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GOING TO THE DOCTOR?

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Abstract

We aim to discover how fast our national health system can get back on its feet and regain the public's confidence after a shock of the magnitude of COVID-19, by studying the evolution of health service appointment cancellations made by both health services and patients from 2020 to 2021. Is one year enough? Using cross sectional data on Portuguese mainland residents of at least 15 years of age, we conclude that from 2020 to 2021 both health services recovered (cancellations of appointments by the latter decreased 11.2 p.p.), and individuals regained confidence in them (cancellations by individuals decreased 4.7 p.p.).

Keywords: Economics; Health; Econometrics; Pandemic; covid-19; Health economics; Access to care; Economics of Health Services; Bivariate Probit; Cancellations

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1. INTRODUCTION

In the end of 2019, the world experienced the first outbreak of cases of the new SARS-CoV-2, in Wuhan, China. Although immediate concern was expressed by communities everywhere and organizations such as the World Health Organization (WHO) helped spread the news and educate countries on best practices to identify, test and deal with possible infections from the beginning of 2020, information on the virus was still very limited and the world was completely unprepared for the proportion that this soon-to-be pandemic would take. In mid-January 2020 the first cases of COVID-19 outside of China were detected and it would not be too long before Portugal saw its first case too.

On the 2nd of March of 2020, the first case of COVID-19 was confirmed and publicly reported in Portugal. Regardless of having the advantage of a delayed start to the marathon that would be life in a pandemic, we were not any more prepared than any other country to deal with it. Fear was soon installed among the public and, with it, schools and workplaces closed and sent students/workers home, restaurants reduced their maximum capacity, bars and clubs closed, and hospitals began to overflow. As the number of infected people increased, hospitals and primary care units started postponing and cancelling non-urgent medical exams and appointments to prioritize infected patients and reduce the spreading of the virus. In addition to the appointments and exams cancelled by health services, individuals began to cancel appointments and exams themselves due to fear of high exposure to the virus.

But eventually the world had to adapt and, as we approached a year on the pandemic, COVID-19 was no longer a novelty. Although infections were still far from reaching their peak in Portugal, life had to start returning to a "new" normal and with more information made publicly available and vaccination spreading across countries, people became used to living with the virus. With hospitals becoming less crowded and infections decreasing, one would expect that, not only people cancelled less appointments due to fear of infection as they became less afraid, but health services felt less need to cancel appointments and medical exams. Therefore, it is relevant to study whether one year on the pandemic led to some adjustment by both health services and individuals – did health services in fact cancel less appointments, and did people cancel less appointments due to fear of the virus?

As a result, we built a research question with two separate sides: a demand side (patients – whether individuals cancelled appointments due to fear of infection) and a supply side (health services – if hospitals and primary care units chose to cancel appointments, regardless of the individual's will). With the help of repeated cross-section data on Portuguese mainland residents, we aim to determine the evolution of cancellations by both sides of the equation from 2020 to 2021 and across different demographic characteristics. The survey we will be using does not include any data on cancellations before 2020 or cancellations arising from motives other than fear of covid-19 so we cannot determine how these cancellations weigh in the total amount of cancellations. Nonetheless, this study has great relevance in determining whether in one year our Portuguese health system was able to get back on its feet and whether one year was sufficient for the population to regain confidence in its health system.

We estimate a bivariate model based on two separate equations, one for each side of the problem. Each equation has its own dependent variable – one indicates whether the individual chose to cancel an appointment at a health service due to the fear of catching COVID-19, the other whether the individual had an appointment cancelled by a health service. The independent variables consist of several demographic characteristics, in addition to individuals' opinions/predictions on specific aspects of health services. Results confirm our suspicions – cancellations by both sides of the equation (demand and supply) are in line with our expectations. In short, our model indicates that risk averse individuals are more likely to both cancel an appointment and have one cancelled by a health service. In addition, those living in good and very good economic conditions were less likely to cancel an appointment, while those suffering from chronic diseases were more likely to have an appointment cancelled by a health service. Women were also found to be more likely to have an appointment cancelled. These results are all true for both 2020 and 2021, and, within each category of the four variables above, the probability of both cancelling and having an appointment cancelled decreases from 2020 to 2021. Finally, a couple variations of our model are also considered and show very similar results to the ones found in this model.

This paper is organized in 6 separate sections: 1. Introduction, 2. Literature Review, 3. Data, 4. Methodology, 5. Results and Discussion, and 6. Conclusion.

2. LITERATURE REVIEW

The year 2020 showed a huge increase in cancellations and postponements of medical appointments, both by health services and patients themselves, compared to 2019, due to COVID-19. While in some countries and health service sectors a higher percentage of cancellations resulted from health services' decisions, in others, they were mainly made by individuals, due to fear of exposure to the virus. Schuster et al. (2021) shows that, during the first few months of the pandemic, cancellations of medical appointments for Dutch older adults (aged 62 and above) were less likely to be initiated by the latter, and more likely to result from a decision of the healthcare professional. Schmid-Küpke et al. (2021) analysed self-reported data on routine vaccinations, from April to June 2020, in Germany, and concluded that, not only had 40% of cancelled visits not yet been rescheduled, but cancellations had been mostly initiated by patients and not the health service responsible.

In addition, Bhatnagar et al. (2021) analysed data on individuals with Cystic Fibrosis (CF) in 2020, in terms of access to medication, employment, hospital visits and mental health. They found that 47,5% of the participants reported having postponed hospital visits for CF-related issues. From these, 69,8% were due to fear of catching COVID-19, while 11,5% were reported to be due to the hospital being closed. Oliveira et al. (2020) studied the effect of the pandemic on two Portuguese cardiology centres during the national emergency state and showed that, compared to 2019, face-to-face medical appointments decreased by more than 70%. The evolution from January to April of 2020 revealed an even more prominent decrease in this percentage.

These results are not just evident in self-reporting as there can be found statistical evidence that corroborates it. Shayganfard et al. (2020) found an association between cancellations/ postponements of routine check-ups in pregnancy and post-partum and fear of becoming infected with the virus. Chaves (2020) conducted a literature review on the impact of the pandemic on patients with Stroke and discovered evidence of a reduction in hospital admissions of patients with Stroke, as well as a decrease in medical appointments.

The impact of the pandemic on the cancellation of hospital visits is visible amongst several groups of the population but higher-risk groups, namely, chronic patients and individuals with grave illness, showed a higher likelihood to cancel a hospital visit. From the sample of senior citizens analysed by Schuster et al. (2021), 35% reported having either avoided, cancelled, or received information of cancellation of a health service visit; the latter being more frequent among chronic patients with multiple conditions. This is also evident in Wegner et al. (2022) where the likelihood of cancellation was higher in individuals with more medical conditions. In pregnant and post-partum women, higher illness severity was shown to predict routine check-up cancellations and postponements by Shayganfard et al. (2020).

Nonetheless, within each of these groups, studies also show that younger individuals (those who are less likely to need an urgent visit and, therefore, the benefit of the visit is less likely to outweigh the risk of exposure to the virus) are more likely to cancel appointments compared to older individuals. Bhatnagar et al. (2021) also found that older patients (>35 years) with CF were half as likely as younger individuals with CF to postpone a hospital appointment.

As the pandemic advanced, postponements were a less effective measure and scheduled appointments concentrated mostly on urgent visits, so cancellations started decreasing. In the US, adults responded to surveys between May and December of 2020 and Wenger et al. (2022) concluded that cancellations and postponements decreased significantly during this period. Of those who had a scheduled appointment, 64% reported having cancelled or postponed the visit in May, as opposed to only 37% in December.

Contrarily, they found that some urgent appointments, such as cancer screening, do not show a change in the percentage of cancellations between May and December, standing around a constant 20%. Regarding demographics, ethnicity, race, and income did not show any strong correlation with postponed/cancelled appointments in Wegner et al. (2022).

Nevertheless, cancellations by both hospitals and individuals were still happening in 2021 at a relevant rate. In a study conducted in Geneva in 2021 with 5397 participants, Menon et al. (2022) finds that 8% experienced a cancelled appointment, the cause of which being either a cancellation by the health service (54%), an individual's decision due to fear of catching COVID-19 (35%), or personal organizational issues (11%).

