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# **Do long waiting times worsen health outcomes of patients with cardiovascular diseases? A study using data from SHARE survey**

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## **Abstract**

Long hospital waits are causing frustrations among patients and are a fiercely debated topic in many OECD countries. Peoples are worrying about that long waiting times might cause deterioration in patients' health. This study investigates whether waiting times have any adverse impact on health in patients with cardiovascular diseases. Using a cross-national sample derived from the Survey of Health, Ageing and Retirement in Europe (SHARE), we estimate the effects of waiting times on three different aspects of health outcomes: self-perceived physical and general health, self-perceived mental health and self-perceived life-expectancy. Our results show that, on one hand, waiting times for non-emergency consultation have generally no adverse impacts on patients' self-perceived health and, on the other hand, waiting times for emergency consultation and excessive waiting time are associated with several types of deteriorations in self-perceived general health and mental health. Hence, health policy should be designed to reduce emergency waits and excessive waits. Additionally, given that hospital waiting list is an ineffective way to ration excessive healthcare demand and creates a deadweight loss to the society, further research on its replacements are therefore required.

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# Table of Contents

<b>Abbreviations</b> .....	3
<b>1 Introduction</b> .....	4
1.1 Purpose and scope .....	4
1.2 Literature .....	5
1.3 Structure .....	7
<b>2 Background</b> .....	8
2.1 Healthcare systems in different OECD countries.....	8
2.1.1 <i>The Beveridge model</i> .....	8
2.1.2 <i>The Bismarck model</i> .....	9
2.2 Waiting times for cardiovascular health care in different OECD countries.....	10
<b>3 Theories</b> .....	12
3.1 Hospital waiting time in economic theory.....	12
3.1.1 <i>The waiting list procedure</i> .....	12
3.1.2 <i>Theories of rationing by waiting list</i> .....	12
3.2 Alternative rationing mechanism .....	13
3.2.1 <i>Threshold rationing</i> .....	14
3.2.2 <i>Price rationing</i> .....	14
3.3 The efficiency of different rationing mechanisms.....	15
<b>4 Methods</b> .....	17
4.1 Measures of waiting time and research strategy.....	17
4.2 Main analysis.....	18
4.2.1 <i>Effect of waiting times on self-perceived physical and general health</i> .....	18
4.2.2 <i>Effect of waiting times on self-perceived mental health</i> .....	20
4.2.3 <i>Effect of waiting times on self-perceived life expectancy</i> .....	21
4.3 Complementary analysis .....	24
<b>5 Data</b> .....	25
<b>6 Results</b> .....	27
6.1 Descriptive statistics.....	27
6.2 Self-perceived physical and general health .....	27
6.3 Self-perceived mental health .....	29
6.4 Self-perceived life expectancy .....	30
6.5 Results from the complementary analysis.....	31
6.5.1 <i>General health</i> .....	31
6.5.2 <i>Mental health</i> .....	32
6.5.3 <i>Life expectancy</i> .....	32
<b>7 Sensitivity analysis</b> .....	34
<b>8 Discussion</b> .....	36
8.1 Policy implications .....	36

8.2	Comparison with previous studies.....	37
8.3	Methodological limitations.....	38
8.4	Extrapolation to other contexts.....	39
<b>9</b>	<b>Conclusion</b> .....	<b>40</b>
	<b>References</b> .....	<b>41</b>
	<b>Appendix</b> .....	<b>45</b>
	Appendix I: Data source.....	45
	Appendix II: Descriptive statistics .....	46
	Appendix III: Regression tables from the main analysis.....	49
	Appendix IV: Regression tables from the complementary analysis.....	61
	Appendix V: Results from the sensitivity analysis.....	68

## Abbreviations

<b>BMI</b>	Body Mass Index
<b>CABG</b>	Coronary artery bypass grafting
<b>CAD</b>	Coronary artery disease
<b>GP</b>	General practitioner
<b>ISCED</b>	International standard classification of education
<b>LPM</b>	Linear probability model
<b>NHS</b>	National Health Service in England
<b>OECD</b>	Organisation for Economic Co-operation and Development
<b>PHI</b>	Private health insurance
<b>PTCA</b>	Percutaneous transluminal coronary angioplasty
<b>QoL</b>	Quality of life
<b>SHARE</b>	Survey of Health, Ageing, and Retirement in Europe
<b>SHI</b>	Statutory health insurance
<b>UNESCO</b>	United Nations Educational, Scientific and Cultural Organization
<b>WHO</b>	World Health Organization

# 1 Introduction

Queuing is a phenomenon which we encounter frequently in our everyday life. According to economic theory, queues may emerge as a result of excessive demand, which in turn occurred when the price of a certain good falls below the market-clearing level. ([Lindsay & Feigenbaum, 1984](#)). Among the various types of queues currently exist in our society, the queuing for health care is a subject of great importance. Long hospital waits have always been a sensitive political issue in many OECD countries, especially in those nations where the health care is publicly funded ([Siciliani & Hurst, 2005](#)). It causes large dissatisfaction among patients and has generally been considered as a problem resulted by inefficiency in the healthcare system ([Bhattacharya, Hyde, & Tu, 2014](#)). There are also profound concerns in that patients' condition of health may deteriorate as a result of long waiting times. The question is, however, is it always the case?

In this thesis, we use data from the Survey of Health, Ageing and Retirement in Europe (SHARE) to investigate whether hospital waiting times might cause deteriorations in the self-perceived health of patients who diagnosed with cardiovascular diseases (i.e. diseases that involve the heart and circulatory system) in twelve OECD countries<sup>1</sup>. The main reason for focusing on cardiovascular diseases is the prevalence of the illness. According to WHO, cardiovascular diseases are the leading cause of death globally and responsible for over 17.7 million deaths each year ([WHO, 2017a](#)). It is also the main cause of mortality in most OECD countries and accounting for 32.3% of all deaths in 2013 ([OECD, 2017](#)). Research concerning waiting times' effect on health outcomes of patients with cardiovascular diseases is therefore of high importance.

## 1.1 Purpose and scope

The main purpose of this thesis is to investigate the effect of waiting times on health by answering the following research question:

Do long waiting times worsen health outcomes of patients with cardiovascular diseases?

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<sup>1</sup> The number of countries included in this study is actually between 12 and 18. In the main analysis, 12 OECD countries are included; In the complementary analysis, 17 OECD countries plus Croatia are included. See section 5 for more details.

Our study is designed to be comprehensive and our main objective is to estimate the effect of waiting times on three different aspects of health outcome, that is to say, the self-perceived physical and general health, the self-perceived mental health, and the self-perceived life expectancy. Based on the waiting time variables provided in SHARE, we conduct two separate analyses: a main analysis and a complementary analysis. The difference between them is the waiting time variables in the main analysis are continuous whereas in the complementary analysis, a binary variable is used (more details in section 4.1).

Another purpose of our study is to form the basis for and give guidance to health policy decision-making. We will first interpret the results in combination with existing economic theories concerning waiting times and its role as a rationing mechanism. After that, a discussion about the policy implications of our results will be provided. According to [Gravelle and Siciliani \(2008b\)](#), rationing the demand for health services by waiting list is inefficient and creates a deadweight loss to the society. Hence, our starting point in the policy discussion is, if our results show that waiting times do affect the patients' self-perceived health negatively, then the alternative rationing methods, such as threshold rationing and price rationing, should be considered. ([Moscelli, Siciliani, & Tonei, 2016](#))

We believe that the strength of our studies lies in its broad coverage of various aspects of health. However, it is beyond the scope of this study to discuss *how* waiting times affect patients' health. We are merely investigating *if* waiting times are associated with any form of deterioration of health, as well as the size of its effect, if there are any.

## 1.2 Literature

Although it may seem intuitive that waiting times adversely affects the patients' health outcomes, there is little evidence in supporting it. The amount of empirical research on whether the hospital waiting times affect patients' health is limited, the majority of the currently existing literature on this topic is conducted using administrative data and focuses particularly on the post-surgery health outcomes. The outcome variables in these studies, such as inpatient mortality, post-surgical length of stay ([Barton H Hamilton & Bramley-Harker, 1999](#); [Barton H. Hamilton, Hamilton, & Mayo, 1996](#); [Barton H Hamilton, Ho, & Goldman, 2000](#)) and readmission rate ([Moscelli et al., 2016](#)), are often measured in an objective manner. Studies that applied such strategy find that there is no evidence of waiting times' adverse effect on health. In the case of emergency care, such as hip fracture surgery, [Barton H. Hamilton et al. \(1996\)](#)

employed a sample of 7848 hip fracture patients in Quebec and investigated the impact of pre-surgery delay (i.e. waiting times following a hip fracture) on inpatient mortality and post-surgical length of stay. Their conclusion is that waiting times have “little effect on either of the two outcome variables” ([Barton H. Hamilton et al., 1996, p. 161](#)). Similar results were obtained by [Barton H Hamilton and Bramley-Harker \(1999\)](#) when they investigated situations in the National Health Service (NHS) in England.

There have been several studies conducted concerning waiting times in cardiovascular care. A majority of them are medical studies by nature, focusing mainly on the correlation between waiting times in elective cardiovascular surgeries, such as coronary artery bypass grafting (CABG), and mortality. Based on a sample of 5453 patients from two Swedish hospitals, [Rexius et al. \(2005\)](#) concluded that there is no evidence suggesting mortality after CABG surgery would be influenced by prolonged waiting time. As for pre-surgery health outcomes, however, evidence has been found that queuing may increase the probability of dying while waiting for CABG surgery ([Rexius et al., 2004](#)). Compare to the medical literature, economic research concerning this issue is relatively scarce. [Moscelli et al. \(2016\)](#) made an attempt by using panel-data from the English Health Episode Statistics (HES), which covers the whole population of CABG patients in England, and concluded that long waits do not have any effect on in-hospital mortality, even though its effect on emergency readmission rate has weakly statistical significance.

While most of the studies on waiting time are conducted on administrative data and focus on extreme measures of health like mortality, little attention has been paid to the health outcomes of a subjective character, e.g. life expectancy and self-perceived health. Only a very few numbers of published articles have attempted to investigate the effect of waits in cardiovascular care on subjective health outcomes. [Jónsdóttir and Baldursdóttir \(1998\)](#) investigated the impact of waits on the quality of life (QoL) of patients awaiting CABG in Iceland and found negative effects of waits on the patients’ work and daily life. A similar result in Canada is obtained by [Sampalis et al. \(2001\)](#) using a larger sample, in which 266 patients with coronary artery disease (CAD) were included. Their conclusion is that long waiting times are associated with significant decrease in patients’ physical and social functioning, both before and after the CABG surgery.

Our study is therefore aimed to contribute to this scarcity of research in waiting times’ effect on self-perceived health. A key difference between our study and the studies of [Sampalis et al. \(2001\)](#) and [Jónsdóttir and Baldursdóttir \(1998\)](#) is that beside the self-perceived general health

and mental health, we also investigate the effect of waiting on self-perceived life expectancy (expressed as the probability of living after ten years). Additionally, we also use panel-level data to investigate whether waiting times have any adverse effect on patients' mental health in future periods. Furthermore, unlike these two studies, whose data are collected at a certain country, our analyses are based on data from the SHARE survey – which is a cross-national sample, that means our results are not limited in a single country. It is also the first time SHARE is used in investigating the adverse effect of waiting times. Among the published journal articles, only two studies concerning hospital waits are done based on the data from SHARE. [Mojon-Azzi and Mojon \(2007\)](#) conducted a descriptive study on the waiting time of cataract surgery in ten European countries using data from the first wave of SHARE; [Siciliani and Verzulli \(2009\)](#) used the same data to investigate the association between hospital waiting time and the socio-economic status of the patient. We will follow their approach in choosing and calculating control variables, especially the calculation of adjusted household income.

### **1.3 Structure**

This thesis will be structured as followed. Section 2 includes a brief overview of the healthcare system in those countries participated in the SHARE survey. Section 3 presents contemporary economic theories about different rationing mechanism in the healthcare market. We introduce our methods in Section 4 and in Section 5, a description of the SHARE-survey is given. Section 6 presents our results. The robustness of the results is tested by a sensitivity analysis, which described in Section 7. In Section 8, we will discuss the policy implications of our result in the light of the existing theories presented in section 3, we will also discuss some issues regarding the interpretations of our results and compare them with results from previous studies. Section 9 includes some concluding comments.



## 2 Background

### 2.1 Healthcare systems in different OECD countries

Before we enter the theory section, it is important to give the readers some background on different types of healthcare systems. Researchers usually divide the healthcare systems into three categories: national health system (also known as Beveridge model), social health insurance system (also known as Bismarck model) and private insurance/private provider system (also known as American model) ([Bhattacharya et al., 2014](#); [Lameire, Joffe, & Wiedemann, 1999](#); [Van der Zee & Kroneman, 2007](#)). In this section, we only introduce the Beveridge model and Bismarck model.

#### 2.1.1 The Beveridge model

The Beveridge model is based on the egalitarian idea that everyone should have equal access to care regardless of his or her ability to pay. The healthcare system in Beveridge countries is characterised by (1) universal, single-payer insurance, which means that all citizens receive insurance coverage through the government and the insurance is financed by taxes rather than premiums; (2) public health care provisions, which means hospitals and clinics in Beveridge countries are funded by government. Physicians, nurses and other hospital personnel are also public employees; and (3) free or low-cost health care at government hospitals and clinics. ([Bhattacharya et al., 2014](#)).

Sweden is an example of a country that applies a Beveridge system. The government involvement in the Swedish healthcare system is presented in all three levels: at the national level, the Ministry of Health and Social Affairs has the responsibility to decide policies with regard to overall health and healthcare; at the regional level, twelve county councils and nine regional bodies are responsible for financing, purchasing and providing all individual health services; at the local level, 290 municipalities are responsible for elderly care and the care of the disabled ([Mossialos et al., 2017](#); [OECD, 2017c](#)).

Sweden has the third highest health spending in the EU, and 84 % of the health expenditures are publicly financed, mainly by regionally and locally established taxes. However, the Swedish health care system does not completely follow the Beveridge model. A portion of health facilities in Sweden are privately run (mainly primary care units) and user charges (in the form of flat-rate payments) for primary and specialist care exists, even in government-run hospitals. ([OECD, 2017c](#))

The share of primary care units has increased fast since 2010 when a new national law to freely establish new primary care clinics with public reimbursement was passed. Residents are allowed to freely choose between primary care providers and contacting specialist directly ([OECD, 2017c](#)). Sweden has also implemented various types of maximum waiting-times guarantee for patients since 1992, but the results are hardly successful and all regions are struggling to meet these rules ([OECD, 2017c](#); [Siciliani & Hurst, 2005](#)). Other countries in this study that applies the Beveridge system are Denmark, Italy and Spain. ([OECD, 2017a](#))

### **2.1.2 The Bismarck model**

Contrary to the Beveridge ideal of regulated and nationalised health care, the core values of the Bismarck system are economic liberty and solidarity ([Bhattacharya et al., 2014](#)). In a Bismarck model, the provision of health care is partially private (in particular primary and ambulatory health care), and partially public ([Hassenteufel & Palier, 2007](#)). Hospitals and clinics in Bismarck countries tend to be privately run and the supply of health care is, for that reason, more abundant than in Beveridge countries, which allows the patients more freedom in choosing healthcare provider ([Bhattacharya et al., 2014](#); [Hassenteufel & Palier, 2007](#)). Another key feature of the Bismarck model is the universal health insurance. In Bismarck countries, nearly all of the population are covered by some kind of health insurance. The public health insurance is financed by payroll and other taxes, and not through insurance premiums based on individual health risks. This means that the healthier and wealthier member of the society are “paying” for the care of poorer and sicker member – a fine gesture of solidarity ([Bhattacharya et al., 2014](#)). Health insurance plan provided by private companies also exists in Bismarck countries, but they are often heavily regulated by the government ([Mossialos et al., 2017](#); [Bhattacharya et al., 2014](#)). In some Bismarck nations, such as France and Japan, the government are also involved in the price negotiations with hospitals. ([Bhattacharya et al., 2014](#); [Hassenteufel & Palier, 2007](#)).

Germany was the first country in the world to apply the social health insurance system. For all German citizens and permanent residents in the country, health insurance is mandatory and provided by two systems: statutory health insurance (SHI) and private health insurance (PHI) ([Mossialos et al., 2017](#); [OECD, 2017b](#)).

