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The impact of healthcare barriers on health care demand and self-medication

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Abstract

The present paper sought to answer the question: “ What is the impact that perceived barriers by patients have on the probability of self-medication?”. I used observations from 2706 individuals who resided in Portugal between 2013 and 2021 and were older than 15 years old. Results show that Financial barriers on appointments had a positive and significant impact on the probability of self-medication and point towards leftover consumption. In the end, I discussed some limitations to these findings and the policy implications stemming from them, such as the need to fight leftover consumption.

Keywords: Health; Access to care; Healthcare barriers; Self-Medication; Waiting Times; Co-payments; Transportation Barriers ;

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1 Introduction

Health care access refers to the possibility to obtain health care when it is required, by either an individual or a group (Gulliford et al. 2002). There is an important distinction between gaining and having access to health care. To gain access is to initiate a procedure to utilize health care. This paper will focus on barriers to having access to care. I will answer the following question: “What is the impact that perceived barriers by patients have on the probability of self-medication?”.One can have barriers to access health care arising from several sources. These range from transportation barriers, organisational barriers, financial barriers, and personal barriers.

Dominique Lescure et al. (2018), argues that self-medication is a behaviour that leads people to self-administer drugs or home remedies, without using the healthcare system. This behaviour often arises due to the presence of healthcare barriers. Individuals who self-medicate may delay appointments when perceived barriers are present. This delay can lead to larger costs for both the patient and the healthcare suppliers. These costs include monetary costs, waiting times. This practice can also have benefits when the healthcare condition is not serious. By resorting to self-medication, patients experience lower financial costs, no waiting times and educate themselves on their conditions.

Having said this, the following paper will seek to answer the previously mentioned research question. To do so, I used a Tobit type II model. This method takes into account the factors pushing people away from healthcare services and towards self-medication. I found evidence that perceived barriers can impact the decision to seek healthcare services and to self-medicate. The largest effects were verified in financial barriers on appointments and waiting times. This paper is divided into seven different chapters: (I) Introduction;(II) Literature Review; (III) Data ; (IV) Methodology; (V) Results and Discussion; (VI) Limitations; (VII) Policy Implication and Conclusion.

2 Literature Review

Chang and Trivedi (2003) sought to develop a theoretical model to explain self-medication. These authors modelled self-medication as both a risky asset and an inferior good. Patients were said to choose between risky self-medication and a risk-free visit to a doctor. These authors found that as income increases risky self-medication decreases. Moreover, self-medication was seen as normal good for the poorer individuals and an inferior good for the richest individuals. This explains why self-medication is more common in poorer nations and poorer groups within nations. Wealthier individuals seeing self-medication as an inferior good, also explains the growing pressure on the healthcare systems of developed economies. Richer nation's citizens substitute self-medication with formal health care.

Economic incentives, such as prices impact the demand for both self-medication and prescribed medication[1]. Akpalu (2008) produced a study on how individuals choose between risky self-medication and risk-free medication. The author found that self-medication reacts to the price of prescribed medication. He noted that if self-medication becomes relatively more expensive, assuming everything else constant, consumers will shift their consumption away from risky self-medication and towards risk-free medication.

Chang and Trivedi (2003) argue that, as the price of medication in a pharmacy increases, self-medication ought to decrease since consumers substitute self-medication with appointments. In this framework, the substitution effect dominates, as price change is likely to have a stronger effect on self-medication. Notice that the existence of generic drugs may lead self-medication to become relatively cheaper.

[1] Prescribed medication was regarded as risk-free by Akpalu (2008)

Ghosh et al. (2015) noted that lack of healthcare affordability was among the main reasons why people self-medicated. Insurance acts to decrease the impact of a price barrier by covering for a portion of the cost. By diminishing the impact of a financial barrier, insurance deviates individuals from self-medication towards formal health care. Tavares (2013) also argued that insurance plays an important role in SM. Lack of government coverage increases the propensity to self-medicate. Hence, healthcare affordability is a way to limit self-medication, by diminishing the impact of the financial barrier (Tavares (2013)). Having both public and private insurance leads to an increase in SM, due to a negative income effect associated with the cost of insurance. Hence the impact of insurance on self-medication is not clear.

When mentioning perceived effects, one needs to consider the role of uncertainty. Chang and Trivedi (2003) found that uncertainty may lead consumers to decrease self-medication. Uncertainty impacts the perceived benefits of self-medication and it decreases as patients become more educated, receive more information or have more experience with medicines. For this reason, education level, experience and chronic conditions can favour self-medication. Lescure et al. (2018) stated that patients who had previous positive experiences with a drug were more likely to self-medicate. The same paper reported contradictory results in the impact of variables such as age, gender, chronic condition, education on self-medication. However, most studies point towards a positive relationship between education and self-medication (Lescure et al. (2018)).

Tavares (2013) also found that the longer individuals work, the lower their willingness to Self-medicate. The author asserted that people who work for longer periods, look for a more efficient way to get better and often have minor health problems. The impact of waiting times impacts is not clear. Waiting for an appointment is costly. However, people are willing to wait for an appointment since they don’t want to change a diagnosis or let go of a prescription in favour of OTC drugs. In opposition, this author noted that patients react to waiting times in surgery waiting rooms and are more likely to search for OTC drugs to self-medicate. People were comfortable waiting for an appointment but were not happy to wait to be seen. Waiting times can be seen as relevant explanatory variables for self-medication since they are considered a barrier to getting care. On a similar point, Ghosh et al.(2015) argued that time savings were an important driver of self-medication.

Chang and Trivedi (2003) found that larger travelling costs cause self-medication to be more prevalent in rural areas. Tavares (2013) mentioned the impact that non-financial costs might have on self-medication. She asserted that patients may prefer to go directly to the pharmacy to get medicine to save on time-related costs. The same author said that the effect of time spent on medical care harmed the probability of self-medicating. She presented two justification for this fact. First, the more time one spends on medical care, the less one needs to spend on self-medication because the healthcare need is being satisfied. Second, an increase in waiting times leads to a drop in income since individuals might have to skip work. A decrease in available income would lead to a drop in both self-medication and medical care consumption by a negative income effect.

Transportation is fundamental for individuals to access health care services. Syet T. et al. (2013) mentions that lack of transportation may result in delays in appointments. These delays may lead patients to miss diagnostics or changes in treatment. Furthermore, lack of transportation may lead to lower access to pharmacies and therefore, lower medication fills and lower adherence to treatment. This barrier can have severe consequences such as sub-optimal medical treatment, unsatisfied health care needs, deterioration in treatment outcomes and disease complications. Wallace et al. (2005) conclude that this barrier affects more those who are: poorer, less educated, older and ethnic minorities. Individuals with a lower socioeconomic status tend to be more affected by lack of transportation. The effects of transportation tend to be larger for those who suffer from chronic illnesses as well.

Socioeconomic Status (SES) is an important driver of health care access. Shahid et al. (2021) stated that both social status and behavioural factors are important determinants of health care access. Cheng and Guo et al. (2019) give an example of the role of socioeconomic status. They found that adult migrants in the US, who did not speak English and were part of an ethnic minority, had difficulties in accessing dental care. The same authors reported that coming from a high-income family with a higher education level, and a higher English proficiency facilitated access to care.

Pathirana TI et al. (2018) claimed that the impact of waiting times is also different for different socioeconomic groups. Both, Landi et al. (2018) and Siciliani et al. (2015) reported a positive relationship between waiting time and socioeconomic status. Lundberg et al (1998) found that individuals who were less educated, younger, and poorer were more affected by financial barriers. Hence a lower socioeconomic status may amplify the impact of barriers.

Lastly, gender was not found to be a relevant factor when deciding to choose between SM and healthcare services. Moreover, as people get older they tend to resort more and more to the healthcare system (Tavares, 2013).