Therefore, we aim to test several different hypotheses. Not only whether cancellations by both sides decreased from 2020 to 2021 and how significantly, but also how individuals and health services behaved separately, and which played a bigger role in cancellations in each year. In addition, we want to analyse how these cancellations fluctuate among different groups of individuals, and which variables play a part in determining the probability of cancelling or having an appointment cancelled, namely age, income and degree of risk aversion.

3. DATA

3.1. Data collection

The statistical analysis was based on a survey about access to healthcare in Portugal, consisting of 6 waves (2013, 2015, 2017, 2019, 2020 and 2021) of repeated cross-section with around 1000 observations in each survey, although, for the purpose of this study, we will only be using data from the 2020 and 2021 waves. The questions were kept very similar throughout the various waves and regard different topics related to the access to health care in Portugal.

The 2021 survey, as a representation of the other waves, consists of 1269 interviews conducted throughout the different regions of the Portuguese mainland, to residents who were at least 15 years old at the time of the interview. These interviewees were selected using quota sampling and divided into groups according to the following factors: region (7 groups), habitat (5 groups), gender (2 groups), age (6 groups), education (2 groups) applied to men, and occupation (2 groups) applied to women. Specific rules instructed the interviewers to distribute their interviews throughout each location, as a replacement for not applying a random route method. Finally, the interviews were conducted in person, with total privacy, inside the homes of the interviewees.

As mentioned in the introduction, this data set does not include any data on cancellations prior to 2020 or regarding other types of cancellations besides fear of infection and cancellations by health services so our analysis regards only the evolution of cancellations instigated by the pandemic – the progression of cancellations by both individuals (due to fear of catching COVID-19) and health services from 2020 to 2021.

The table below describes the data for the two cancellation dependent variables in 2020 and 2021, as a broad image. Although our initial suspicions are confirmed by expectations (based on the literature review), the decrease in cancellations from 2020 to 2021 was considerably more evident in the supply side, suggesting that health services recovered at a faster speed than that with which individuals regained confidence in them.

Table 1 - Frequency counts for cancelling an appointment due to fear of catching COVID-19 and having an appointment cancelled by a health service. Difference between 2020 and 2021.

	2020		2021		Difference (2021-2020)
	Freq.	Percent	Freq.	Percent	
Cancelled an appointment	183	14.40%	122	9.61%	-4.79 p.p.
Had an appointment	255	20.06%	152	11.98%	-8.08 p.p.

cancelled by a health service					
Joint probability	104	8.18%	47	3.7%	-4.48 p.p.

3.2. Variable description

Table 2 shows the name and type of each variable included in the model, along with a short description for each. Our two dependent variables are *cancel_apoint* and *had_appoint_cancel*. The independent variables are a combination of demographic variables with variables pertaining to individuals' opinions of health services, in addition to the variable serving as a proxy for the number of appointments booked prior to cancellations. These variables vary slightly for each of the two equations in our model, since the equation for *cancel_appoint* considers all the independent variables in the table, whereas the one for *had_appoint_cancel* does not consider the two variables referring to one's perception of healthcare services, i.e. *confidence_pcu* (degree of confidence one has in their primary care unit) and *time_perceived* (amount of time an individual expects to wait at an emergency department).

Table 2 - Description of the variables included in the model post cleaning process

Name of variable	Description	Type
cancel_appoint	Whether the individual cancelled a hospital visit due to fear of catching covid-19.	Binary
had_appoint_cancel	Whether (in the 3 months prior to the survey) the individual had an appointment cancelled by the healthcare service, regardless of his/her will.	Binary
confidence_pcu	The amount of confidence the individual feels towards the primary care unit the individual would attend, in case of need. The higher the value, the higher the confidence in the primary care unit.	Binary (set of 3)
time_perceived	The perception the individual has regarding the waiting time in the primary care unit the individual would attend, in case of need. In minutes.	Discrete
chronic_patient	Whether the individual suffers from a chronic disease that requires specific medication.	Binary
avoid_crowd	Whether, in the 3 months prior to the survey, the individual avoided crowded places due to fear of catching covid-19. Acts as a proxy for risk aversion.	Binary
health_perceived	The individual's self-assessment of his/her health. The higher the value, the healthier the individual considers him(her)self. Considers three separate levels: very bad /	Binary (set of 3)

	bad health, intermediate health, good / very good health.	
economic_condition	The difficulty one has in making ends meet. The higher the value, the less difficulty there is.	Binary (set of 4)
female	The individual's gender.	Binary
age	The individual's age at the time of the survey. In years.	Discrete
education	The individual's degree of education. The higher the value, the higher the degree of education completed by the individual.	Binary (set of 3)
er_visits	The number of times the individual went to the ER in the past year. Used as a proxy for the number of appointments each individual had booked before cancellations.	Discrete
year	The year in which the observation was collected.	Binary

Table 3 contains the descriptive statistics of all the variables included in the model, for the years of 2020 and 2021 alone, after having undergone a cleaning process. A description of the data cleaning process can be found in the section below.

Table 3 - Descriptive statistics of the variables included in the model after undergoing a cleaning process. The information in this table refers only to the years of 2020 and 2021.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
cancel_appoint	1923	0.134	0.341	0	1
had_appoint_cancel	1923	0.187	0.390	0	1
confidence_pcu	1923	2.671	0.537	1	3
time_perceived (minutes)	1923	45.760	38.249	5	240
chronic_patient	1923	0.310	0.463	0	1
avoid_crowd	1923	0.786	0.410	0	1
health_perceived	1923	2.547	0.609	1	3
economic_condition	1923	2.495	0.853	1	4
female	1923	0.560	0.497	0	1
age	1923	47.942	18.075	15	94
education	1923	1.840	0.593	1	3
er_visits	1923	0.369	0.809	0	4
year	1923	2020.522	0.500	2020	2021

3.3. Data cleaning process

Before working the data, the latter overwent a cleaning process. The variable *time_perceived* (minutes) was created as function of the variables representing, respectively, the hours and minutes that people reported. In order to facilitate interpretation, *chronic_patient* which was coded 1 for "yes" answers and 2 for "no", was recoded as 0 for answers "no" and categorical variables with more than 4 initial categories, such as *confidence_pcu* and *health_perceived*, were recoded with aggregated categories. In addition, non-demographical discrete variables, such as *er_visits* and *time_perceived* were winsorized, by cutting out the highest and lowest 1% observations, to remove outliers. With the raw data, the variables with the most observations had 7572 observations, while the ones with the least had 2540 observations each. However, after eliminating the observations relating to the years we do not use (2013, 2015, 2017 and 2019), we lost 5032 and the number of observations per variable is between 2540 and 1967. Given that not all variables have the same number of observations for the period we are studying, we lose some observations in the model, ending up with 1923 observations per variable, as can be seen in Table 3.

4. METHODOLOGY

Our model (Model 1) consists of two equations, one for the demand side: the decision of individuals to cancel an appointment due to fear of catching covid-19, and the other for the supply side: the decision of health services to cancel an individual's appointment, regardless of their will. The first equation aims to explain the demand side: *cancel_appoint* is the independent variable and all the dependent variables included in the model are part of this equation, from demographic factors to individuals' perceptions of health services. The second equation tries to describe the supply side: *had_appoint_cancel* is the independent variable and variables pertaining to individuals' perceptions of health services were excluded since they should not impact the health service's decision to cancel a hospital visit. The two equations are described below.

Equation (1) – Decision to cancel appointment in health centre (demand side effect)

$$
\begin{aligned}
(1)\ cancel\_appoint &= \beta_0 + \beta_1 confidence\_pcu + \beta_2 time\_perceived + \beta_3 chronic\_patient \\
&+ \beta_4 avoid\_crowd + \beta_5 health\_perceived + \beta_6 economic\_condition \\
&+ \beta_7 female + \beta_8 age + \beta_9 education + \beta_{10} er\_visits + \beta_{11} year
\end{aligned}
$$

Equation (2) – Having a visit to a health centre cancelled (supply side effect)

$$(2)\ had\_appoint\_cancel = \beta_0 + \beta_1 chronic\_patient + \beta_2 avoid\_crowd + \beta_3 health\_perceived + \beta_4 economic\_condition + \beta_5 female + \beta_6 age + \beta_7 education + \beta_8 er\_visits + \beta_9 year$$

Er_visits was included in both equations as a control variable, serving as a proxy to the number of appointments individuals had booked before cancellations occurred. It captures the point that someone with a higher demand for consultations will also have a higher number of ER episodes.[1]

We estimated first simple probit models (Model 0) and then moved to a bivariate probit model (Model 1). Marginal effects and plots of these marginal effects are used to interpret the results in the model. Marginal effects were computed, per variable, relating to the joint probability of both cancelling an appointment and having one cancelled by a health service. In addition, we derived the marginal effects separately for each variable for each equation.