The SHI is competing, not-for-profit and nongovernmental ([Mossialos et al., 2017](#)). All employed citizens earning less than EUR 54,900 per annum (the threshold level in 2017)

are automatically covered by SHI. In 2017, there are totally 133 SHI in Germany and covers 88% of the population. Meanwhile, the PHI covers approximately 10 % of the German population. It is a substitutive insurance plan that follows a different rule for funding and financing compare with the SHI. Only peoples who earn above the EUR 54,900 threshold, self-employed and civil-servant can choose this type of insurance ([OECD, 2017b](#)).

Contrary to the Swedish case, the government in Germany has virtually no role in both the provision of health care and the financing ([Mossialos et al., 2017](#)). The German healthcare system is decentralised, the federal government defines the legal framework and delegates the regulatory issues to the Federal Joint Committee (German: *Gemeinsamer Bundesausschuss*), which is the highest decision-making body regarding health care in Germany. The Federal Joint Committee consists of representatives of associations of sickness funds, physicians/dentist, hospitals as well as patients' representatives (without voting right). The Committee takes decisions on SHI benefits, reimbursement systems, and quality assurance. Each of the 16 states in Germany supervises the self-governing bodies at state level and are in charge of hospital investments and planning ([OECD, 2017b](#)). Other than Germany, countries like Austria, Belgium, France, Israel, the Netherlands, and Switzerland also follows the Bismarck system. ([Mossialos et al., 2017](#); [OECD, 2017a](#))

## **2.2 Waiting times for cardiovascular health care in different OECD countries**

Although we will not conduct our analyses based on the data from OECD Health Statistics, it still contains valuable information which is relevant to our research question, namely, the severity of the waiting-time problem in cardiovascular care. The OECD Health Statistics provides data on waiting times for two medical procedures regarding cardiovascular diseases: (1) coronary artery bypass grafting (CABG), which is a common procedure for patients with serious coronary heart disease involving surgery that connects a healthy artery or vein from the body to the blocked coronary artery ([NHLBI, n.d](#)); and (2) percutaneous transluminal coronary angioplasty (PTCA), which is a less invasive procedure that improve blood circulation to the heart by open up blocked coronary arteries. ([Dugdale & Chen, 2012](#)).

Among the twelve countries that participated in the first wave of SHARE, Austria, Belgium, France, Germany, Switzerland, and Greece are absent from the statistics since these countries do not monitor waiting times at national level ([OECD Health Statistics, 2017a](#)). Furthermore, the waiting times are also measured in different ways in different countries. For coronary bypass surgery, OECD Health Statistics provides data for Denmark, Israel, Italy, the Netherlands, Spain, and Sweden. Lowest average days waiting from specialist assessment to treatment in 2015 was 9 days in Israel, while the highest was 46.7 days in Spain. Average days waiting was 19.8 days in Denmark, 22.3 days in Italy and 34.5 days in the Netherlands. In Israel, only 1% of patients had to wait more than three months to receive treatment after seeing a specialist, while the same number was 1.3% in Denmark, 4.9% in Italy and 17.8% in Spain ([OECD Health Statistics, 2017b](#)). OECD is unable to calculate the mean waiting time for Sweden since the waiting time data in this country are presented in intervals ([OECD Health Statistics, 2017a](#)). The waiting times in Sweden are also measured in a different way. Statistics show that in 2016, 8.5% of the patients on the CABG waiting list have waited more than three months for the surgery ([OECD Health Statistics, 2017b](#)).

Regarding percutaneous transluminal coronary angioplasty (PTCA), data from Denmark, Italy, the Netherlands and Spain are available. In 2015, the lowest average days waiting time from specialist assessment to treatment was 15.5 days in the Netherlands, followed by 16.5 days in Denmark, 20.7 days in Spain and 21.3 days in Italy. When the waiting times are measured in percentage of all patients waiting more than 3 months, the situation is slightly different. In 2015, no one (0%) in Spain has to wait more than 3 months for a PTCA surgery after his or her first assessment with the specialist, while this percentage was 1.6% in Denmark and 3.3% in Italy. ([OECD Health Statistics, 2017b](#))

## 3 Theories

### 3.1 Hospital waiting time in economic theory

In the economic theory, queues may emerge under these two circumstances: (1) as a by-product of fluctuations in market demand or supply (or both), where the market failed to adjust instantaneously; (2) when prices of a good is below or above the market-clearing level. The queueing for health care, which is a common phenomenon of countries who adopt the Beveridge model, belongs to the latter case. ([Lindsay & Feigenbaum, 1984](#))

As mentioned in section 2.1, in a Beveridge system, the health care is nationalised and provided at governmental hospital for free or at a very low cost ([Bhattacharya et al., 2014](#)). The demand of healthcare will therefore always exceed the supply. Since the price of healthcare is below the market-clearing level, the supply must be rationed at the point of use ([Lindsay & Feigenbaum, 1984](#)). Among those rationing mechanisms in the healthcare sector, rationing by waiting list is observed most frequently. ([Iversen & Siciliani, 2011](#))

#### 3.1.1 The waiting list procedure

For countries with a national health service, except in emergency situation, patients usually cannot refer themselves directly to a surgeon, a referral from their general practitioner (GP) is therefore required. When hospital receives GP's referral, the patient receives time for assessment by a hospital surgeon. During the assessment, the surgeon will investigate if the patient meets the threshold for her to be added on the waiting list. If the patient failed to fulfil the requirement, he/she will be referred back to the GP (or to another specialist). If it involves emergency, the patient will be proceeded to surgery without delay, otherwise they will be put on the hospital waiting list. Patients do not have to pay for joining the queue. At this stage, patients have also the choice of exit the queue and seek treatment in private care. ([Martin & Smith, 1999](#); [Siciliani & Hurst, 2005](#))

#### 3.1.2 Theories of rationing by waiting list

According to [Lindsay and Feigenbaum \(1984\)](#), the rationing power of hospital waiting list lies in the "influence of delay on the value of the service delivered" (p. 417). A key assumption in their theory is that the value of good or service perceived by a demander diminishes when the receipt is delayed. The longer one has to wait in order to obtain a certain good, the lower the value of that good is perceived by him. In case of health care, the membership of hospital waiting list costs nothing in monetary terms, and the queueing itself does not imply that the patient has to wait physically (i.e. no opportunity cost in terms of wasted time). Therefore, the

force that brings the demand for and supply of healthcare in equilibrium is the diminishing value of health service perceived by the patient due to waiting, rather than increasing cost of obtaining such service.

However, the fact that the membership of hospital waiting list is free does not necessarily imply there are no costs for an individual to join the list. Such cost may be the costs incurred to qualify for the waiting list or transaction costs. [Lindsay and Feigenbaum \(1984\)](#) argued that an individual will only join the hospital waiting list if his or her expected benefit from treatment exceed the costs. In the Lindsay-Feigenbaum framework of waiting list rationing, the costs are assumed to be constant with respect to waiting time; the expected benefits, as noted above, diminish over time and therefore will be discounted by the so-called decay rate. It is defined as “the rate at which the effect of treatment deteriorates as the waiting time goes by” ([Iversen, 1993, p. 67](#)). Furthermore, the decay rate is not merely an economic discounted device, it also reflects the negative effects associated to the delayed treatment, such as continued suffering, loss of earning and reduced QoL ([Martin & Smith, 1999](#)). Since both the expected benefits and the costs vary across individuals, the theory of Lindsay and Feigenbaum implies, waiting discourages demand in a way that patients with relatively low expected gain from the treatment are discouraged from joining the waiting list and thus rations the supply.

The contribution of waiting time on the convergence of demand and supply does not limit on the demand side. Empirical evidence has found concerning the positive influence of waiting times on the quantity of healthcare supplied. For instance, [Lindsay and Feigenbaum \(1984\)](#) showed that the waiting time is positively related to the cases treated per thousand population in British NHS. One possible explanation for this phenomenon is altruism. When waiting times are long, healthcare providers may exert greater effort and treat a larger volume of patients. In countries such as the UK, waiting time has the function of a performance indicator. Managers of hospitals may lose their job if the waiting times are too long, which gives them incentives to expand the volume of hospital activity in order to bring down waiting times. ([Iversen & Siciliani, 2011](#))

### **3.2 Alternative rationing mechanism**

Since there are some issues of inefficiency (reviewed in section 3.3) regarding to waiting time as rationing device, some alternatives rationing mechanism was discussed in previous studies.

This section includes a brief presentation of two alternatives to waiting time rationing: threshold rationing and price rationing.

### 3.2.1 Threshold rationing

The threshold rationing is similar to waiting time rationing in the sense that patients with highest benefits are prioritised for treatment. It is a type of non-price rationing mechanism under which all patients whose expected benefit are above a certain threshold level receives treatment without delay, while patients whose expected benefit are under this level are refused for treatment ([Gravelle & Siciliani, 2008a](#); [Iversen & Siciliani, 2011](#)). In order to implement threshold rationing, it is necessary that the patients benefit from treatment is observable to the healthcare provider. In practice, some characteristics of patients, such as age, could reveal information about their expected benefit and are observable to the providers ([Gravelle & Siciliani, 2008a](#)). However, if the providers could perfectly observe patients' expected benefit – which is seldom the case in practice – the threshold rationing is more efficient than waiting list rationing. The reason is that under threshold rationing, patients with high expected benefit do not suffer from the adverse effect associated with waiting, such as reduced utility from treatment. ([Iversen & Siciliani, 2011](#))

### 3.2.2 Price rationing

Rationing by price is common in countries where the provision of healthcare is privatised, such as Germany, France and the United States. Patients in these countries need to pay the healthcare provider in order to receive treatment. Since the treatment may not be affordable to everyone, especially those with low income, countries under this system usually provide health insurance to its citizen ([Bhattacharya et al., 2014](#)). However, in the insurance setting, the presence of moral hazard may lead to overconsumption of healthcare<sup>2</sup>. In order to reduce healthcare utilisation, some methods of cost-sharing are used, including co-payment (the insured pays a fixed amount for a given medical service), co-insurance (the insured pays a percentage of the total cost) and deductibles (a fixed amount that the insured must pay out-of-pocket before the coverage is provided) ([Chernew & May, 2011](#)). Evidence has been found that these “user fees” imposed on patients do have a negative effect on healthcare consumption. The price elasticity of healthcare demand is estimated approximately equal to -0.2 in the United States ([Manning et al., 2008](#)) and it may varies depending on the co-insurance rate.

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<sup>2</sup> For instance, if the insured knows that the insurance company will cover all her medical cost, she will then demand all medical care that provides her any positive utility, including expensive procedures which would give her little utility but cost the insurer millions. ([Bhattacharya et al., 2014](#))



([Zweifel & Manning, 2000](#)). However, several studies, conducted mainly in developing countries, have found a positive effect of the introduction of user fees on healthcare utilisation, indicating the effect of the unobserved variables that changes simultaneously as the user fee. ([Schokkaert & Van de Voorde, 2011](#))

### **3.3 The efficiency of different rationing mechanisms**

There are some arguments in favour of waiting time as a rationing mechanism. For instance, [Iversen \(1993\)](#) argued that increase in waiting time could decrease health providers' cost by decreasing the probability of idle capacity in the hospital. However, the consensus among economists is that waiting time rationing is inefficient. As noted in section 3.1, the patients' (consumers) expected benefit from treatment deteriorates while waiting. This creates a deadweight loss to the society because the decreased consumer welfare does not provide any gain to the provider in return ([Gravelle & Siciliani, 2008b](#); [Lindsay & Feigenbaum, 1984](#)). Therefore, waiting time rationing is inferior to price rationing, since the latter generates revenues to the healthcare provider ([Iversen & Siciliani, 2011](#)). Furthermore, the administration of waiting list requires resources. As noted by [Iversen \(1993\)](#), under the fixed budget, an increase in waiting time would permit capacity utilisation and temporarily increase the number of admissions. In the long run, however, the increased delay expands the waiting list and pull resources away from medical treatment to administrative tasks related to the waiting list, resulting in a decrease in treatment capacity and the number of admissions.

Regarding the threshold rationing, [Gravelle and Siciliani \(2008a\)](#) showed that it is still superior to waiting time rationing even if the providers cannot perfectly observe patients' expected benefit, by reason of the loss of those who were rejected from treatment does not outweigh the gain of patients with higher expected benefit accrue from immediate treatment. However, despite its efficiency, threshold rationing has not yet been implemented widely in practice. One possible explanation is that threshold rationing may generate disutility to the provider. Since hospitals are public-funded, patients who are being rejected for treatment might insist their right to health care (as taxpayers) and make a formal complaint to the hospital, which causes disutility for the hospital personnel ([Iversen & Siciliani, 2011](#)). Furthermore, the main idea behind nationalised health care is that everyone should be treated equally ([Bhattacharya et al., 2014](#)). The explicit refusal of treatment in threshold rationing might be politically controversial since it would violate the solidarity principle the Beveridge model based upon ([Iversen & Siciliani, 2011](#)).



Concerning the price rationing, as we have noted earlier, waiting time rationing are inefficient in comparison to this type of rationing. [Gravelle and Siciliani \(2008b\)](#) showed that a necessary condition for positive waiting time to be welfare optimal is the marginal cost of waiting is higher for those with small benefit from treatment. This seems unlikely to happen. It is more likely that this marginal cost is higher for patients with higher benefit from treatment, which is a sufficient condition for price rationing methods to dominate ([Iversen & Siciliani, 2011](#)). Regarding the optimal level of user fee, [Felder \(2008\)](#) concluded that neither no insurance nor full insurance is welfare optimal, the optimal co-insurance rate is a positive value smaller than one. He also shows that under certain circumstances, for instance when the choice of co-insurance rate is restricted, it might be optimal to maintain a positive waiting time. However, if co-insurance rate is set optimally, the optimal waiting time should equal to zero.

Price rationing also faces equity issues similar to threshold rationing. There is empirical evidence of the reduction of healthcare utilisation caused by user fee are stronger among the poor than the rich. Poor people are also more responsive to price changes and might postpone necessary treatment due to high user fee ([Schokkaert & Van de Voorde, 2011](#)). Therefore, price rationing methods might deprive low-income people of valuable care ([Bhattacharya et al., 2014](#)). Many countries (mainly developed economies) tried to mitigate these negative effects of user fee by introducing an exemption system. Examples for such arrangement can be granting reduction for a certain group or relate the maximum amount of user fee to individuals' level of income ([Schokkaert & Van de Voorde, 2011](#)). Another way to promote equity is to give tax breaks to non-profit hospitals, which deliver charity care to the poor ([Bhattacharya et al., 2014](#)).

## 4 Methods

In this section, we describe the methods and econometric framework of our study. Since nearly all our outcome variables are binary (except for some cases concerning self-perceived life expectancy), we use linear probability model (LPM) when estimating the effect of waiting times on health. LPM is one of the most widely-used techniques for estimating equations with binary outcomes and this research tactic has been employed by several influential health-related studies, including the Oregon Health Insurance Experiment ([Finkelstein et al., 2012](#)). Another argument in favour of LPM is its simplicity in the interpretation of coefficients comparing to the alternative methods, such as Logit and Probit ([Gujarati & Porter, 2009](#)). However, we use the Probit regression model as a sensitivity test in order to check the robustness of our estimated result.