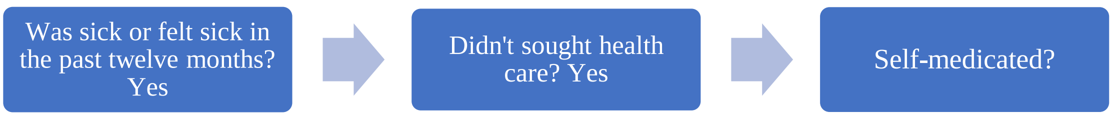
Lescure et al. (2018) speculated that country-specific characteristics, unobservable factors such as social norms, or even spurious relations, could be behind the contradictory relationships found in the literature.

Bennadi et al. (2014) sought to study self-medication and the consequences of allopathic drugs self-medication. At an individual level, patients gained some independence. This practice educates people about health conditions and teaches them to prevent health conditions. Patients were also reported to experience lower costs since they spend less time travelling and waiting. Bennadi et al. (2014) also advert to the risks and negative consequences of self-medication. There is the risk of a wrong diagnosis. If the diagnosis was wrong the patient would take the wrong drugs, in the wrong doses for an incurred time. Patients could fail to recognize dangerous contraindications and chemical interactions between drugs.

From the literature review, I draw several relevant hypotheses to test in this paper. I will evaluate whether individuals who experience barriers are more likely to self-medicate. I will also test if financial[2] costs have a stronger impact than non-financial[3] costs on the probability of self-medication. Lastly, I will seek to explore if chronic patients are more likely to self-medicate and if self-medication is an inferior good.

3 Methodology

I assumed that the decision mechanism behind self-medication was a sequential one with three stages. In the first stage, one might have been sick or not. If one has been sick, then one can either look for care in the healthcare system or not. If one did not seek care in health care services, one is assumed to either self-medicate or simply wait for the condition to pass.



The estimation methodology requires special care. It was designed to answer the following research question: “ What is the impact that perceived barriers by patients have on the probability of self-medicating? “. To do so, the population of interest are the

[2] Such as Co-payments
[3] Such as waiting times and travelling times

individuals who had to choose whether to seek health care or not and to self-medicate or not.

Ideally, one would have a complete data set for each of these sequential decisions. However, this is not the case. There is data missing for "Self-medicated"[4] as only those who had been sick and did not seek health care engaged in self-medication. This is what one calls a truncated data framework. A consequence of truncated data is the possibility of a selection bias in one of the selection stages, given that part of the sample of those who self-medicated may not be randomly distributed within the sample. This is happening since the data for the self-medication variable is not missing at random.

The selection indicator of the first stage is "Having_been_sick"[5]. I assumed that having been sick was random and given by nature. One can have habits that decrease the probability of being sick. However, getting sick is assumed to be given by nature. As such, if there were missing observations for individuals who are not sick, they would be missing completely at random and there would be no selection bias for this stage. For this reason, I dropped all observations relative to individuals who had not been sick or did not feel sick.

In the second stage of the process described above, the variable behind the selection process is "Didn't_Sought_Care". The decision to seek healthcare services is not random. There are explanatory factors behind this decision, such as demographic indicators, perceived barriers, socioeconomic status, waiting times and financial costs. This selection mechanism leads me to conclude that there can be a selection bias stemming from this stage and special care is required with it.

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[4] See appendix 2 for a small description of this variable.
[5] See appendix 2 for a small description of this variable.

To control for the selection factors and eliminate a potential selection bias I will resort to a Tobit type II model using a Two-step estimation method. To use Tobit type II I need two equations. The first equation is a Probit selection equation for “Didn’t_sought_care" on explanatory variables. The fitted values of this regression will be used to compute the Inverse Mill’s ratio (imr). The imr is controlling for the selection factors of the first stage. The selection bias can be seen as an omitted variable bias when imr is missing. In the second equation, there is an LPM regression equation of “Self_medicated” on the second group of covariates which include the Inverse Mill’s Ratio.

The Probit selection equation parameters are relevant since they inform the reader on the direction of the effect that covariates have on the probability of not seeking care. By evaluating the coefficients signals, one can see the direction of the impact of covariate X on the probability of not seeking care. Moreover, by comparing the relative size of Probit coefficients I can see the relative size of the impact of each covariate on the probability of not seeking care. The LPM model also allows the reader to see the direction and the relative impact that covariates have on the probability of self-medicating.

I require four assumptions[6] to estimate a Tobit type II model. The first assumption states that there can’t be missing observations in covariates in the selection equation and emphasises the selection problem. The second assumption states that regressors must be exogenous. The third assumption states that the errors of the Probit selection equation follow a normal distribution with 0 mean and standard variation 1. Given the distributional nature of the assumption, it is a strong assumption. The last assumption just states that one needs linearity on the population regressions of the errors of both equations mentioned above.

[6] See Wooldrige “Econometric Analysis of Cross Section and Panel Data” Chapter 17, pages 561-566

A general population model can be given by the following equations:

$$\text{Self-medicated} = \beta X1 + u1 \quad (1)$$

$$\text{Didn't\_Sought\_Care} = 1[X\delta 2 + v2 > 0] \quad (2)$$

The first equation represents the response equation, which is partially observed and the second represents the previously mentioned selection indicator for the second stage. Assuming all the assumptions hold to obtain the vector of interest, β, one must first estimate the equation bellow.

$$E(\text{Self\_Medicated } |X, u1) = X\beta + E(u1|x, v2) = X\beta + \gamma v2 \quad (3)$$

From it, it follows that if γ was different from 0 I would not be able to estimate this equation given that $v2$ is not observed, only "Didnt_sough_care" is. When the parameter γ is different from 0 when there is a selection bias. For this reason, I must recover $v2$.

To recover the effect of $v2$, I computed a Probit of "Didnt_sough_care" on the vector of controls X, conditional on having been sick. Having done this, I took the fitted values of the Probit and computed the inverse mill's ratio, which is given by:

$$\hat{\lambda}i2(X\delta 2) = \phi(X\delta 2)/\Phi(X\delta 2) \quad (4)$$

The vector $\hat{\lambda}i2$ is what allows recovery $v2$ control for the selection factors since $E(\, v2|X, \text{Didn't\_Sought\_Care}) = \hat{\lambda}i2$ (5)

Having recovered the effects of v2, I ran an OLS regression of Self_Medicated on Xi1,$\hat{\lambda}i2$. This is the main equation of interest.

$$E(Self - medicated|X, \text{Didnt\_sough\_care} = 1) = X1\beta 1 + \gamma\lambda(X\delta 2) \quad (6)$$

I would like to highlight that there is data missing for several explanatory variables which is a violation of the first assumption of Tobit type II. To respect the assumptions of this method, I used "Economic_Condition"[7] as a proxy for income. The income reported in the survey was not missing at random since it was declared income. As such, the decision to declare or not income has underlying factors for which I can't control and that can generate endogeneity issues. "Economic_Condition" is only available for the years 2020 and 2021. Regardless, including "Economic_Condition" in a model allows me to get some valuable insights on potential income effects without risking further selection biases.

There may be a latent variable of socioeconomic status for which "Education"[8] is a good proxy. As such, education may capture some of the effects generated by this variable, spawning an omitted variable bias if this latent variable was not included. Mattson et al. (2017) described "Education" as being a good proxy for socioeconomic status. As such, I may have an omitted variable bias, if I didn't control for the socioeconomic status. Socioeconomic status was described in the literature as an important explanatory variable of not seeking care which amplified the impact of perceived barriers. I used the variable "Status"[9] as a proxy to socioeconomic status to prevent endogeneity arising from an omitted variable bias. Status was computed based on the education level and occupation of the main household contributor.

In this paper, the results were estimated using survey data. To control for nonresponses and unequal response probabilities I used weights. I used the variable " Weights", to transform all observations when computing regressions. This transformation ensures that the sample is representative. Not controlling for these two phenomena could bias my results.

[7] See appendix 2 for a small description of this variable.
[8] See appendix 2 for a small description of this variable.
[9] See appendix 2 for a small description of this variable.

4 Data

4.1 Database

This paper uses repeated cross-section data. The database has 7507 observations of individuals who were older than fifteen years old and resided in Portugal, over the period [10]2013 to 2021.

The data was collected by Gfk via a direct interview in the private residence of the participants. The data collection methodology used in 2021 was similar to the one used in previous years. Nova SBE Health Economics and Management Knowledge Center designed the survey and it varied slightly from year to year.

