more specific study than those already performed, in the sense that it regards assistance as a direct response to sickness.[64]

For what concerns determining if necessary or unnecessary (or both) use of care is favoured, in this case we are unable to really infer anything. Indeed, the variable of interest takes value 1 whenever the individual felt sick and looked for help in the health system. Hence, it is referred to a specific situation, and for all the respondents who did so, care was indeed needed at the time.

Before performing the regression, we present some charts to have a better understanding of the data. In particular, in Graph 1 of Table 19, we can see the difference between exempted and non-exempted individuals for what concerns the distribution of "*feltsick*". The chart shows that for both exempted and non-exempted, the majority (respectively 54.48% and 69.37%) of individuals did not feel sick even though there is a visible difference between the two groups. We can link this finding to the fact that exemption is often assigned on the basis of health issues, which may be the reason for which the individuals felt sick. In this case, our interest relies on those observations who declared to having felt sick. A nice feature is the fact that among exempted and non-exempted, the number of individuals who felt sick is similar, 1387 for the former group and 1324 for the latter. Hence, we have two groups of similar and considerable dimensions in the sample we will employ for this regression.

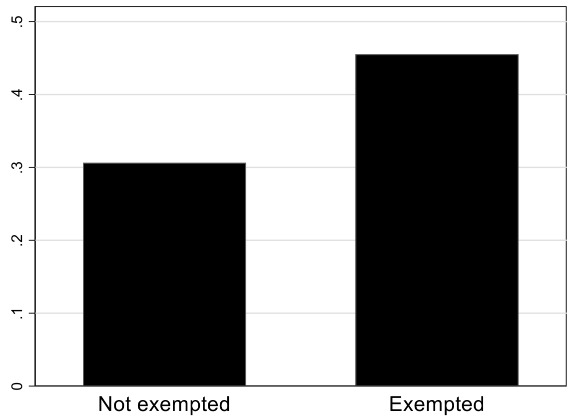
Graph 2 of Table 19 shows instead how the variable of interest ("*help_health*") is distributed across the same two groups. Again, we see similar (although not equal) situations for exempted and non-exempted individuals. For the latter, 239 out of 1324 observations (18.05% of the total) did not recur

[64] The variables "*app_centrosaude*" and "*times_urgency*" (other than the variables derived from the latter) were not limited to the cases in which the individual felt sick. Indeed, if we look at the distribution of "*app_centrosaude*", we have that 40.72% of the observations that did not feel sick had a visit in emergency departments (for "*urgencia_dummy*", this proportion is 15.6%).

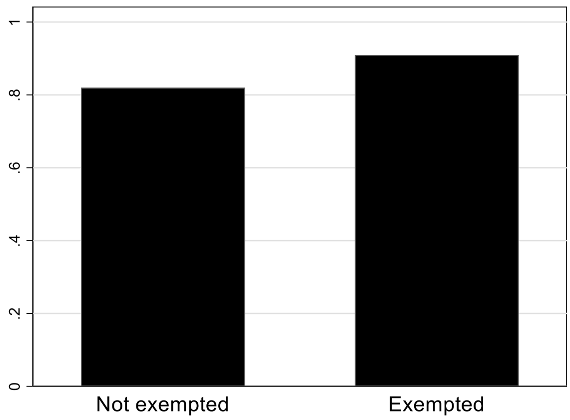
to help when they were sick, while for the other group only 126 out of 1387 observations (9.08%) decided not to look for help in the health system. Hence, in both groups the vast majority did require help, but for the not exempted, the percentage of those who chose not to look for assistance is double with respect to the exempted. What we are interested in determining is whether this difference is due to the fact that those exempted were indeed induced by the fact that the service was offered for free, or if there is some other reason underlying their decision.

In this sense, it can be helpful to look at the graphs of the variable "*help_health*" divided for exemption and presence of a chronic disease in the individual, which we can find in Graph 3 of Table 19. We notice that individuals with chronic disease (right side of the graph) are more likely than non-afflicted individuals to look for assistance from the health system when they feel sick, both in case of exemption and in case of non-exemption. However, when we compare the situation for individuals having the same situation regarding chronic disease, we see that also the exemption plays a role, and its impact is bigger for non-chonic observations. For individuals suffering from a chronic disease, the difference between those exempted and those not, is just 3.03% (95.57%-91.54%). On the contrary, for those not afflicted, the difference is 9% (85.94%-76.94%), as if the exemption leads to higher services utilization for less severe health conditions (individuals without chronic disease).

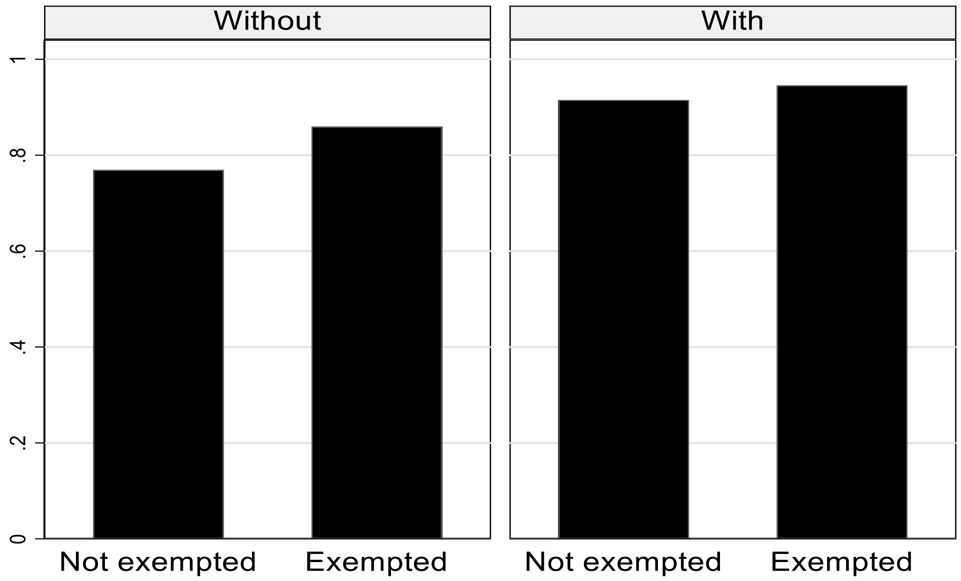
Table 19



Graph 1 Proportion of people that felt sick by exemption status



Graph 2 Proportion of people that looked for help when sick by exemption status



Graph 3 Proportion of people that looked for help when sick by exemption status and chronic condition

To check this last statement, we can look at the proportions of those who looked for help in any of the categories of the "*health_state*" variable for those exempted and those not. Unfortunately, the sizes of the different groups are not always large enough to obtain reliable information.[65] For the groups with more observations, we can look at those who declared to be in a "*Bad*" state (189 observations) and see that for those exempted 6 out of 147 (4.08%) individuals decided not to look for help, while for those not exempted all 42 recurred to the assistance of the health system. For those in "*Reasonable*" condition (544 observations), for the exempted people we have that 21 out of 330

[65] For example, for those who declared to be in a "*Very good*" state we have a total of 33 observations of the variable "*help_health*". Among these, 12 are exempted, with 1 having decided not to look for assistance in the help system, while for the other 31, 4 individuals have a value of "*help_health*" equal to 0.

(6.36%) did not look for help, while for not exempted they were 26 out of 214 (12.15%). Finally, for those in "*Good*" conditions (355 observations), among the exempted, 17 out of 135 (12.59%) decided not to seek assistance, while for the non-exempted 46 out of 220 (20.91%) did the same. Hence, it seems that when the individuals are more in need of help, the effect of the exemption is smaller with respect to the case in which they are lees in need (when the situation is more delicate, they are looking for help independently from the fact that they possess the exemption).

With the following probit model, we will try to study this phenomenon. We employ as regressors the following variables: "*cronica*", "*exempt*", "*condicao_generated*", "*cronica_exempted*", "*age_groups*", "*edu_level*", "*fam_doctor*", "*alcohol_cons*", "*treated_well*" and "*year*", which are all familiar at this point. The estimates of the average partial effects that we obtain are stored in Table 20.

By looking at the significant estimates, we notice that they suggest that individuals with chronic disease or in possess of the exemption are more likely to require assistance from the health system when they feel sick (respectively, the increase in the response probability is of .072 and .065, both significant at the 5% level).[66] Moreover, we notice than differently from the previous studies, the interaction term's coefficient is not significant, which does not allow us to draw the same conclusions and impedes us to confirm significantly what we were suggesting previously.

A weird result is represented by the coefficient of "*treated_well*" which is negative, implying that those who were treated well the last time they received assistance by a health professional, are less likely to look for help in case they are sick. Finally, the coefficients referred to the year 2021 is negative, implying that with respect to 2019 individuals were less likely to seek assistance, probably because of COVID pandemic (while it is difficult to understand why the effect of 2020 is not significant).

With respect to the studies performed previously, we notice that belonging to different age groups or being in different income situations does not play a role, along with the education level possessed by the individual, his/her drinking habits, whether or not the respondent has a private insurance, or a family doctor assigned.

[66] Regarding the exoneration from moderating fees, the ATE estimates give for the first-time contrasting results, one significant and similar to the coefficient of the regression (nearest neighbour estimation), and the other not significant.

Table 20

Regression on *help_health*			
Variables	Coefficients		
exempt	.064**		
cronica	.072***		
cronica_exempted	-.042		
age_groups:			
30-44	.012		
45-64	.020		
65-79	.007		
80+	.02		
condicao_generated:			
somehow difficult	-.001		
somehow easy	.029		
easy	-.039		
insured	.029		
female	-.009		
fam_doctor	0		
treated_well	-.068***		
alcohol_cons:			
medium drinker	-.044		
light drinker	-.048*		
not drinker	.016		
edu_level:			
Basico	-.053**		
Secundario	-.025		
Superior	-.025		
year:			
2020	-.018		
2021	-.075***		
R^2	.0867		
Number of obs:	1086		
Significance levels	10% = *	5% = **	1% = ***
ATE – nearest neighbour	.083***		
ATE – propensity score	.039		

Study V: Discontinuity at 18 years

According to the law, from 2015, individuals are exempted from the payment of user charges while they are minor. Hence, we should observe a value of "*exempt*" equal to one for these observations. However, if we take a look at the data at our disposal, we observe a different situation, because for those aged less than 18, in the years after 2015, the proportion of exempted individuals is 52.17% (84 observations out of 161).