### 4.1 Measures of waiting time and research strategy

The conventional measures of hospital waiting times are (1) *waiting time of patient selected for treatment* and (2) *waiting time of patient on the list at a census date*. The first one measures the period between the date at which the patient is added to the waiting list and the date of treatment; The second one measures the time that patients have waited on the list at a census date ([Iversen & Siciliani, 2011](#); [Siciliani & Hurst, 2005](#)). However, different measures of waiting times have been used in the SHARE surveys. In the first wave, there are two continuous variables concerning hospital waiting: *Days waiting for emergency consultation to specialist* and *Weeks waiting for non-emergency consultation*. These variables describe how long time the respondent (or more precisely, patients who diagnosed with cardiovascular diseases) has to wait for a certain consultation, which he or she had obtained during a twelve-months period before the date of interview<sup>3</sup>. ([Börsch-Supan et al., 2005](#)). Unfortunately, however, these two variables do not appear in later waves, since questions about hospital wait had not been asked after Wave 1. Nevertheless, there is one variable that relates indirectly to waiting time in Wave 5 and Wave 6, called *UnmetNeedWait*, which is a dummy variable that equal to one if the respondent has during past twelve months unable to meet a doctor due to too long waits. ([Börsch-Supan & Malter, 2015](#); "[Questionnaire Wave 5 \(English\)](#)," 2015)

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<sup>3</sup> Before the question about waiting time is asked, the respondents must answer a question about whether they have contact with a health specialist in past twelve month, if the answer is yes, they were asked to specify whether it is an emergency consultation or not. ([Börsch-Supan et al., 2005](#))

Given the information SHARE provides, we decided to conduct two regression analyses with different explanatory variables for waiting times. In our main analysis, we use the two continuous variables *Days waiting for emergency consultation to specialist* and *Weeks waiting for non-emergency consultation* in Wave 1 as regressors. Since this specification limits the main analysis to data collected in 2004, we conduct an additional complementary analysis using the dummy variable *UnmetNeedWait* in Wave 5 and Wave 6 as explanatory variable in order to overcome this limitation.

We would also like to highlight that the main analysis and the complementary analysis are two separate analyses independent of each other. The focus of this study will be on results from the main analysis, since the waiting time variables used in this analysis are continuous, which provide more information than the binary waiting time variable used in the complementary analysis. However, we still think that the results from the complementary analysis may be valuable since it answers the research question from a different angle. Therefore, our advice to the readers is to treat the results from the complementary analysis as a *supplement* to results from the main analysis.

## 4.2 Main analysis

### 4.2.1 Effect of waiting times on self-perceived physical and general health

We estimate the effect of waiting time on self-perceived physical and general health by estimating the following equation:

$$G_{ij} = \alpha + \beta_1 W_{ij} + C_i + C_j + \varepsilon_{ij} \quad (1)$$

Where  $G_{ij}$  is a binary variable that denotes different self-reported health outcomes for individual  $i$  living in country  $j$ . In our estimation,  $G_{ij}$  could be respondent's self-reported general health and symptoms related to the cardiovascular diseases, namely, chest pain and breathlessness. In SHARE, two different scales had assigned to question about respondents' self-reported general health (the respondent replied both): the European scale (very good, good, fair, bad, very bad) and the US scale (excellent, very good, good, fair, poor), respectively. We decide to follow the example of [Finkelstein et al. \(2012\)](#) and construct two types of binary outcome variable for each scale: (1) *Good health*, a dummy variable

equal to one if respondent had replied “excellent”, “very good” and “good”<sup>4</sup>; and (2) *Health not poor*, a dummy variable equal to one if the respondent does *not* answer “poor”<sup>5</sup> in the question about general health. As for variables for the symptoms related to cardiovascular diseases, both variables are equal to one if the respondent replied “yes” in question about whether he or she had suffered from chest pain or breathlessness during a twelve-month period before the interview date.

$W_{ij}$  is variable for waiting times. In our estimation,  $W_{ij}$  could be one of the two waiting times measures in SHARE we described in section 4.1. The core of this analysis is to estimate  $\beta_1$ , which is the coefficient of  $W_{ij}$  and can be interpreted as the effect of waiting times on respondents’ health outcome. We are interested in the sign and the size of  $\beta_1$ . In order to avoid any kind of biases in estimation of  $\beta_1$ , we add control variables at individual and country level – denoted by  $C_i$  and  $C_j$ <sup>6</sup>, respectively – into the regression model. The choice of control variables is based on previous medical and health economic studies related to hospital waiting times – more specifically, the studies of [Sampalis et al. \(2001\)](#) and [Moscelli et al. \(2016\)](#). However, despite the fact that some control variables can be obtained directly from SHARE (e.g. gender and age of the respondents), we have to generate some variables on our own and modify some existing variables in order to make the interpretation less complex. The generated and modified variables are listed as follows:

- *Obesity*: a dummy variable equals to one if the respondent’s body mass index is equal to or greater than 30. ([WHO, 2017](#))
- *High educated*: a dummy variable equals to one if the respondent has an education level of 5 or 6 according to UNESCO’s International standard classification of education 1997 (ISCED-1997). ([UNESCO, 1997](#))
- *Logarithmised adjusted total household gross income*: a continuous variable which is the sum of the income of each member of the respondent’s household during 2003.

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<sup>4</sup> “very good”, “good” in the equivalent European scale.

<sup>5</sup> “bad”, “very bad” in the equivalent European scale

<sup>6</sup>  $C_i$  is a set of covariates that are potentially correlated with the health outcome at individual level, such as respondent’s gender, education level, age etc., while  $C_j$  is a single dummy variable equal to one if the respondent comes from a Beveridge country (i.e. country with national health service)

We follow the example of [Siciliani and Verzulli \(2009\)](#) and adjust the total household gross income with purchasing power parity (PPP)<sup>7</sup> and the household size<sup>8</sup>.

- *Beveridge*: a dummy variable equal to one if the country has a nationalised health care system. In the main analysis, we classify Sweden, Denmark, Italy, and Spain under “Beveridge countries”. This classification is based on [OECD Country Health Profile 2017](#) and [Mossialos et al. \(2017\)](#).

A full list of control variables is provided in Appendix II.

#### 4.2.2 Effect of waiting times on self-perceived mental health

##### 4.2.2a Estimation using cross-section data (Wave 1)

We estimate the effect of waiting time on self-perceived mental health by estimating the following equation:

$$M_{ij} = \alpha + \beta_1 W_{ij} + C_i + C_j + \varepsilon_{ij} \quad (2a)$$

Where  $M_{ij}$  is a binary variable that denotes different self-reported mental health for individual  $i$  living in country  $j$ . For example,  $M_{ij}$  could be an indicator variable for depression, which equals to one if the respondent answered that he or she felt sad or depressed in the one-month period before the interview date. Other than *Depression*,  $M_{ij}$  could also be one of the following mental health outcomes:

- *Suicidal feeling*
- *Fatigue*
- *Irritability*
- *Appetite*<sup>9</sup>
- *Insomnia*<sup>10</sup>
- *Concentration on entertainment*
- *Concentration on reading*

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<sup>7</sup> This adjustment is achieved by multiplying the value of income (in term of euro) by the ratio of exchange rate used in Wave 1 and PPP-adjusted exchange rate in 2004. After the adjustment, the total household gross income is denominated in price level in Germany 2005. ([SHARE, 2018](#))

<sup>8</sup> This adjustment is achieved by dividing the PPP-adjusted income value by the square root of the number of household member. ([Siciliani & Verzulli, 2009](#))

<sup>9</sup> The respondents were asked whether their desire for food had diminished.

<sup>10</sup> The respondents were asked whether they have experienced sleeping problems

The definition of  $W_{ij}$ ,  $C_i$  and  $C_j$  are identical to equation (1). Besides, although we run a number of regression with different mental health outcomes, the set of control variables is nearly the same across these regressions. The only exception is the model with *Depression* as dependent variable, where we added an extra control, *Depression ever*, which equals to one if the respondent has suffered from symptoms of depression previously, into the regression.

#### 4.2.2b Estimation using panel data (Wave 1 + Wave 2)

In order to investigate whether hospital waits in a certain point of time have effect on the mental health outcome in future period, we extend our analysis using panel data and estimate the following equation:

$$M_{ij,w2} = \alpha + \beta_1 W_{ij,w1} + \beta_2 M_{ij,w1} + C_{i,w2} + C_{j,w2} + \varepsilon_{ij} \quad (2b)$$

Where  $M_{ij,w2}$  is a binary variable that denotes different self-reported mental health outcomes in Wave 2 for individual  $i$  living in country  $j$ . Since the second wave of SHARE was conducted in 2006/2007 ([SHARE, 2018a](#))<sup>11</sup>,  $M_{ij,w2}$  can also be roughly interprets as the mental health outcomes of the patients four years after he or she had experienced hospital wait (except for Israel).  $W_{ij,w1}$  denotes the waits that individual  $i$  living in country  $j$  had experienced in year 2003 (Wave 1) and similar to the cross-section variant, we are interested in the size and the sign of its coefficient,  $\beta_1$ .  $C_{i,w2}$  and  $C_{j,w2}$  are control variables at individual level and country level obtained from Wave 2. A major difference between the panel data analysis and the cross-sectional one is that we include respondent's mental health outcomes from Wave 1,  $M_{ij,w1}$ , into the model, since it is reasonable to assume that the mental health outcomes in Wave 2 might correlate with the outcome in previous period and failing to control that might leads to biased estimation.

#### **4.2.3 Effect of waiting times on self-perceived life expectancy**

In SHARE, the question that relates to the respondents' self-perceived life expectancy is: "What are the chances that you will live to be age XXX or more?", where the target age assigned to each respondent varies, depending on the age of the respondent by the time of inter-

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<sup>11</sup> Data collection in Israel was conducted in 2009/2010

view. Furthermore, instead of expressing age in numerical value, SHARE had divided the respondents into age intervals. These age intervals and their respective target age are listed as the following ([SHARE, 2018a](#)):

**Table 1**

Age intervals and target age in question about life expectancy

<b>Respondents' age</b>	<b>Target age in question about life expectancy</b>
age < 65	75
age > 64 and age < 70	80
age > 69 and age < 75	85
age > 74 and age < 80	90
age > 79 and age < 85	95
age > 84 and age < 95	100
age > 94 and age < 100	105
age > 99 and age < 105	110
age > 104	120

As table 1 shows, for those respondents with an age  $\leq 90$ , we can interpret the outcome variable *Life expectancy* as their “probability<sup>12</sup> of living after ten years”, since the difference between the respondent’ age at the time of interview and the target age assigned to him in the question is at least 10.

Another issue we have noticed is that our outcome variable does not follow normal distribution. As Figure 1 shows, many respondents have rated their chances of living after ten years equal to 0 and 1, leading to a huge number of observations were allocated to both “tails”. A possible solution for this kind of problem is to exclude these observations. However, we have reason to believe that these observations contain information that are valuable to our analysis. It is a part of our interest in investigating whether waiting times contribute to the occurrence of such “tail behaviours” (i.e. to state that their own chances of living after ten years equals to 0 or 1). Therefore, we decided to construct two binary outcome variables: (1)  $l_{0,ij}$ , which equals to one if the respondent’s *Life expectancy* equals to 0; and (2)  $l_{1,ij}$ , which equal to one

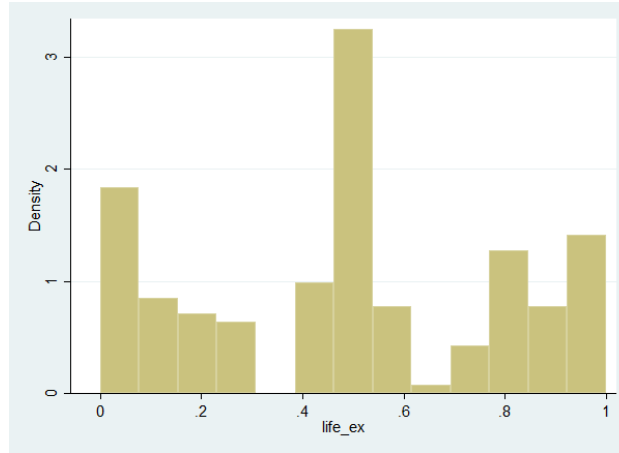
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<sup>12</sup> The respondents were asked to rate their chances of living until a certain age in a scale between 0 to 100, where 0 implies “absolutely no chance” and 100 implies “absolutely certain”. We transformed the outcomes into percentage by dividing it by 100.

if the respondent's *Life expectancy* equals to 1. We will also estimate the effect of waiting times on the original outcome,  $L_{ij}$ , and the adjusted outcome (i.e. those respondents who answered 0 or 1 are excluded),  $l_{ij}$ .

**Figure 1**

Distribution of variable "life expectancy"



Thus, we estimate the effect of waiting time on self-perceived life expectancy by estimating the following four equations:

$$L_{ij} = \alpha + \beta_1 W_{ij} + C_i + C_j + \varepsilon_{ij} \quad (3)$$

$$l_{ij} = \alpha + \beta_1 W_{ij} + C_i + C_j + \varepsilon_{ij} \quad (4)$$

$$l_{1,ij} = \alpha + \beta_1 W_{ij} + C_i + C_j + \varepsilon_{ij} \quad (5)$$

$$l_{0,ij} = \alpha + \beta_1 W_{ij} + C_i + C_j + \varepsilon_{ij} \quad (6)$$

Nonetheless, it should be highlighted that the control variables for age in these four specifications slightly differs from previous equations. We replace the continuous variables *age* with five dummies corresponding to the age intervals set by SHARE<sup>13</sup>. The reason for this adjustment is that using the continuous variable for respondents' age might cause our interpretation of the outcome variable as "probability of living after ten years" to be incorrect, since this interpretation, as we mentioned above, is based upon age intervals rather than respondents' actual age.

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<sup>13</sup> These five dummies are: *age65\_69*, *age70\_74*, *age75\_79*, *age80\_84* and *age85\_90*. Respondents who are younger than 65 is the reference group.



### 4.3 Complementary analysis

As mentioned above, the complementary analysis is based on data collected from 2013 (Wave 5) and 2015 (Wave 6). We estimate the effect of long hospital wait by estimating following equation:

$$H_{ij} = \alpha + \beta_1 V_{ij} + \beta_2 K_{ij} + \beta_3 (V_{ij} * K_{ij}) + C_i + C_j + \varepsilon_{ij} \quad (7)$$

Where  $H_{ij}$  is the outcome variable that corresponds to all outcome variables we mentioned in the main analysis, i.e.  $G_{ij}$ ,  $M_{ij}$ ,  $L_{ij}$ ,  $l_{ij}$ ,  $l_{1,ij}$  and  $l_{0,ij}$ . The variable of interest is  $V_{ij}$ , which is a binary variable equal to one if respondent  $i$  in country  $j$  has during a twelve-months period before the interview date unable to meet a doctor due to too long waits<sup>14</sup>;  $K_{ij}$  is another binary variable that equals to one if the respondent has to give up a certain treatment due to high cost; and  $V_{ij} * K_{ij}$  is the interaction term. As mentioned in section 3.3, high user fee might cause low income people to postpone necessary treatment and it is reasonable to think that such action might adversely affect the health outcomes of these people. Thus, in order to obtain an unbiased result, we include  $K_{ij}$  into the model as control variable. In addition, we also control for the interaction term  $V_{ij} * K_{ij}$ , since it is not unlikely that high user fee and long hospital wait occur simultaneously.

$C_i$  and  $C_j$  in the complementary analysis is similar to the main analysis. However, the control variable *Beveridge* changes slightly due to more countries are added into the SHARE survey. After Portugal joined the Wave 6, there are now five Beveridge countries in the variable *Beveridge*.

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<sup>14</sup> Unfortunately, the form of wait (e.g. physical wait in the hospital or waiting list) is not specified in the SHARE survey. Furthermore, the definition of “long wait” is far from clear.

## 5 Data

The Survey of Health, Ageing and Retirement in Europe (SHARE) is a cross-national panel database of micro data on health, socio-economic status and social and family networks of individuals aged 50 and/or older ([SHARE, 2016](#)). The main aim of SHARE is "understanding ageing and how it affects individuals in the diverse cultural settings of Europe" ([Börsch-Supan et al., 2005, p. 5](#)). According to the official methodology volume, SHARE data was collected using computer assisted personal interviewing (CAPI), an interviewing technique where an interviewer conducts face-to-face interviews using digitalised survey questionnaire installed on a laptop. ([Börsch-Supan et al., 2005](#)).

Regarding the design of the survey, SHARE consists of various thematic blocks or modules, ranging from demographic information to respondents' expectation about the future. The majority of variables used in this study are obtained from the following four questionnaire modules ([SHARE, 2018a](#)):

- *Physical Health* (PH): consists information regarding self-reported general health, longstanding illness or disability.
- *Mental Health* (MH): consists information regarding the respondents' mental and emotional health.
- *Health Care* (HC): consists information related to health care, such as recent doctor visits, hospital stays, and health insurance. The variables of waiting times are provided in this module.
- *Expectations* (EX): consists information about respondent's expectations, such as the level of certainty they feel about the future.