Besides Model 1, we also estimated some variations of the latter. We derived a new model (Model 2) in which all variables for both equations are significant, by construction, and these results will be compared to Model 1 in the next chapter. During this process, we ended up dropping all categorical variables with more than 2 categories and split the variable *economic_condition* into four separate dummy variables (*ec_very_difficult, ec_difficult, ec_somewhat_easy, and ec_easy*), including in the first equation the two categories which had been significant in the initial model: *ec_somewhat_easy* and *ec_easy*. The two demand and supply side equations for Model 2 (equations 3 and 4) can be found in Appendix 2.

[1] The decision to include *er_visits* as a control initially arose from the behaviour of the variable *female* when first running an experimental model. This variable was significant in both equations and including *er_visits* was the trigger to make it non-significant. Although in our final model, described above, the gender variable is no longer significant when excluding *er_visits*, we decided to keep this variable as it is still relevant to control for frequency of visits. The effects of including *er_visits* can be found in Appendix 1.

Finally, as a form of robustness check, we regressed four separate OLS models: one for each of the two equations in both Models 1 and 2. Although these models are based on these equations, not all variables were kept the same since we transformed the three discrete variables (*age*, *time_perceived*, and *er_visits*) into categorical variables. The goal of this transformation was to only have categorical variables in the model, so that the OLS was a non-parametric model (having no functional form) unlike the probit.

Given that *er_visits*'s observations vary from 0 to 4 (5 "categories"), we simply enter the variable into our OLS regression as a categorical variable, without any further alterations. This way, each category of the variable is treated as a dummy (0/1). However, *time_perceived* and *age* have too many different observations to proceed in the same way as *er_visits* so, for each of the two, we aggregated observations into separate intervals and created a new categorical variable that takes a different value for each interval. The variable *age* was separated into five categories – ages 15-29, ages 30-44, ages 45-64, ages 65-80 and ages 80-94 – generating the new age variable *age_c*. *Time_perceived* was split into three different categories – a short waiting time: 5 to 30 minutes, a medium waiting time: 31 to 90 minutes, and a long waiting time: 91 minutes to 4 hours – generating the variable *time_perceived_c*. As with *er_visits*, each interval (category) that was created for these variables is treated as a separate dummy (0/1). These two categorical variables were then included in the model as substitutions for *age* and *time_perceived*.

5. RESULTS AND DISCUSSION

5.1. Models 1 and 2

The table below shows the results (coefficients, standard errors, and significance) of Models 0, 1 and 2, side-by-side, for each variable in each equation.

*Table 4 - Comparison of the coefficients from Models 0, 1 and 2. Significances are identified by the asterisks (**

*p<0.1, ** p<0.05, *** p<0.01). Standard errors in brackets below each coefficient.*

	Model 0	**Model 1**	**Model 2**
CANCEL_APPOINT			
confidence_pcu (medium)	0.017	0.128	-
	(0.209)	(0.201)	
confidence_pcu (high)	-0.065	0.119	
	(0.202)	(0.195)	
chronic_patient	-0.080	-0.073	-
	(0.099)	(0.098)	
avoid_crowd	0.280***	0.268***	0.242***
	(0.101)	(0.099)	(0.087)
health_perceived (medium)	0.042	0.035	-
	(0.158)	(0.156)	
health_perceived (good / very good)	-0.157	-0.160	-
	(0.182)	(0.178)	
age	0.003	0.003	0.004**
	(0.003)	(0.003)	(0.002)
education (6^{th}-12^{th} grade)	0.019	0.035	-
	(0.110)	(0.108)	
education (university)	0.188	0.214	-
	(0.158)	(0.157)	
female	0.068	0.062	-
	(0.076)	(0.076)	
time_perceived	0.000	0.001	
	(0.001)	(0.001)	
economic_condition (difficult)	0.0262	0.037	-
	(0.111)	(0.111)	
economic_condition (somewhat easy)	-0.268**	-0.263**	-0.303***
	(0.116)	(0.116)	(0.071)
economic_condition (easy)	-0.602***	-0.611***	-0.617***
	(0.182)	(0.182)	(0.129)
er_visits	0.200***	0.205***	0.234***
	(0.043)	(0.042)	(0.037)
year (2021)	-0.244***	-0.232***	-0.216***
	(0.079)	(0.078)	(0.070)
HAD_APPOINT_CANCEL			
chronic_patient	0.500***	0.458***	0.633***
	(0.083)	(0.089)	(0.065)
avoid_crowd	0.309***	0.284***	0.320***
	(0.085)	(0.093)	(0.084)
health_perceived (medium)	0.192	0.206	-
	(0.137)	(0.144)	
health_perceived (good / very good)	-0.071	-0.087	-
	(0.156)	(0.166)	
age	0.002	-0.001	-
	(0.003)	(0.003)	
education (6^{th}-12^{th} grade)	0.024	-0.021	-
	(0.094)	(0.100)	
education (university)	0.130	0.001	-
	(0.133)	(0.147)	
female	0.170*	0.128*	0.165***
	(0.066)	(0.071)	(0.062)

economic_condition (difficult)	0.122	0.154	-
	(0.103)	(0.109)	
economic_condition (somewhat easy)	-0.064	-0.018	-
	(0.106)	(0.112)	
economic_condition (easy)	-0.024	0.080	-
	(0.138)	(0.152)	
er_visits	0.251***	0.233***	0.266***
	(0.038)	(0.040)	(0.036)
year (2021)	-0.438***	-0.463***	-0.425***
	(0.068)	(0.074)	(0.065)

From the several potential effects considered, only a small of them have, according to the estimates, a systematic relationship with cancellation of appointments

Individuals suffering from a chronic disease seem to be less likely to cancel an appointment due to fear of infection. But the variable is not significant in equation (1), meaning we cannot reject the null that its coefficient is very close to 0, regardless of being positive or negative. However, *chronic_patient* did prove to be highly significant in equation (2), meaning that, since its coefficient for this equation is positive, these patients are more likely to have an appointment cancelled by a health service. Chronic diseases are defined as being of slow progression and mainly requiring medication that can be self-administered after being prescribed by a physician, as well as routine medical check-ups. Therefore, there are two main drivers that justify our results: on one hand, those who suffer from chronic diseases have less urgent appointments booked, since the disease progresses at a slower pace than many other diseases and these patients already have a diagnosis and prescribed medication, which should be mainly adequate for self-administration. On the other hand, since most chronic diseases require routine medical check-ups, within the category of non-urgent appointments, these patients will, on average, have more appointments booked than others, meaning that in a random system of cancellations of non-urgent appointments, chronic patients have a higher probability of having an appointment cancelled, which may not be entirely captured by *er_visits*' effect.

People who avoid crowds are significantly more likely to cancel an appointment and significantly more likely to have an appointment cancelled by a health service. The first result matches our expectations as, since *avoid_crowd* acts as a measure of risk aversion, it seems logical that these individuals would avoid hospitals and other places where the percentage of infected people is likely to be high. However, we did not expect this variable to be significant in the second equation, as one would assume there be very little connection between a health service cancelling an individual's appointment and that individual taking measures to avoid exposure. Given that health services prioritized cancellations of non-urgent appointments, it seems that individuals who are risk averse also have, on average, more non-urgent appointments booked. A possible interpretation is that risk averse people take better care of their health, leading to more less-urgent appointments. Another possibility is that, for the same situation, risk averse individuals book more appointments, on average, than those who are less risk averse, and the remaining variables do not control for the entirety of this effect.