Since these observations are automatically exempted from payment of user fees, we should observe almost the entire subsample of people aged less than 18 being exempted (we say almost to allow for reporting error). However, as just said, the proportion of exempted individuals is far from being the expected one. The fact that there exists a threshold which clearly defines (at least theoretically) the assignment of the exemption would have been ideal for the application of a regression discontinuity analysis. Indeed, we could have considered individuals within a certain age range as similar (especially if we account for possible differences by controlling for specific covariates), implying that the only difference in the outcome variable (being it "*help_health*", "*app_centrosaude*", "*times_urgency*" or "*urgencia_dummy*") is due to the fact that individuals to the left of the threshold (the minors) are in possess of the exemption and the remaining are not.[67]

If we take a look at how the exemption is distributed after the threshold, employing a 3-year range (so, considering individuals aged less than 21) we get that only 32.06% of these observations is exempted (67 out of 209). The difference is significant with respect to the underaged, implying that indeed age has an impact in exemption assignment, but still, it is hard to explain why the percentage of underaged exempted is so low. If we want to be more precise and take out individuals that might be exempted for reasons different from the age, we can look at the same figures we just analysed but for individuals without chronic diseases, not unemployed, and that declared that their family income is at least "*reasonable*".[68] We obtain that for minors the percentage of the exempted is 55.84% (43 out of 77), while for those over 18 but below 21 this percentage amounts to 33.71% (30 out of 89). Graph 1 in Table 21 shows the percentage of people with the features mentioned above in possess of the exemption around the cut-off (on the left the three bars correspond to 15-, 16- and 17-years old people and on the right to 18-, 19- and 20-years old people). So, even if by picking individuals with

[67] Exemption can be granted for reasons different from age, but we can rule out some of the causes, like the presence of chronic diseases or low family income, by selecting proper individuals.

[68] The criterion for the exclusion in this case is arbitrary: since the variable refers to a subjective assessment of wealth, we do not know whether a value of 1 or 2 entails eligibility for the exemption. Since we employ the variable "*condicao_generated*" to take into account the financial situation of the respondent, we will use observations from 2019.

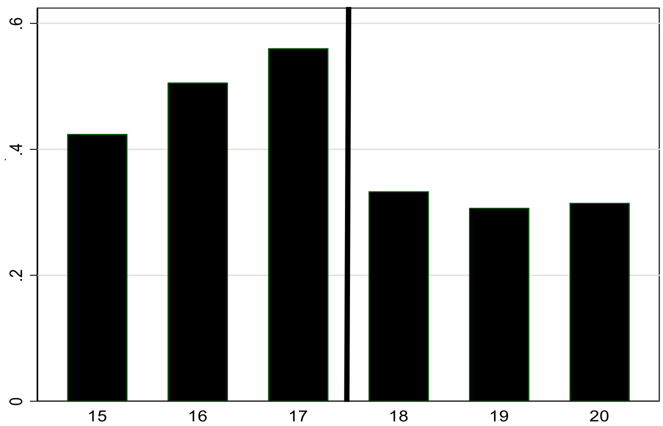
particular characteristics we further restricted our sample passing from 370 observations to 166, we still observe a discontinuous behaviour around the 18 years old threshold.

The idea to estimate the impact of the exemption in this fuzzy design is restricting the sample to a subgroup of individuals with similar characteristics and whose age is around the 18 years threshold. In this way, when we look at individuals on one side of the cut-off or on the other, the only difference is indeed the side where they stand. This, as we know, entails different probability of being exempted, so if we finally observe differences in the outcome variables for these observations, we can reconduct this imbalance to the effect of the exemption.

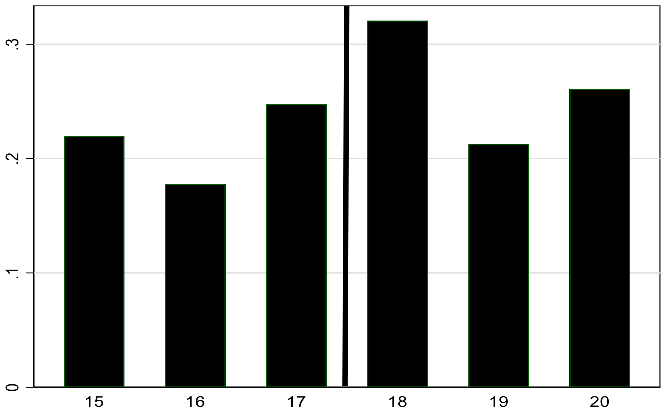
Hence, the next element that is needed is a discontinuity in service utilization between the two sides of the threshold. Regarding the variables to study, we can exclude "*help_health*" for lack of observations: indeed, we only have 11 minors and 18 adults with the characteristics we are looking for. For "*urgencia_dummy*" instead, we can observe graphically in Graph 2 of Table 21 that it is unlikely that an effect on ES is attributable to the exemption for young people around the age of consent. In fact, not only these tend to be services for which the effect of the exemption is smaller (in line with the results obtained previously) but also are services which young people require less. So, independently from the reason, we see no impact of being a minor on this kind of service.

We are left with "*app_centrosaude*", whose distribution in the age-span we are considering can be seen in Graph 3 of Table 21. This shows that the peak is reached again by those aged 17, while for the other observations the situation is more balanced. Also in this case, it does not seem that the exemption (instrumented by the two sides of the threshold) has an impact, because we do not observe consistent higher usage for minors (except, as said before, if we focus just on those in proximity of the threshold), but we will try to determine this analytically.

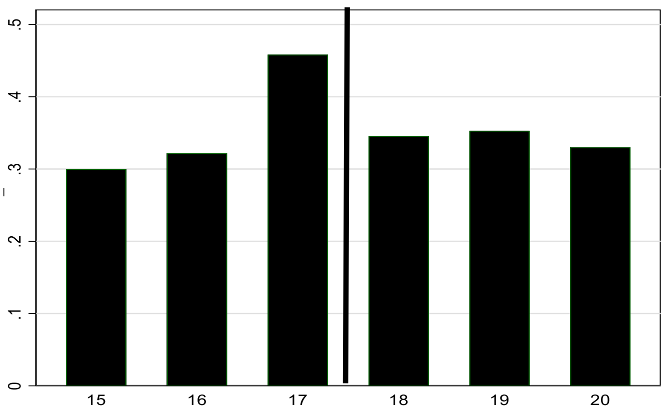
Table 21



Graph 1 Proportion of exempted people by age around the threshold



Graph 2 Proportion of people that visited emergency departments around the threshold



Graph 3 Proportion of people that had an appointment in health centers around the threshold

We propose two approaches to estimate such effect: a non-parametric estimation and a parametric one. The first implies employing the following formula:

$$\alpha^{RD,FUZZY}(z^*) = \frac{E[y_i|z_i < z^*] - E[y_i|z_i \geq z^*]}{P(d_i = 1|z_i < z^*) - P(d_i = 1|z_i \geq z^*)}$$

Where z represents the forcing variable (in our case *age*), z^* is the threshold value for the forcing variable (in our case 18 years), *d* represents treatment assignment (1 meaning the individual received the treatment, i.e., the exemption), and $E[y_i|z_i]$ is the expected value of the outcome variable ("*app_centrosaude*") given the value of *z*.

If we were in the case of a sharp discontinuity, the formula would have consisted only of the numerator (because in the denominator it would have been $1 - 0$), instead here we need to take into account the fact that we do not have 0/1 probabilities, so we scale up the difference in the variable of interest observed between the two sides of the cut-off.[69] The reason is that we are interested in estimating the effect of the exemption only on those in possess of a particular characteristic (aged less than 18), which should automatically determine treatment assignation (at least on one side of the threshold). However, we have spill overs: people who should not be treated are treated (exemption for individuals aged more than 18) and people who should be treated are not (minors not exempted). This then impacts on the variable of interest, by decreasing the actual difference that would exist between minors and adults. Hence, we scale such difference up by dividing by the difference of the probabilities.

So, concerning the denominator, we have that $P(d_i = 1|z_i < z^*)$ represents the probability of belonging to the group of exempted people for those below but close to 18 years and $P(d_i = 1|z_i \geq z^*)$ representing the probability of being exempted for those above but close to 18 years.[70] Hence, the difference amounts to $.5556 - .3162 = .2329$ (recall that we are considering only individuals with no chronic disease and that we are ruling out individuals in a difficult economic situation): being minor implies that it is 23.29% more likely to be exempted. The difference between these two means is statistically different from 0 at the 1% level.

On the numerator instead, we have $E[y_i|z_i < z^*] = .3363$ (113 observations) and $\lim_{z \to z^{*+}} E[y_i|z] = .2778$ (108 observations), which implies that $\alpha^{RD,FUZZY}(z^*) = .2512$. However, the mean difference is not significant at any level, implying that the difference between the utilization of minors and adults is not significantly different, so through this approach we cannot conclude that the exemption for minors has an impact on service utilization.

Now we show the parametric approach, which consists in a two-stage least squares estimation of the local effect of the exemption. We fit two linear models (O'Keeffe, Baio 2016), first regressing treatment assignment (i.e., exemption assignment), *d*, on "*age_dummy*", *z*, which is a dummy taking value 0 if the person is a minor and 1 otherwise, "*age_disc*", *x*, that is a variable representing the

[69] Indeed, since we have a difference between two probabilities, we will always have a value smaller than 1 in the denominator, implying that we scale up the value at the numerator.
[70] We considered again 3 years as an adequate time span.

distance of the age of the observations from 18 (hence values range from -3 to 3 and 1 represents people with 18 years old, so that we do not have a 0 among the values), and "*inter_disc*" that is the interaction term between these two mentioned variables. We consider again only individuals without chronic disease, not unemployed and not in a poor economic condition.
Hence:

$$d_i = \alpha_0 + \alpha_1 z_i + \alpha_2 x_i + \alpha_3 z_i x_i + \varepsilon_i$$

The vector of fitted values from the first stage, $\hat{t} = (\hat{t}_i, \dots, \hat{t}_n)^T$, is extracted and employed in the second stage, where the dependent variable, *y*, is "*app_centrosaude*":

$$y_i = \beta_0 + \beta_1 \hat{t}_i + \beta_2 x_i + \beta_3 \hat{t}_i x_i + \beta_4$$

However, the approach does not fit with the nature of our (centred) assignment variable, which is not a continuous variable. This causes the vector of fitted values to take only 6 possible values, which produces unprecise estimates in the second stage.