To date, SHARE has collected and released six waves of data (Wave 1-6). Data has been collected from more than 297 000 interviews with over 120 000 respondents ([SHARE, 2016](#)). Wave 1, the first wave, was collected in 2004 and contain data from twelve countries: Austria, Belgium, Switzerland, Germany, Denmark, Spain, France, Greece, Italy, Netherlands, Sweden, and Israel. Since then, the number of countries included have increased. In Wave 6, the last released wave of data, 18 countries were included. Of the original twelve, only the Netherlands is absent. The other seven countries that participated in SHARE Wave 6 are Czech Republic, Poland, Luxembourg, Portugal, Slovenia, Estonia, and Croatia ([SHARE, 2018c](#)). Our analyses in this study are based on data from Wave 1,2,5 and 6. The reason why we excluded Wave 3 and Wave 4 is the absence of variable for hospital waiting times in these

waves ([SHARE, n.d](#)). The design of the third wave, SHARELIFE, is also completely different from other waves since it focuses in particular on respondents' life histories. ([SHARE, 2018b](#))

## 6 Results

### 6.1 Descriptive statistics

Table 2a in Appendix II provides the descriptive statistics for our main analysis. On average, the waiting times for non-emergency consultation are approximately 3.85 weeks. In the case of emergency consultations, the mean waiting time for a patient to received treatment is approximately 5.47 days. 3730 patients who diagnosed with cardiovascular diseases are included in the original sample from SHARE, 1582 of them are dropped in the process of constructing control variables<sup>15</sup>, resulting a sample that consists 2148 respondents<sup>16</sup>. The average age of these respondents is 69 years and approximately 57% of them are male. Additionally, only 12% of the respondents have attended college/university and the reported household incomes after adjustment of household size are EUR 763.57 per annum on average, in terms of the price level in Germany 2005.

The summary statistics for the complementary analysis are provided in Table 2b and 2c in Appendix II. Since more country has been added to the SHARE survey, the sample sizes of complementary analysis are also larger than the main analysis. The mean age of respondents is 71.17 years (Wave 5) and 72.08 years (Wave 6), respectively. Regarding the waiting times, around 10.8% (Wave 5) and 15% (Wave 6) of the respondents could not see a doctor due to too long waits. The percentage of respondents who are prevented from treatment due to high costs are approximately 7% for both waves, which might indicate that the problem of excessive hospital waiting times is more common than the problem of high hospital user fee among OECD countries.

### 6.2 Self-perceived physical and general health

Table 3 and 4 in Appendix III provides results for the main analysis, with self-perceived physical and general health as the outcome variables, as in equation (1). In Table 3, we use *Weeks waiting for non-emergency consultation* (hereinafter *non-emergency waits*) as a measurement of waiting times, while in Table 4, the variable will be *Days waiting for emergency consultation to specialist* (hereinafter *emergency waits*).

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<sup>15</sup> Respondents who did not answered questions about their general health, mental health and life expectancy are excluded, as well as those who refuses to reply in the income questions.

<sup>16</sup> The number of observations in our regressions is, however, much smaller than 2148. This is mainly due to missing values in the two variables of waiting times. Only 214 respondents had answered the question about non-emergency waits and 159 respondents the question about emergency waits.

Results from Table 3 show that in general, non-emergency waits do not adversely affect the self-perceived physical and general health outcome of patients with cardiovascular diseases. A majority of our estimates for waiting times' effect are also statistically insignificant, with some exceptions in column (5), (6) and (7), where the outcome variables are generated from the US-version of health general questions. The results showed in these columns are counter-intuitive, since they imply that waiting times have a positive effect on patients self-perceived health outcome. For instance, the result in column (6) can be interpreted as “an increase of one week in non-emergency waits increases the probability of a patient reporting his or her own health as “excellent”, “very good” or “good” (hereinafter *probability of good health*) with 1.48%.” The reason for this positive effect is unclear. However, we do suspect that it might be a result of failing to control for patients' severity since it is reasonable to think that patients who are seriously ill are prioritised to treatment, while the relatively “healthier” patients often have to wait longer<sup>17</sup>.

Among the control variables, the coefficient of *Forgo treatment due to costs* are statistically significant and negatively associated to the probability of good health in column (6), indicating that high hospital user fees might impose damage on the patients' self-perceived health. The probability of good health for those patients who must abandon the treatment due to the costs is about 22% lesser compared with those who did not. It is also clear that the total amount of income in the patients' household is positively associated with their health outcomes, especially in the probability of a patient *not* reporting his or her own health as “poor” (hereinafter *probability of not-poor health*). The country-specific control variable *Beveridge* is generally insignificant across different regressions, indicating that there are no differences in the general health outcomes between patients in Beveridge countries and in countries with other types of healthcare systems. This finding might indicate that non-emergency waits have little or no effect on the self-perceived physical and general health.<sup>18</sup>

In the case of emergency, as results from Table 4 show, the probability of good health tends to decrease when the waits for emergency care become longer. The coefficient of emergency waits is statistically significant when the US-scale of good health is used, and weakly significant at 10% level when the EU-scale is used. In our estimations, an extra day of waiting for

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<sup>17</sup> This suspicion has been confirmed by Prof. Kristian Bolin during a supervisor meeting at 22 May.

<sup>18</sup> In the preparatory phase of the main analysis, we run bivariate regressions in order to investigate whether waiting times differs significantly between countries in our samples. We find significant differences in non-emergency waits (but not emergency waits) and patients in Beveridge countries have to wait about 4.3 weeks more than patient in countries with other types of healthcare system.

emergency care reduces the probability of good health with about 0.53% and 0.38%, respectively. The emergency waits are also negatively associated with the probability of not-poor health (in both scale) and the probability of suffering from chest pain and breathlessness, but none of these coefficients are statistically significant.

### **6.3 Self-perceived mental health**

The results of waiting time's effect on the self-perceived mental health of patients with cardiovascular diseases are provided in Tables 5a–6d in Appendix III. Results from regressions using non-emergency waits as explanatory variable are showed in Tables 5a–d and in Tables 6a–d, results concerning the emergency waits are provided.

In Tables 5a and 5b, we find that non-emergency waits are positively associated with the probabilities of having suicidal feelings, appetite problems and problems in concentration on entertainment. For mental health outcomes like depression, fatigue, irritability, sleeping disorders, problems in concentration on reading, the associations are negative. However, none of these are statistically significant, which implies that the non-emergency waits do not have any short-run effect on mental health. As for the long-run, the results from the panel-data analysis in Table 5c and 5d show that non-emergency waits generally do not have statistically significant effects on future mental outcomes. The only exception is depression: a one-week increase of non-emergency waits increases a patient's probability of suffering from depression by 0.787%.

Similar to the results from self-perceived general health, we also find evidence of the adverse effect of high hospital user fee on mental health. The coefficient of *Forgo treatment due to costs* is positive and statistically significant in column (8) in Table 5a, which implies that patients who have to abandon treatment due to high costs are more likely to be irritated compare with those who do not.

In contrast to non-emergency waits, results from Table 6a and 6b show that emergency waits have positive and statistically significant associations with several types of deterioration in mental health, including depression, fatigue (marginally significant at 10% level), irritability and sleeping disorders. As waiting times for emergency care increase by one day, the probabilities of suffering from these negative mental outcomes will increase by 0.504% (depression), 0.524% (fatigue), 0.869% (irritability) and 0.716% (sleeping disorders), respectively. These are clear evidence of the adverse effect of hospital waiting times on patients' health in the short-run, even though their sizes are relatively small compared to some control variables,

such as variable for gender, whose estimated effect on mental outcomes are much larger (around 27 % – 30 %). As for the long-run, we only find one statistically significant effect of emergency waits on fatigue. Interestingly, compared with its cross-sectional variant, the significance of the coefficient of emergency waits slightly improves in the panel-data analysis, but the size of the coefficient is virtually unchanged. As for the rest of the mental health outcomes, the effect of emergency waits is insignificant.

#### **6.4 Self-perceived life expectancy**

The results of waiting time's effect on the self-perceived life expectancy of patients with cardiovascular diseases are provided in Tables 7 and 8 in Appendix III. Table 7 shows the results using non-emergency waits as explanatory variable and in Table 8 the emergency waits.

In Table 7, we find no adverse effect of non-emergency waits on the patients' self-perceived life expectancy. On the contrary, the signs of the coefficients show positive associations between non-emergency waits and health, although most of them are not statistically significant. The only exception is the bivariate regression in column (3) that uses the adjusted life expectancy as the outcome variable, where patients who rated their probability of living after ten years equal to 0% and 100% are excluded. The coefficient for non-emergency waits in this regression is statistically significant and indicates that for those patients who did not answer "absolutely no chance" or "absolutely certain" in the life expectancy question, a one-week increase in non-emergency waits will lead to an approximately 0.8% decrease in their probability of living after ten years. Nevertheless, this coefficient becomes insignificant when we added control variables into the model. Additionally, results from Table 7 also show that rather than waiting times, the self-perceived life expectancy is appearing to be depended on patients' age, since many of the age interval dummies are moderately significant at 1% level and at 5% level. We also find that high hospital user fees have significant negative effects on health even when the outcomes are now measured in life expectancy.

Nevertheless, the situations in emergency waits are, as we expected, different from the non-emergency cases. Among the regressions in Table 8, only column (2) is statistically significant and it shows that emergency waits are negatively associated with the self-perceived life expectancy. The coefficient of emergency waits is also highly significant at 1% level, which implies that a one-day increase in emergency waits decreases the patient's probability of living after ten years by approximately 0.45%. It should be noticed that the outcome variable in column (2) is not normally distributed, which might lead to inaccuracy in the significance tests since our sample size is not reasonably large ([Field, 2009](#)).

## 6.5 Results from the complementary analysis

As mention in section 4.1, we conduct a complementary analysis in order to overcome the limitations of data in the main analysis. Just as the name implies, the complementary analysis is designed to *complement* the main analysis with more recent data, rather than to replace it. In the complementary analysis, the explanatory variable of waiting time is *UnmetNeedWait* (recoded as *Long wait* in our analysis for explanation purpose), which is a binary outcome variable that equals to one if the patient could not meet a doctor due to too long waits. In our estimations, we interpret the coefficient of this variable as the effect of *excessive*<sup>19</sup> waits on different self-perceived health measures.

### 6.5.1 General health

The effects of excessive waits on the self-perceived general health of patient with cardiovascular diseases are provided in Tables 9 in Appendix IV. It shows that patients who experienced excessive waits have generally lower self-perceived general health than patients without such experience. The coefficients for *Long wait* are statistically significant across all regressions. However, even though the estimated effects of excessive waits are statistical significant and have identical signs in both waves, there is still differences in the effect size, especially when the health outcome is measured as probability of good health: in Wave 5, the probability of good health reduces by approximately 23% if the patient has experienced excessive waits; in Wave 6, however, the size of this reduction is approximately 12%. Compared to results obtained from Wave 5, the estimated effect of excessive wait using data from Wave 6 are generally smaller. Additionally, the differences in effect size also exists between outcome measures, the estimated effect of excessive wait on the probability of good health are generally larger than on the probability of not-poor health.

Similar to the main analysis, we find significant adverse effects of high user fee on the patients' general health outcome using data from Wave 5. Other control variables that have statistically significant effects on the general health are household income (positive association), education (positive association) and obesity (only in Wave 5, negative association). The coefficient of country-level control *Beveridge* is generally insignificant, a result similar to our finding in the main analysis.

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<sup>19</sup> We also assume that the type of wait in the survey question is non-emergency waits.



### **6.5.2 Mental health**

The effects of excessive waits on the self-perceived mental health of patients with cardiovascular diseases are provided in Tables 10a-11b in Appendix IV. Surprisingly, we find that excessive waits are positively associated with every type of deteriorations in mental health in both waves. For Wave 5, the estimated effects of excessive waits are statistically significant in every single regression (marginally significant in appetite), even after control variables are included. As Tables 10a and 10b show, excessive waits have largest effect on fatigue (the probability of feeling tired are about 21.29 % higher for patients who has experienced excessive waits), followed by irritability (19.2%), depression (14.83%) and sleep disorders (14.61%); For Wave 6, the estimated effect have shown statistically significant effect on half of the mental health outcomes, including depression (marginally significant), suicidal feeling, sleep disorders and concentration on entertainment (marginally significant). Similar to the general health, the estimated effect sizes of excessive waits in Wave 6 are generally lower compared to estimations in Wave 5, except for sleeping disorder.

As for control variables, the coefficients for high user fee generally have a positive sign, but its statistical significance differs across waves. The education level is negatively associated with the deterioration in mental health, and in some cases, its effects are highly significant at a 1% level.

### **6.5.3 Life expectancy**

The result of excessive waits' effect on the self-perceived life expectancy of patients with cardiovascular diseases are reported in Tables 12 and 13 in Appendix IV. We find that excessive waits are not associated with patients' probability of living after ten years. This finding is consistent with our result in section 6.4, that the non-emergency waits do not adversely affect patients' self-perceived life expectancy. Furthermore, Table 12 and 13 also suggest that the changes in probabilities of living after ten years are mainly driven by patients' age, a result similar to what we obtained from the main analysis.

Interestingly, both Table 12 and 13 suggest that patients from Beveridge countries have higher probabilities of living after ten years (or less likely to answer "absolutely no chance" in life expectancy question). The coefficients for the country level control are also highly significant in Wave 6, which contradicts our finding in the main analysis. One possible explanation

is that more nations, in particular, Eastern European countries<sup>20</sup>, are included in Wave 6, which causes changes in the definition of variable *Beveridge*. According to Country Health Profiles 2017, the health spending per capita in these countries are all below the EU average ([OECD, 2017a](#)). In the Czech Republic, Poland and Estonia, the life expectancy at age 65 are also noticeably lower than the OECD average, which is not a surprise since health expenditures are often positively associated with life expectancy ([OECD, 2017](#)). We suspect that health expenditures also affect the *self-perceived* life expectancy, and the inclusion of countries with lower health spending per capita might have caused the self-perceived life expectancy in non-Beveridge countries to fall relative to Beveridge countries.

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<sup>20</sup> i.e. Czech Republic, Poland, Croatia, Estonia and Slovenia. These countries are also classified as non-Beveridge countries since they apply a Bismarck system.

## 7 Sensitivity analysis

In order to see whether our estimation of waiting times' effects is sensitive to changes in model specifications and in control variables, we re-estimate all equations in the main analysis using the Probit model and doing several alterations in the definition of following control variables:

1. *Household income*. One possible source of imprecision is the choice of using the logarithmised household income, which leads to people who have zero income are excluded from the sample. We therefore replace it with the PPP-adjusted household income expressed in thousand euros.
2. *Education*. The control variable for education in our model, *high educated*, is a variable with categorical outcomes. It is therefore reasonable to replace it with *years of education* since it is a continuous variable and provides more information than the categorical one. However, we still think that the choice of *high educated* as a proxy of the respondents' education level is superior in our case, especially when we are using a cross-national sample. We can expect that diversity exists in the educational systems across countries, which makes the years of education incomparable. Furthermore, longer school years does not necessarily mean that the respondent has higher education level.
3. *Obesity*. Using the same logic in the case of the education variable, we replace the binary control variable *Obesity* with its continuous alternative *BMI*.
4. *Beveridge*. We also re-defined the country-specific control variable, considering the dividing line between Beveridge countries and non-Beveridge countries might be unclear. There is some degree of convergence in health policy in the developed world, many Beveridge nations have experimented to introduce some elements from the Bismarck model in order to overcome the disadvantages of a nationalised health care, and the Bismarck countries do the same as well ([Bhattacharya et al., 2014](#)). Therefore, we alter the definition of variable *Beveridge* from "equal to one if the country has a *nationalised healthcare system*" to "equal to one if the country has reported *waiting-time problem for public patients*". According to [Siciliani and Hurst \(2005\)](#), following countries (that participated in SHARE survey) falls into this definition: Sweden, Denmark, Italy, The Netherlands and Spain.

The results of sensitivity analysis are provided in Table 14 in Appendix V. It shows that the re-estimated effects of waiting times are, in general, similar to the results before alterations are made, in both the sign and the size of the coefficients. We can therefore conclude that our estimations have passed the robustness check.