The participants were distributed across Portugal and were selected using a quotas system to be nationally representative. This system considered the following variables: Region; Habitat; Gender; Age; Education; Occupation. An important detail is that education and occupation were only used on men and women respectively. Using a matrix, the researchers collected several surveys, from randomly selected locations.

This sample is representative of the entire population of Portugal. In table 10[11], the reader can see, that there is data for individuals of different ages and gender. Moreover, I have data on observations for people living in every district in Portugal. These individuals come from different socio-economic backgrounds, have different professional situations and heterogeneous education levels.

[10] This data was collected in the years, 2013,2015,2017,2019, 2020 and 2021.
[11] See appendix 3

4.2 Summary Statistics

I have eliminated all observations for individuals who had not been sick the past twelve months relative to the survey data. This leaves me with 2706 observations. Henceforth, all the results are conditional on individuals having been sick.

In Tables 10 - 14[12], the reader can find descriptive statistics for the dependent variables of the selected models and the explanatory variables used in this study. “Didn’t_sought_care” is the dependent variable of the first selection stage. This variable is a dummy that takes the value of 1 if an individual didn’t seek care in the healthcare system and 0 otherwise. “Self-medicated” is the main variable of interest. It is also a dummy, which takes the value of 1 if one engaged in self-medication and 0 if an individual waited. I dropped all the observations of individuals who claimed they didn’t know if they had self-medicated.

One can see that the average age is slightly above 51 years old. The youngest individual had 15 years at the time of the data collection, while the older had 97. Age2 represents the square of the variable “age” and its summary statistics have no interpretation. Gender is a dummy variable that takes the value of one if an individual is a woman, and 0 if he is a man. Close to 62.5% of the individuals were women.

Education[13] takes values between 1 and 8 for each category. The lower the number, the higher the education level. In table 4 it can be seen that only 6.25% of the individuals had higher education completed, without accounting for polytechnic education. Close to 71.43% hadn't finished High School, reflecting low education rates. The profession variable takes values between 1 and 10[14][15] for each category, excluding seven to nine.

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[12] See appendixes 3 - 6
[13] See appendix 3
[14] See appendix 4
[15] The category for which profession is equal to 10 was not known

Each number represents an occupation status. In table 5, the reader can confirm that close to 49,58% of the individuals were active in the labour market, as employers, employees or unemployed. The variable "Chronic_patient" is a dummy variable that takes a value of 1 if someone is taking medicine for a chronic illness, and 0 otherwise. This variable reflects the severity of conditions[16] and the experience with said conditions. I assumed that the value for this variable was 0 if the value was missing.

As stated in the literature there are several sources of barriers to health care. These can be financial, transportation or psychological barriers. To capture the effects of these barriers a sentence containing a specific situation for each barrier was read. Having done this the researcher asked individuals if, in the last year relative to the survey data, they had experienced similar situations for each of the barriers. Perceived barriers to accessing care are dummy variables that take the value of one if a barrier was said to be present for a certain individual. "Financial_barriers_on_Medication" is a dummy that takes the value of one if someone did not acquire all medicines because of lack of funds and 0 otherwise. "Financial_barrier_appointment" is a price barrier on medical appointments. It takes the value of one if a person did not attend an urgent appointment due to financial constraints.

"Branded_for_generic" is a barrier that accesses if someone exchanged branded medicines for generic drugs. It takes the value of one if this happened and 0 otherwise. "Transportation_barrier" is a dummy variable that represents a transport barrier. It takes the value of either one is an individual did not seek care because of the transportation price and zero otherwise. "Day_salary_barrier" is a dummy variable that represents a daily salary barrier, where one would not go to the hospital urgencies out of fear of losing a day salary. This barrier is only relevant for those who work.

[16] Chronic illnesses are long-term conditions which can endanger one's life and/or limit one's quality of life

Lastly, "Covid_barrier" and "Appointment_Cancelled" are healthcare barriers related to the COVID-19 pandemic. "Covid_barrier" is a dummy, that takes a value of one if someone has chosen to skip an appointment due to fear of catching covid. On a similar note, "Appointment_Cancelled" is a dummy variable that takes a value of one if someone had an appointment cancelled due to COVID, between March and June.

The variable "Main_healthcare_provider" refers to the different healthcare providers[17]. It may take values between one and six. Similarly to the profession, each value represents a different provider. The Portuguese National Healthcare System (SNS) was the largest healthcare provider. In table 6 the reader can see that 93.2% of the individuals stated that SNS was their main provider. "Has_Health_Insurance" is a dummy, that takes a value of either one or zero. If it takes a value of one, then the individual has private insurance. The variable "Exempt_from_copayments", which is a dummy variable that is equal to one if someone was exempt from co-payment in the Portuguese National Healthcare System.

Status is a variable that takes a value between 0 and 5. The lower the number, the higher the socioeconomic status. Status is determined based on the education and occupation of the main household contributor. Since some observations were missing, I sought to fill them. To do so, I regressed "Status" on education and occupation dummies using an Order Probit. Having done this, I computed the fitted values of the regression and used them to fill the missing observations of "Status". This variable represents a proxy to Socio-Economic Status.

Economic_Condition is a variable that varies between one and four, depending on the ability of someone to survive with their monthly income. It is a good proxy to income,

[17] See appendix 5

however, it is only available for the COVID-19 pandemic period. The larger the value, the larger the ability to survive with the current income. If the variable had a value of four, then a person would easily survive with their current income. “Region”[18] is a variable that takes values between 1 and 7, depending on where the individual lived. In table 7 it can be seen that close to 82.56% of individuals lived either on the North Coast, Porto Metropolitan Area or Lisbon Metropolitan Area

The variable “tempo_csp” refers to the expected time one has to wait to be seen in a primary care centre. On average it takes 62 minutes to be seen in a primary care centre. “tempo_hosp” accounts for the expected waiting time one has to wait to be seen in the emergency services in a hospital. The average individual has to wait around 168 minutes to be seen in a hospital. Lastly, “tempo_urg” represents the expected travelling time when going to the emergency services in a hospital. The average travelling time is 51 minutes. On a final note, all waiting time variables had missing observations. I computed the regional means and used them to fill the missing observations.[19]

5 Results and Discussion

This section includes the results of two models[20]. The first model is a Tobit type II model which includes data from all the years. The second Tobit type II model includes only the subsample of data collected during the Covid-19 pandemic. I included several tables with smaller sections of the full table of results so that it becomes easier for the reader to read the discussion. To see the full table of results see Appendix 7.

The research question focuses on the impact that perceived barriers have on the probability of self-medication. For this reason, I will start by discussing the impact that

[18] See appendix 6
[19] In appendix 2 the reader can find a small description of the variables used in this paper
[20] There was little difference between using Tobit type II and OLS . See appendix 10

these barriers have. Given the results in the in table 1, I would argue that financial constraints when acquiring medicines hurt the probability of self-medication. Financial_barriers_medication is statistically significant at a 5% significant level. This is the case since individuals who didn't seek care and can't access medication must wait for their illnesses to go away. Given that individuals were less likely to self-medicate, there was no evidence of leftover consumption for the individuals that reported financial barriers when acquiring medicines.

Table 1: Impact of Financial Barriers to medication on the probability of Self-medication

	LPM1	LPM2
VARIABLES	Self_Medicated	Self_medicated
1.Financial_barriers_medication	-0.284**	0.194
	(0.143)	(0.342)
Observations	344	78
Pandemic Year	NO	YES
Economic Condition	NO	YES
Covi Barriers	NO	YES
Year FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In table 2, the reader can see that the variable "Financial_barriers_appointments" is statistically significant at a 5% significance level and it has a positive impact on the probability of self-medication. To self-medicate, a person may require a prescription from a doctor. In Tavares (2013), it was stated that one of the major sources of self-medication were leftovers from the previous prescription. Hence, when someone lacks the funds to seek healthcare services, that person may resort to leftover consumption. Moreover, some lighter conditions, don't require a prescription, which may lead individuals to resort to self-medication. The relative relevance of this effect was exacerbated during the Covid-19 pandemic. As such, one can argue that leftover consumption became more prevalent during Covid-19.