Hence, in this section we tried to estimate the difference in service utilization among those aged less than 18 and those aged more than 18 due to the exemption assigned to the former group. We saw that in a sample restricted to individuals with no chronic disease, not unemployed and without family income issues and built around the age cut-off, the percentage of exempted observations changes discontinuously (even if theoretically we should observe sharper situation). However, when it comes to service utilization, by simply comparing means, we do not notice significant differences between those on the left and on the right of the threshold. From the regressions run instead, we cannot learn anything on this regard because the forcing variable we use, "*age*", is not continuous but discrete, hence when we reduce the sample to include only observations around the cut-off, we are left with only 6 possible values. Since the other elements to include are a dummy, "*age_dummy*" and an interaction between these two and the dependent variable of the first stage is a dummy (exemption status) we obtain only 6 possible fitted values. On their turn, these are used in the second stage regression where the dependent variable is again not a continuous one. Hence in the two stages we have little variability either for the dependent and the independent variables, which causes our estimates to be unprecise.

So, the results we obtain from this study show no difference due to the age-exemption when it comes to service utilization of the young people. However, we cannot consider such results conclusive, and we believe that further research can be done in this regard by obtaining data that do not contain the issues mentioned above (exemption should be possessed by all/the great majority of minors, age information should be collected in a continuous way, i.e., include days, and a bigger amount of data would be preferred).

Conclusions

In this paper we tried to evaluate the impact of the exemption from moderating fees on the utilization of different public health services in Portugal. It was immediately apparent from graphical inspections that this exoneration makes people require more assistance, no matter the type of service. However, this could be caused by the characteristics of some of those exempted, which make them prone to seek assistance more often. To overcome this issue and obtain reliable estimates, in our models we included several possible confounders, and employed two methods for the estimation of treatment effects as a robustness check. The findings are many.

First, we find that, for all types of services here considered, the exemption has a positive effect on utilization. This is confirmed by the ATE estimations.

Second, the impact of the exemption is generally stronger for appointments in health centers compared to visits at emergency departments. The effect on assistance sought as a direct response to sickness is even smaller. This suggests that the impact of the exemption is not constant across the population and is related to urgency: the more urgent the care needed, the lower the effect of not paying fees. The result is not surprising: it is easy to imagine that as an individual needs a more urgent kind of care, an economic incentive (which, as said at the beginning of the paper, never exceeds 40€) plays a less important role compared to a situation in which not receiving care might lead to less serious or no consequences.

Third, we find that, for appointments in health centers and visits at emergency departments, the effect of the exemption depends on the health conditions of the person. Specifically, the effect of the exemption is lower when we consider individuals with worse health conditions or more vulnerable individuals. In the first 3 studies we have found that the effect of the exoneration decreases with age and that it is attenuated for individuals afflicted by at least a chronic diseases.[71] Again, the result is reasonable: the incentive represented by the exemption is less impactful on people who might suffer more serious consequences by not receiving care, and on the contrary represents a stronger stimulus for people in good health, who otherwise would have a low service utilization. The same happens when we consider people with and without a chronic disease: for the former we always get non-significant or slightly significant but lower estimates than the ones we get for the latter, which are always statistically significant. This again suggest that the exemption is more effective in increasing healthcare service usage when we consider healthier individuals.

[71] In addition, when looking at the same age groups, the impact of the exemption for those without a chronic disease was always bigger than the impact for those with the disease.

Fourth, when we focused on assistance sought as a direct response to sickness, we found no attenuation due to the presence of chronic disease. This is probably due to the fact that in those circumstances the gravity and urgency of the situation make people respond in the same way to the incentive represented by the exemption (hence whether the person has also a chronic condition does not attenuate its effect). Similarly, when we focused on individuals that felt and did not feel sick in the year of the survey, we saw that there is no attenuation on exemption effect for those that felt sick. All in all, the evidence suggest that the exemption might represent an incentive to seek assistance in any case, rather than functioning as a facilitator for needy categories. If the establishment of moderating fees was meant to fight moral hazard and regulate excessive demand for a free service, the exoneration from their payments seems to favour exactly that type of behaviour the charges were meant to contrast. If it is reasonable and not worrying that the impact of the exemption differs between types of services, being stronger on "light" services as appointments in health centers, the fact that there exists a difference between the impact that it has on people, and in particular that "unnecessary" care (for how we defined it) is favoured, probably signals that the objective of such an instrument is not fully reached. However, given that we are not in possess of the data relative to health outcomes, we cannot exclude that the exemption is beneficial for the society and desirable from the government. Indeed, the fact that the exoneration has a stronger effect for the less vulnerable, does not automatically imply that this instrument does not have a positive impact (still recalling that the effect exists also for those with poorer health).

It must be noted the presence of many shortcomings in this work that, if solved, might provide more reliable results. Many issues regard the collection of data: we miss precise information regarding the economic condition of the individual, and the data that we have are limited to two years. Also, it would be a great upgrade possessing information, preferably objective, relative to the health status of the individuals. A collection of data performed directly by hospitals and health centers could help in this sense: information would be related directly to the NHS number and maximum precision would be granted regarding also the number of visits, reasons, and exemption status. Other limitations prevented us to perform the study around the 18 years threshold to detect the effect of the exemption assigned to minors. Moreover, it must be noted that the years we considered in this paper are mainly the one characterized by COVID, which might not perfectly represent the typical situation.

Therefore, we believe that with tailored information obtained with the scope of performing analyses of this type, it is possible to have more reliable results and hence a better grasp of the process leading to the decision to seek assistance, and in particular of the role played by the exemption. This knowledge could be employed in order to suggest changes and modifications to the legislation regarding user charges and exemption from their payment.

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Appendix

Methodology

The logistic link function used in the zero-inflated model is:

$$\pi_i = \frac{\lambda_i}{1+\lambda_i}$$

Where $\lambda_i = \exp\,(\alpha_1 z_{1i} + \alpha_2 z_{2i} + \cdots + \alpha_m z_{mi})$. The *z's* are the *m* regressor variables for the process defining certain zeros.

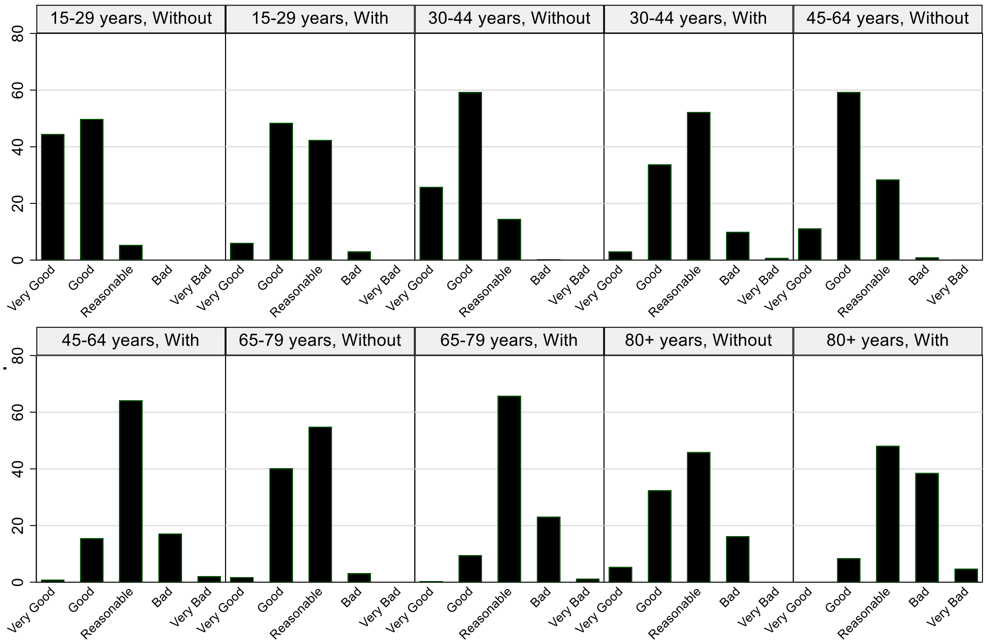
The negative binomial distribution instead is given by:

$$g(y_i) = P(Y = y_i|u_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i + 1)}\left(\frac{1}{1+\alpha\mu_i}\right)^{\alpha^{-1}}\left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)^{y_i}$$

Where $\lambda_i = \exp\,(\beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_3 x_{3i})$. The *x's* are the *k* regressor variables for the negative binomial model (the model generating counts).

Chronic diseases and age as indicators of serious condition

In Graph 1 of the Appendix, it is showed the distribution of the health status of the observations of the sample by chronic condition and age group. For each age group, the graph with those with a chronic diseases seems to be "moved" to the right by one category, indicating a worsening of the condition. Regarding the division for age group, if we look at those without the disease, we notice that those in a "*Bad*" condition are less than 20% only in the 80+ group, while for the other groups, more than 95% of the observation is in the first three health states. When we look at those with a chronic disease, as said before, we see a right shift in the panels, and a discrete proportion is already in bad health state in the group 30-44 years.



Graph 1 Distribution of health status across age groups and by chronic condition

Study I

In Table *22* and in Table 23 we report the results of the same regressions of Table 5 and Table 8 respectively, except for the use of "*condicao_economica*" in place of "*condicao_generated*". The coefficients relative to the exemption effect are lower but comparable, as those referred to the presence of the chronic disease and the interaction term "*cronica_exempted*". The same holds for the majority of the estimates, included those relative to the wealth of the family. A major difference can be found in the coefficients of the variable "*insured*" which here is most of the times significant.