## 8 Discussion

### 8.1 Policy implications

The result from both the main analysis and the complementary analysis show that waiting times do have adverse effects on several self-perceived health outcomes, especially when the waiting times is *excessive* and when emergency situations are involved. The waiting times for non-emergency consultations are in general not negatively associated with patients' health. Thus, our results imply that one of the primary objectives for one country's health policy is to prevent excessive (non-emergency) wait and to reduce days of waiting in emergency consultation. Since there are no significant differences between Beveridge countries and non-Beveridge countries, this policy implication is applicable regardless what type of healthcare systems one country has. In the following paragraph, we will discuss some of the policy interventions to reduce waiting times. However, it is reasonable to think that the political instruments for achieving the above-mentioned objective in a country with nationalised health care might be different from a country where the provision of healthcare is privatised. For the purpose of simplicity, we only discuss policies conducted under a Beveridge system, since long waiting times are more common and have become a serious political issue in Beveridge countries.

[Siciliani and Hurst \(2005\)](#) compiled different health policies in twelve OECD countries that were used to tackle excessive waiting times. They show that excessive waits can be reduced by policies that target on the supply side (e.g. increase productivity by funding extra activities, improving waiting list management, promote private sector) and the demand side (e.g. raising clinical thresholds using score system) of the healthcare market, or acting on the waiting times directly (e.g. maximum waiting-time guarantee). However, they also argued that if the hospital budget is fixed, policies that temporarily adding resources in order to create extra activity will have little success, due to the dynamic nature of waiting time. In their opinion, a supply-side policy that rewards hospitals with high productivity using a dynamic budget (so-called activity-based payment) is therefore more preferable.

As for emergency waits, a great amount of published articles investigates the phenomenon *emergency department crowding*, where waiting times are measured in minutes or hours instead of days ([Andersson & Karlberg, 2001](#); [Hoot & Aronsky, 2008](#)). In order to reduce this type of wait, policies such as increasing resources (e.g. hospital personnel, beds, medical ob-

ervation units) and demand management (e.g. triage) are suggested and have shown to be effective ([Hoot & Aronsky, 2008](#)). Although waiting times that arise due to crowding in hospitals' emergency department is not the same as the emergency waits in this study, we see no problems of adopting the above-mentioned policies into our case, namely *days waiting for emergency consultation to specialist*, or at least using the logic behind to develop policies suitable to this type of emergency waits.

However, as mentioned in section 3.3, rationing health care by waiting list is not welfare optimal. Relative to other rationing mechanisms, waiting list rationing is less efficient. Combining with our result about excessive and emergency waits' adverse effects on health, a proposal of completely abandon waiting list rationing and adopting some of the alternative rationing mechanisms should be considered. Nevertheless, our results also show that high hospital user fee may also contribute deteriorations of several health outcomes. In order to develop an optimal size of user fee, more detailed and comprehensive research on alternative rationing mechanisms is therefore required.

## **8.2 Comparison with previous studies**

Even though our results partially support the previous findings of [Sampalis et al. \(2001\)](#) and [Jónsdóttir and Baldursdóttir \(1998\)](#), there are still considerable differences between our study and theirs, which made them not directly comparable to each other.

The most important difference is the research focus. The works of [Sampalis et al. \(2001\)](#) and [Jónsdóttir and Baldursdóttir \(1998\)](#) both focuses on the preoperative wait and includes only patients who are awaiting CABG surgery in the sample, while in this study, our sample consists patients who *diagnosed* with cardiovascular diseases and had experienced waits over the last twelve months by the time of interview before receiving his or her (inpatient) treatment. The type of treatment at which the patients are waiting for is, however, not specified in our study. This is a caveat that readers should bear in mind when interpreting our results for the simple reason that patients who diagnosed with cardiovascular diseases do not necessarily seek treatments in cardiovascular care. Hence, all waiting times variables used in this study do not only measure the waiting times for treatment in cardiovascular care but also other types of treatment as well.

In fact, there are variables in the SHARE survey that could help us to distinguish different types of treatment from one and another, where following inpatient treatments in cardiovas-

cular care are included: *insertion, replacement and removal of pacemaker, CABG, and cardiac catheterisation*. However, these variables have serious problems of missing values, which is also the reason why we choose to exclude them from our models.

Other than the difference in research focus, there are some minor differences in choice of variables. For instance, [Jónsdóttir and Baldursdóttir \(1998\)](#) included health-related habits in their study, and [Sampalis et al. \(2001\)](#) had *vitality* as one of their QoL measurements. Both these variables are absent in our study. There are also differences in methods: the study of [Jónsdóttir and Baldursdóttir \(1998\)](#) has more of a descriptive nature and concentrates on describing *what* are the negative effect of prolonged waiting times on patients self-perceived health; [Sampalis et al. \(2001\)](#) employed a sample with two groups when they investigated the effect waiting times on patients QoL. Both approaches share little similarity with methods used in our study.

### **8.3 Methodological limitations**

Other than the limitation of old data, which we already have mentioned, there are several drawbacks in our methods, which might cause our estimates of waiting times' effect to deviate from its true value. We need to highlight the possible omitted variable bias in our estimations. For instance, we have not included control variable for severity in our model since there are no such variables in the SHARE survey that are suitable for our analyses. This, in our opinion, might be the reason for the counter-intuitive results shown in section 6.2. The difference in estimations between Wave 5 and Wave 6 might also be a consequence of unobserved components, such as policy change. Furthermore, the results from general health question might suffer from biases due to differences in language and culture between countries. The waiting time measures in this study could also be problematic since they are defined differently from the conventional measures. A direct consequence of this difference in definition is the decreased comparability of our results with other research concerning waiting times.

We also want to remind the reader about the fact that, in addition to the methods used in this study, there are other possible approaches in investigating the effect of waiting times on health outcomes. For instance, we could have done a panel data analysis that examines

whether waiting times at Wave 1 affects health outcomes in later waves<sup>21</sup>, instead of doing two independent cross-section analyses with waiting time data collected in three different observation time point. However, this approach would be difficult to implement due to loss of observations. As mentioned in 6.1, the mean age of our sample population in Wave 1 is 69 years. Since there are 14 years between Wave 1 and Wave 6, the sample size is likely to diminish over time by reason of, for example, death.

#### **8.4 Extrapolation to other contexts**

As for the validity of our result, we have already discussed one interpretation issue in section 8.2. However, there are more caveats the readers should bear in mind: Firstly, our findings only speak to the self-perceived health outcomes of patients with cardiovascular diseases in OECD countries at a certain point of time. That means our result may not be applicable to patients with other types of illness or patients in developing countries; Secondly, the use of the results from complementary analysis should be done in a prudent manner. Even though it has a larger sample size and shows more statistically significant results, it is still less informative than the main analysis, subjected to the vague definition of the waiting time variable. Our interpretation of the coefficient of variable *UnmetNeedWait* as the effect of excessive waits is only one of many possible interpretations.

Nevertheless, the result from sensitivity analysis shows that our estimations are robust for changes in model specification and in control variables.

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<sup>21</sup> By using health outcomes in Wave 1,2,4,5 and 6 as dependent variable and waiting time measurements in Wave 1 as explanatory variable.



## 9 Conclusion

Using a cross-national sample, we investigate the effect of hospital waiting times on the self-perceived health outcomes of patients with cardiovascular diseases in OECD countries. For the self-perceived physical and general health outcome, we found generally no evidence of adverse effects of non-emergency waits. However, we do find evidence of emergency waits and excessive wait affects general health outcome negatively. For the self-perceived mental health, we found generally no negative association between non-emergency waits and the mental health outcome in the same period. However, the increase of emergency waits may induce an increase in the probability of suffering from depression, irritability, and sleeping disorders at the conventional significance level (5%). Excessive waits are positively associated with nearly all types of deterioration in mental health. When we extend our analysis to the long-run mental health effects, we find evidence of an increase in the probability of suffering from depression is associated with an increase in non-emergency waits; and an increase in the probability of suffering from fatigue is associated with an increase in emergency waits. For the self-perceived life expectancy, we find that only emergency waits have adversely impact on patients' probability of living after ten years.

Our results would seem to suggest that the health policy should be designed to bring down emergency waits and excessive waits. However, giving the efficiency concerns of waiting times as rationing mechanism, alternative rationing methods such as threshold rationing and price rationing (i.e. co-payment, co-insurance, and deductibles) should also be considered as a potential replacement of waiting time rationing. Detailed research on the alternative rationing methods, especially in determining the welfare optimal size of hospital user fee is therefore required.

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## Appendix

### Appendix I: Data source

This thesis uses data from SHARE Waves 1, 2, 5 and 6 (DOIs: [10.6103/SHARE.w1.610](https://doi.org/10.6103/SHARE.w1.610), [10.6103/SHARE.w2.610](https://doi.org/10.6103/SHARE.w2.610), [10.6103/SHARE.w5.610](https://doi.org/10.6103/SHARE.w5.610), [10.6103/SHARE.w6.610](https://doi.org/10.6103/SHARE.w6.610)), see Börsch-Supan et al. (2013) for methodological details.

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## Appendix II: Descriptive statistics

**Table 2a**

Descriptive statistics for Main analysis

	Mean	SD	Min	Max
<b><i>Outcome variables</i></b>				
Good health (EU-scale)	0.2767	0.4475	0	1
Good health (US-scale)	0.3881	0.4874	0	1
Health not poor (EU-scale)	0.7354	0.4412	0	1
Health not poor (US-scale)	0.7968	0.4025	0	1
Chest pain	0.4209	0.4938	0	1
Breathlessness	0.2961	0.4566	0	1
Depression	0.4527	0.4979	0	1
Depression (Wave 2)	0.4175	0.4933	0	1
Suicidal feeling	0.1391	0.3462	0	1
Suicidal feeling (Wave 2)	0.1152	0.3194	0	1
Fatigue	0.4494	0.4976	0	1
Fatigue (Wave 2)	0.4636	0.4989	0	1
Irritability	0.2871	0.4525	0	1
Irritability (Wave 2)	0.2920	0.4549	0	1
Appetite	0.1346	0.3414	0	1
Appetite (Wave 2)	0.1445	0.3518	0	1
Insomnia	0.4001	0.4900	0	1
Insomnia (Wave 2)	0.4004	0.4902	0	1
Concentration on entertainment	0.1875	0.3904	0	1
Concentration on entertainment (Wave 2)	0.1986	0.3991	0	1
Concentration on reading	0.2346	0.4239	0	1
Concentration on reading (Wave 2)	0.2364	0.4250	0	1
Probability of living after ten years	0.4885	0.3091	0	1
Probability of living after ten years (adjusted)	0.4878	0.2354	0.01	0.99
Probability of living after ten years = 0	0.1044	0.3059	0	1
Probability of living after ten years = 1	0.1007	0.3011	0	1
<b><i>Explanatory variables</i></b>				
Non-emergency waiting times (weeks)	3.8458	6.3030	0	40
Emergency waiting times (days)	5.4654	12.3492	0	98
Male	0.5717	0.4950	0	1
High educated	0.1283	0.3345	0	1
ln(total household income)	6.6380	1.7622	0.8292	12.2164
Beveridge	0.3366	0.4727	0	1
Age	69.0065	9.6321	29	90
Age < 64 (reference group)	0.3310	0.4707	0	1
Age 65–69	0.1718	0.3773	0	1
Age 70–74	0.1820	0.3860	0	1
Age 75–79	0.1564	0.3633	0	1
Age 80–84	0.1173	0.3219	0	1
Age 85–90	0.0414	0.1993	0	1
Obesity	0.2356	0.4245	0	1
Forgo treatment due to costs	0.0887	0.2843	0	1
Age at first diagnosis of cardiovascular disease	57.7640	13.7093	0	88
Consulted heart specialist recently	0.3520	0.4777	0	1
Wished treatment to be earlier	0.4682	0.4999	0	1
Depression ever	0.2981	0.4575	0	1

**Sample size=2,148**

**Table 2b**

Descriptive statistics for Complementary analysis (Wave 5)

	Mean	SD	Min	Max
<b><i>Outcome variables</i></b>				
Good health (US-scale)	0.2987	0.4577	0	1
Health not poor (US-scale)	0.7063	0.4555	0	1
Depression	0.4835	0.4998	0	1
Suicidal feeling	0.1186	0.3233	0	1
Fatigue	0.5331	0.4990	0	1
Irritability	0.3560	0.4789	0	1
Appetite	0.1317	0.3382	0	1
Insomnia	0.4544	0.4980	0	1
Concentration on entertainment	0.1716	0.3770	0	1
Concentration on reading	0.1825	0.3863	0	1
Probability of living after ten years	0.4899	0.3186	0	1
Probability of living after ten years (adjusted)	0.4930	0.2564	0.01	0.99
Probability of living after ten years = 0	0.0930	0.2905	0	1
Probability of living after ten years = 1	0.0849	0.2787	0	1
<b><i>Explanatory variables</i></b>				
Long wait	0.1079	0.3103	0	1
High cost	0.0729	0.2600	0	1
Interaction (Long wait*High cost)	0.0310	0.1732	0	1
Male	0.5600	0.4964	0	1
High educated	0.1199	0.3250	0	1
ln(total household income)	6.2206	1.7624	0.3763	39.92658
Beveridge	0.2246	0.4173	0	1
Age	71.1689	9.3147	42	90
Age < 64 (reference group)	0.2514	0.4339	0	1
Age 65–69	0.1680	0.3739	0	1
Age 70–74	0.1914	0.3934	0	1
Age 75–79	0.1782	0.3827	0	1
Age 80–84	0.1367	0.3435	0	1
Age 85–90	0.0744	0.2624	0	1
Obesity	0.3022	0.4593	0	1
Age at first diagnosis of cardiovascular disease	56.7740	14.8045	0	87

**Sample size=5,393**



**Table 2c**

Descriptive statistics for Complementary analysis (Wave 6)

	Mean	SD	Min	Max
<b><i>Outcome variables</i></b>				
Good health (US-scale)	0.2809	0.4495	0	1
Health not poor (US-scale)	0.7037	0.4567	0	1
Depression	0.4911	0.5000	0	1
Suicidal feeling	0.1102	0.3131	0	1
Fatigue	0.5437	0.4981	0	1
Irritability	0.3495	0.4769	0	1
Appetite	0.1439	0.3510	0	1
Insomnia	0.4546	0.4980	0	1
Concentration on entertainment	0.1662	0.3723	0	1
Concentration on reading	0.1862	0.3893	0	1
Probability of living after ten years	0.5001	0.3122	0	1
Probability of living after ten years (adjusted)	0.4981	0.2512	0.01	0.99
Probability of living after ten years = 0	0.0838	0.2771	0	1
Probability of living after ten years = 1	0.0869	0.2817	0	1
<b><i>Explanatory variables</i></b>				
Long wait	0.1503	0.3574	0	1
High cost	0.0754	0.2641	0	1
Interaction (Long wait*High cost)	0.0437	0.2044	0	1
Male	0.5527	0.4973	0	1
High educated	0.1010	0.3014	0	1
ln(total household income)	5.8511	1.4897	0.1554	12.0709
Beveridge	0.2325	0.4224	0	1
Age	72.0831	9.2616	37	90
Age < 64 (reference group)	0.2190	0.4136	0	1
Age 65–69	0.1672	0.3732	0	1
Age 70–74	0.1817	0.3856	0	1
Age 75–79	0.1911	0.3932	0	1
Age 80–84	0.1525	0.3595	0	1
Age 85–90	0.0885	0.2840	0	1
Obesity	0.3028	0.4595	0	1
Age at first diagnosis of cardiovascular disease	55.4806	15.4836	0	89

**Sample size=5,515**

### Appendix III: Regression tables from the main analysis

**Table 3**

Effect of waiting times on self-perceived physical and general health (non-emergency)