In terms of the gender variable, *female* is only significant at the 10% level for equation (2). But when the model did not yet include the variable *er_visits*, which is a proxy for the number of appointments one had booked before any cancellation (see Appendix 1 for more differences between models with and without *er_visits*), *female* was closer to the 5% significance level, indicating that, on average, women book more medical appointments than men, therefore having a higher probability of cancellations by women. This finding is common to several studies, namely Deb and Trivedi (2002), Briscoe (1987), Cartwright, Hu and Huang (1992), and Deb and Trivedi (1997), among others. This reasoning also leads us to assume that, since we are only using a proxy for the number of appointments booked and not the true number itself, the small significance still present in the variable *female* may be a leftover effect of women booking more appointments that is unaccounted for by the proxy. In fact, Deb and Trivedi (1997) found that while women seek more appointments than men, men have longer hospital stays, and Cartwright, Hu and Huang (1992) found that women seek more insurance and medical care while men end up spending more when they do seek care. Both papers indicate the possibility that women seek medical attention more regularly and men, although less often, end up needing more serious medical care. This would explain why women have a higher probability of having an appointment cancelled by a health service – not only do they book more medical appointments but they also tend to have less urgent appointments than men.

As expected, *economic_condition* is not significant in predicting the probability of having an appointment cancelled. Nonetheless, the two highest levels of *economic_condition* (people who find it easy or somewhat easy to make ends meet) are significant in equation (1) and show that people with less difficulty in making ends meet are less likely to cancel an appointment at a health service, compared to those with worse economic conditions. Although one may associate this result to the fact that people with more difficulty in making ends meet have worse health, thus being more likely to cancel an appointment due to being higher-risk individuals, one can also argue that individuals of worse economic condition are less likely to risk catching the virus not for health reasons, but because they cannot afford to miss work for mandatory quarantine since this would impact their economic condition more strongly than it would someone with less difficulty in making ends meet (higher opportunity cost). There is also a third effect that may have contributed to this result. People with better economic conditions are less likely to need / use public transports and more likely to have the possibility of working from home. In addition, they may believe that they are better prepared and educated on how to avoid the virus. This way, there may be some overconfidence in people with better economic condition in believing that they are less likely to contract the virus, leading them to be less likely to cancel an appointment due to fear of infection.

We also found that, the more frequently one goes to the ER, the more likely one is to cancel an appointment or have an appointment cancelled. Since we use *er_visits* as a proxy for the number of appointments one has scheduled, we were expecting these results and the variable to be highly significant, as it is. The more appointments one has booked, the more likely they are that one of them is cancelled.

Finally, in both equations, the probability of cancelling an appointment or having an appointment cancelled by a health service is lower in 2021 compared to 2020, at a 1% significance level. This allows us to conclude what we meant to find with this study – a year on the pandemic was enough for health services in Portugal to start progressing back to their initial, pre-pandemic state (less cancellations of appointments by the latter) and enough, also, for patients to regain trust in the Portuguese health system (less cancellations by individuals due to fear of catching covid-19). In the descriptive statistics of the data we had a first confirmation of our expectations since it shows that the probability of cancelling an appointment due to COVID-19 decreased 4.79 percentage points from 2020 to 2021 and the probability of having an appointment cancelled by a health service decreased 8.08 percentage points, resulting in an overall decrease in cancellations of 12.87 p.p. Looking at the marginal effects of *year* in our model, we find a second confirmation of our expectations: the joint probability of both cancelling an appointment and having one cancelled, according to our model, decreases from 9.1% in 2020 to 4.8% in 2021 (-4.3p.p.). These values are very similar to the joint probabilities of the descriptive statistics where the joint probabilities were 8.18% in 2020 and 3.7% in 2021, leading to a decrease of 4.48 p.p. from 2020 to 2021. Therefore, the correction made by our model to the initial data is small.

The remaining variables in the model were not significant in determining the probability of cancelling an appointment due to fear of the virus and having an appointment cancelled by a health service, so the only interpretation possible is that we cannot reject the null that these variables' coefficients are close to zero, meaning they have little or no contribution to predicting the probability of a cancellation. Health, education, age, gender, the amount of confidence one has in their primary care unit, and whether one suffers from a chronic disease do not seem to influence the probability of cancelling an appointment due to fear of contracting the virus. In addition, individuals do not seem to associate a longer waiting time to be seen at a health service with an increased probability of becoming infected. In terms of cancellations by the health services we find that education, self-assessed health, gender, age and economic condition were not taken into account when choosing which appointments to cancel, indicating that the latter were chosen at random.

In order to further understand how the significant variables in the model behave in 2020 and 2021 separately, we reran the model with some interaction terms between *year* and the following variables: *chronic_patient*, *avoid_crowd*, *economic_condition*, and *female*. Marginal effects of these interaction terms show that the interpretations above are valid for both 2020 and 2021 individually. We also find that for each category within these variables, the joint probability of cancelling an appointment or having one cancelled by a health service consistently decreases from 2020 to 2021. The result that most stands out here is the fact that this probability decreases considerably less for individuals with worse economic conditions, compared to those with better conditions. Graphs with the marginal effects of these interaction terms can be found in Appendix 3.

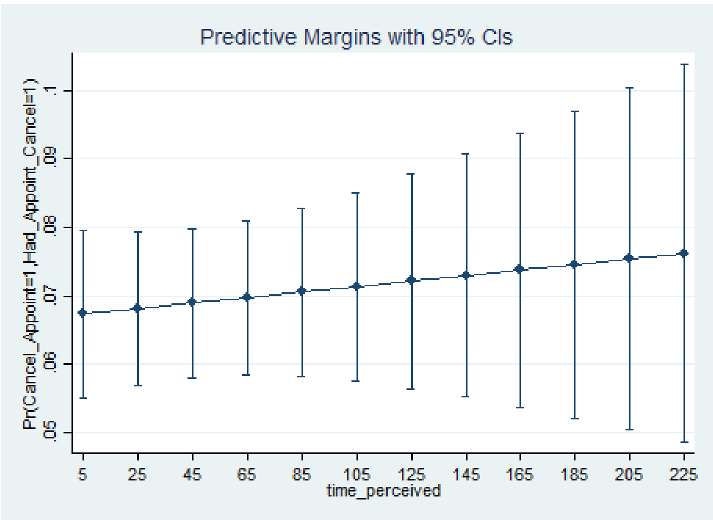
To provide a better understanding of the results discussed, the tables below present the marginal effects of the joint probability of cancellations for the variables in Models 1 and 2.

Table 5 - Marginal effects of the joint probability of both cancelling an appointment and having one cancelled by a health service for the variables in Models 1 and 2. Marginal effects for time_perceived are presented in Figure 1 to facilitate interpretation.

Variable – Model 1		**Margin**	**Variable – Model 2**		**Margin**
confidence_pcu	small	0.060			
	medium	0.070			
	high	0.069			
chronic_patient	0	0.061	*chronic_patient*	0	0.046
	1	0.081		1	0.078
avoid_crowd	0	0.043	*avoid_crowd*	0	0.035
	1	0.075		1	0.063
health_perceived	very bad / bad	0.071			
	intermediate	0.088			
	good / very good	0.055			
age	15-24	0.063	*age*	15-24	0.048
	25-34	0.065		25-34	0.050

	35-44	0.066		35-44	0.053
	45-54	0.068		45-54	0.056
	55-64	0.069		55-64	0.058
	65-74	0.071		65-74	0.061
	75-84	0.072		75-84	0.064
	85-94	0.074		85-94	0.066
education	1	0.067			
	2	0.068			
	3	0.083			
female	male	0.062	*female*	0	0.052
	female	0.074		1	0.060
economic_condition	very difficult	0.075	*ec_somewhat_easy*	0	0.065
	difficult	0.088		1	0.045
	somewhat easy	0.055	*ec_easy*	0	0.061
	easy	0.036		1	0.026
er_visits	0	0.054	*er_visits*	0	0.043
	1	0.083		1	0.072
	2	0.123		2	0.115
	3	0.174		3	0.172
	4	0.237		4	0.245
year	2020	0.091	year	2020	0.074
	2021	0.048		2021	0.040

Figure 1 - Marginal effects of the joint probability of both cancelling an appointment and having one cancelled by a health service for the variable time_perceived.