Table 22

Regression on *app_centrosaude*					
Variables	Coefficients				
	Column I	Column II *cronica = 0*	Column III *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
age_groups_exempted:					
30-44 not exempted	.086**	.069**	not estimable	.069*	.117
45-64 not exempted	.094***	.074**	not estimable	.079**	.09
65-79 not exempted	.268***	.264***	not estimable	.319***	.173*
80+ not exempted	-.014	.034	not estimable	.074	-.158
15-29 exempted	.16***	.17***	not estimable	.140***	.193**
30-44 exempted	.216***	.232***	not estimable	.218***	.182**
45-64 exempted	.280***	.242***	not estimable	.291***	.204**
65-79 exempted	.295***	.256***	not estimable	.308***	.220**
80+ exempted	.225***	.179**	not estimable	.257**	.183*
cronica	.208***	//	//	.309***	.081*
cronica_exempted	-.063	//	//	-.113*	-.025
condicao_economica:					
somehow difficult	-.07**	-.042	-.111***	-.027	-.133***
somehow easy	-.087***	-.049**	-.153***	-.049	-.132***
easy	-.120***	-.11***	-.087	-.082*	-.178**
insured	-.071***	-.097***	.001	-.061*	-.082*
female	.062***	.083***	.021	.074***	.019
fam_doctor	.246***	.225***	.318***	.254***	.224***
feltsick	.202***	.282***	.065**	//	//
alcohol_cons:					
medium drinker	.027	-.024	.031	.041	-.027
light drinker	.055**	.068**	.029	.089***	-.025
not drinker	.032	.019	.053	.058*	-.041
edu_level:					
Basico	-.012	-.012	-.006	-.003	-.041
Secundario	-.005	-.002	-.012	-.014	-.041
Superior	-.044	-.032	-.124	-.027	-.111
year:					
2021	-.037**	-.012	-.095***	-.022	-.075**
R^2	.2015	.1398	.1402	.1519	.1319
Number of obs:	2406	1723	683	1710	696
Significance levels	10% = *		5% = **		1% = ***

Table 23

Regression on *app_centrosaude*					
Variables	Coefficients				
	Column I	Column II *cronica = 0*	Column III *cronica = 1*	Column IV *feltsick = 0*	Column V *feltsick = 1*
Exempt	.14***	.145***	.044	.145***	.108**
cronica	.216***	//	//	.32***	.0715
cronica_exempted	-.072*	//	//	-.122**	-.018
age_groups:					
30-44	.073**	.066**	.174**	.07**	.068
45-64	.101***	.073**	.230***	.102***	.057
65-79	.166***	.141***	.295***	.185***	.097
80+	.047	.026	.208**	.087	.007
condicao_economica:					
somehow difficult	-.07**	-.044	-.111**	-.03	-.129***
somehow easy	-.089***	-.051	-.152***	-.056	-.122***
easy	-.121***	-.11**	-.088	-.084*	-.183**
insured	-.072***	-.098***	-.001	-.066**	-.073*
female	.061***	.083***	.014	.073***	.015
fam_doctor	.247***	.225***	.323***	.254***	.234***
feltsick	.203***	.284***	.064**	//	//
treated_well	.003	.011	-.035	.028	-.099**
alcohol_cons:					
medium drinker	.027	.022	.036	.039	-.024
light drinker	.056**	.070**	.036	.091***	.026
not drinker	.032	.019	.058	.056*	-.035
edu_level:					
Basico	-.012	-.007	-.017	-.001	-.04
Secundario	.003	-.004	.005	-.107	-.04
Superior	-.046	-.032	-.147	-.0299	-.125*
year:					
2021	-.037***	-.010	-.095***	-.021***	-.079**
R^2	.1996	.1381	.1347	.1498	.1357
Number of observations:	2406	1723	683	1710	696
Significance levels	10% = *		5% = **		1% = ***
ATE – nearest neighbour	.192***	.182***	.05	.194***	.094**
ATE – propensity score	.163***	.197***	.05	.189***	.08**

In Table 24 we rerun the same regression of Table 8 but we include the variable "*health_state*" to compare the estimates. We do not see any relevant differences for the coefficients of "*exempt*" and "*cronica_exempted*", although we see that the values of the estimates relative to the impact of a chronic disease are lower. Probably this is due to the fact that the coefficients of the variable "*health_state*" capture a part of the effect previously attributed to the chronic disease. The same holds for the categories indicating to which age group the observation belongs and whether the individual felt sick in the year of the survey.

Table 24

Regression on *app_centrosaude*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
exempt	.153***	.16***	.049*	.165***	.112***
cronica	.165***	//	//	.274***	.023
cronica_exempted	-.086**	//	//	-.130**	-.04
age_groups:					
30-44	.030	.022	.145**	.027	.035
45-64	.045*	.027	.159**	.049*	.015
65-79	.089***	.062	.211***	.110**	.035
80+	.017	-.008	.163**	.069	-.026
condicao_generated:					
somehow difficult	-.051**	-.028	-.079**	-.018	-.075**
somehow easy	-.075***	-.046	-.105***	-.044	-.089**
easy	-.096***	-.086*	-.072	-.067	-.135**
insured	-.032	-.042	-.009	-.01	-.069**
female	.069***	.093***	.007	.082***	.028
fam_doctor	.238***	.223***	.288***	.259***	.208***
feltsick	.179***	.257***	.044*	//	//
treated_well	-.004	-.005	-.018	.012	-.069**
alcohol_cons:					
medium drinker	.001	-.001	.023	.013	-.01
light drinker	.036	.045*	.027	.06**	-.002
not drinker	.029	.032	.023	.051*	-.013
edu_level:					
Basico	-.02	-.009	-.039	-.012	-.037
Secundario	-.001	-.01	.007	0	-.009
Superior	-.023	-.007	-.076	-.015	-.044
year:					
2020	-.087***	-.097***	-.052*	-.093***	-.053*
2021	-.127***	-.113***	-.15***	-.118***	-.138***
health_state:					
Good	.107***	.01***	.071	.099***	.083
Reasonable	.206***	.239***	.074	.204***	.175**
Bad	.237***	.298**	.112	.242**	.228***
Very Bad	.289**	.121	.202*	.49***	.264***
R^2	.2290	.1752	.1383	.1683	.1536
Number of observations:	3457	2476	981	2371	1086
Significance levels	10% = *		5% = **		1% = ***
ATE – nearest neighbour	.171***	.164***	.056	.17***	.098***
ATE – propensity score	.139***	.189***	.073**	.187***	.082**

In Table 25 we use "*health_state*" as the indicator of necessity of care to determine if the exemption effect is stronger when care is "less needed". In particular we generate an interaction term together with "*exempt*" as we did for "*age_groups_exempted*". Across the different Columns, and specially from the first one, we notice that the trend we found previously persists: the effect of the exemption is bigger in magnitude for those in a better health condition, and declines when we look at the categories for which the condition is worse.

Table 25

Regression on *app_centrosaude*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
cronica	.156***	//	//	.260***	.024
cronica_exempted	-.066	//	//	-.098*	-.045
age_groups:					
30-44	.031	.022	.154**	.027	.042
45-64	.046*	.028	.166**	.05*	.021
65-79	.091***	.066	.218***	.119**	.042
80+	.017	-.003	.165**	.071	-.024
condicao_generated:					
somehow difficult	-.05*	-.024	-.079**	-.014	-.077**
somehow easy	-.072***	-.041	-.105***	-.039	-.087**
easy	-.095***	-.083*	-.071	-.065	-.138**
insured	-.032	-.044*	-.007	-.011	-.07**
female	.069***	.094***	.007	.082***	.027
fam_doctor	.244***	.23***	.295***	.259***	.214***
feltsick	.180***	.259***	.046*	//	//
treated_well	-.005	-.006	-.017	.009	-.073**
alcohol_cons:					
medium drinker	.007	-.002	.024	.013	-.013
light drinker	.035	.041	.028	.06**	-.002
not drinker	.029	.03	.025	.049*	-.013
edu_level:					
Basico	-.021	-.01	-.029	-.011	-.037
Secundario	-.004	-.006	.005	-.004	-.006
Superior	-.023	-.004	-.078	-.013	-.042
year:					
2020	-.087***	-.095***	-.053*	-.091***	-.054**
2021	-.127***	-.112***	-.152***	-.117***	-.141***
health_state_exempted:					
Good & not exempted	.118***	.103***	Not estimable	.096***	.163
Reasonable & not exempted	.243***	.27***	Not estimable	.251***	.245**
Bad & not exempted	.277***	Not estimable	Not estimable	.032	.381***
Very Bad & not exempted	.056**	Not estimable	Not estimable	Not estimable	.216
Very Good & exempted	.207***	.201***	Not estimable	.196***	.335**
Good & exempted	.291***	.287***	Not estimable	.294***	.27***
Reasonable & exempted	.368***	.39***	Not estimable	.350***	.376***
Bad & exempted	.403***	.386***	Not estimable	.462***	.399***
Very Bad & exempted	Not estimable	Not estimable	Not estimable	Not estimable	Not estimable
R^2	.2279	.1746	.1368	.1699	.1552
Number of observations:	3444	2467	969	2369	1074
Significance levels	10% = *		5% = **		1% = ***

In Table 26 we run an OLS regression employing the same coefficients of Table 8 and we notice that we have comparable coefficients for all the regressor, which is not surprising since we have all binary and categorical variables.

Table 26

Regression on *app_centrosaude*					
Variables	Coefficients				
	Column I	Column II *cronica = 0*	Column III *cronica = 1*	Column IV *feltsick = 0*	Column V *feltsick = 1*
exempt	.191***	.185***	.056**	.194***	.140***
cronica	.247***	//	//	.360***	.087**
cronica_exempted	-.138***	//	//	-.153***	-.072
age_groups:					
30-44	.058**	.051**	.161**	.052**	.067
45-64	.103***	.084***	.187***	.1***	.071
65-79	.157***	.147***	.245***	.177***	.107**
80+	.082*	.087	.189**	.132*	.055
condicao_generated:					
somehow difficult	-.036	-.025	-.065**	-.021	-.062**
somehow easy	-.077***	-.066*	-.096***	-.068*	-.082***
easy	-.112***	-.122***	-.064	-.098**	-.174**
insured	-.033	-.040	-.017	-.01	-.098**
female	.075***	.099***	.003	.085***	.027
fam_doctor	.216***	.176***	.428***	.193***	.307***
feltsick	.214***	.307***	.056**	//	//
treated_well	.005	.005	-.02	.02	-.063**
alcohol_cons:					
medium drinker	.003	-.003	.018	.01	-.016
light drinker	.042*	.052*	.029	.068**	.005
not drinker	.032	.038	.025	.054*	-.003
edu_level:					
Basico	-.027	-.024	-.03	-.022	-.04
Secundario	-.008	-.005	-.002	-.011	-.002
Superior	-.034	-.024	-.089	-.029	-.056
year:					
2020	-.09***	-.101***	-.054**	-.1***	-.058**
2021	-.125***	-.114***	-.153***	-.12***	-.139***
cons	.149***	.156***	.281**	.111*	.522***
R^2	.2640	.1587	.1373	.1944	.1454
Number of observations:	3457	2476	981	2371	1086
Significance levels	10% = *		5% = **		1% = ***

In Table 27 we keep fixed "*exempt*" in order to see if it is the effect of the exemption that gets attenuated for those with a chronic condition or if it is the impact of the chronic disease that is reduced for exempted individuals, or both. From the results we see that across not exempted and exempted people, the impact of the chronic disease is highly statistically significant, while when we constrained on "*cronica*" we saw that the coefficient of "*exempt*" for those with the chronic disease was slightly significant and much smaller in magnitude. Hence, this suggests that when having a chronic disease, being in possess of the exemption or not does not make a big difference in the choice to seek assistance, while it does play a role for non-chronic individuals. On the contrary, the chronic disease has an effect both when we look at individuals not exempted and those exempted. This leads us to say that it is mainly the effect of the exemption that is attenuated in the presence of a chronic disease, rather than the effect of the chronic condition that is attenuated for those exonerated. Still, there exists a difference between the coefficients of Column I and II of Table 277. We can explain it relying on the fact that given two identical individuals, one exempted and one not, the former requires more assistance than the latter. Hence, for the ones that have to pay, starting from a lower demand, the impact of a chronic disease on usage is bigger than the effect for those exonerated. However, we still observe a significant effect of the disease for those exempted.