Table 2: Impact of Financial Barriers to appointments on the probability of Self-medication

VARIABLES	LPM1 Self_Medicated	LPM2 Self_medicated
1.Financial_barriers_appointments	0.394***	0.754***
	(0.136)	(0.219)
Observations	344	78
Pandemic Year	NO	YES
Economic Condition	NO	YES
Covi Barriers	NO	YES
Year FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the literature review, it was stated that the existence of a transportation barrier may lead to delays in appointments (Syet T. et al. 2013) and lower adherence to treatment. Having said this, one would expect that this barrier would decrease the probability of self-medication. This is was not verified during the Covid-19 pandemic as can be seen in table 3. As such, there is evidence that individuals may seek alternatives to care when faced with transportation barriers (5% significance level). Transportation barriers in the survey were present for an individual when he or she felt the transportation price was large As such, individuals may have summed the travelling cost to the cost of the appointment, leading to an increase in the price of healthcare services relative to self-medication. Assuming that the substitution effect dominates, a larger price would lead individuals to seek more self-medication and fewer healthcare services as stated by Akpalu(2008).

When one uses the entire sample, this barrier was the only barrier significant at a 5% significance level. When deciding whether to seek healthcare services or not. It was found that individuals experiencing transportation barriers were more likely to seek care. This may be driven by the Portuguese public healthcare system. The Portuguese public healthcare system offers transportation to individuals that meet economic and health criteria, thus mitigating the effect of this barrier. As such, individuals that would be eligible for this policy would be driven to healthcare services even if they lack funds to pay for transportation. This result can also be attributed to the healthcare need some individuals face. Within the sample, I have Chronic patients. This sub-sample has larger healthcare needs since chronic diseases can be very damaging to someone health and quality of life. If the healthcare need was large enough, due to the seriousness of the illness, then individuals who faced transportation barriers would still seek care due to the expected benefits of seeking care.

Tables 3: Impact of Transportation Barriers on the probabilities of self-medication and not seeking care

VARIABLES	1st Probit Selection model Didn't_Sought Care	LPM1 Self_Medicated	2nd Probit Selection model Didn't_Sought Care	LPM2 Self_Medicated
Transportation_barrier	-0.368**	0.129	-0.385	0.521**
	(0.175)	(0.139)	(0.554)	(0.241)
Observations	2,671	344	2,693	78
Pandemic Year	NO	NO	YES	YES
Economic Condition	NO	NO	YES	YES
Covi Barriers	NO	NO	YES	YES
Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I only found evidence of the impact that changes in relative prices can have on the probability of self-medication during the Covid-19 pandemic. In table 4 the reader can see that this variable was weakly significant. As described in Chang and Trivedi (2003) and Akpalu(2008), on average and ceteris paribus, the availability of cheaper drugs leads patients to be more likely to not seek care, since the costs of self-medication were relatively lower. However, it was only relevant for the individuals that had to decide to seek care or not during the Covid-19 pandemic.

Table 4: Impact of having exchanged branded medicines for generic ones

VARIABLES	1st Probit Selection model Didn't_Sought_Care	LPM1 Self_Medicated	2nd Probit Selection model Didn't_Sought_Care	LPM2 Self-Medicated
Branded_for_generic	0.0967	0.146	0.258*	-0.0831
Observations	2,671	344	2,693	78
Pandemic Year	NO	NO	YES	YES
Economic Condition	NO	NO	YES	YES
Covi Barriers	NO	NO	YES	YES
Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In table 5 it can be seen that "Covid_barrier" was only statistically significant when deciding whether to visit a healthcare provider or not. It had a positive impact on the probability of not seeking care, but it had no impact on the probability of self-medicating. This shows that the Portuguese patients actively sought to avoid any sort of healthcare provider during the pandemic.

Tables 5:Impact of Covid_barrier on the probabilities of self-medication and not seeking care

VARIABLES	2nd Probit Selection model Didn't_Sought_Care	LPM2 Self_medicated
Covid_barrier	0.455**	0.118
	(0.189)	(0.132)
Observations	2,693	78
Pandemic Year	YES	YES
Economic Condition	YES	YES
Covi Barriers	YES	YES
Year FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Of all the barriers, Financial barriers on appointments ought to be considered as the most relevant barrier when deciding to self-medicate. It had the strongest relative impact out of all the barriers mentioned. From here one can obtain two implications: first, the fact that this barrier has a positive impact on the probability of self-medication shows that healthcare services and self-medication have some degree of substitutability; second, it shows that even when prescriptions are not available, individuals still self-medicate using alternative sources of medicines, for example, leftovers.

The main goal of this analysis was to answer the research question mentioned in the methodology section. I found that the impact of perceived barriers to healthcare differed. Except for financial barriers to medication and the covid-19 barrier, all perceived barriers had a positive impact on the probability of self-medicating. This impact was not constant, since some interactions between the barriers and year dummies were not statistically significant, while others were.

I also sought to test the remaining hypothesis made at the end of the literature review. I evaluated the relative impact of financial and non-financial barriers on self-medication to find out which one is stronger. I included this analysis in table 6.

As stated in the literature review, waiting times are perceived as a cost by users. For this reason, it is not surprising that the expected waiting times in primary care centres have a positive and statistically significant impact on the probability of self-medication. As stated by Ghosh et al.(2015), individuals engage in self-medication to save time. This time-saving mechanism is also found in expected waiting times in the emergency services of hospitals. Even though it had no impact on self-medication, expected waiting times in hospitals pushed people away from healthcare services. The increase in the probability of not seeking care due to larger waiting times can be explained by two factors. First, the time-saving mechanism mentioned before, where individuals see waiting as a cost and seek to save time by not seeking care. Second, as mentioned by Tavares (2013), an increase in waiting times can lead to a drop in disposable income as individuals spend less time working. This would generate a pure negative income effect, that would push people away from both healthcare consumption and self-medication.

In the literature review travelling time to the emergency services of a hospital was also described as a cost faced by the users. This variable was weakly significant and it decreased the probability of self-medication, however, this effect disappeared during the Covid-19 pandemic. During 2020 and 2021, the travelling time was only significant when deciding whether to seek care or not. Only individuals with larger needs for health care services went to the emergency services of the hospitals during the COVID-19 pandemic. Due to the seriousness of the condition, emergency travelling times were not relevant enough to dissuade some patients from seeking care during the pandemic.

"Exempt_from_copayments", allows me to understand the impact that the absence of financial costs when seeking care can have. Co-payment exemption did not have a statistically significant effect on the probability of self-medicating, However, it harmed the probability of not seeking care at a 5% significance level. The coefficient of the variable Exempt_from_copayments is positive. This variable is also statistically significant at a 5% significance level. On average and ceteris paribus when the cost of health care services decreases, people will consume more healthcare services and less self-medication. People react to changes in the relative price of health care and self-medication. This follows the findings of both Chang and Trivedi (2003) and Akpalu(2008). During the Covid-19 pandemic, this variable stopped affecting the decision to seek care. As such, I would argue that the fear of getting Covid-19 nullified the impact that financial incentives, such as co-payment exemption, had on users.

When evaluating the relative impact of expected waiting times, travel times and healthcare financial costs, one can see that waiting times in primary care centres had the strongest impact on the probability of self-medication. This shows that the time-saving mechanism is stronger than the pure negative income effect described above.

Tables 6: The impact of waiting times, travelling time and co-payments on the probability of self-medicating and not seeking care.