In contrast, by construction, all variables in Model 2 are highly significant, although magnitudes are in line with the remaining models. The main finding is that there were no changes to the polarity of the coefficient for any variable, conclusions are, therefore, kept mostly unchanged, at least for variables that were already significant in Model 1. However, increases in significance did allow for some slight changes in the interpretation of certain variables. Overall, variables that were already significant at the 1% significance level in Model 1 maintain their significance and those that were only significant at the 5% or 10% significance level become significant at the 1% level as well. The variables that are kept unaltered from one model to the other experience a very similar behaviour of marginal effects in both models, since, within each variable, marginal effects increase in the same direction for both models, i.e. if marginal effects, for example, for the variable *age* increase with the latter in Model 1, the same behaviour is evident in Model 2. In addition, most variables present a small decrease across marginal effects for all categories from Model 1 to Model 2. An exception to this is the variable *er_visits* which is the only variable that, although remaining unchanged from one model to the other, experiences a decrease in marginal effects around 1 p.p. from Model 1 to Model 2 for most values of the variable (0 to 3) and then an increase in marginal effects of 0.8 p.p. from Model 1 to Model 2 in the remaining value (4). In particular, differences between marginal effects in the two models for this variable are smaller in the centre value (2) and larger in the extremes (0 and 4).

The variable that is not kept unchanged from one model to the next is *economic_condition*, while in Model 1 we consider the variable *economic_condition* as a whole, in Model 2, we are only considering the two highest categories within this variable and treating them as individual binary variables (*ec_somewhat_easy* and *ec_easy*). These separate categories proved to be more significant when entering the model independently and, as with most variables, in Model 2 their marginal effects are approximately 1 p.p. smaller than in Model 1. Becoming more significant means that we can affirm at a higher significance level that people with better economic conditions are less likely to cancel an appointment due to fear of infection.

Finally, the variables whose significance changed the most were *female* and *age*. Although in Model 1 we could not reject the null that *female*'s coefficient was close to zero at a 5% significance level, in Model 2 it is now possible to reject this hypothesis at a 1% significance level, leading to a stronger conclusion that women are more likely to have an appointment cancelled by a health service. As *female* becomes more significant when removing several variables from the model, it is likely that some of the variables that were removed when building Model 2 explained part of *female*'s behaviour in predicting the likelihood of having an appointment cancelled and were serving as controls by decreasing part of the significance of the variable that can be explained by factors other than health services selecting more women's appointments to cancel.

On the other hand, *age* was not a significant variable in either of the equations in Model 1 but, when removing some of the variables from the model, the latter becomes significant at a 5% significance level in predicting the probability of cancelling an appointment. This way, we decided to include *age* in equation (3), making it significant in predicting that older people are more likely to cancel an appointment out of fear of the virus. Since older individuals are more likely to have severe symptoms and are considered, in general, of higher risk, it would make sense that they act as being more risk averse, and thus more likely to cancel an appointment.

Overall, we find that individuals regained confidence in the Portuguese health system in 2021 and that risk averse individuals and those with lower economic condition are more likely to cancel an appointment due to fear of infection in both years. Unfortunately, it seems that, although in general probabilities of cancellations decreased from 2020 to 2021 across all categories of all variables, individuals with greater difficulty in making ends meet have a reduction in the joint probability of cancellations that is much smaller than the other three categories of *economic_condition*. Apparently, health services canceled appointments at random (for the external observer) and according to the severity of the situation underlying the appointments (*chronic_patients* being one of the few significant variables here), preserving neutrality to income and other characteristics that would be discriminatory without reason.

5.2. Robustness check

A robustness check was performed using four separate OLS models, mimicking Models 1 and 2 and the two equations that each contains. The equations (5 to 8) for these four robustness check models can be found in Appendix 4. Table 6 shows the results for the OLS models next to the equivalent results for the bivariate probits, to facilitate comparison between the two. A table with the coefficients, significances, and standard errors of both OLS and probit models can be found in Appendix 5.

Table 6 - Comparison of OLS's coefficients with the differences in marginal effects for the probits. Significances of coefficients are identified by the asterisks (p<0.1, ** p<0.05, *** p<0.01).*

	OLS 1	**Model 1**	**OLS 2**	**Model 2**
CANCEL_APPOINT				
confidence_pcu (medium)	0.010	0.024	-	-
confidence_pcu (high)	-0.009	0.023	-	-
chronic_patient	-0.019	-0.015	-	-
avoid_crowd	0.051***	0.050***	0.041***	0.042***
health_perceived (medium)	0.000	0.008	-	-
health_perceived (good / very good)	-0.048	-0.033	-	-
age_c (30-44)	0.259	0.008	0.023	0.010**
age_c (45-64)	-0.022	0.017	-0.002	0.021**
age_c (65-79)	0.043	0.029	0.058***	0.037**
age_c (80-94)	0.052	0.039	0.043	0.050**
education (6^{th}-12^{th} grade)	0.006	0.004	-	-
education (university)	0.023	0.046	-	-
female	0.008	0.013	-	-
time_perceived_c (medium)	0.059	0.003	-	-
time_perceived_c (long)	-0.019***	0.006	-	-
economic_condition (difficult)	-0.001	0.008	-	-
economic_condition (somewhat easy)	-0.067**	-0.055**	-0.071***	-0.055***
economic_condition (easy)	-0.106***	-0.105***	-0.105***	-0.086***
er_visits (1)	0.087***	0.043***	0.101***	0.045***
er_visits (2)	0.107***	0.095***	0.126***	0.103***
er_visits (3)	0.150**	0.156***	0.136**	0.172***
er_visits (4)	0.131**	0.411***	0.151***	0.251***
year (2021)	-0.041***	-0.047***	-0.042***	-0.040***
HAD_APPOINT_CANCEL				
chronic_patient	0.134***	0.119***	0.158***	0.157***
avoid_crowd	0.057***	0.064***	0.059***	0.310***
health_perceived (medium)	0.051	0.053	-	-
health_perceived (good / very good)	-0.010	-0.020	-	-
age_c (30-44)	-0.018	-0.005	-	-
age_c (45-64)	0.004	-0.010	-	-
age_c (65-79)	-0.005	-0.016	-	-
age_c (80-94)	-0.049	-0.020	-	-
education (6^{th}-12^{th} grade)	0.004	-0.005	-	-
education (university)	0.022	0.000	-	-
female	0.034*	0.030*	0.038***	0.035***

economic_condition (difficult)	0.025	0.037	-	-
economic_condition (somewhat easy)	-0.019	-0.004	-	-
economic_condition (easy)	-0.006	0.019	-	-
er_visits (1)	0.065***	0.058***	0.071***	0.061***
er_visits (2)	0.133***	0.126***	0.146***	0.136***
er_visits (3)	0.254***	0.203***	0.261***	0.223***
er_visits (4)	0.296***	0.473***	0.296***	0.319***
year (2021)	-0.092***	-0.112***	-0.095***	-0.092***

When building the OLS model, we altered the continuous variables (*er_visits*, *time_perceived*, and *age*), transforming them into categorical variables. The goal was to create a non-parametric OLS model so that it contrasted with the probit models (which are parametric). Comparing Model 1 with the equivalent OLS model, we find that most results are similar and that, in general, our conclusions should not change for the OLS.

One of the few differences is the fact that while in Model 1 individuals with very good economic condition were more likely to have an appointment cancelled by a health service than those with very bad economic conditions, in the OLS model the opposite seems to happen. However, this variable is not significant in either model so we can only conclude that both models indicate a very small impact of economic condition on predicting the likelihood of having an appointment cancelled. The other two variables that exhibit some differences are *age* and *time_perceived*, in this case in terms of significance. While in Model 1 *time_perceived* is not significant, the third category of this variable (91 to 240 minutes of waiting time) is significant (1%) in the OLS model. Similarly, in Model 2 *age* is a continuous variable and significant at the 5% significance level, while in the OLS that mimics model 2, only the fourth interval is significant (65 to 79 years of age), at the 1% significance level.

Finally, we find that all the models present similar results in terms of the probabilities of cancellations between 2020 and 2021. While the probability of cancelling an appointment due to fear of infection decreases from 2020 to 2021 by 4.7 p.p. in Model 1 and 4.1 p.p. in OLS 1, the probability of having an appointment cancelled by a health service decreases from 2020 to 2021 11.2 p.p., according to Model 1, and 9.2 p.p., according to OLS 1 (similar results for both types of cancellations for Model 2 and OLS 2).