Table 27

Regression on *app_centrosaude*		
Variables	Coefficients	
	Column I exempted = 0	Column II exempted = 1
cronica	.205***	.127***
age_groups:		
30-44	.06**	.047
45-64	.074**	.126***
65-79	.19***	.161***
80+	-.003	.152***
condicao_generated:		
somehow difficult	-.095**	-.021
somehow easy	-.134***	-.047
easy	-.152***	-.129**
insured	-.024	-.054
female	.073***	.074***
fam_doctor	.284***	.170***
feltsick	.231***	.176***
treated_well	-.007	.033
alcohol_cons:		
medium drinker	.015	-.006
light drinker	.052*	.026
not drinker	.055*	.003
edu_level:		
Basico	-.087**	.02
Secundario	-.073**	.043
Superior	-.095**	.01
year:		
2020	-.078***	-.1***
2021	-.076***	-.189***
R^2	.1789	.1654
Number of observations:	1965	1492
Significance levels	10% = * 5% = **	1% = ***

Study II

In Table 28 we store the results for the same Tobit model of Table 10 but employing the variable "condicao_economica" in place of "condicao_generated". We notice that for the relevant estimates, hence those referred to the effect of the exemption, the chronic disease, and their interaction we obtain the same levels of significance, and that the estimates of Table 288 are a little lower.

Table 28

Regression on *times_urgency*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
exempt	.795***	.767***	.113	.869***	.783***
cronica	1.367***	//	//	2.523***	.963***
cronica_exempted	-.645*	//	//	-1.574***	-.354
age_groups:					
30-44	-.052	-.176	-1.025**	-.051	-.377
45-64	-.476*	-.562*	-.549	-.55	-.639**
65-79	-1.226***	-.932*	-1.6***	-1.4**	-1.426***
80+	-2.419***	-2.7**	-2.577***	-18.47**	-2.198***
condicao_economica:					
somehow difficult	-.221	.144	-.3	-.01	-.34
somehow easy	-.301***	-.584*	-.027	-1.049**	-.251
easy	-.746***	-1.059**	-.133	-1.747***	-.031
insured	.298	.465*	.096	.706***	-.008
female	-.088	-.16	.012	-.049	-.245
fam_doctor	.025	.206	-.742	.236	-.051
feltsick	2.622***	2.758***	2.429***	//	//
treated_well	.228	.579**	-.371	.108	.327
alcohol_cons:					
medium drinker	.312	-.27	.314	.766**	-.062
light drinker	.729***	1.076***	.263	1.73***	-.028
not drinker	.379	.243	.535	.797	.133
edu_level:					
Basico	-.253	-.026	-.381	-.05	-.527
Secundario	.076	.333	-.292	-.066	-.038
Superior	-.108	.033	.140	-.381	.082
year:					
2021	.525***	.866***	-.132	1.347***	-.076
cons:	-4.021***	-4.635***	-.908	-5.667***	.351
R^2	.1121	.1228	.0591	.0635	.0234
Number of obs:	2535	1688	665	1672	681
Left-censored	1874	1437	437	1503	371
Significance levels	10% = *		5% = **		1% = ***

In Table 29 we perform again the regression of Table 10 but this time we include the variable "*health_state*". Regarding the variable "*exempt*" and "*cronica_exempted*" we notice slight changes in the estimates of the coefficients, while these are more relevant for the variable "*cronica*" whose coefficients are largely smaller, probably because a part of its effect is now captured by "*health_state*". Still, among these three variables, when significance was achieved in Table 10, it is also achieved in Table 29.

Table 29

Regression on *times_urgency*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
exempt	.912***	.808***	.211	1.117***	.742***
cronica	.925***	//	//	1.618***	.763***
cronica_exempted	-.683**	//	//	-1.638***	-.344
age_groups:					
30-44	-.529***	-.43**	-.85**	-.511*	-.749***
45-64	-1.355***	-1.327***	-1.182***	-1.552***	-1.432***
65-79	-1.947***	-1.78***	-1.886***	-2.249***	-2.025***
80+	-2.671***	-2.442***	-2.619***	-3.282**	-2.578***
condicao_generated:					
somehow difficult	-.031	.143	-.106	-.212	.095
somehow easy	-.442	-.462*	-.184	-.699*	-.183
easy	-.639	-.612	-.357	-1.2**	-.255
insured	.437	.615***	.087	1.018***	-.084
female	.216	.13	.325	.383	.002
fam_doctor	-.083	.15	-.753	.091	-.121
feltsick	2.383***	2.312***	2.372***	//	//
treated_well	.039	.448**	-.636**	-.162	.174
alcohol_cons:					
medium drinker	.009	-.102	.222	.244	-.216
light drinker	.267	.569**	-.111	.907***	-.197
not drinker	.023	-.245	.364	.113	.032
edu_level:					
Basico	-.113	.134	-.347	-.066	-.257
Secundario	.09	.24	-.072	.007	-.05
Superior	.055	.064	.186	-.230	.186
year:					
2020	-.733***	-.717***	-.817***	-1.031***	-.567***
2021	-.203	.048	-.649**	.142	-.568**
health_state:					
Good	1.169***	.923***	.971	1.309***	.834*
Reasonable	1.935***	1.953***	1.039	2.571***	1.237**
Bad	2.909***	2.603***	2.27**	3.883***	2.232***
Very Bad	3.422	2.649	2.853**	4.287***	2.691***
cons:	-3.635***	-3.99***	-.844	-4.688***	-.198
R^2	.1319	.1402	.0769	.0748	.0355
Number of obs:	3404	2441	963	2333	1071
Left-censored	2624	2038	586	2083	541

In Table 30 Column I we report the marginal effects on $E[x, y > 0]$ for the regression of Table 10, while in Column II we perform an OLS regression of the same dependent variable on the same regressors of Table 10. We see that in both cases the estimates are attenuated with respect to the ones of the Tobit model, and we see similarities between the columns, however with the OLS we do not obtain a significant coefficient for the interaction term "*cronica_exemtped*".

Table 30

Regression on *times_urgency*		
Variables	Coefficients	
	Column I Tobit, y > 0	Column II OLS
exempted	.223***	.1889***
cronica	.324***	.306***
cronica_exempted	-.165***	-.14
age_groups:		
30-44	.073	.071
45-64	.218***	.21***
65-79	.309***	.358***
80+	-.394***	.455***
condicao_generated:		
somehow difficult	-.042	-.08
somehow easy	-.172***	-.186**
easy	-.244***	-.203***
insured	-.085**	-.035
female	.044	.046
fam_doctor	-.01	-.069
feltsick	.502***	.644***
treated_well	.033	.021
alcohol_cons:		
medium drinker	.006	-.028
light drinker	.084*	.065
not drinker	.024	.048
edu_level:		
Basico	-.037	-.051
Secundario	-.01	-.001
Superior	-.004	-.022
year:		
2020	-.175***	-.205***
2021	-.051	-.113***
cons	//	.46

Study III

In Table 31 we report the results of the regressions having as dependent variable "*urgencia_dummy*" contained in Table 14, Table 15, and Table 16 but employing "*condicao_economica*" in place of "*condicao_generated*". Also in this case, we notice that in Table 31 the significance for the coefficients of interest is reached whenever it is reached in the Tables we are comparing, and the estimated coefficients are very similar.

Table 31

Regression on *urgencia_dummy*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
exempt	.076***	.061***	.002	.044***	.158***
cronica	.13***	//	//	.143***	.144**
cronica_exempted	-.075**	//	//	-.09**	-.089
age_groups:					
30-44	.015	.037*	-.199**	.03	-.077
45-64	-.035	-.019***	-.196**	-.011	-.14**
65-79	-.098***	-.06**	-.295***	-.045	-.266**
80+	-.175***	-.117	-.421***	-.082**	-.415***
condicao_economica:					
somehow difficult	-.028	-.019	.034	0	.076
somehow easy	-.031	-.044	-.022	-.065**	.046
easy	-.074**	-.09***	-.023	-.94***	-.039
insured	-.047**	.054**	.036	.049**	.025
female	-.034**	-.033*	-.042	-.02	-.088**
fam_doctor	.007	.012	-.045	.025	-.05
feltsick	.255***	.243***	.284***	//	//
treated_well	-.004	.018	-.071	-.015	.019
alcohol_cons:					
medium drinker	.035*	.02	.077	.038	.015
light drinker	.07***	.081	.069	.099***	.067
not drinker	.041*	.023	.086*	.051**	.016
edu_level:					
Basico	-.041*	-.031	-.057	-.013	-.112**
Secundario	-.006	0	-.029	-.003	-.018
Superior	-.024	.019	-.039	-.038	.003
year:					
2021	-.033**	.051***	-.003	-.053***	-.031***
R^2	.1637	.1612	.1051	.0719	.0497
Number of observations:	2406	1723	683	1710	696
Significance levels	10% = *		5% = **		1% = ***
ATE – nearest neighbour	.061***	.051**	.007	.03	.06
ATE – propensity score	.036	.044*	.039	.018	.075

In Table 32 we perform again the same regressions of Table 14, Table 15, and Table 16 having as dependent variable "*urgencia_dummy*", but we add "*health_state*" as a regressor to see what changes. Even in this case we see that in Table 32 significance is achieved whenever it is achieved in the other tables, and the magnitude of the effects is comparable, specifically for what concerns those referred to "*exempt*" and "*cronica_exempted*". The coefficient representing the effect of the chronic disease in the Table of the Appendix instead, is lower enough to suggest that a part of the impact previously attributed to the disease, is now captured by the health categories of the variable "*health_state*".