VARIABLES	1st Probit Selection model Didn't_Sought Care	LPM1 Self_medicated	2nd Probit Selection model Didn't_Sought Care	LPM2 Self_medicated
tempo_csp	0.000748	0.00152**	0.00467	-0.00621
	(0.000788)	(0.000680)	(0.00451)	(0.00605)
tempo_hosp	0.00108***	-6.23e-06	0.000446	-0.000873
	(0.000286)	(0.000247)	(0.000679)	(0.000676)
tempo_urg	-0.000510	-0.00117*	-0.00842**	0.00418
	(0.000847)	(0.000678)	(0.00380)	(0.00461)
Exempt_from_copayments	-0.256***	0.0597	-0.100	0.0963
	(0.0744)	(0.0589)	(0.159)	(0.142)
Observations	2,671	344	2,693	78
Pandemic Year	NO	NO	YES	YES
Economic Condition	NO	NO	YES	YES
Covi Barriers	NO	NO	YES	YES
Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The variable Chronic_patient provides an insight into the impact that more information and experience can have on the probability of not seeking care and self-medicating. I found that being a Chronic Patient is insignificant when deciding whether to self-medicate or not. However, this variable has a strong impact and negative impact on the probability of not seeking care. Chronic diseases are long-term health conditions, which can be very aggressive and extremely damaging to one's quality of life. The duration of the illness provides experience to the patient. One would argue that being a chronic patient leads people to seek care to prevent their condition from worsening .

The proxy for Income was only included for the Covid-19 sub-sample. This variable has a positive and statistically significant impact on the probability of self-medicating. I would argue that individuals who have more difficulties in surviving with their income, tend to self-medicate more. This is evidence, that self-medication is an inferior good.

Table 7: The impact of being a Chronic patient and of the Economic_condition on the probability of self-medicating.

VARIABLES	LPM1 Self_Medicated	LPM2 Self_medicated
Chronic_patient	-0.151	-0.169
	(0.0972)	(0.145)
Economic_Condition		0.244***
		(0.0607)
Observations	344	78
Pandemic Year	NO	YES
Economic Condition	NO	YES
Covi Barriers	NO	YES
Year FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Limitations

The data used in this paper was collected face to face in the participants' private residences using a survey. Using a face-to-face methodology may condition certain answers since people will not answer anonymously. Consequently, people may answer what they believe the researcher wants to hear. Similarly, participants must understand the questions. Failure in answering any doubts may lead to biased results.

Surveys often require agents to resort to recollection when answering questions. This is another potential source of behavioural biases and it can limit the validity of the results. An example of these behavioural biases is the availability and confirmation bias. Longer recalled periods were said to lead to more inaccuracies. Another source of bias is the measurement errors stemming from the utilization of proxies throughout the paper. I have data on individuals who are only older than fifteen years old, thus limiting the scope of the paper since it does not include children, which is one of the most vulnerable groups. Moreover, there was no distinction between chronic patients. Patients suffering from different chronic diseases have different probabilities of not seeking care.

7 Conclusions and Policy Implications

Through this paper, I sought to answer the following question: "What is the impact that perceived barriers by patients have on the probability of self-medication?". To do so I used, a Tobit Type II model.

I found that financial barriers to appointments have the strongest impact on the probability of self-medication. With the exemption of Covid-19 related barriers and financial barriers on medication, all perceived barriers had a positive impact on the probability of self-medication. On a similar note, I found that expected waiting times in primary care had a stronger impact relative impact on the probability of self-medication than both travelling time and co-payment exemption. However, Co-payment exemption seems to have a stronger impact on the probability of not seeking care than waiting times and travelling time. I found that as individuals have larger difficulties surviving with their disposable income, they tend to self-medicate more, hence self-medication is an inferior good. Lastly, it was stated that chronic patients were not more likely to self-medicate but were more likely to seek care.

From these results, several policy implications ought to be considered. First, the fact that financial barriers on appointments have such a strong impact on the probability of self-medication leads me to argue that the utilization of leftovers is still prevalent. Better controls on prescription and campaigns towards limiting leftover consumption could mitigate this impact. Additionally, lower waiting times could be used to diminish the probability of self-medication and push people towards healthcare services.

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9 Appendix

Appendix 1 – Literature review principal findings
Table 8: Literature review

Income elasticity of self-medication	Inferior good for richer individuals and normal good for poor individuals	Chang and Trivedi (2003)
Income elasticity of self-medication	SM is a normal good	Akpalu (2008)
Income effect on self-medication	An increase in income led to an increase of SM and healthcare services, by a positive income effect	Tavares (2013)
Income effect on self-medication	Having public and private insurance can increase SM by the negative income effect	Tavares (2013)
Evaluation of benefits and costs	The main driver of SM are expected benefits and costs	Akpalu (2008)
Socioeconomic Status	Social status and behavioural factors facilitate access to care	Cheng and Guo et al. (2019)
Socioeconomic Status	Higher Socioeconomic Status facilitated access to care	Shahid et al. (2021)
Risk Aversion	As individuals become more risk-averse they SM Less	Tavares (2013)
Uncertainty	May lead consumers away from SM due to uncertainty on effects	Chang and Trivedi (2003)
Experience	Patients who had previous experience with medicine were more likely to SM	Lescure et al. (2018)
Experience	Education had a positive relationship with SM	Tavares (2013)
Experience	Being a chronic patient had a positive relationship with SM	Tavares (2013)
Experience	As patients got older, they tended to resort more to the healthcare system	Tavares (2013)
Experience	Mix evidence on the role of education, chronic diseases on SM	Lescure et al. (2018)
Experience	There was mixed evidence on the role of age on SM	Lescure et al. (2018)
Prices (Substitution Effect is dominant)	SM decreases as the relative price to risk-free medication decreased	Akpalu (2008)
Prices (Substitution Effect is dominant)	Prince increase in pharmacy prices leads to a substitution of SM for appointment	Chang and Trivedi (2003)
Prices (Substitution Effect is dominant)	Not reimbursement of pharmacy expenses led people to SM	Grigoryan et al. (2008)
Financial Barrier	Lack of affordability of care was one of the main reasons for SM	Ghosh et al. (2015)
Financial Barrier	Healthcare affordability is a way to decrease SM	Tavares (2013)
Professional life	Individuals who work for longer periods	Tavares (2013)
Waiting times	People are willing to wait for an appointment	Tavares (2013)
Waiting times	Patients are more likely to SM if exposed to long waiting times in surgery waiting rooms	Tavares (2013)

Waiting times	Patients willing to wait for an appointment but not willing to wait to be seen	Tavares (2013)
Waiting times	Time savings were among the main reasons for patients to SM	Ghosh et al.(2015)
Travelling times	Increased travelling times make self-medication more common in rural areas	Chang and Trivedi (2003)
Benefits of SM	Less costly for the healthcare system and patients; Time savings; Patient empowerment; Educates the patient	Bennadi et al. (2014)
Disadvantages of SM	Excessive medicine consumption; dangerous chemical interactions;	Hughes et al. (2001),
Consequences	SM is a good candidate to explain antibiotic resistance.	Lescure et al. (2018)

Appendix 2 – Variable description

Table 9 : Variable description

Variables	**Description**
Having_been_sick	If the person felt or was sick in the 12 months before the data collection
Didnt_sough_care	If the person sought healthcare services the last time he or she felt sick
age	Age of individual i
age2	Square of the age of individual i
Self_medicated	If the individual was sick and didn't seek care what did he do
gender	If someone is male or female
education	Completed education level
profession	Occupation of the individual i
Chronic_patient	If someone was taking drugs for a chronic condition
Financial_barriers_medication	If in the last year the individual I did not acquire all medicine because of lack of funds
Financial_barriers_appointments	If in the last year the individual I did not go to an emergency appointment or a scheduled appointment because of lack of funds
Branded_for_generic	If in the last year the individual i exchanged a branded medicine for a generic one because it was cheaper
Transportation_barrier	If in the last year individual i didn't go to the emergency services or appointments because of the price of transportation
Day_salary_barrier	If in the last year the individual i didn't go to the emergency services or appointments to not lose the salary
Covid_barrier	If in the last year the individual i skipped an appointment out of fear of getting infected with Covid-19
Appointment_canceled	If in the last year the individual i skipped an appointment out of fear of getting infected with Covid-20
Exempt_from_copayments	If the individual i was exempt from co-payments