6. CONCLUSION

Our goal with this study was to discover whether a year on the pandemic was enough for the Portuguese health system to start recovering and for the public to regain trust in the latter, so as to understand how both supply and demand of healthcare might behave in the presence of a shock of the magnitude that the pandemic took. When analysing our results for the bivariate probit (Model 1) we found that many variables had little or no significance in determining the probability of either cancelling of having an appointment cancelled by a health service. Variables proving to be very significant in deciding the probability of one or both types of cancellations happening were *chronic_patient*, *avoid_crowd*, *economic_condition*, *er_visits*, and *year*.

We found evidence that patients suffering from chronic illnesses are 11.9 p.p. more likely than patients who do not have a chronic illness of having an appointment cancelled by a health service. In addition, risk averse individuals (those who avoid crowds) have a joint probability of cancelling or having an appointment cancelled of 7.5%, while non-risk-averse individuals have a probability of only 4.4%. As we move from a very bad economic condition to a very good one, the probability of a cancellation due to fear of becoming infected decreases considerably. Comparing individuals with very big difficulties in making ends meet with those with ease in doing so, the probability of cancellation decreases 10.5 p.p. Finally, while individuals who did not go once to the ER in the past year had a joint probability of cancelling an appointment due to fear of infection and having one cancelled by a health service of 5.4%, those who went 4 times had a probability of 23.5%.

Results for the OLS regression constructed with the goal of checking the robustness of our model were very similar to the ones mentioned above. So were the ones from Model 2 (in which all variables were significant, by construction).

To sum up, for the most part, these results match our initial expectations, especially since results show that the probability of cancelling an appointment due to fear of infection decreases around 4.5 p.p. in all models and that of having an appointment cancelled by a health service decreases around 10 p.p. in all models. We also find that the joint probability of both cancelling and having an appointment cancelled by a health service decreased from 9.2% in 2020 to 4.7% in 2021 (Model 1). This leads us to determine that indeed one year was enough for health services to start recovering and individuals to regain trust. We also conclude that health services choose appointments to cancel according to the urgency of appointments and at random, variables such as age, sex, education and economic conditions not playing a part in this decision. However, there is also evidence that economic condition plays a role in determining whether an individual cancels an appointment and lower economic conditions showed a smaller decrease in cancellations between the two years.

Since our data limited our analysis to our main goal, there are several opportunities for further analysis around this topic with a more detailed database. Namely, it would be relevant to determine how these cancellations are divided between hospital appointments and appointments at primary care units, or between the public and private sectors to see whether the different sectors coped with the pandemic in different ways, and which recovered faster. Another possibility would be to study the actual impact of the pandemic on cancellations of health service appointments by individuals, by calculating the weight that cancellations motivated by fear of infection had in the total amount of cancellations. We consider it interesting to repeat this study for the following years, to further determine the evolution of health services and individuals' confidence in the latter and derive a picture of any existing long-term effects of the pandemic. In addition, including data on vaccination as an explanatory variable would allow for an analysis of the efficiency of this policy in returning supply and demand of health services' appointments to their pre-pandemic values.

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8. APPENDIX

Appendix 1 – Comparison of Model 1 with and without the variable *er_visits*

Table 7 - Comparison of Model 1 with and without er_visits. Significance of coefficients is identified by the asterisks (p<0.1, ** p<0.05, *** p<0.01). Standard errors are below each coefficient in brackets.*

	Model 1	**Model 1 without *er_visits***
CANCEL_APPOINT		
confidence_pcu (medium)	0.128	0.142
	(0.201)	(0.204)
confidence_pcu (high)	0.119	0.120
	(0.195)	(0.199)
chronic_patient	-0.073	-0.050
	(0.098)	(0.097)
avoid_crowd	0.268***	0.236**
	(0.099)	(0.097)
health_perceived (medium)	0.035	-0.091
	(0.156)	(0.152)
health_perceived (good / very good)	-0.160	-0.357**
	(0.178)	(0.171)
age	0.003	0.001**
	(0.003)	(0.003)
education (6th-12th grade)	0.035	0.028
	(0.108)	(0.108)
education (university)	0.214	0.209
	(0.157)	0.156
female	0.062	0.051
	(0.076)	(0.075)
time_perceived	0.001	0.001
	(0.001)	(0.001)
economic_condition (difficult)	0.037	0.065
	(0.111)	(0.109)
economic_condition (somewhat easy)	-0.263**	-0.260**
	(0.116)	(0.114)
economc_condition (easy)	-0.611***	-0.618***
	(0.182)	(0.181)
er_visits	0.205***	-
	(0.042)	-
year	-0.232***	-0.215***
	(0.078)	(0.077)
HAD_APPOINT_CANCEL		
chronic_patient	0.458***	0.492***
	(0.089)	(0.088)
avoid_crowd	0.284***	0.298***
	(0.093)	(0.093)
health_perceived (medium)	0.206	0.055
	(0.144)	(0.140)
health_perceived (good / very good)	-0.087	-0.308*

	(0.166)	(0.159)
age	-0.001	-0.004
	(0.003)	(0.003)
education (6th-12th grade)	-0.021	-0.001
	(0.100)	(0.101)
education (university)	0.001	-0.034
	(0.147)	(0.147)
female	0.128*	0.135*
	(0.071)	(0.071)
economic_condition (difficult)	0.154	0.165
	(0.109)	(0.107)
economic_condition (somewhat easy)	-0.018	-0.038
	(0.112)	(0.111)
economic_condition (easy)	0.080	0.034
	(0.152)	(0.152)
er_visits	0.233***	-
	(0.040)	-
year	-0.463***	-0.437***
	(0.074)	(0.073)

As explained above, the decision to include *er_visits* in the model initially arose as an attempt to explain the gender variable's behaviour, through the rationale that women are more likely to have an appointment cancelled or cancel one themselves because they are more likely to have appointments booked in the first place (Briscoe (1987), Deb and Trivedi (2002), among others). Regardless, of this variable no longer being significant when excluding er_visits from our model, we found that the latter was highly significant and decided to include it in our final model. When comparing the outputs for both models (with and without *er_visits*), the variable that stands out the most is actually *health_perceived*. In specific, the p-values of self-reported good / very good health's coefficients, increase by a multiple of almost 10, when *er_visits* is included. Since *er_visits*' coefficients are both positive and *health_perceived*'s third category's are negative, results lead us to conclude that people who self-perceive as having a good or very good health state, in general, book less hospital visits than those who believe they have an intermediate, bad, or very bad health state. This explains why, without the control variable, individuals with good or very good self-assessed health had significantly less probability of both cancelling an appointment and having an appointment cancelled by a health service.

Appendix 2 – Equations for Model 2 (significant variables only, by construction)

Equation 3 – Decision to cancel appointment in a health centre (demand side) – Model 2

$$(3)\ cancel\_appoint = \beta_0 + \beta_1 avoid\_crowd + \beta_2 age + \beta_3 ec\_somewhat\_easy + \beta_4 ec\_easy + \beta_5 er\_visits + \beta_6 year$$

Equation 4 – Having a visit to a health centre cancelled (supply side) – Model 2

$$(4)\ had\_appoint\_cancel = \beta_0 + \beta_1 chronic\_patient + \beta_2 avoid\_crowd + \beta_3 female + \beta_4 er\_visits + \beta_5 year$$