Table 32

Regression on *urgencia_dummy*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
exempt	.086***	.67***	.011	.061***	.132***
cronica	.093***	//	//	.097***	.132***
cronica_exempted	-.079***	//	//	-.101**	-.085
age_groups:					
30-44	-.046**	-.032	-.158**	-.021	-.131***
45-64	-.122***	-.100***	-.223***	.088***	-.216***
65-79	.175***	-.135***	-.308***	.115***	-.324***
80+	.225***	-.165***	-.401***	.13***	-.412***
condicao_generated:					
somehow difficult	.001	.015	-.015	-.01	.027
somehow easy	-.047**	-.039	-.05	-.042	-.041
easy	-.07**	-.062*	-.061	-.065**	-.088
insured	.054***	.068***	.006	-.067***	-.008
female	-.005	-.005***	-.013	.007	-.047
fam_doctor	-.007	.002	-.051	.015	-.059
feltsick	.237***	.212***	.295***	//	//
treated_well	-.007	.019	-.078**	-.025	-.035
alcohol_cons:					
medium drinker	.009	-.007	.064	.016	-.018
light drinker	.031	.048**	.019	.055**	-.019
not drinker	.01	-.014	.065	.016	-.008
edu_level:					
Basico	-.015	-.001	-.043	-.005	-.049
Secundario	-.007	-.011	.02	.001	-.009
Superior	-.011	-.003	.051	-.018	-.076
year:					
2020	-.042***	-.031*	-.08**	-.026	-.063*
2021	-.007	-.018	-.75**	.023	-.076**
health_state:					
Good	.116***	.086***	.201**	.073***	.161**
Reasonable	.197***	.204***	.0176**	.170***	.21***
Bad	.281***	.271**	.298***	.281**	.319***
Very Bad	.348**	.178	.404***	.307	.396***
R^2	.2030	.1941	.1451	.0983	.0604
Number of observations:	3457	2476	981	2371	1086
Significance levels	10% = *		5% = **		1% = ***
ATE – nearest neighbour	.068***	.065**	.014	.043**	.107***
ATE – propensity score	.036*	.068***	-.03	.055**	.062

In Table 33 we use again "*health_state*" as the indicator of necessity of care to determine if the exemption effect is stronger when care is "less needed". Across the different Columns, and specially from the first one, we notice that the trend we found previously persists: the effect of the exemption is bigger in magnitude for those in a better health condition, and declines when we look at the categories for which the condition is worse.

Table 33

Regression on *urgencia_dummy*					
Variables	Coefficients				
	Column I	*Column II* *cronica = 0*	*Column III* *cronica = 1*	*Column IV* *feltsick = 0*	*Column V* *feltsick = 1*
cronica	.084***	//	//	.09***	.112**
cronica_exempted	-.064*	//	//	-.086**	-.059
age_groups:					
30-44	-.045**	-.033	.156**	-.021	-.132***
45-64	-.122***	-.1***	.223***	-.086***	-.215***
65-79	-.176***	-.135***	.311***	-.111***	-.327***
80+	-.226***	-.162***	.403***	-.128***	-.421***
condicao_generated:					
somehow difficult	.001	.016	-.016	-.007	.029
somehow easy	-.046**	-.037	-.048	-.037	-.035
easy	-.07**	-.06*	-.055	-.061	-.089
insured	.053	-.067***	.005	.065***	-.013
female	-.006	-.005	-.015	.008	-.05
fam_doctor	-.007	.005	.05	.013	.067
feltsick	.237***	.213***	.296***	//	//
treated_well	-.008	.017	-.08**	-.026*	.033
alcohol_cons:					
medium drinker	.008	-.008	.061	.016	-.021
light drinker	.03	.046**	.02	.051**	-.023
not drinker	.009	-.014	.067*	.015	-.011
edu_level:					
Basico	-.015	0	-.043	-.003	-.047
Secundario	.006	.008	.022	0	-.013
Superior	.013	.003	.054	-.017	-.089
year:					
2020	-.042***	-.031*	-.081**	-.025	-.061
2021	-.007	-.018	-.077**	.023	-.076**
health_state_exempted:					
Good & not exempted	.106***	.083***	Not estimable	.066***	.101
Reasonable & not exempted	.191***	.209**	Not estimable	.18***	.147*
Bad & not exempted	.334***	.248	Not estimable	Not estimable	.445***
Very Bad & not exempted	.128	Not estimable	Not estimable	Not estimable	.16
Very Good & exempted	.074**	.072**	Not estimable	.054**	-.023
Good & exempted	.197***	.157***	Not estimable	.132***	.249***
Reasonable & exempted	.277***	.271***	Not estimable	.215***	.3***
Bad & exempted	.354***	.365***	Not estimable	.412***	.352***
Very Bad & exempted	.572***	Not estimable	Not estimable	Not estimable	.545
R^2	.2043	.1947	.1492	.1010	.0662
Number of observations:	3457	2473	981	2365	1086
Significance levels	10% = *		5% = **		1% = ***

In Table 34 we keep fixed "*exempt*" in order to see if it is the effect of the exemption that gets attenuated for those with a chronic condition or if it is the impact of the chronic disease that is reduced for exempted individuals, or both. From the results we conclude what we already stated: across not exempted and exempted people, the impact of the chronic disease is highly statistically significant, while when we constrained on "*cronica*" the coefficient of "*exempt*" for those with the chronic disease was slightly significant and much smaller in magnitude. Hence, this suggests again that when having a chronic disease, being in possess of the exemption or not does not make a big difference in the choice to seek assistance, while it does play a role for non-chronic individuals. On the contrary, the chronic disease has an effect both when we look at individuals not exempted and those exempted.

Table 34

Regression on *urgencia_dummy*		
Variables	Coefficients	
	Column I exempted = 0	Column II exempted = 1
cronica	.114***	.072***
age_groups:		
30-44	-.022**	.012
45-64	-.062**	-.072*
65-79	-.091***	-.132***
80+	-.14***	-.183***
condicao_generated:		
somehow difficult	0	-.012
somehow easy	-.059*	-.076**
easy	-.114***	-.088*
insured	.04**	.067*
female	.011	-.023
fam_doctor	.012	-.021
feltsick	.227***	.319***
treated_well	-.009	.02
alcohol_cons:		
medium drinker	.009	.001
light drinker	.014	.065**
not drinker	-.008	.042
edu_level:		
Basico	-.061**	-.001
Secundario	-.047	.037
Superior	-.008	.059
year:		
2020	-.015	-.088***
2021	.036*	-.063**
R^2	.1765	.1686
Number of observations:	1965	1492
Significance levels	10% = * 5% = **	1% = ***

Study IV

In Table 35 we perform the same regression of Table 20, however this time we employ "*condicao_economica*" in place of "*condicao_generated*". Also in this case, we observe significance for the same estimates and very similar coefficients relative to the effect of the exemption and of the chronic disease.

Table 35

Regression on *help_health*			
Variables	Coefficients		
exempt	.073**		
cronica	.083***		
cronica_exempted	-.037		
age_groups:			
30-44	.021		
45-64	.018		
65-79	.032		
80+	.021		
condicao_generated:			
somehow difficult	-.009		
somehow easy	.03		
easy	-.031		
insured	.01		
female	-.023		
fam_doctor	.006		
treated_well	-.075**		
alcohol_cons:			
medium drinker	-.016		
light drinker	-.061*		
not drinker	.022		
edu_level:			
Basico	-.026		
Secundario	-.006		
Superior	-.006		
year:			
2021	-.055**		
R^2	.0769		
Number of obs:	696		
Significance levels	10% = *	5% = **	1% = ***
ATE – nearest neighbour	.089**		
ATE – propensity score	.032		

In Table 36 instead, we include in the regression of Table 20 the variable "*health_state*". Similarly to what happened previously, the coefficient of "*exempt*" remains significant and changes only slightly. On the other hand, the coefficient relative to the impact of the chronic disease loses significance, probably because its effect is now captured by the newly employed variable.

Table 36

Regression on *urgencia_dummy*			
Variables	Coefficients		
exempt	.059**		
cronica	.047		
cronica_exempted	-.038		
age_groups:			
30-44	.007		
45-64	.004		
65-79	-.016		
80+	-.013		
condicao_generated:			
somehow difficult	.007		
somehow easy	.037		
easy	-.027		
insured	.3		
female	-.007		
fam_doctor	.001		
treated_well	-.068***		
alcohol_cons:			
medium drinker	-.042		
light drinker	-.053**		
not drinker	.001		
edu_level:			
Basico	-.05**		
Secundario	-.02		
Superior	-.02		
year:			
2020	-.0145		
2021	-.072***		
health_state:			
Good	-.059		
Reasonable	-.006		
Bad	.037		
Very Bad	Not estimable		
R^2	.0984		
Number of obs:	1068		
Significance levels	10% = *	5% = **	1% = ***

Summary

The scarcity of resources – both human capital and means such as facilities, equipment, and medications - has led to the introduction of user charges in healthcare systems indirectly financed by taxes. In these systems, if no payment has to be made at the moment of accessing care, there is the risk of moral hazard: users could use more services than they would if they were to pay themselves. User charges are the instrument devised to control service demand, trying to ensure that care is sought when needed, therefore allocating public resources to those who most need them.

To avoid that some categories refrain from using health services when needed, exemption from payment of fees is usually granted to people meeting certain criteria, as poor people, those with chronic conditions, and pregnant women. Indeed, these categories suffer the most severe consequences of the charges.

The main questions this paper addresses are whether user exemptions have an impact on services utilization and, in that case, whether they increase demand for unnecessary care, acting against the rationale for which the charges were introduced in the first place.

Given how the exemption is assigned, we need to consider that just comparing those exempted with those who are not leads us to incur in a selection bias. For this reason, the analysis includes relevant cofounders in order to isolate and precisely quantify the impact of the exemption. To determine whether the exemption favours moral hazard, we use some indicators of necessity of care, which will allow us to identify vulnerable individuals - people that, ceteris paribus, should be more inclined to seek assistance.

The health system in Portugal is mainly organized around the National Health Service, NHS (*Serviço Nacional de Saúde*, SNS), whose funding derives for most part from governmental budget (around 9.5% of GDP in 2019, below the EU average of 9.9%), hence from taxes. The NHS offers a wide range of healthcare services tendentiously free of charge for the users. The costs they incur in, called user charges (or in Portuguese *taxas moderadoras*), are standardized and mainly serve to fight moral hazard, filtering unnecessary access to services and excessive consumption, rather than as a source of funding.