	Good health (EU-scale)		Health not poor (EU-scale)		Good health (US-scale)		Health not poor (US-scale)		Chest pain		Breathlessness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Waiting times (weeks)	-0.00022 (-0.04)	0.01052 (1.43)	-0.00021 (-0.05)	0.00320 (0.63)	0.00785* (1.68)	0.01480*** (2.86)	0.00566** (2.34)	0.00465 (1.36)	0.00492 (0.92)	0.00539 (0.70)	0.00519 (1.00)	0.00549 (0.81)
Male		0.08728 (1.26)		-0.00846 (-0.11)		0.06950 (0.92)		0.05814 (0.86)		-0.03995 (-0.50)		-0.03249 (-0.44)
High educated		0.10629 (0.86)		0.04918 (0.55)		0.17489 (1.55)		0.02116 (0.25)		0.06084 (0.49)		0.12276 (1.05)
ln(total household income)		0.01553 (0.86)		0.04547** (2.50)		0.03185* (1.69)		0.05358*** (3.14)		0.01229 (0.67)		0.00928 (0.50)
Beveridge		-0.11290 (-1.57)		-0.04335 (-0.54)		0.08714 (1.13)		-0.03375 (-0.47)		-0.14813* (-1.78)		-0.08898 (-1.17)
Age		-0.00367 (-0.82)		-0.00745 (-1.51)		-0.00848* (-1.76)		-0.00006 (-0.01)		-0.00006 (-0.01)		0.00233 (0.47)
Obesity		0.02750 (0.35)		0.11243 (1.50)		-0.09458 (-1.20)		0.10623 (1.64)		0.02987 (0.36)		0.15433* (1.82)
Forgo treatment due to costs		-0.05347 (-0.50)		-0.22259 (-1.49)		-0.21792** (-2.30)		-0.25691* (-1.68)		0.27388* (1.97)		0.08983 (0.64)
Age at first diagnosis		0.00068 (0.24)		0.00244 (0.78)		0.00195 (0.66)		0.00126 (0.44)		0.00401 (1.30)		0.00335 (1.09)
Consulted heart specialist recently		0.06608 (0.86)		-0.08856 (-1.15)		0.00091 (0.01)		0.00151 (0.02)		0.18314** (2.21)		-0.00575 (-0.07)
Wished treatment to be earlier		-0.19635** (-2.51)		-0.08026 (-0.97)		-0.20061** (-2.42)		0.00941 (0.13)		0.05853 (0.69)		0.08452 (1.06)
Constant	0.27314*** (7.42)	0.37842 (1.18)	0.70971*** (20.01)	0.82290*** (2.72)	0.35347*** (9.09)	0.63633** (2.01)	0.75058*** (22.84)	0.29486 (0.99)	0.36601*** (9.33)	-0.00412 (-0.01)	0.27575*** (7.56)	-0.19221 (-0.62)
Prob > F	0.9673	0.0158	0.9627	0.0405	0.0939	0.0000	0.0204	0.0148	0.3588	0.0728	0.3178	0.1924
Observations	n=213	n=170	n=213	n=170	n=211	n=168	n=211	n=168	n=213	n=170	n=213	n=170

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 4**

Effect of waiting times on self-perceived physical and general health (emergency)

	Good health (EU-scale)		Health not poor (EU-scale)		Good health (US-scale)		Health not poor (US-scale)		Chest pain		Breathlessness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Waiting times (days)	-0.00175 (-1.11)	-0.00376* (-1.90)	-0.00344 (-0.92)	-0.00511 (-1.29)	-0.00317* (-1.91)	-0.00529** (-2.60)	-0.00528 (-1.34)	-0.00615 (-1.62)	-0.00312 (-0.88)	-0.00203 (-0.47)	0.00091 (0.27)	-0.00066 (-0.22)
Male		0.25190*** (4.11)		0.11015 (1.23)		0.25583*** (3.46)		0.01248 (0.15)		0.05622 (0.62)		-0.06750 (-0.74)
High educated		0.17890 (1.43)		0.18582 (1.57)		0.26032** (2.10)		0.06859 (0.61)		-0.10500 (-0.74)		-0.00148 (-0.01)
ln(total household income)		0.00313 (0.16)		-0.01486 (-0.59)		0.01810 (0.84)		-0.01194 (-0.51)		-0.00447 (-0.17)		0.01129 (0.45)
Beveridge		0.04073 (0.63)		-0.06192 (-0.67)		0.12062 (1.54)		0.16233* (1.87)		-0.03898 (-0.43)		0.11942 (1.28)
Age		-0.00789** (-2.16)		0.00103 (0.23)		-0.00112 (-0.23)		-0.00362 (-0.85)		-0.00509 (-0.90)		0.00338 (0.69)
Obesity		0.10710 (1.44)		-0.18970* (-1.90)		-0.01633 (-0.20)		-0.13505 (-1.43)		0.07851 (0.80)		0.22819** (2.13)
Forgo treatment due to costs		-0.12509* (-1.84)		-0.22938* (-1.89)		0.01484 (0.14)		-0.27364** (-2.47)		0.10739 (0.99)		0.13919 (1.14)
Age at first diagnosis		0.00566*** (2.64)		-0.00327 (-1.22)		0.00113 (0.35)		-0.00463** (-2.01)		0.00598 (1.42)		0.00054 (0.16)
Constant	0.19422*** (5.76)	0.21397 (0.77)	0.60461*** (13.88)	0.83860** (2.15)	0.26561*** (7.04)	-0.02720 (-0.09)	0.69742*** (16.90)	1.28389*** (3.53)	0.64114*** (15.13)	0.62837 (1.48)	0.46641*** (10.66)	0.05325 (0.14)
Prob > F	0.2688	0.0003	0.3564	0.0058	0.0580	0.0000	0.1828	0.0013	0.3827	0.6189	0.7879	0.3290
Observations	n=157	n=135	n=157	n=135	n=157	n=135	n=157	n=135	n=157	n=135	n=157	n=135

Notes: \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 5a**

Effect of waiting times on self-perceived mental health (non-emergency)

	Depression		Suicidal feeling		Fatigue		Irritability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (weeks)	-0.00419 (-0.85)	-0.00521 (-0.82)	0.00489 (1.03)	0.00502 (0.84)	0.00011 (0.02)	-0.00483 (-0.65)	0.00068 (0.13)	-0.00318 (-0.52)
Male		-0.16818** (-2.00)		-0.02627 (-0.46)		-0.15040* (-1.80)		0.08998 (1.22)
High educated		-0.11293 (-0.95)		-0.03693 (-0.46)		-0.15977 (-1.46)		0.03012 (0.25)
ln(total household income)		-0.00564 (-0.27)		0.00035 (0.03)		-0.02705 (-1.25)		-0.00981 (-0.45)
Beveridge		-0.08872 (-1.00)		-0.02042 (-0.36)		-0.04993 (-0.56)		-0.03433 (-0.43)
Age		-0.00644 (-1.28)		0.00406 (0.99)		0.00190 (0.35)		0.00874* (1.81)
Obesity		0.04492 (0.52)		-0.11209** (-2.32)		-0.00250 (-0.03)		-0.00742 (-0.10)
Forgo treatment due to costs		0.01904 (0.14)		0.09301 (0.71)		0.06615 (0.43)		0.30215** (2.07)
Depression ever		0.12985 (1.40)						
Age at first diagnosis		-0.00052 (-0.17)		-0.00407 (-1.39)		0.00068 (0.22)		-0.00802** (-2.53)
Consulted heart specialist recently		-0.09820 (-1.07)		-0.03184 (-0.62)		0.02895 (0.34)		-0.02311 (-0.30)
Wished treatment to be earlier		0.10806 (1.17)		0.09018 (1.52)		0.08797 (0.95)		0.18199** (2.20)
Constant	0.49692*** (12.34)	1.09501*** (3.03)	0.11265*** (4.03)	0.08199 (0.38)	0.46847*** (11.58)	0.55195 (1.50)	0.30988*** (8.24)	0.12503 (0.36)
Prob > F	0.3968	0.0090	0.3052	0.1150	0.9835	0.0469	0.8937	0.0067
Observations	n=208	n=164	n=205	n=163	n=209	n=166	n=208	n=165

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p≤0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 5b**

Effect of waiting times on self-perceived mental health (non-emergency)

	Appetite		Insomnia		Concentration on entertainment		Concentration on reading	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (weeks)	0.00078 (0.20)	0.00094 (0.19)	0.00121 (0.22)	-0.00671 (-0.99)	0.00549 (1.12)	0.00081 (0.13)	0.00276 (0.61)	-0.00288 (-0.65)
Male		-0.08136 (-1.50)		-0.16337** (-1.99)		0.02923 (0.45)		-0.07687 (-1.02)
High educated		-0.06410 (-0.79)		0.09469 (0.76)		0.01753 (0.18)		-0.14393* (-1.77)
ln(total household income)		0.01421 (1.11)		-0.01676 (-0.74)		0.00715 (0.45)		0.01563 (0.70)
Beveridge		-0.09184 (-1.39)		-0.02840 (-0.32)		0.00447 (0.06)		0.03193 (0.40)
Age		0.00633 (1.50)		0.00081 (0.15)		0.00074 (0.15)		-0.00120 (-0.24)
Obesity		-0.02797 (-0.51)		-0.05637 (-0.66)		-0.07203 (-1.09)		0.00550 (0.07)
Forgo treatment due to costs		0.00821 (0.07)		-0.00208 (-0.01)		0.21719 (1.51)		0.11652 (0.76)
Age at first diagnosis		-0.00241 (-0.82)		-0.00164 (-0.46)		0.00004 (0.02)		0.00262 (1.10)
Consulted heart specialist recently		-0.03638 (-0.67)		-0.00586 (-0.07)		-0.02488 (-0.36)		-0.10239 (-1.41)
Wished treatment to be earlier		-0.00869 (-0.14)		0.21568** (2.35)		0.06678 (0.88)		-0.01101 (-0.13)
Constant	0.13097*** (4.76)	-0.14657 (-0.56)	0.44990*** (11.17)	0.64512* (1.66)	0.18371*** (5.77)	0.04834 (0.16)	0.24297*** (7.20)	0.16940 (0.46)
Prob > F	0.8388	0.4443	0.8258	0.1284	0.2647	0.8045	0.5424	0.2897
Observations	n=209	n=166	n=209	n=166	n=210	n=167	n=209	n=166

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. T-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 5c**

Effect of waiting times in Wave 1 on self-perceived mental health in Wave 2 (non-emergency)

	Depression (Wave 2)		Suicidal feeling (Wave 2)		Fatigue (Wave 2)		Irritability (Wave 2)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (weeks in Wave 1)	0.00278 (0.82)	0.00787** (2.11)	-0.00072 (-0.59)	-0.00097 (-0.65)	0.00590** (2.34)	0.00358 (1.22)	0.00490 (1.59)	0.00219 (0.67)
Depression (Wave 1)		0.48571*** (5.74)						
Suicidal feeling (Wave 1)				0.38407** (2.34)				
Fatigue (Wave 1)						0.18235* (1.88)		
Irritability (Wave 1)								0.19546** (2.14)
Male		0.07732 (0.82)		0.01286 (0.27)		-0.00534 (-0.05)		0.12616 (1.64)
High educated		-0.08537 (-0.85)		0.05415 (0.65)		-0.18102 (-1.50)		0.03373 (0.28)
ln(total household income)		-0.04214 (-1.56)		-0.00603 (-0.49)		-0.03852 (-1.27)		-0.00155 (-0.05)
Beveridge		-0.04298 (-0.45)		0.02048 (0.33)		0.08255 (0.77)		0.12702 (1.35)
Age		0.00525 (1.01)		-0.00252 (-1.09)		0.00092 (0.14)		-0.00134 (-0.25)
Obesity		-0.17674 (-1.55)		0.08544 (1.08)		-0.08293 (-0.69)		0.18535 (1.44)
Forgo treatment due to costs (wave 1)		-0.11871 (-0.84)		0.09233 (0.78)		0.13087 (0.91)		0.09574 (0.61)
Depression ever		0.22850** (2.54)						
Age at first diagnosis		0.00006 (0.01)		0.00054 (0.21)		0.00034 (0.07)		-0.00371 (-0.90)
Constant	0.36074*** (7.79)	-0.13010 (-0.36)	0.07854*** (3.15)	0.18472 (1.06)	0.39334*** (8.52)	0.44654 (0.99)	0.23458*** (5.74)	0.29949 (0.78)
Prob > F	0.4163	0.0000	0.5550	0.5427	0.0209	0.0086	0.1153	0.0175
Observations	n=133	n=112	n=134	n=110	n=134	n=113	n=134	n=113

Notes: \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 5d**

Effect of waiting times in Wave 1 on self-perceived mental health in Wave 2 (non-emergency)

	Appetite (Wave 2)		Insomnia (Wave 2)		Concentration on entertainment (Wave 2)		Concentration on reading (Wave 2)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (weeks in Wave 1)	0.00389 (1.19)	0.00321 (1.03)	0.00196 (0.56)	-0.00051 (-0.11)	0.00266 (0.76)	-0.00101 (-0.23)	0.00448 (1.40)	0.00177 (0.45)
Appetite (Wave 1)		.12419 (0.72)						
Insomnia (Wave 1)				0.40011*** (4.14)				
Concentration on entertainment (Wave 1)						0.07504 (0.71)		
Concentration on reading (Wave 1)								0.31461*** (2.93)
Male		0.04163 (1.00)		-0.00349 (-0.04)		0.04628 (0.58)		-0.06161 (-0.69)
High educated		0.00792 (0.14)		-0.00077 (-0.01)		0.04316 (0.39)		0.17402 (1.28)
ln(total household income)		-0.02835** (-2.16)		-0.03071 (-0.98)		-0.01893 (-0.57)		-0.01008 (-0.34)
Beveridge		0.02451 (0.43)		0.14884 (1.36)		0.14930 (1.41)		0.18131* (1.81)
Age		-0.00223 (-1.31)		-0.00124 (-0.22)		0.00503 (1.00)		0.00209 (0.39)
Obesity		-0.01277 (-0.25)		-0.15739 (-1.62)		-0.02268 (-0.24)		-0.07194 (-0.72)
Forgo treatment due to costs (wave 1)		0.11645 (0.93)		0.03903 (0.28)		0.14743 (0.90)		0.14318 (1.15)
Age at first diagnosis		-0.00046 (-0.22)		0.00073 (0.14)		-0.00023 (-0.05)		-0.00332 (-0.74)
Constant	0.04605* (1.76)	0.34827** (2.03)	0.36248*** (7.85)	0.37354 (0.81)	0.17347*** (4.50)	-0.13573 (-0.30)	0.24622*** (5.86)	0.24465 (0.57)
Prob > F	0.2381	0.6031	0.5781	0.0004	0.4499	0.5414	0.1635	0.0068
Observations	n=134	n=113	n=134	n=113	n=134	n=112	n=134	n=112

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 6a**

Effect of waiting times on self-perceived mental health (emergency)

	Depression		Suicidal feeling		Fatigue		Irritability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (days)	0.00501*** (2.86)	0.00504** (2.44)	0.00085 (0.30)	0.00331 (1.01)	0.00379* (1.76)	0.00524* (1.94)	0.00848*** (3.86)	0.00869*** (3.62)
Male		-0.28064*** (-3.29)		-0.26345*** (-3.48)		-0.27512*** (-3.13)		-0.07260 (-0.84)
High educated		0.01156 (0.08)		-0.01395 (-0.15)		-0.20863* (-1.79)		-0.17767 (-1.29)
ln(total household income)		-0.00081 (-0.03)		-0.00094 (-0.04)		0.00244 (0.10)		-0.00491 (-0.18)
Beveridge		-0.03865 (-0.46)		-0.11096 (-1.48)		-0.02754 (-0.32)		-0.12276 (-1.39)
Age		-0.00061 (-0.12)		-0.00009 (-0.02)		0.00347 (0.68)		-0.00873 (-1.62)
Obesity		-0.02358 (-0.25)		0.16152* (1.79)		-0.11529 (-1.15)		-0.02946 (-0.30)
Forgo treatment due to costs		0.05139 (0.44)		0.20896 (1.62)		0.24521** (2.19)		0.05936 (0.47)
Depression ever		0.11041 (1.23)						
Age at first diagnosis		0.00178 (0.44)		0.00196 (0.82)		-0.00157 (-0.41)		0.00072 (0.19)
Constant	0.61158*** (14.53)	0.66952* (1.84)	0.27462*** (7.02)	0.25529 (0.79)	0.54723*** (12.71)	0.56593 (1.56)	0.36692*** (8.78)	1.04280** (2.62)
Prob > F	0.0048	0.0025	0.7681	0.0001	0.0804	0.0001	0.0002	0.0161
Observations	n=155	n=133	n=154	n=132	n=155	n=133	n=155	n=133

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.