Main_healthcare_provider	Main healthcare provider of individual i
Has_Health_Insurance	If the individual i has a private health insurance
tempo_csp	The preception of waiting times in the primary care unit individual i would attend
tempo_hosp	The preception of waiting times in the emergency services of the hospital individual i would attend
tempo_urg	The travel time to the emergency services of the hospital
region	The region where individual i lives
year	The year in which the observation was collected
covidpandemic	Sub-sample of data collected in 2020 na 2021
Financial_barriers_medication_co	Similar to the Financial_barriers_medication condition but it refers only to the data collected in 2020 and 2021
Financial_barriers_appointments_co	Similar to the Financial_barriers_appointments condition but it refers only to the data collected in 2020 and 2021
Branded_for_generic_covid	Similar to Branded_for_generic but it refers only to the data collected in 2020 and 2021
Transportation_barrier_covid	Similar to Transportation_barriers but it refers only to the data collected in 2020 and 2021
Day_salary_barrier_covid	Similar to the Financial_barriers_medication condition but it refers only to the data collected in 2020 and 2021
Economic_Condition	The ability that someone has to survive with their current income. The higher the value, the harder it is to survive.
status	This variable works as a proxy for Socioeconomic status

Appendix 3– Summary Statistics

Table 10: Summary Statistics

Variable Name	Mean	Obs	Median	SD	Max	Min
Having_been_sick	1.000	2706	1.000	0.000	1.000	1.000
Didnt_sough_care	0.134	2706	0.000	0.341	1.000	0.000
age	51.374	2706	52.000	18.806	97.000	15.000
age2	2992.774	2706	2704.000	1934.548	9409.000	225.000
Self_medicated	0.699	359	1.000	0.459	1.000	0.000
gender	0.625	2706	1.000	0.484	1.000	0.000
education	5.464	2706	6.000	1.782	8.000	1.000
profession	3.830	2706	4.000	2.418	10.000	1.000
Chronic_patient	0.297	2706	0.000	0.457	1.000	0.000

Financial_barriers_medication	0.173	2706	0.000	0.379	1.000	0.000
Financial_barriers_appointments	0.089	2706	0.000	0.284	1.000	0.000
Branded_for_generic	0.381	2706	0.000	0.486	1.000	0.000
Transportation_barrier	0.056	2706	0.000	0.230	1.000	0.000
Day_salary_barrier	0.072	2706	0.000	0.258	1.000	0.000
Covid_barrier	0.190	706	0.000	0.392	1.000	0.000
Appointment_canceled	0.251	706	0.000	0.434	1.000	0.000
Exempt_from_copayments	0.512	2674	1.000	0.500	1.000	0.000
Main_healthcare_provider	1.111	2705	1.000	0.517	6.000	1.000
Has_Health_Insurance	0.116	2703	0.000	0.320	1.000	0.000
tempo_csp	62.233	2706	54.324	70.705	1200.000	5.000
tempo_hosp	167.372	2706	150.000	109.647	1200.000	4.000
tempo_urg	51.116	2706	39.834	68.430	1220.000	0.000
region	3.494	2706	4.000	1.766	7.000	1.000
yearcovid2020	0.126	2706	0.000	0.332	1.000	0.000
year	2017.024	2706	2017.000	2.819	2021.000	2013.000
covidpandemic	0.261	2706	0.000	0.439	1.000	0.000
yearcovid2020	0.126	2706	0.000	0.332	1.000	0.000
yearcovid2021	0.135	2706	0.000	0.341	1.000	0.000
Financial_barriers_medication_covid	0.021	2706	0.000	0.142	1.000	0.000
Financial_barrier_appointments_covid	0.009	2706	0.000	0.094	1.000	0.000
Branded_for_generic_covid	0.091	2706	0.000	0.288	1.000	0.000
Transportation_barrier_covid	0.008	2706	0.000	0.090	1.000	0.000
Day_salary_barrier_covid	0.011	2706	0.000	0.106	1.000	0.000
covidpandemic	0.261	2706	0.000	0.439	1.000	0.000
Economic_Condition	2.334	706	2.000	0.883	4.000	1.000
status	3.549	2706	4.000	0.967	5.000	0.000

Appendix 3 – Education statistics

Table 11: Education level

Education	Frequency	Percentage	Cumulative
University degree excluding polytechnic	169	6.25	6.25
Plotythecnic degree	28	1.03	7.28
Attended University but did not finish studies	43	1.59	8.87
High School	533	19.70	28.57
9th grade	545	20.14	48.71
6th grade	334	12.34	61.05
Primary Education	861	31.82	92.87
Illiterate / Didn'tfinish primary education	193	7.13	100.00
Total	2,706	100.00	

Appendix 4 – Profession statistics

Table 12: Profession classes

Profession	Frequency	Percentage	Cumulative
Employer	173	6.39	6.39
Employee	859	31.74	38.14
Unemployed	310	11.46	49.59
Retired	784	28.97	78.57
Housekeeper	168	6.21	84.77
Student	138	5.10	89.87
10	274	10.13	100.00
Total	2,706	100.00	

Appendix 5 – Healthcare Providers

Table 13: Main health care provider classes

Main Healthcare Provider	Frequency	Percentage	Cumulative
Portuguese National Healthcare System (SNS)	2,521	93.20	93.20
Assistance to Public Servants (ADSE)	132	4.88	98.08
Assistance to patients from the military and militarized curtains (ADMF)	20	0.74	98.82
Medical and Social Assistance Services (SAMS)	12	0.44	99.26
Community Health Agent (ACS)	7	0.26	99.52
Other	13	0.48	100.00
Total	2,705	100.00	

Appendix 6 – Region statistics

Table 14: Regions

Region	Frequency	Percentage	Cumulative
North Coast	557	20.58	20.58
Porto Metropeltan Area	362	13.38	33.96
Interior	347	12.82	46.78
Center Coast	424	15.67	62.45
Lisbon Metropoleatn area	774	28.60	91.06
Alentejo	126	4.66	95.71
Algarve	116	4.29	100.00
Total	2,706	100.00	

Appendix 7 – Main results

Table 15: Main results

VARIABLES	1st Probit Selection model Didn't_Sough_Care	1st LPM Self_medicated	2nd Probit Selection model Didn't_Sough_Care	2nd LPM Self_medicated
1.Financial_barriers_medication		-0.284**		0.194
		(0.143)		(0.342)
2015.year	0.173	0.125		
	(0.108)	(0.104)		
2017.year	0.584***	0.114		
	(0.146)	(0.112)		
2019.year	0.0590	0.0847		
	(0.126)	(0.131)		
2020.year	0.263*	0.120		
	(0.146)	(0.133)		
2021.year	0.450***	0.126	-0.0353	0.0900
	(0.129)	(0.127)	(0.195)	(0.141)
1.Financial_barriers_medication#2015.year		0.376		
		(0.237)		
1.Financial_barriers_medication#2017.year		0.155		
		(0.220)		
1.Financial_barriers_medication#2019.year		0.596***		
		(0.216)		
1.Financial_barriers_medication#2020.year		0.406		
		(0.406)		
1.Financial_barriers_medication#2021.year		0.329		0.126
		(0.373)		(0.458)
1.Branded_for_generic		0.146		-0.0831
		(0.0977)		(0.199)
1.Branded_for_generic#2015.year		-0.289*		
		(0.153)		
1.Branded_for_generic#2017.year		-0.166		
		(0.161)		
1.Branded_for_generic#2019.year		0.0585		
		(0.193)		
1.Branded_for_generic#2020.year		-0.473**		
		(0.195)		
1.Branded_for_generic#2021.year		-0.186		0.0348
		(0.173)		(0.239)
Imr1		0.0806		
		(0.121)		
1.Financial_barriers_appointments		0.394***		0.754***
		(0.136)		(0.219)
1.Financial_barriers_appointments#2015.year		-0.491**		
		(0.242)		
1.Financial_barriers_appointments#2017.year		-0.134		
		(0.231)		