In January 2012 a new regime regarding user fees in hospitals and primary care services came into force in the context of the international financial crisis, which hit the Portuguese economy hard. The revision did not entail a change in the purpose of these fees: it was explicitly reaffirmed in the preamble of the new law that they were meant to rationalize the use of the resources and control the expenditures, guiding towards an appropriate use of the health services.

In the Memorandum of Understanding (MoU) signed by Portugal, the attention regarding user fees was given to two main aspects: their levels and the exemption rationale. In particular, it was explicitly required a revision of the existing exemption categories and an increase in fees for certain services.
In response to the requirements of the MoU, a legislation setting the new levels of user charges together with norms of their yearly updates according to inflation, and new rules defining exemption groups was enacted. The newly set levels of user charges were among the highest in Europe. The value of the fees is defined annually by the Government, however the total amount due per episode of treatment cannot exceed the value of 40.00€.
Historically, exemptions were conceded to four categories of people: poor people, chronic patients, children and pregnant women, and individuals positively contributing to the society like blood donors and firemen. After 2012, the income threshold for the exemption related to poverty was raised, implying that a bigger proportion of the population can now benefit from the exemption. At the same time, exemptions for special groups and chronic patients were limited (for example, chronic patients receive exemption only when the care is related to their condition).
To conduct this study, we use data from six survey waves on access to health care in Portugal. For the main analysis we use waves from 2019, 2020 and 2021, while for the descriptive statistics we also consider data from 2013, 2015 and 2017. This choice is due to the fact that the first three waves do not include some questions that are relevant in the main analysis.
The dependent variables we deal with are binary, count and ordinal. For this reason, we are going to employ different models: probit, tobit type I, zero-inflated negative binomial, and ordered probit (and logit). In all these models, to avoid the already mentioned selection bias issue, we are going to add as controls the observable characteristics that influence exemption. As a robustness checks, in some of the studies we also compare the effect of the exemption obtained via regressions with the ones resulting from the STATA's average treatment effect estimation.
In order to understand the effect of the exemption on healthcare services utilization, and in particular to determine if it favours unnecessary use of care, we need to find an indicator of seriousness of individuals' condition which we can employ to determine whether or not care is indeed necessary. At the same time, it must be noted that necessity of care is not something totally objective, so our indicator only aims at determining which individuals, given the information at our disposal, should be more propense to receive care.
We decided not to use the health self-assessment information recorded in the variable "*health_state*" for this objective to avoid problems of reverse causality. Instead, the main variable we employ to take into account the health status of the individuals is the dummy "*cronica*", which takes a value of 1 if the individual is affected by (at least) one chronic disease which requires specific medication, and 0

otherwise. Among the conditions mentioned by the individuals undertaking the surveys, the most common are hypertension, diabetes, and arthrosis. In addition, we include in the regressions "*age_groups*" to consider individuals' age. As the health status generally worsens with age, it is reasonable to assume that older individuals are more vulnerable and consequently more in need of healthcare.

The dataset at our disposal contains income information in "*condicao_economica*", an ordinal variable whose values, referred to the family's economic situation, range from 1 to 4 (from "*difficult*" to "*easy*"). Unfortunately, this variable is only available in 2020 and 2021 for a total of 2540 observations. Restricting our sample to these two survey waves would mean to focus only on two very particular years, those of the COVID-19 pandemic.

To overcome this problem, we estimate the economic condition of the 2019 respondents to later use it in the regression models. Given the nature of this variable, first we employ an ordered logit model on observations post-2020. The regression includes variable such as those relative to age, education, profession, gender, region, and presence of a private insurance. Next, we use the coefficient estimated in this first stage to find the individuals' probability of ending up in each of the four categories of "*condicao_economica*" for 2019. Then, we assigned each person to the category for which the probability was the highest.

In this first study we focus on understanding the effect of the exemption on appointments in health centers. The main dependent variable is "*app_centrosaude*", a binary variable equal to 1 if respondents have had an appointment in a health centre in the last year and 0 otherwise. The distribution is pretty balanced, with 53.7% of individuals with at least one appointment in the previous year. However, the situation changes when we look at some specific segments of the sample: a higher proportion of exempted individuals (70%) tends to go to medical appointments with respect to non-exempted individuals (44%). Is this due to the fact that those exempted have poorer health, therefore more in need of medical attention? Or are they induced to use the health system even in cases when it is not strictly necessary just because they do not have to pay for it? Or is it a mixture of both?

In the first regression for this study, we will regress having had an appointment in a health centre on the age group and the presence of a chronic disease, both interacted with the presence of the exemption. By employing the interaction term on age and by subtracting the marginal effects for the individuals in the same age group, we are able to determine the effect of the exemption for individuals aged differently and see if it varies with age. As control we use the gender, economic condition and education level of the respondent, the presence of a private insurance, whether the respondent has a family doctor, alcohol consumption habits, whether the respondent felt sick in the previous 12 months, and the year.

Regarding the results, the coefficients referred to the age groups are telling us that, with respect to the benchmark category of non-exempted individuals aged between 15 and 29 years, all the other categories are more likely to go to a visit in a health centre, implying that both age and the exemption positively impact on our dependent variable. Moreover, as we expected, individuals affected by a chronic disease are more likely to have an appointment at health centers (increase of 0.212 in the response probability). However, in case the individual is both exempted and afflicted by a chronic disease, we detect an attenuation on the impact of the exoneration (interaction term's coefficient of -0.088). We rely on the logic assumption that it is mainly the exemption effect for chronic individuals with respect to non-chronic individuals that gets attenuated, rather than the effect of the chronic disease that gets attenuated for exempted individuals with respect to non-exempted individuals. It is hard to believe that for an exempted individual having a chronic disease has a smaller impact than not having a chronic disease when deciding to seek assistance.

By combining together the results we have additional interesting findings. First, the difference between those exempted and those who are not is always bigger for individuals not afflicted by chronic disease, for any age group. Second, the difference of the effects of the exemption for the individuals in the same age group gets smaller when we consider the oldest age group, both for people afflicted by chronic disease and those who are not.

These results suggest that for more vulnerable individuals the effect of the exemption on appointments in health service is attenuated. Possibly, for the most vulnerable ones - in this case, the oldest and/or those with chronic diseases - whether they have to pay for the service represent a less impactful incentive. All in all, these findings suggest that the exemption leads to more services utilization in general, but that the intensity of this effect is attenuated when we look at the individuals more in need of help, either because they are older or because they suffer from a chronic disease.

Moving on to the control variables, it is worth mentioning the negative effect of wealth and the positive impact of the presence of a family doctor, that causes a strong increase in the expected response probability (+.25). Similarly, being a woman is associated with higher probability of attending to a visit in health centre. Unexpectedly, also the effect of the variable "*feltsick*" is strongly positive, implying that those who felt sick in the year in which the survey was taken are more likely to have had an appointment in a health centre. Finally, the negative effects related to the years 2020 and 2021 might be an indicator of the effects that COVID pandemic has had on services utilization (either disruption of services and/or people's fear of catching the virus).

We also studied the effect of the exemption separately for observations with and without a chronic disease. For the former, we notice that for many categories of the interaction between age groups and exemption the estimates are not significant. For those not afflicted by a chronic disease, we see that the coefficients of the categories of "*age_groups_exempted*" are similar to those of the regression on the entire sample, hence we can state that older groups are associated with higher service utilization and that the exemption makes individuals seek more assistance for any age group considered. However, we notice again that the effect of the exemption gets smaller for the oldest significant age group.

In a second analysis we consider only chronic disease as indicator of necessity to care, hence we employ as regressors "*exempt*", "*age_group*", "*condicao_economica*", "*cronica*", "*insured*", "*edu_level*", "*fam_doctor*", "*cronica_exempted*", "*female*", "*feltsick*", "*treated_well*", "*alcohol_cons*" and "*year*".

Regarding the impact of each of the regressors on the response probability, chronic disease and exemption increase the likelihood of a visit in health centers (respectively, they cause an increase in the expected response probability of .217 and .164), but when these two features are present in the same individual, the probability is attenuated (by -.095). In this case, we also performed an estimation of the ATE of the exemption, and we obtained results similar to those of the regression.

In addition to this, as in the previous model, we see that as individuals belong to different age groups the response probability is differently affected, with the peak reached for individuals in the range 65-79 years (.152 increase in the response probability). For the other regressors the implications are similar too: wealth is inversely correlated with appointments in health centers, the presence of a family doctor has a strong, positive effect, as the fact of the individual feeling sick in the year of the survey and the gender of individual (being a women is associated with higher likelihood of seeking assistance). Finally, we find again that drinking habits have no significant effect on services utilization and that COVID years negatively impacted on the choice to seek assistance in the health system under the form of appointments in health centers.

Also the results of this regression suggest that the exemption leads to higher services utilization in the same way as suffering from a chronic disease. However, the effect of both characteristics together (hence of the interaction term) is negative. This implies that the effect of the exemption alone is stronger for individuals not affected by chronic disease, while for those afflicted the effect of the exemption alone is attenuated.

To double check these results, we run the regressions considering only individuals afflicted and not afflicted by a chronic disease and from the coefficients we notice that for the regression which involves only affected individuals the coefficient of "*exempt*" is significant at the 10% while, in the other regression, it is significant at the 1% level. Moreover, there is a strong difference is in the magnitude of the effect of the exemption on the response probability in the two cases: for individuals not afflicted it amounts to .17, more than 3 times the impact on afflicted individuals (.05). When looking at the results obtained through the ATE estimates, we see similar effects.

In the second study we focus on the effect of the exemption on the number of visits in emergency departments. The dependent variable in this case is a count variable with a huge mass of data at zero, which explains why we opted for a tobit type I and a zero-inflated negative binomial model for the analysis.

From a graphical analysis, we see that there exists a difference in the distribution of this variable between those exempted and those not (66% of the observations have 0 visits for the former and 80% for the latter) but to obtain more precise estimates we run the models mentioned above.

For the tobit model, we regress the number of visits to emergency departments in the last year on the presence of the exemption ("*exempt*"*)*, the presence of a chronic disease ("*cronica*") and their interaction ("*cronica_exempted*"). We control for the patients' gender ("*female*") education level ("*edu_level*"), their age group ("*age_groups*"*)*, economic conditions ("*condicao_generated*"), whether they have an health insurance ("*insured*"*)*, whether they have been assigned a family doctor ("*fam_doctor*"), whether they were treated well the last time they received assistance ("*treated_well*"), whether they felt sick in the year the survey was taken ("*feltsick*"), their drinking habits ("*alchool_cons*") and the year in which the survey was taken ("*year*").