Appendix 3 – Marginal effects of the four interaction terms

Figure 2 - Marginal effects of the interaction term avoid_crowd#year

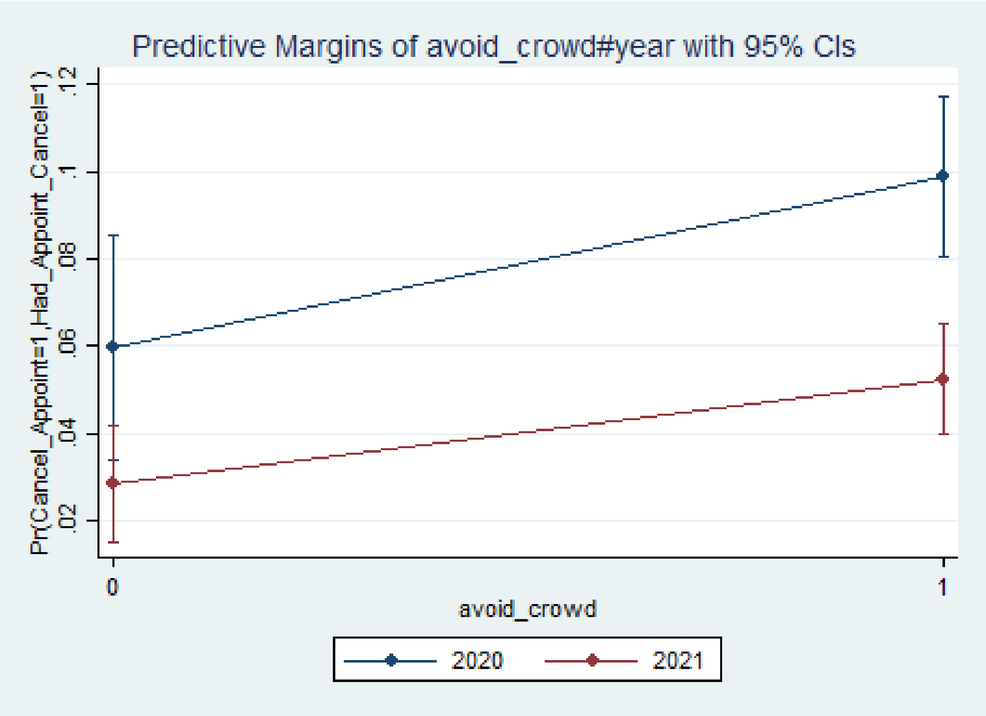


Figure 3 - Marginal effects of the interaction term chronic_patient#year

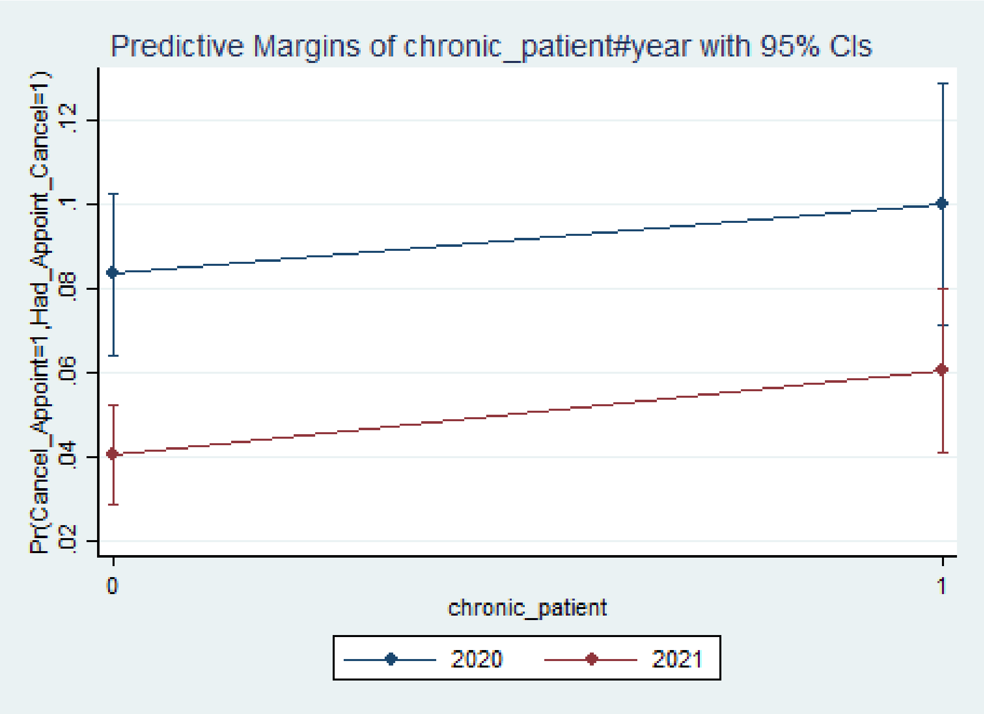


Figure 4 - Marginal effects of the interaction term economic_condition#year

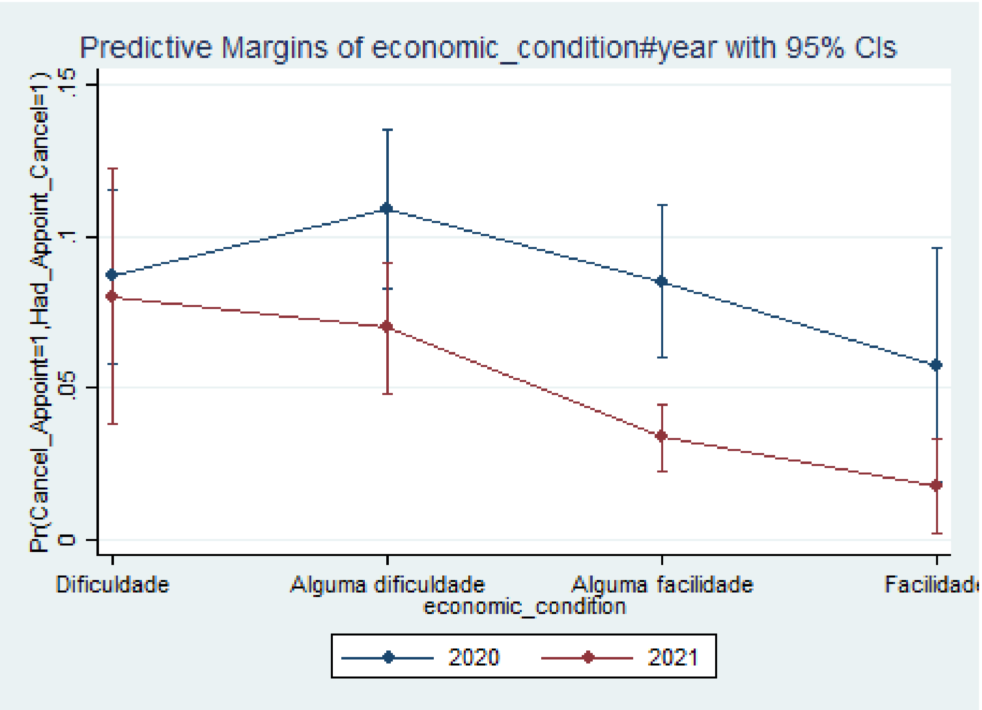
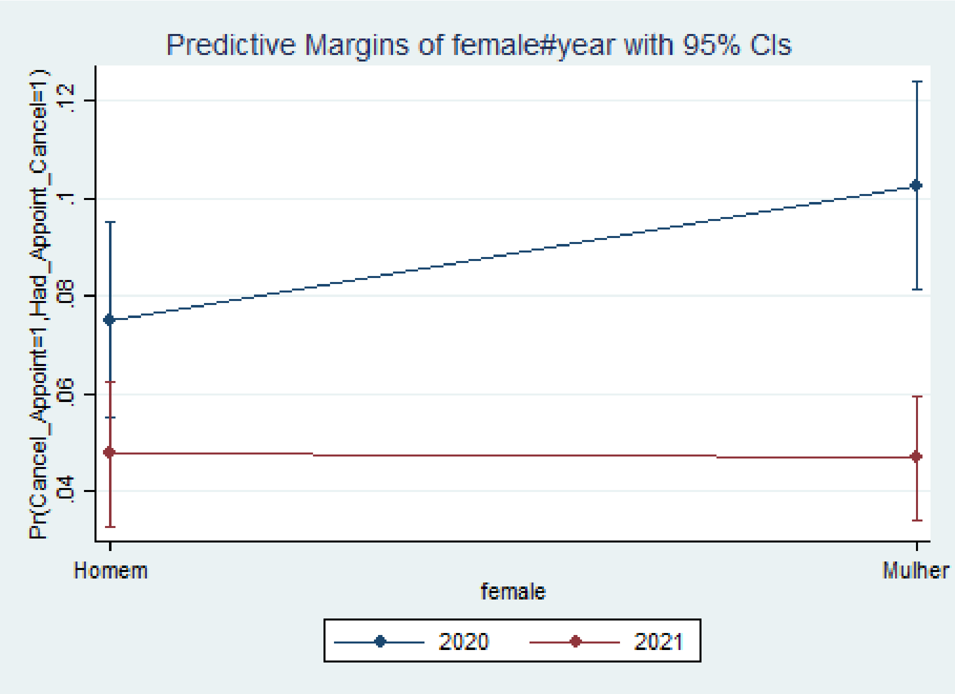


Figure 5 - Marginal effects of the interaction term female#year



To understand how the significant variables in the model behave in 2020 and 2021 separately, we reran the model with some interaction terms: *chronic_patient#year*, *avoid_crowd#year*, *economic_condition"year*, and *female#year*. Marginal effects of these interaction terms show that for each category within these variables, the probability of either cancelling an appointment or having one cancelled by a health service consistently decreases from 2020 to 2021.