**Table 6b**

Effect of waiting times on self-perceived mental health (emergency)

	Appetite		Insomnia		Concentration on entertainment		Concentration on reading	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (days)	0.00395 (1.17)	0.00223 (0.88)	0.00641*** (3.22)	0.00716*** (3.38)	0.00244 (0.84)	0.00374 (1.15)	0.00381 (1.07)	0.00560 (1.33)
Male		-0.08599 (-1.08)		-0.30932*** (-3.50)		0.07501 (0.96)		0.02583 (0.34)
High educated		-0.09644 (-1.30)		0.00521 (0.04)		-0.05963 (-0.58)		-0.00481 (-0.04)
ln(total household income)		0.00114 (0.05)		0.00748 (0.29)		-0.02419 (-1.21)		-0.00742 (-0.37)
Beveridge		-0.04290 (-0.61)		-0.07508 (-0.85)		-0.02538 (-0.36)		0.00417 (0.06)
Age		-0.00053 (-0.17)		0.00504 (0.97)		0.00257 (0.68)		0.00113 (0.33)
Obesity		0.17571* (1.82)		0.05572 (0.55)		0.04458 (0.50)		0.22252** (2.30)
Forgo treatment due to costs		-0.01613 (-0.16)		0.05961 (0.51)		0.32128** (2.63)		0.51433*** (4.80)
Age at first diagnosis		0.00269 (1.16)		-0.00473 (-1.19)		0.00018 (0.07)		0.00192 (0.94)
Constant	0.17861*** (5.21)	0.09261 (0.33)	0.50076*** (11.54)	0.53159 (1.33)	0.20613*** (5.89)	0.09805 (0.36)	0.25360*** (6.51)	-0.03272 (-0.12)
Prob > F	0.2425	0.0815	0.0016	0.0007	0.4045	0.1253	0.2861	0.0000
Observations	n=155	n=133	n=155	n=133	n=155	n=133	n=153	n=132

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 6c**

Effect of waiting times in Wave 1 on self-perceived mental health in Wave 2 (emergency)

	Depression (Wave 2)		Suicidal feeling (Wave 2)		Fatigue (Wave 2)		Irritability (Wave 2)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (days in Wave 1)	0.00244 (0.92)	0.00097 (0.34)	-0.00079 (-0.32)	-0.00252 (-1.23)	0.00449** (2.15)	0.00527** (2.44)	-0.00008 (-0.03)	-0.00543 (-1.59)
Depression (Wave 1)		0.15979 (1.17)						
Suicidal feeling (Wave 1)				0.52545*** (4.18)				
Fatigue (Wave 1)						0.43650*** (3.89)		
Irritability (Wave 1)								0.44169*** (3.93)
Male		-0.03397 (-0.28)		0.01873 (0.23)		-0.22468** (-2.08)		0.06729 (0.62)
High educated		0.13571 (0.88)		-0.06598 (-0.94)		0.08473 (0.59)		0.01540 (0.12)
ln(total household income)		-0.04568 (-1.29)		-0.01016 (-0.40)		-0.04751 (-1.46)		0.00100 (0.03)
Beveridge		0.05957 (0.52)		0.04831 (0.56)		-0.01996 (-0.18)		0.09721 (0.84)
Age		-0.00241 (-0.35)		0.00026 (0.05)		-0.00091 (-0.16)		-0.00030 (-0.04)
Obesity		-0.04861 (-0.36)		-0.12028 (-1.56)		-0.02937 (-0.29)		-0.03151 (-0.22)
Forgo treatment due to costs (wave 1)		0.30524* (2.00)		0.12376 (0.78)		0.01920 (0.13)		-0.06920 (-0.39)
Depression ever		0.21217* (1.69)						
Age at first diagnosis		0.00221 (0.56)		0.00354 (1.64)		-0.00933*** (-2.82)		0.00104 (0.28)
Constant	0.51067*** (9.39)	0.60965 (1.10)	0.21750*** (4.79)	-0.04716 (-0.12)	0.55667*** (10.39)	1.25786*** (3.04)	0.38158*** (7.14)	0.13277 (0.23)
Prob > F	0.3593	0.0093	0.7529	0.0006	0.0342	0.0000	0.9791	0.0457
Observations	n=104	n=84	n=104	n=84	n=105	n=84	n=105	n=84

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 6d**

Effect of waiting times in Wave 1 on self-perceived mental health in Wave 2 (emergency)

	Appetite (Wave 2)		Insomnia (Wave 2)		Concentration on entertainment (Wave 2)		Concentration on reading (Wave 2)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (days in Wave 1)	-0.00162 (0.87)	-0.00090 (-0.47)	0.00406 (1.65)	0.00228 (0.71)	0.00014 (0.06)	-0.00013 (-0.05)	-0.00254 (-1.24)	-0.00305 (-1.41)
Appetite (Wave 1)		0.11828 (0.89)						
Insomnia (Wave 1)				0.35297*** (2.74)				
Concentration on entertainment (Wave 1)						0.22336* (1.71)		
Concentration on reading (Wave 1)								0.26373** (2.01)
Male		-0.08143 (-0.78)		-0.17642 (-1.31)		-0.05159 (-0.57)		-0.08702 (-0.97)
High educated		0.10289 (0.86)		-0.00761 (-0.06)		0.12566 (0.95)		-0.07431 (-0.74)
ln(total household income)		-0.05150 (-1.48)		-0.00134 (-0.04)		-0.06000* (-1.93)		-0.00070 (-0.02)
Beveridge		0.04660 (0.48)		-0.02833 (-0.25)		0.03887 (0.43)		0.00661 (0.08)
Age		0.00771 (1.48)		0.00267 (0.37)		-0.00229 (-0.42)		0.00278 (0.56)
Obesity		0.04020 (0.34)		0.09858 (0.82)		-0.13807 (-1.49)		0.01686 (0.17)
Forgo treatment due to costs (wave 1)		-0.02859 (-0.19)		0.13105 (0.82)		0.32590* (1.96)		0.40974** (2.44)
Age at first diagnosis		-0.00524 (-1.30)		-0.00016 (-0.04)		0.00219 (0.99)		-0.00243 (-0.55)
Constant	0.21217 (4.85)	0.29959 (0.76)	0.45519*** (8.44)	0.20355 (0.38)	0.26560*** (5.64)	0.58616 (1.40)	0.28946*** (5.93)	0.11929 (0.37)
Prob > F	0.3850	0.4107	0.1022	0.0009	0.9538	0.0114	0.2193	0.0041
Observations	n=105	n=84	n=105	n=85	n=105	n=84	n=103	n=82

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 7**

Effect of waiting times on self-perceived life expectancy (non-emergency)

	$L_{ij}$		$l_{ij}$		$l_{1,ij}$		$l_{0,ij}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (weeks)	-0.00400 (-0.85)	0.00124 (0.18)	-0.00799*** (-2.93)	-0.00533 (-1.39)	0.00260 (0.48)	0.00500 (0.64)	-0.00137 (-0.56)	-0.00462 (-1.19)
Male		-0.04014 (-0.75)		-0.01153 (-0.25)		-0.02103 (-0.38)		0.02507 (0.47)
High educated		-0.05593 (-0.67)		0.06627 (0.99)		-0.05101 (-0.70)		0.13044 (1.25)
ln(total household income)		-0.00246 (-0.17)		0.00856 (0.62)		-0.00883 (-0.63)		0.00623 (0.49)
Beveridge		0.00034 (0.01)		-0.03172 (-0.55)		0.02944 (0.42)		-0.01530 (-0.23)
Age 65–69		-0.07985 (-1.04)		-0.04927 (-0.79)		-0.03264 (-0.40)		0.04760 (0.77)
Age 70–74		-0.16226* (-1.91)		-0.10488 (-1.44)		-0.02324 (-0.26)		0.15383* (1.90)
Age 75–79		-0.26982*** (-3.33)		-0.16458** (-2.08)		-0.07101 (-0.93)		0.21093** (2.06)
Age 80–84		-0.21953* (-1.74)		-0.05418 (-0.43)		0.06780 (0.62)		0.40378*** (2.93)
Age 85–90		-0.58639*** (-5.92)				-0.07187 (-0.64)		1.05945*** (9.76)
Obesity		-0.03951 (-0.67)		-0.09075* (-1.84)		0.10298 (1.55)		0.04526 (0.79)
Forgo treatment due to costs		-0.15179** (-2.00)		-0.07331 (-1.01)		-0.11957** (-2.32)		0.09738 (0.87)
Age at first diagnosis		-0.00103 (-0.37)		-0.00012 (-0.04)		-0.00614** (-2.11)		-0.00386 (-1.28)
Consulted heart specialist recently		-0.00314 (-0.06)		-0.00965 (-0.21)		0.00843 (0.16)		-0.03416 (-0.62)
Wished treatment to be earlier		-0.09910 (-1.50)		-0.07328 (-1.24)		-0.04008 (-0.58)		0.04225 (0.66)
Constant	0.50586*** (17.89)	0.78993*** (3.94)	0.53515*** (23.67)	0.62590*** (2.86)	0.09373*** (3.23)	0.52357** (2.41)	0.13545*** (4.94)	0.15263 (0.80)
Prob > F	0.3962	0.0000	0.0040	0.0001	0.6332	0.4520	0.5751	0.0000
Observations	n=184	n=145	n=140	n=109	n=184	n=145	n=184	n=145

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.  $L_{ij}$  is defined as “probability of living after ten years”;  $l_{ij}$  is the adjusted version of  $L_{ij}$ ;  $l_{1,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 1;  $l_{0,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 0.

**Table 8**

Effect of waiting times on self-perceived life expectancy (emergency)

	$L_{ij}$		$l_{ij}$		$l_{1,ij}$		$l_{0,ij}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Waiting times (days)	-0.00111 (-0.59)	-0.00446*** (-2.82)	-0.00218** (-2.05)	-0.00351** (-2.56)	0.00052 (0.22)	-0.00228* (-1.80)	-0.00082 (-0.58)	0.00054 (0.28)
Male		0.13790** (2.49)		0.10313** (2.01)		0.04879 (0.93)		-0.09267 (-1.61)
High educated		0.05116 (0.59)		0.05692 (0.67)		-0.07579 (-0.97)		-0.07666 (-1.50)
ln(total household income)		-0.00924 (-0.60)		-0.00228 (-0.18)		0.00557 (0.35)		0.01908 (0.97)
Beveridge		-0.00185 (-0.03)		0.01172 (0.23)		-0.03722 (-0.66)		-0.00469 (-0.07)
Age 65–69		-0.14116* (-1.85)		-0.05616 (-0.79)		-0.19861*** (-3.10)		0.01637 (0.20)
Age 70–74		-0.11287 (-1.29)		-0.10671 (-1.46)		-0.09678 (-0.93)		-0.03218 (-0.50)
Age 75–79		-0.26855*** (-3.25)		-0.16819** (-2.06)		-0.19860*** (-3.03)		0.09105 (0.97)
Age 80–84		-0.12320 (-1.09)		-0.02115 (-0.20)		-0.14990** (-2.00)		0.06838 (0.50)
Age 85–90		-0.17528 (-1.10)		0.04416 (0.30)		-0.20727** (-2.61)		0.25320 (1.25)
Obesity		-0.10984* (-1.79)		-0.08841 (-1.56)		-0.01934 (-0.31)		0.12026 (1.38)
Forgo treatment due to costs		-0.12376 (-1.48)		-0.00010 (-0.00)		-0.12142*** (-2.66)		0.12063 (1.08)
Age at first diagnosis		-0.00205 (-0.81)		-0.00230 (-1.01)		-0.00064 (-0.36)		0.00007 (0.03)
Constant	0.44333*** (15.22)	0.70407*** (4.11)	0.45446*** (18.04)	0.61011*** (4.23)	0.08928*** (3.28)	0.22711 (1.31)	0.13225*** (4.36)	-0.02495 (-0.13)
Prob > F	0.5565	0.0017	0.0426	0.1274	0.8236	0.4683	0.5598	0.2596
Observations	n=141	n=123	n=110	n=97	n=141	n=123	n=141	n=123

Notes: \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.  $L_{ij}$  is defined as “probability of living after ten years”;  $l_{ij}$  is the adjusted version of  $L_{ij}$ ;  $l_{1,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 1;  $l_{0,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 0.

## Appendix IV: Regression tables from the complementary analysis

**Table 9**

Effect of long hospital wait on self-perceived general health

	Wave 5 (2013)				Wave 6 (2015)			
	Good health (US-scale)		Health not poor (US-scale)		Good health (US-scale)		Health not poor (US-scale)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long wait	-0.16126*** (-9.78)	-0.22837*** (-5.08)	-0.11935*** (-5.60)	-0.13599** (-2.46)	-0.14361*** (-9.96)	-0.11817** (-2.44)	-0.12622*** (-6.91)	-0.11427** (-2.03)
High cost		-0.24790*** (-4.57)		-0.35375*** (-4.47)		-0.00015 (-0.00)		0.00021 (0.00)
Interaction (Long wait*High cost)		0.24673** (2.50)		0.28174** (2.03)		0.00695 (0.07)		0.08964 (0.84)
Male		0.05075** (1.96)		0.05396** (2.20)		0.01101 (0.33)		0.10395*** (2.86)
High educated		0.06359 (1.62)		0.07524** (2.59)		0.13560** (2.29)		0.15641*** (3.28)
ln(total household income)		0.03645*** (4.52)		0.03199*** (4.29)		0.02273** (2.16)		0.02799*** (2.66)
Beveridge		0.02200 (0.83)		-0.00398 (-0.17)		-0.06396 (-1.42)		-0.00738 (-0.15)
Age		-0.00435*** (-2.86)		-0.00417*** (-2.82)		-0.00713*** (-4.06)		-0.00546*** (-2.70)
Obesity		-0.06983** (-2.52)		-0.06603** (-2.45)		0.00336 (0.09)		-0.03067 (-0.84)
Age at first diagnosis		0.00282*** (3.09)		0.00221** (2.35)		0.00400*** (3.72)		0.00377*** (2.86)
Constant	0.31762*** (47.13)	0.27385** (2.25)	0.72072*** (110.96)	0.69532*** (5.94)	0.30341*** (45.03)	0.45150*** (3.40)	0.72429*** (110.59)	0.60987*** (4.21)
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	n=5355	n=1429	n=5355	n=1429	n=5483	n=783	n=5483	n=783

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 10a**

Effect of long hospital wait on self-perceived mental health (Wave 5)

	Depression		Suicidal feeling		Fatigue		Irritability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long wait	0.14826*** (6.88)	0.16442*** (2.89)	0.06178*** (3.75)	0.13624*** (2.99)	0.18579*** (9.05)	0.21287*** (3.81)	0.18859*** (8.58)	0.19195*** (3.41)
High cost		0.26424*** (3.50)		0.11722* (1.73)		0.22012*** (2.79)		0.09976 (1.23)
Interaction (Long wait*High cost)		-0.01613 (-0.14)		-0.02424 (-0.19)		-0.23154* (-1.66)		0.12529 (0.93)
Male		-0.18373*** (-6.74)		-0.07487*** (-4.18)		-0.15813*** (-5.77)		-0.03160 (-1.22)
High educated		-0.00080 (-0.02)		-0.05167*** (-2.72)		0.00171 (0.04)		-0.07399** (-2.08)
ln(total household income)		-0.01501** (-1.81)		0.00471 (0.88)		-0.01813** (-2.19)		-0.01753** (-2.21)
Beveridge		-0.09429*** (-3.52)		-0.04638*** (-2.98)		0.04238 (1.54)		0.00435 (0.17)
Age		-0.00202 (-1.25)		0.00104 (1.00)		0.00100 (0.61)		-0.00447*** (-2.87)
Obesity		0.05054* (1.73)		0.02572 (1.33)		0.11025*** (3.72)		-0.00144 (-0.05)
Age at first diagnosis		0.00000 (0.01)		-0.00007 (-0.11)		-0.00000 (-0.01)		-0.00103 (-1.04)
Constant	0.46633*** (63.92)	0.78752*** (6.24)	0.11099*** (24.09)	0.05039 (0.58)	0.51229*** (70.08)	0.54685*** (4.29)	0.33497*** (48.53)	0.82108*** (6.81)
Prob > F	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	n=5253	n=1413	n=5222	n=1409	n=5250	n=1412	n=5251	n=1413

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 10b**

Effect of long hospital wait on self-perceived mental health (Wave 5)

	Appetite		Insomnia		Concentration on entertainment		Concentration on reading	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long wait	0.06891*** (4.01)	0.07896* (1.84)	0.16528*** (7.62)	0.14609** (2.55)	0.04558** (2.54)	0.11632** (2.40)	0.03743** (2.07)	0.13021** (2.51)
High cost		0.08875 (1.44)		0.06958 (0.88)		0.24399*** (3.16)		0.17997** (2.35)
Interaction (Long wait*High cost)		0.05383 (0.44)		-0.00670 (-0.05)		-0.10302 (-0.75)		-0.15823 (-1.14)
Male		-0.04641** (-2.57)		-0.21541*** (-7.91)		-0.02119 (-1.03)		-0.02402 (-1.10)
High educated		-0.04266** (-2.07)		-0.09171 (-2.43)		-0.11425*** (-5.31)		-0.04922 (-1.79)
ln(total household income)		-0.00379 (-0.75)		0.00085 (0.10)		-0.00052 (-0.08)		-0.00724 (-1.15)
Beveridge		0.01659 (0.94)		-0.05892** (-2.20)		0.02896 (1.41)		0.05043** (2.33)
Age		0.00001 (0.01)		-0.00149 (-0.92)		0.00241* (1.90)		0.00093 (0.68)
Obesity		-0.01832 (-1.01)		0.07727*** (2.62)		0.01814 (0.80)		0.04703* (1.93)
Age at first diagnosis		0.00071 (1.12)		-0.00004 (-0.04)		-0.00092 (-1.16)		-0.00065 (-0.81)
Constant	0.12447*** (25.82)	0.11133 (1.34)	0.43577*** (60.15)	0.63934*** (5.04)	0.16596*** (30.52)	0.04578 (0.46)	0.17761*** (31.72)	0.17217 (1.64)
Prob > F	0.0001	0.0000	0.0000	0.0000	0.0110	0.0000	0.0384	0.0004
Observations	n=5266	n=1415	n=5260	n=1414	n=5254	n=1414	n=5234	n=1405

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.