1.Financial_barriers_appointments#2019.year		-0.920***		
		(0.322)		
1.Financial_barriers_appointments#2020.year		0.170		
		(0.203)		
Transportation_barrier	-0.368**	0.129	-0.385	0.521**
	(0.175)	(0.139)	(0.554)	(0.241)
Day_salary_barrier	-0.0506	0.0545	-0.459	0.121
	(0.138)	(0.0937)	(0.354)	(0.258)
Porto Metropolitan Area	-0.251**	0.339***	-0.442	0.473**
	(0.128)	(0.0917)	(0.283)	(0.221)
Interior	-0.101	0.158	-0.187	0.464**
	(0.123)	(0.105)	(0.265)	(0.224)
Center Coast	0.0144	0.330***	-0.0199	0.386*
	(0.112)	(0.0840)	(0.245)	(0.194)
Lisbon Metropolitan Area	0.114	0.309***	0.244	0.538***
	(0.0959)	(0.0772)	(0.205)	(0.175)
Alentejo	0.390**	0.376***	0.770**	0.515**
	(0.157)	(0.103)	(0.313)	(0.207)
Algarve	-0.364*	0.0935	0.281	0.373
	(0.191)	(0.178)	(0.313)	(0.240)
Cronic_patient	-0.437***	-0.151	-0.267*	-0.169
	(0.0979)	(0.0972)	(0.160)	(0.145)
tempo_csp	0.000748	0.00152**	0.00467	-0.00621
	(0.000788)	(0.000680)	(0.00451)	(0.00605)
tempo_hosp	0.00108***	-6.23e-06	0.000446	-0.000873
	(0.000286)	(0.000247)	(0.000679)	(0.000676)
tempo_urg	-0.000510	-0.00117*	-0.00842**	0.00418
	(0.000847)	(0.000678)	(0.00380)	(0.00461)
Exempt_from_copayments	-0.256***	0.0597	-0.100	0.0963
	(0.0744)	(0.0589)	(0.159)	(0.142)
gender	-0.0771		0.110	
	(0.0695)		(0.145)	
education	-0.0320		-0.0210	
	(0.0301)		(0.0657)	
age	-0.00720		-0.0237	
	(0.0115)		(0.0249)	
age2	-1.33e-05		9.28e-05	
	(0.000117)		(0.000261)	
Financial_barriers_medication	0.161		-0.126	
	(0.118)		(0.294)	
Financial_barriers_appointments	-0.0632		-0.189	
	(0.150)		(0.553)	
Branded_for_generic	0.0967		0.258*	
	(0.0775)		(0.156)	
Main_healthcare_provider	0.0106		-0.0419	
	(0.0631)		(0.174)	
Has_Health_Insurance	-0.0454		0.0717	
	(0.112)		(0.211)	
Employee	-0.113		-0.493**	
	(0.140)		(0.245)	

Unemployed	-0.255		-1.033***	
	(0.167)		(0.391)	
Retired	-0.275		-0.506	
	(0.171)		(0.330)	
Housekeeper	-0.561***		-1.240**	
	(0.213)		(0.526)	
Student	0.0822		-1.527***	
	(0.208)		(0.505)	
10.profession	-0.257			
	(0.208)			
status	0.122***		0.303**	
	(0.0450)		(0.139)	
Economic_Condition			0.115	0.244***
			(0.106)	(0.0607)
Covid_barrier			0.455**	0.118
			(0.189)	(0.132)
Appointment_canceled			-0.109	-0.0715
			(0.189)	(0.130)
Imr2				-0.0647
				(0.224)
Constant	-1.068***	0.208	-0.780	-0.0665
	(0.348)	(0.227)	(0.853)	(0.414)
Observations	2,671	344	2,693	78
Pandemic Year	NO	NO	YES	YES
Economic Condition	NO	NO	YES	YES
Covid Barriers	NO	NO	YES	YES
Year FE	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The main results are comprised of two Tobit type two models. In the first collum, there is the first Probit selection model and in the second collum, there is the LPM. These two stages include observation for the entire sample. The second Tobit model can be found in the third and fourth columns. These two columns refer only to the subsample of 2020 and 2021. The third collum has the results for the Probit selection stage and the fourth collum has the results for the LPM.

Appendix 8 – A covid-19 alternative model

Table 16: 3rd Tobit type II model

VARIABLES	3rd Probit Selection model Didn't_Sought_Care	3rd LPM Self_Medicated
1.Financial_barriers_medication		-0.287**
		(0.143)
2015.year	0.171	0.126
	(0.108)	(0.105)
2017.year	0.586***	0.119
	(0.147)	(0.111)
2019.year	0.0566	0.0820
	(0.126)	(0.131)
2020.year	0.198	0.114
	(0.158)	(0.133)
2021.year	0.370**	0.122
	(0.145)	(0.125)
1.Financial_barriers_medication#2015.year		0.380
		(0.236)
1.Financial_barriers_medication#2017.year		0.157
		(0.220)
1.Financial_barriers_medication#2019.year		0.598***
		(0.216)
1.Financial_barriers_medication#2020.year		0.421
		(0.409)
1.Financial_barriers_medication#2021.year		0.337
		(0.373)
1.Branded_for_generic		0.142
		(0.0976)
1.Branded_for_generic#2015.year		-0.289*
		(0.153)
1.Branded_for_generic#2017.year		-0.166
		(0.161)
1.Branded_for_generic#2019.year		0.0591
		(0.193)
1.Branded_for_generic#2020.year		-0.457**
		(0.196)
1.Branded_for_generic#2021.year		-0.164
		(0.176)
Imr3		0.0990
		(0.118)
1.Financial_barriers_appointments		0.398***
		(0.135)
1.Financial_barriers_appointments#2015.year		-0.492**

		(0.241)
1.Financial_barriers_appointments#2017.year		-0.137
		(0.231)
1.Financial_barriers_appointments#2019.year		-0.917***
		(0.321)
1.Financial_barriers_appointments#2020.year		0.129
		(0.206)
Transportation_barrier	-0.314*	0.125
	(0.187)	(0.138)
Day_salary_barrier	0.00698	0.0565
	(0.153)	(0.0937)
Porto Metropoletan Area	-0.240*	0.337***
	(0.129)	(0.0913)
Interior	-0.0976	0.156
	(0.123)	(0.105)
Center Coast	0.00808	0.329***
	(0.112)	(0.0840)
Lisbon Metropoletan Area	0.116	0.310***
	(0.0961)	(0.0773)
Alentejo	0.381**	0.378***
	(0.159)	(0.102)
Algarve	-0.380**	0.0882
	(0.190)	(0.178)
Cronic_patient	-0.446***	-0.159*
	(0.0983)	(0.0957)
tempo_csp	0.000684	0.00152**
	(0.000790)	(0.000681)
tempo_hosp	0.00109***	5.29e-06
	(0.000286)	(0.000244)
tempo_urg	-0.000427	-0.00116*
	(0.000847)	(0.000678)
Exempt_from_copayments	-0.256***	0.0545
	(0.0746)	(0.0583)
education	-0.0301	
	(0.0303)	
gender	-0.0789	
	(0.0697)	
age	-0.00716	
	(0.0116)	
age2	-1.32e-05	
	(0.000118)	
Financial_barriers_medication	0.153	
	(0.128)	
Financial_barriers_appointments	-0.0182	
	(0.160)	
Branded_for_generic	0.0294	
	(0.0904)	
Financia barriers_appointments_covid	-0.577	
	(0.552)	
Financial_barriers_medication_covid	0.0588	

	(0.312)	
Branded_for_generic_covid	0.283	
	(0.176)	
Transportation_barrier_covid	-0.513	
	(0.588)	
Day_salary_barrier_covid	-0.433	
	(0.379)	
Main_healthcare_provider	0.00832	
	(0.0627)	
Has_Health_Insurance	-0.0259	
	(0.113)	
status	0.119***	
	(0.0449)	
Employee	-0.117	
	(0.140)	
Unemployed	-0.259	
	(0.167)	
Retired	-0.284*	
	(0.172)	
Housekeeper	-0.576***	
	(0.212)	
Student	0.0913	
	(0.209)	
10.profession	-0.268	
	(0.209)	
Imr3		
Constant	-1.044***	0.182
	(0.348)	(0.220)
Observations	2,671	344
Pandemic Year	NO	NO
Economic Condition	NO	NO
Covi Barriers	NO	NO
Year FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The model in table 16, was prepared as an alternative method to study the impact that Covid-19 had on the probabilities of not seeking care and on the probabilities of Self-medication. To do so, I created an interaction between the Barriers and Pandemic Year. It can be seen in table 16, that there are no significant changes when compared with the model in table 15. This could be since using this method, removes the impact of Covid-19 related barriers and the impact of Economic_Condition. The exclusion of these two variables generates an omitted variable bias. However, I decided to include it in the annexe section since it provides an alternative avenue to study the impact that Covid-19 had.