Although both risk averse and chronic patients are more likely to cancel or have an appointment cancelled by a health service than individuals who are not risk averse or do not suffer from a chronic illness and these results are true for both years individually, we find that the probability of any of these categories of individuals cancelling an appointment or having an appointment cancelled decreases from 2020 to 2021. In addition, we find that women are more likely to have an appointment cancelled by a health service in both years, even though both men and women's likelihood of having a cancellation decreases from 2020 to 2021. We do, however, find that the largest difference in cancellations between genders is evident in 2020. Finally, not only do cancellations due to fear of infection decrease from 2020 to 2021 in all categories of *economic_condition* but as economic condition increases, the decrease in the probability of a cancellation from 2020 to 2021 becomes considerably larger (especially when comparing the evolution, the two lowest levels to that of the two highest). This indicates that individuals with better economic conditions regained trust in the health services faster than those with more difficulties in making ends meet.

Appendix 4 – Equations for Robustness Check models: OLS 1 and OLS 2

Equation 5 – Decision to cancel appointment in health centre (demand side) – OLS 1

$$(5)\ cancel\_appoint = \beta_0 + \beta_1 confidence\_pcu + \beta_2 chronic\_patient + \beta_3 avoid\_crowd + \beta_4 health\_perceived + \beta_5 age\_c + \beta_6 education + \beta_7 female + \beta_8 time\_perceived\_c + \beta_9 economic\_condition + \beta_{10} er\_visits + \beta_{11} year$$

Equation 6 – Having a visit to a health centre cancelled (supply side) – OLS 1

$$(6)\ had\_appoint\_cancel = \beta_0 + \beta_1 chronic\_patient + \beta_2 avoid\_crowd + \beta_3 health\_perceived + \beta_4 age\_c + \beta_5 education + \beta_6 female + \beta_7 economic\_condition + \beta_8 er\_visits + \beta_9 year$$

Equation 7 – Decision to cancel appointment in a health centre (demand side) – OLS 2

$$(7)\ cancel\_appoint = \beta_0 + \beta_1 avoid\_crowd + \beta_2 age\_c + \beta_3 ec\_somewhat\_easy + \beta_4 ec\_easy + \beta_5 er\_visits + \beta_6 year$$

Equation 8 – Having a visit to a health centre cancelled (supply side) – OLS 2

$$(8)\ had\_appoint\_cancel = \beta_0 + \beta_1 chronic\_patient + \beta_2 avoid\_crowd + \beta_3 female + \beta_4 er\_visits + \beta_5 year$$

Appendix 5 – Comparison of Models 1 and 2 with their equivalents in the OLS models

Table 8 - Comparison between Models 1 and 2 and the OLS models. Standard errors in brackets. Significances represented by asterisks (p<0.1, ** p<0.05, *** p<0.01).*

	OLS 1	**Model 1**	**OLS 2**	**Model 2**
CANCEL_APPOINT				
confidence_pcu (medium)	0.010	0.128	-	-
	(0.044)	(0.201)		
confidence_pcu (high)	-0.009	0.119	-	
	(0.043)	(0.195)		
chronic_patient	-0.019	-0.073	-	-
	(0.021)	(0.098)		
avoid_crowd	0.051***	0.268***	0.041***	0.242***
	(0.019)	(0.099)	(0.015)	(0.087)
health_perceived (medium)	0.000	0.035	-	-
	(0.036)	(0.156)		
health_perceived (good / very good)	-0.048	-0.160	-	-
	(0.040)	(0.178)		
age_c (30-44)	0.259		0.023	
	(0.230)		(0.018)	
age_c (45-64)	-0.022		-0.002	*age:*
	(0.024)	*age:*	(0.018)	0.004**
age_c (65-79)	0.043	0.003	0.058***	(0.002)
	(0.032)	(0.003)	(0.022)	
age_c (80-94)	0.052		0.043	
	(0.050)		(0.037)	
education (6th-12th grade)	0.006	0.035	-	-
	(0.023)	(0.108)		
education (university)	0.023	0.214	-	-
	(0.033)	(0.157)		
female	0.008	0.062	-	-
	(0.015)	(0.076)		
time_perceived_c (medium)	0.059		-	
	(0.017)	*time_perceived:*		
time_perceived_c (long)	-0.019***	0.001	-	-
	(0.029)	(0.001)		
economic_condition (difficult)	-0.001	0.037	-	-
	(0.025)	(0.111)		
economic_condition (somewhat easy)	-0.067**	-0.263**	-0.071***	-0.303***
	(0.025)	(0.116)	(0.014)	(0.071)
economic_condition (easy)	-0.106***	-0.611***	-0.105***	-0.617***
	(0.333)	(0.182)	(0.021)	(0.129)
er_visits (1)	0.087***		0.101***	
	(0.023)		(0.020)	
er_visits (2)	0.107***	*er_visits:*	0.126***	*er_visits:*
	(0.032)	0.205***	(0.028)	0.234***
er_visits (3)	0.150**	(0.042)	0.136**	(0.037)
	(0.061)		(0.053)	
er_visits (4)	0.131**		0.151***	
	(0.062)		(0.054)	
year	-0.041***	-0.232***	-0.042***	-0.216***
	(0.016)	(0.078)	(0.013)	(0.070)

HAD_APPOINT_CANCEL				
chronic_patient	0.134***	0.458***	0.158***	0.633***
	(0.020)	(0.089)	(0.016)	(0.065)
avoid_crowd	0.057***	0.284***	0.059***	0.320***
	(0.017)	(0.093)	(0.017)	(0.084)
health_perceived (medium)	0.051	0.206	-	-
	(0.035)	(0.144)		
health_perceived (good / very good)	-0.010	-0.087	-	-
	(0.038)	(0.166)		
age_c (30-44)	-0.018		-	
	(0.020)			
age_c (45-64)	0.004		-	
	(0.021)	*age:* -0.001 (0.003)		-
age_c (65-79)	-0.005		-	
	(0.031)			
age_c (80-94)	-0.049		-	
	(0.047)			
education (6th-12th grade)	0.004	-0.021	-	-
	(0.022)	(0.100)		
education (university)	0.022	0.001	-	-
	(0.030)	(0.147)		
female	0.034*	0.128*	0.038***	0.165***
	(0.014)	(0.071)	(0.014)	(0.062)
economic_condition (difficult)	0.025	0.154	-	-
	(0.024)	(0.109)		
economic_condition (somewhat easy)	-0.019	-0.018	-	-
	(0.024)	(0.112)		
economic_condition (easy)	-0.006	0.080	-	-
	(0.030)	(0.152)		
er_visits (1)	0.065***		0.071***	
	(0.022)		(0.022)	
er_visits (2)	0.133***		0.146***	
	(0.031)		(0.031)	
er_visits (3)	0.254***	*er_visits:* 0.233*** (0.040)	0.261***	*er_visits:* 0.266*** (0.036)
	(0.059)		(0.058)	
er_visits (4)	0.296***		0.296***	
	(0.061)		(0.060)	
year	-0.092***	-0.463***	-0.095***	-0.425***
	(0.015)	(0.074)	(0.014)	(0.065)

The difference between this table and Table 6 is that while Table 6 represents the differences between the marginal effects of each category of each variable and the first category of that variable (which is equivalent to the OLS coefficients but not to the probit ones), this table shows a comparison between the coefficients of each model, with respective standard errors and significances.