**Table 11a**

Effect of long hospital wait on self-perceived mental health (Wave 6)

	Depression		Suicidal feeling		Fatigue		Irritability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long wait	0.16064*** (8.50)	0.10582* (1.77)	0.06559*** (4.67)	0.09075** (2.01)	0.11615*** (6.19)	0.08304 (1.39)	0.13521** (7.03)	0.09449 (1.60)
High cost		0.03224 (0.38)		0.17264** (2.30)		0.04335 (0.53)		-0.00080 (-0.01)
Interaction (Long wait*High cost)		0.15091 (1.30)		-0.16599 (-1.62)		0.04618 (0.40)		-0.05259 (-0.46)
Male		-0.18848*** (-4.95)		-0.07767*** (-2.86)		-0.13576*** (-3.52)		0.04330 (1.15)
High educated		-0.06302 (-1.01)		-0.04058 (-1.14)		-0.20070*** (-3.49)		-0.09829* (-1.67)
ln(total household income)		0.00590 (0.49)		0.00009 (0.01)		-0.00914 (-0.79)		-0.02814** (-2.41)
Beveridge		0.00077 (0.01)		-0.04246 (-1.41)		0.04147 (0.74)		0.06906 (1.26)
Age		0.00044 (0.21)		0.00144 (0.96)		0.00549*** (2.61)		-0.00347 (-1.62)
Obesity		0.02174 (0.55)		0.06401** (2.27)		0.03852 (0.98)		0.02744 (0.70)
Age at first diagnosis		-0.00199 (-1.43)		-0.00032 (-0.33)		-0.00321** (-2.24)		-0.00068 (-0.47)
Constant	0.46628*** (61.71)	0.61032*** (4.02)	0.09979*** (21.98)	0.05573 (0.54)	0.52570*** (69.49)	0.43930*** (2.91)	0.32890*** (46.20)	0.77187*** (5.05)
Prob > F	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0194
Observations	n=5140	n=721	n=5139	n=721	n=5137	n=721	n=5137	n=721

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 11b**

Effect of long hospital wait on self-perceived mental health (Wave 6)

	Appetite		Insomnia		Concentration on entertainment		Concentration on reading	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long wait	0.03178** (2.20)	0.01917 (0.45)	0.17271*** (9.06)	0.14899** (2.58)	0.05118*** (3.29)	0.09441* (1.86)	0.06502*** (3.96)	0.01229 (0.26)
High cost		0.05849 (0.85)		0.04018 (0.45)		0.10451 (1.48)		0.10154 (1.38)
Interaction (Long wait*High cost)		-0.05930 (-0.62)		0.00144 (0.01)		-0.10559 (-1.03)		0.01171 (0.11)
Male		-0.04248 (-1.48)		-0.15637*** (-4.09)		-0.09591*** (-3.15)		-0.08840*** (-2.73)
High educated		-0.08751*** (-2.73)		-0.05024 (-0.83)		-0.04679 (-1.16)		-0.04554 (-1.01)
ln(total household income)		0.00035 (0.04)		-0.00107 (-0.09)		-0.00512 (-0.59)		0.00229 (0.24)
Beveridge		0.05490 (1.26)		-0.02817 (-0.52)		0.10418** (2.18)		0.10576** (2.16)
Age		0.00331* (1.93)		0.00552** (2.64)		0.00529*** (3.19)		0.00339* (1.83)
Obesity		-0.02039 (-0.74)		-0.04514 (-1.15)		-0.00039 (-0.01)		0.04616 (1.41)
Age at first diagnosis		-0.00129 (-1.22)		-0.00372** (-2.60)		-0.00097 (-0.87)		-0.00082 (-0.70)
Constant	0.13873*** (26.50)	0.01261 (0.11)	0.42857*** (57.18)	0.36323** (2.39)	0.15780*** (28.58)	-0.08209 (-0.72)	0.17529*** (30.39)	0.01081 (0.09)
Prob > F	0.0279	0.0278	0.0000	0.0000	0.0010	0.0001	0.0001	0.0014
Observations	n=5141	n=721	n=5141	n=721	n=5140	n=721	n=5121	n=718

**Notes:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.

**Table 12:**  
Effect of long hospital wait on self-perceived life expectancy (Wave 5)

	$L_{ij}$		$l_{ij}$		$l_{1,ij}$		$l_{0,ij}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long wait	-0.02306 (-1.53)	-0.01322 (-0.37)	-0.03399** (-2.54)	-0.04301 (-1.39)	0.01336 (0.93)	0.01468 (0.39)	0.00593 (0.41)	-0.03217 (-1.14)
High cost		-0.12904** (-2.16)		-0.12731** (-2.37)		0.01074 (0.17)		0.08997 (1.32)
Interaction (Long wait*High cost)		0.01253 (0.12)		0.05633 (0.54)		-0.06294 (-0.63)		0.00284 (0.03)
Male		0.01396 (0.77)		0.00414 (0.25)		-0.00714 (-0.39)		-0.03096* (-1.83)
High educated		-0.00091 (-0.04)		0.01730 (0.74)		-0.04770** (-2.03)		-0.01347 (-0.67)
ln(total household income)		-0.00142 (-0.26)		-0.00435 (-0.88)		-0.00252 (-0.43)		-0.00653 (-1.45)
Beveridge		0.03041* (1.71)		0.02149 (1.32)		-0.00701 (-0.38)		-0.03401** (-2.16)
Age 65–69		-0.03404 (-1.30)		-0.03342 (-1.43)		-0.01133 (-0.36)		0.00658 (0.34)
Age 70–74		-0.05961** (-2.29)		-0.02674 (-1.14)		-0.08469*** (-3.05)		0.00302 (0.14)
Age 75–79		-0.19765*** (-7.08)		-0.12550*** (-4.83)		-0.14031*** (-5.37)		0.05240** (2.08)
Age 80–84		-0.22237*** (-6.77)		-0.16593*** (-5.46)		-0.09502*** (-2.99)		0.09154*** (2.69)
Age 85–90		-0.33319*** (-6.89)		-0.15393*** (-3.06)		-0.14824*** (-3.98)		0.30056*** (4.99)
Obesity		-0.05813*** (-2.93)		-0.05492*** (-3.03)		-0.02188 (-1.08)		0.00049 (0.03)
Age at first diagnosis		0.00108 (1.57)		0.00039 (0.62)		0.00101 (1.56)		-0.00050 (-0.72)
Constant	0.49342*** (100.23)	0.56421*** (10.40)	0.49646*** (112.29)	0.58599*** (11.96)	0.09180*** (20.53)	0.14964*** (2.53)	0.09923*** (21.34)	0.15560*** (3.25)
Prob > F	0.1271	0.0000	0.0111	0.0000	0.3530	0.0000	0.6813	0.0000
Observations	n=4676	n=1295	n=3773	n=1033	n=4676	n=1295	n=4676	n=1295

Notes: \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.  $L_{ij}$  is defined as “probability of living after ten years”;  $l_{ij}$  is the adjusted version of  $L_{ij}$ ;  $l_{1,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 1;  $l_{0,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 0.

**Table 13**

Effect of long hospital wait on self-perceived life expectancy (Wave 6)

	$L_{ij}$		$l_{ij}$		$l_{1,ij}$		$l_{0,ij}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long wait	-0.02842** (-2.17)	-0.03591 (-0.96)	-0.01485 (-1.25)	-0.03083 (-0.85)	-0.01036 (-0.90)	-0.02678 (-0.82)	0.02255* (1.80)	-0.00392 (-0.12)
High cost		-0.00632 (-0.11)		-0.04301 (-0.84)		0.00075 (0.01)		-0.05603 (-1.38)
Interaction (Long wait*High cost)		0.04998 (0.65)		0.07359 (1.03)		-0.00591 (-0.09)		0.01782 (0.30)
Male		0.08022*** (3.37)		0.05745** (2.60)		-0.00315 (-0.14)		-0.08180*** (-3.60)
High educated		0.04803 (1.30)		0.06245 (1.84)		-0.01787 (-0.48)		0.00458 (0.13)
ln(total household income)		-0.00271 (-0.38)		0.00028 (0.04)		0.00909 (1.20)		0.01585*** (2.63)
Beveridge		0.11427*** (3.20)		0.02908 (0.86)		0.12081*** (2.78)		-0.07200*** (-3.44)
Age 65–69		-0.07240** (-2.12)		-0.04914 (-1.56)		-0.04849 (-1.47)		0.01202 (0.49)
Age 70–74		-0.09883*** (-2.76)		-0.07503** (-2.29)		-0.04027 (-1.14)		0.03441 (1.15)
Age 75–79		-0.22772*** (-6.67)		-0.16334*** (-4.90)		-0.08612*** (-3.12)		0.10567*** (2.82)
Age 80–84		-0.26395*** (-5.88)		-0.18178*** (-4.18)		-0.06133 (-1.58)		0.20068*** (3.61)
Age 85–90		-0.35599*** (-5.80)		-0.22504*** (-3.23)		-0.06049 (-1.27)		0.32081*** (4.03)
Obesity		-0.00291 (-0.12)		0.01099 (0.50)		-0.01200 (-0.55)		0.01441 (0.63)
Age at first diagnosis		0.00323*** (3.73)		0.00270*** (3.11)		0.00060 (0.87)		-0.00149 (-1.47)
Constant	0.50474*** (103.92)	0.38337*** (6.38)	0.50040*** (116.04)	0.37754*** (6.50)	0.09534*** (20.73)	0.04204 (0.71)	0.08652*** (19.65)	0.07977 (1.38)
Prob > F	0.0301	0.0000	0.2121	0.0000	0.3662	0.1423	0.0721	0.0000
Observations	n=4786	n=689	n=3907	n=564	n=4786	n=689	n=4786	n=689

Notes: \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets. OLS regressions with robust standard errors. Even-numbered columns report results from bivariate regression without control variables; odd-numbered columns report results from multivariate regression with control variables.  $L_{ij}$  is defined as “probability of living after ten years”;  $l_{ij}$  is the adjusted version of  $L_{ij}$ ;  $l_{1,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 1;  $l_{0,ij}$  is a binary outcome variable equals to one if the respondent stated his/her probability of living after ten years = 0.

## Appendix V: Results from the sensitivity analysis

**Table 14**

Re-estimated effects of different waiting time measures on health

Health outcomes	Non-emergency waiting time (weeks)		Emergency waiting times (days)	
	OLS	Probit	OLS	Probit
Good health (EU-scale)	0.01030* (1.70)	0.01115** (2.02)	-0.00323** (-2.17)	-0.00322* (-1.66)
Good health (US-scale)	0.01699*** (3.48)	0.01910*** (3.15)	-0.00408*** (-2.66)	-0.00536** (-2.05)
Health not poor (EU-scale)	0.00360 (0.80)	0.00245 (0.49)	-0.00379 (-1.12)	-0.00397 (-1.16)
Health not poor (US-scale)	0.00679** (2.36)	0.00858* (1.87)	-0.00582 (-1.66)	-0.00589* (-1.72)
Chest pain	0.00644 (0.93)	0.00647 (0.99)	-0.00394 (-1.01)	-0.00393 (0.273)
Breathlessness	0.00269 (0.42)	0.00353 (0.65)	0.00111 (0.34)	0.00112 (0.34)
Depression	-0.00877 (-1.43)	-0.00984 (-1.40)	0.00510*** (3.06)	0.00750** (2.25)
Depression (Wave 2)	0.00928** (2.63)	0.01189*** (3.06)	0.00095 (0.36)	0.00146 (0.44)
Suicidal feeling	0.00470 (0.91)	0.00320 (1.11)	0.00170 (0.56)	0.00210 (0.71)
Suicidal feeling (Wave 2)	-0.00128 (-0.87)	-0.0007 (-1.23)	-0.00100 (-0.49)	-0.00011 (-0.05)
Fatigue	-0.00689 (-1.06)	-0.00703 (-1.07)	0.00563*** (2.93)	0.00708** (2.35)
Fatigue (Wave 2)	0.00565* (1.97)	0.00628* (1.68)	0.00483** (2.39)	0.00971** (2.37)
Irritability	-0.00368 (-0.70)	-0.00404 (-0.73)	0.00878*** (3.93)	0.01130*** (2.81)
Irritability (Wave 2)	0.00171 (0.54)	0.00167 (0.46)	-0.00376 (-1.11)	-0.00447 (-1.25)
Appetite	0.00026 (0.06)	-0.00013 (-0.04)	0.00435 (1.37)	0.00454** (2.38)
Appetite (Wave 2)	0.00399 (1.25)	0.0000 (0.12)	-0.00094 (-0.45)	-0.00074 (-0.29)
Insomnia	-0.00527 (-0.87)	-0.00544 (-0.87)	0.00795*** (4.51)	0.01069*** (2.94)
Insomnia (Wave 2)	0.00039 (0.09)	-0.00003 (-0.01)	0.00379 (1.41)	0.00453 (1.32)
Concentration on entertainment	0.00330 (0.54)	0.00272 (0.59)	0.00255 (0.84)	0.00247 (0.99)
Concentration on entertainment (Wave 2)	0.00093 (0.24)	0.00063 (0.23)	0.00071 (0.27)	0.00160 (0.60)
Concentration on reading	-0.00147 (-0.28)	-0.00124 (-0.24)	0.00356 (0.93)	0.00363 (1.14)
Concentration on reading (Wave 2)	0.00511 (1.48)	0.00512 (1.59)	-0.00152 (-0.75)	-0.00163 (0.53)
Probability of living after ten years	0.00076 (0.12)		-0.00176 (-0.89)	
Probability of living after ten years (adjusted)	-0.00623* (-1.68)		-0.00246** (-2.06)	
Probability of living after ten years = 0	-0.00442 (-1.14)	-0.00637 (-1.36)	-0.00037 (-0.24)	0.00024 (0.24)
Probability of living after ten years = 1	0.00631 (0.99)	0.00530* (1.66)	-0.00018 (-0.08)	-0.00014 (-0.05)

**Note:** \*p<0.10, \*\*p<0.05, \*\*\*p<0.01. t-statistics in brackets for linear probability model (LPM), z-statistics in brackets for Probit model. Coefficients in columns named "OLS" are the estimated effects of (1) non-emergency waiting times and (2) emergency waiting times on health outcomes obtained from OLS-regression; Coefficients in columns named "Probit" are the estimated marginal effects of (1) non-emergency waiting times and (2) emergency waiting times on health outcomes after probit regression.