Appendix 9- Using robust standard errors without the command svy

Table 17: 4th Tobit type II model

VARIABLES	4th Probit Selection model Didn't_Sought_Care	4th LPM Self_Medicated
1.Financial_barriers_medication		-0.330**
		(0.158)
2015.year	0.177*	0.123
	(0.107)	(0.110)
2017.year	0.546***	0.110
	(0.144)	(0.116)
2019.year	0.0222	0.103
	(0.125)	(0.137)
2020.year	0.207	0.145
	(0.142)	(0.141)
2021.year	0.394***	0.118
	(0.129)	(0.132)
1.Financial_barriers_medication#2015.year		0.429
		(0.260)
1.Financial_barriers_medication#2017.year		0.179
		(0.236)
1.Financial_barriers_medication#2019.year		0.617***
		(0.224)
1.Financial_barriers_medication#2020.year		0.504
		(0.424)
1.Financial_barriers_medication#2021.year		0.364
		(0.384)
1.Branded_for_generic		0.145
		(0.105)
1.Branded_for_generic#2015.year		-0.295*
		(0.168)
1.Branded_for_generic#2017.year		-0.156
		(0.170)
1.Branded_for_generic#2019.year		0.0325
		(0.208)
1.Branded_for_generic#2020.year		-0.509**
		(0.204)
1.Branded_for_generic#2021.year		-0.174
		(0.180)

Imr4		
1.Financial_barriers_appointments		0.413***
		(0.147)
1.Financial_barriers_appointments#2015.year		-0.514*
		(0.263)
1.Financial_barriers_appointments#2017.year		-0.168
		(0.252)
1.Financial_barriers_appointments#2019.year		-0.915***
		(0.341)
1.Financial_barriers_appointments#2020.year		0.169
		(0.214)
Transportation_barrier	-0.286	0.161
	(0.177)	(0.146)
Day_salary_barrier	-0.0261	0.0540
	(0.139)	(0.103)
Porto Metropoletan Area	-0.229*	0.339***
	(0.126)	(0.0960)
Interior	-0.0690	0.159
	(0.122)	(0.110)
Center Coast	0.0642	0.331***
	(0.112)	(0.0872)
Lisbon Metropoletan Area	0.126	0.293***
	(0.0945)	(0.0816)
Alentejo	0.431***	0.358***
	(0.154)	(0.111)
Algarve	-0.343*	0.114
	(0.194)	(0.185)
Cronic_patient	-0.423***	-0.138
	(0.0949)	(0.103)
tempo_csp	0.000559	0.00154**
	(0.000772)	(0.000775)
tempo_hosp	0.00116***	-6.44e-05
	(0.000273)	(0.000247)
tempo_urg	-0.000329	-0.00119
	(0.000826)	(0.000763)
Exempt_from_copayments	-0.272***	0.0572
	(0.0733)	(0.0638)
education	-0.0200	
	(0.0293)	
gender	-0.0640	
	(0.0687)	
age	-0.00559	
	(0.0114)	
age2	-3.14e-05	
	(0.000115)	
Financial_barriers_medication	0.129	
	(0.116)	

Financial_barriers_appointments	-0.118	
	(0.145)	
Branded_for_generic	0.0941	
	(0.0760)	
Main_healthcare_provider	0.0168	
	(0.0630)	
Has_Health_Insurance	-0.0559	
c	(0.109)	
status	0.113**	
	(0.0449)	
Employee	-0.0701	
	(0.138)	
Unemployed	-0.212	
	(0.164)	
Retired	-0.226	
	(0.166)	
Housekeeper	-0.483**	
	(0.212)	
Student	0.150	
	(0.206)	
10.profession	-0.203	
	(0.200)	
Imr4		0.0525
		(0.133)
Constant	-1.178***	0.265
	(0.344)	(0.249)
Observations	2,671	344
Pandemic Year	NO	NO
Economic Condition	NO	NO
Covid-19 Barriers	NO	NO
Year FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17 was constructed as part of a robustness test. This table was estimated without using the command svy, but by using the command robust. The goal was to access the impact of using robust standard errors. As such these variables are not weighted, however, these are heteroskedastic robust estimated. In the table above, the reader can see that there is little difference between the model in table 15 and the model in table 16. The only variable that suffered any significant impact was Transportation barriers in the Probit stage. This variable stopped being statistically significant at a 5% significance level.

Appendix 10- OLS results

Table 18: Initial analysis using OLS

VARIABLES	OLS1 Self-medicated	OLS2 Self-medicated
1.Financial_barriers_medication	-0.285**	0.195
	(0.142)	(0.343)
2015.year	0.138	
	(0.103)	
2017.year	0.0902	
	(0.104)	
2019.year	0.101	
	(0.130)	
2020.year	0.124	
	(0.133)	
2021.year	0.108	0.107
	(0.123)	(0.135)
1.Financial_barriers_medication#2015.year	0.343	
	(0.236)	
1.Financial_barriers_medication#2017.year	0.147	
	(0.221)	
1.Financial_barriers_medication#2019.year	0.594***	
	(0.212)	
1.Financial_barriers_medication#2020.year	0.396	
	(0.395)	
1.Financial_barriers_medication#2021.year	0.314	0.129
	(0.369)	(0.461)
1.Branded_for_generic	0.150	-0.0791
	(0.0966)	(0.200)
1.Branded_for_generic#2015.year	-0.287*	
	(0.152)	
1.Branded_for_generic#2017.year	-0.174	
	(0.161)	
1.Branded_for_generic#2019.year	0.0352	
	(0.191)	
1.Branded_for_generic#2020.year	-0.483**	
	(0.196)	
1.Branded_for_generic#2021.year	-0.194	0.0385
	(0.173)	(0.237)
1.Financial_barriers_appointments	0.406***	0.741***
	(0.135)	(0.212)
1.Financial_barriers_appointments#2015.year	-0.490**	
	(0.244)	

1.Financial_barriers_appointments#2017.year	-0.127	
	(0.232)	
1.Financial_barriers_appointments#2019.year	-0.936***	
	(0.317)	
1.Financial_barriers_appointments#2020.year	0.165	
	(0.204)	
Transportation_barrier	0.152	0.509**
	(0.134)	(0.245)
Day_salary_barrier	0.0431	0.111
	(0.0922)	(0.254)
Porto Metropolitan Area	0.336***	0.465**
	(0.0887)	(0.223)
Interior	0.145	0.473**
	(0.104)	(0.224)
Center Coast	0.315***	0.391*
	(0.0834)	(0.197)
Lisbon Metropolitan Area	0.291***	0.558***
	(0.0760)	(0.161)
Alentejo	0.343***	0.557***
	(0.101)	(0.168)
Algarve	0.103	0.397*
	(0.176)	(0.223)
Cronic_patient	-0.114	-0.190
	(0.0758)	(0.143)
tempo_csp	0.00152**	-0.00604
	(0.000673)	(0.00584)
tempo_hosp	-6.60e-05	-0.000888
	(0.000225)	(0.000680)
tempo_urg	-0.00118*	0.00389
	(0.000672)	(0.00420)
Exempt_from_copayments	0.0907*	0.0769
	(0.0521)	(0.131)
Economic_Condition		0.243***
		(0.0600)
Covid_barrier		0.133
		(0.128)
Appointment_canceled		-0.0676
		(0.132)
Constant	0.344***	-0.168
	(0.111)	(0.250)
Observations	346	78
Pandemic Year	NO	NO
Economic Condition	NO	NO
Covid-19 Barriers	NO	NO
Year FE	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results using Tobit type II and OLS are very similar. This is not unexpected since the Inverse Mill's Ratio was not statistically significant in either of the two main models.