The results confirm what has been observed via visual inspection: being exempted has a positive effect on the number of times the individual goes to the emergency room (.996 more visits). The coefficient is significant at the 1% significance level. Likewise, having a chronic disease positively impacts on the number of visits in emergency departments (1.444 more visits). At the same time, the coefficient on the interaction term is negative and statistically significant as well: for those who are afflicted by a chronic disease, the effect of the exemption gets attenuated (.735 less visits).

For the other coefficients we find that having a private insurance is positively and significantly linked to the number of visits, meaning that insured individuals tend to visit the emergency departments more often than non-insured individuals. While education does not seem to have an impact, wealthier individuals tend to visit the emergency departments in public hospitals less often, similarly to what we observed in the study of appointments in health centers. Weirdly, the coefficients referred to the age groups are all negative and decreasing, implying that age has a negative effect on secondary care. An interesting result is the one referred to the "*fam_doctor*" regressor: it implies that having a doctor assigned has no impact on the number of visits at the emergency departments, similarly to what happens with the gender of the individual. Instead, as expected, whether the individual felt sick in the year in which the survey was taken has a strong impact on the dependent variable (2.681 more visits). Alcoholic consumption, and whether the patient was treated well in the past seem not to play a role here. Finally, looking at the coefficients referred to the year, we see that only the one relative to 2020 is negative and significant, reflecting probably the impact that the COVID pandemic had on people's choice to seek help. In fact, with respect to 2019 (last year prior to the outbreak of the pandemic), 2020 is associated with a negative effect (-.798). 2021's effect instead is not significant: this is probably because on one side services' offer returned to levels similar to those pre-pandemic, and on the other people started to go back to normality thanks to the increased awareness and the developments of the research against the virus (vaccines mainly).

We then run two regressions considering separately individuals with and without chronic disease. We notice that when we study only individuals with chronic disease the exemption coefficient is highly significant and positive, while it is not significant when we focus on observations with a chronic disease (recall that for appointments in health centers it was significant at the 10% level and much smaller in magnitude with respect to the coefficients for those without the disease).

These results point to the fact that for individuals affected by chronic diseases the impact of the exemption on services utilization is attenuated, even for visits in emergency departments. For healthier individuals, we have a different situation, and those exempted tend to benefit from the help of the health system more than those who are not exempted (with respect to those in worse health condition). This might be an indicator that the exemption pushes individuals less in need of healthcare support to go to the hospital.

In the zero-inflated negative binomial model we assume that the zero counts are generated by two processes: one regarding those who would look for assistance if needed and the other, generating "certain zeros", involving those not willing to look for help even if the circumstances would be suggesting differently (people without confidence or scared by the type of care provided in ES, people with bad experiences in emergency departments, people living too far away, people in possess of a private insurance and consequently relying on private institutions to receive assistance, etc.). We run two different regressions, one in which we specify the variables for the logistic model underpinning the generation of "certain zeros",[72] and the other in which we leave constant inflation (inflation on a mass point), hence without providing any explanatory variable. Regarding the variables employed for the remaining counts (the ones deriving from the negative binomial) we use the same variables of the tobit model.

Regarding the results, we report the incident-rate ratio, which are defined as the ratios of the expected values of the dependent variable computed keeping all the covariates equal and unitarily changing

[72] These are "*generico*", "*insured*", "*distance_to_urgency*", "*time_to_urgency*", "*treated_well*", and "*import_confidence*".

the regressor relative to the coefficient taken in consideration. If the ratio is bigger than 1, it means that the regressor positively impacts on "*times_urgency*", and vice versa if it is smaller than 1.

The IRRs (from both regressions) relative to "*exempt*" suggest that for two individuals having all the same characteristics except for the exemption status, the one exempted has around 100% more visits at emergency departments than the other.[73] The effect of the chronic disease is similar in magnitude, but even in this case when these two characteristics are present together, the effect of the exemption is attenuated. Indeed, with respect to individuals for which the value of the intersection is 0, those with a value of 1 have 40% less visits.

Transforming "*times_urgency*" in the ordinal variable "*urgencia_grouped*" according to the following rules:

- "*urgencia_grouped*" = 0 if "*times_urgency*" = 0,
- "*urgencia_grouped*" = 1 if "*times_urgency*" is between 1 and 3 (included),
- "*urgencia_grouped*" = 2 if "*times_urgency*" > 3,

gives us the possibility to study the impact of the exemption through an ordered probit model.

By employing the same regressors of the previous studies, we find that the exemption has a negative impact on the probability to be in the first group, and a positive impact on the probability of being in the last two, higher for the group with 1 to 3 visits. Also in this case, we have that the coefficient of the interaction between the exemption and the chronic disease go in opposite directions.

Transforming "*times_urgency*" in the dummy "*urgencia_dummy*" according to the rule:

- "*urgencia_dummy*" = 0 if "*times_urgency*" = 0
- "*urgencia_dummy*" = 1 otherwise

allows us to employ again a probit model to assess the impact of the exemption on secondary care, and also gives us the possibility to perform a comparison with the study on appointments in health centers.

As we have seen in the previous studies on visits in emergency departments, we find a positive impact of the exemption also in this case. Similarly, the impact of the interaction between the exemption and the chronic disease is negative. Also for all the other regressors, the direction of their impact is the same as in the tobit model.

However, it is interesting to notice the differences between the results of the studies performed on the two different variables. In particular, we have that age impacts positively on service utilization when it comes to appointments in health centers, while it is negatively associated with the demand for secondary care. Similarly, the presence of a family doctor has no impact on visits to emergency

[73] The IRR is indeed close to 2, implying that the expected value of y for the individual with the exemption is almost double the one of the individual without. The average value of "*times_urgency*" for the years we are considering is .42, and for the same period the mean value for those exempted is .62 and for those not exempted .28.

departments but strongly influences health centers consultations. Another difference worth mentioning is related to the year: if both type of services were negatively impacted in 2020 by COVID pandemic, for 2021 we observe a negative impact only for primary care.

Constraining on chronic condition brings us to the same conclusions of the previous studies: when we look only at individuals with a disease, the impact of the exemption is null also on "*urgencia_dummy*".

Moreover, it is interesting to notice the difference in magnitude of the exemption effect for the two services. Indeed, we find that the effect of the exemption for the lighter service (appointments in health centers) is bigger than the effect for the more demanding and urgent service (visits at emergency departments).

Further, we perform another study in which we use both age and chronic condition as indicators of health condition. What we obtain is similar to the findings of the study on appointments in health centers previously discussed: the coefficients referred to the age groups are telling us that, with respect to the non-exempted individuals, for any age groups, those exempted are more likely to go to a visit in a health centre, implying that the exemption positively impacts on the dependent variable. Moreover, as we expected, individuals affected by a chronic disease are more likely to have an appointment at health centers. However, in case the individual is both exempted and afflicted by a chronic disease, we detect an attenuation on the impact of the exoneration (interaction term's coefficient of -0.067).

Again, these results bring us to interesting conclusions. First, the difference between those exempted and those who are not is always bigger for individuals not afflicted by chronic disease, for any age group. Second, the difference of the effects of the exemption for the individuals in the same age group gets smaller when we consider the oldest age group, both for people afflicted by chronic disease and those who are not.

In the fourth study we focus on the impact of the exemption on all types of care sought as a response to sickness. So, in this case, the dependent variable ("*help_health*") is a dummy that takes value 1 if the observations that felt sick looked for assistance in that occurrence, and 0 if they did not.

For what concerns determining if necessary or unnecessary (or both) use of care is favoured, in this case we are unable to really infer anything. Indeed, the variable of interest takes value 1 whenever the individual felt sick and looked for help in the health system. Hence, it is referred to a specific situation, and for all the respondents who did so, care was indeed needed at the time.

Also in this case, by graphical inspection we notice that exempted individuals have higher service utilization, and that the difference in usage between those exempted and those who are not is bigger for the subsample composed by people not afflicted by chronic disease.

When we run the regression however, if we detect the positive impact of the exemption, we do not obtain significant estimates for the coefficient relative to the interaction term between the presence of a chronic disease and the possess of the exemption, as we did in the previous study.
For the other regressors, we find few significant regressors. So, in this case where care is sought as a direct consequence of sickness, we find that the (positive) impact of the exemption is equal for chronic and non-chronic individuals, and that few others have an impact, suggesting that for urgent care only some factors play a role in the decision to seek assistance.
In this paper we tried to evaluate the impact of the exemption from moderating fees on the utilization of different public health services in Portugal. It was immediately apparent from graphical inspections that this exoneration makes people require more assistance, no matter the type of service. However, this could be caused by the characteristics of some of those exempted, which make them prone to seek assistance more often. To overcome this issue and obtain reliable estimates, in our models we included several possible confounders, and employed two methods for the estimation of treatment effects as a robustness check. The findings are many.
First, we find that, for all types of services here considered, the exemption has a positive effect on utilization. This is confirmed by the ATE estimations.
Second, the impact of the exemption is generally stronger for appointments in health centers compared to visits at emergency departments. The effect on assistance sought as a direct response to sickness is even smaller. This suggests that the impact of the exemption is not constant across the population and is related to urgency: the more urgent the care needed, the lower the effect of not paying fees.
Third, we find that, for appointments in health centers and visits at emergency departments, the effect of the exemption depends on the health conditions of the person. Specifically, the effect of the exemption is lower when we consider individuals with worse health conditions or more vulnerable individuals.
Fourth, when we focused on assistance sought as a direct response to sickness, we found no attenuation due to the presence of chronic disease. Similarly, when we focused on individuals that felt sick in the year of the survey for the regressions on "*app_centrosaude*", "*times_urgency*" and "*urgencia_dummy*", we saw that there is no attenuation on the exemption effect for those that felt sick.
All in all, the evidence suggest that the exemption might represent an incentive to seek assistance in any case, rather than functioning as a facilitator for needy categories. If the establishment of moderating fees was meant to fight moral hazard and regulate excessive demand for a free service, the exoneration from their payment seems to favour exactly that type of behaviour the charges were

meant to contrast. The fact that there exists a difference between the impact that it has on people, and in particular that “unnecessary” care (for how we defined it) is favoured, probably signals that the objective of such an instrument is not fully reached. However, given that we are not in possess of the data relative to health outcomes, we cannot exclude that the exemption is beneficial for the society and desirable from the government. Indeed, the fact that the exoneration has a stronger effect for the less vulnerable, does not automatically imply that this instrument does not have a positive impact (still recalling that the effect exists also for those with poorer health).